Innovation Diffusion within Organizations

Word of mouth and the effectiveness of intra-organizational innovation implementation

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Innovation Diffusion within Organizations

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Invitation

for attending the public defense of the thesis

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Word of mouth and the effectiveness of intra-organizational innovation implementation

On Friday, March 13th 2015 at 12:30 hrs in the aula of the Radboud University Nijmegen, Comeniuslaan 2 in Nijmegen.

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Preface

During my studies at the University of Mannheim, Germany, I chose production and operations management as one of my majors. One of the core lectures of this major was system dynamics. I still remember how I sat in the train from Mannheim back home to Zwickau, trying to solve the first exercise of this course. It took me almost the entire travel, comprising almost six hours, to build and analyze my first simulation model of a so-called “aging chain”, a model that simulates the development of different age cohorts within a population. From that time on, I was fascinated by the ability of computer simulation models to structure, analyze, and ultimately improve real-world systems.

My positive experiences with system dynamics in the course of my studies encouraged me to use system dynamics as the underlying methodology of my diploma thesis which is entitled “Impact of the communication structure on the implementation of innovations”. It analyzes how objective and subjective information influences the implementation of an innovation within a specific communication structure. While writing my diploma thesis, I realized that the available time and scope only permitted me to touch briefly on some issues regarding the implementation of innovations. Even though most of my friends told me beforehand that after completing their theses they were fed up with research, I, instead, felt the urge to take it to the next level by broadening and deepening the scope of my research of innovation implementation processes. Therefore, I did not hesitate when I was offered the opportunity to pursue a PhD at the renowned system dynamics group of the Radboud University Nijmegen, the Netherlands.

The results of my PhD research over the past four years are documented in this book. On the following pages, this dissertation aims to contribute to a better understanding of why many organizations fail to implement necessary innovations, while others succeed in doing so. To achieve this goal, this research analyzes how four different factors that influence the word of mouth about an innovation affect the implementation of this innovation within an organization. Inspired by my diploma thesis, I chose to examine the communication structure within an organization in greater detail. The influence of peers, employees’ intolerance of ambiguity, and senior management’s influence constitute the other three factors analyzed in this dissertation. In particular, it is examined how different combinations of these four factors affect the word of mouth about an innovation within an organization and thereby the likelihood that this innovation is accepted and used by the employees of that organization.

To analyze the influence of these factors on the intra-organizational innovation implementation process, this research introduces a system dynamics model
which simulates the diffusion of an innovation within an organization. Research has shown that intense communication between employees might signal a high uncertainty among employees regarding an innovation’s profitability. The simulation results of this dissertation suggest that it is precisely during such periods that senior management should concentrate its efforts on limiting the negative word of mouth of employees who do not use the innovation, instead of promoting employees who do already use it and spread positive word of mouth about it. This approach improves the likelihood that the innovation diffuses throughout the whole organization. The simulation results of this dissertation also suggest that groups of employees using the innovation should communicate with each other, while groups of employees that do not yet use the innovation should be isolated from each other. In addition, senior managers should focus their efforts on groups of employees that are peripherally located and proximate to each other because those groups are easier to convince than a set of very central and dispersed groups. However, the analysis of simulations of different communication structures indicates that under some circumstances (e.g., highly centralized structures) the proximity of influenced groups is much more important than their peripheral location.

Specifying the research questions of a dissertation, building a dynamic simulation model, and analyzing the simulation results constitute an iterative process. Many times I adjusted my research questions and/or improved the structure of my model, making it necessary to start my analyses again. I would like to thank everyone who supported me on this long and sometimes bumpy road. I apologize for not listing everybody. A few individuals played a major role in making this book happen. First of all, I would like to thank my supervisors Jac Vennix and Andreas Größler who have always been very approachable and invaluable discussion partners whenever I ran into a dead end. The same holds for my friend Bert van Nistelrooij with whom I had the pleasure to share an office and who served as an excellent devil’s advocate. I would also like to thank my other colleagues at the Radboud University Nijmegen, Etienne Rouwette, Hubert Kozlitius, Hendrik Stouten, Inge Bleijenbergh, Marleen McCardle, Sandrino Smeeets, Vincent de Gooyert, Stephan Raaijmakers, Eric Jacobs, Brigit Fokkinga, Ad van Deemen, Rick Aalbers, Vincent Marchau, and Piet Verschuren for their support and the pleasant work environment.

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stability and motivation to pursue my PhD. I want to specifically thank my mother for putting her family always first and supporting it wherever she can, my dad for his valuable advice and motivating encouragement, my dear brother for being my best friend, and my wonderful girlfriend for bringing so much love, warmth, and light into my life.

Philipp Wunderlich
Nijmegen, November 2014
1. Using multidimensional models to analyze the impact of social communication on the effectiveness of intra-organizational implementation processes

The intensification of competition and the rapid evolution of technology necessitate a frequent implementation of innovations within organizations (Choi & Chang, 2009, p. 245). In addition, a growing number of customers expect from firms to act ecologically and socially responsible. These circumstances force enterprises to adopt and implement innovations even beyond their core businesses. Nevertheless, the results of innovation implementation processes are in many cases not satisfactory (Klein, Conn, & Sorra, 2001, p. 811). For example, Aiman-Smith and Green (2002, p. 421) stated that a 47% failure rate of new technology implementations “is a major concern of U.S. manufacturing managers and researchers.” Similarly, Chen, Law, and Yang (2009) mentioned a survey which found that 40% of enterprise resource planning projects failed to meet the business case. For some types of change projects, failure rates of two-thirds and more are common (Burnes, 2004, p. 886). Unsuccessful implementation efforts not only waste time and resources, but might even jeopardize organizational survival. In order to remain competitive, implementing new practices promptly and successfully is vital for organizations, especially in rapidly changing industries such as telecommunications and media and entertainment.

Several studies have shown that an organization’s failure to benefit from an adopted innovation can often be attributed to an inadequate implementation process rather than to the innovation itself (Aiman-Smith & Green, 2002, p. 421; Gary, 2005, p. 644; Karimi, Somers, & Bhattacherjee, 2007, p. 123; Klein & Sorra, 1996, p. 1055). In addition, the degree of implementation success is considered to be a better indicator for innovation quality than the degree of adoption success, due to the fact that not all adopted innovations get ultimately implemented (Karimi et al., 2007, p. 103). For those reasons, the organizational implementation phase, which is defined as the critical period between an organization’s decision to adopt an innovation and its routine usage (Klein & Sorra, 1996, p. 1057; Rogers, 2003, p. 435; Simpson & Dansereau, 2007), has received increasing attention by scholars.

However, despite the growing number of studies that identify multiple causes of unsuccessful implementation processes, literature is lacking multidimensional models that explain the difference between successful and unsuccessful implementation efforts. Such models should take into account multiple and to some extent interrelated drivers of implementation success (Dean Jr. & Bowen, 1994, p. 393; Klein et al., 2001, p. 811; Klein & Sorra, 1996,
Chapter 1

p. 1056; Repenning, 2002, p. 110). Greenhalgh, Robert, Bate, Macfarlane, and Kyriakidou (2005, p. 135) criticized that much literature implicitly assumes that “the determinants of innovation can be treated as variables whose impact can be isolated and independently quantified.” They stated, however, that more recent studies suggest that “in reality the different determinants of organizational innovativeness interact in a complex way with one another” (Greenhalgh et al., 2005, p. 135).

In response to the call for multidimensional models, the overarching research question of this dissertation asks how several determinants of implementation effectiveness are interrelated and how combinations of these factors influence the intra-organizational implementation of an innovation. However, it is not the goal of this research to uncover and quantify empirical correlations. Neither is the goal to establish an all-encompassing theory or framework of factors influencing implementation effectiveness. Instead, this research focuses on the dynamics among a few well-established factors and their combined influence on implementation effectiveness in order to improve the understanding and effectiveness of intra-organizational implementation processes. To achieve this goal, the dissertation builds on empirical studies by combining their findings within a dynamic simulation model.

Since organizational change processes are “created, sustained, and managed in and by communications” (Ford & Ford, 1995, p. 560), this dissertation focuses on factors that pertain to the innovation-related communication within an organization. Thereby, this dissertation follows the Communication Constitutes Organizations (CCO) approach, which argues that “organizations can be conceptualized as fundamentally shaped by discourse” (Blaschke, Schoeneborn, & Seidl, 2012, p. 880). That is, organizational change processes are essentially driven by the dynamics of communication among organizational members (Kuhn, 2008). In particular, this dissertation focuses on four communication-related factors that influence implementation effectiveness: (i) the communication among employees, (ii) the influence of ambiguity intolerance on their communication behavior, (iii) the intra-organizational communication network among groups of employees, and (iv) the communication between senior management and employees.

With regard to the first factor, this dissertation contributes to implementation research by focusing not only on positive word-of-mouth communication but also on negative word-of-mouth communication. In light of the current debate whether positive or negative word of mouth has a stronger impact on decision-makers (e.g., Berger & Milkman, 2012; Park & Lee, 2009), this research aims to answer the question how different strengths of positive and negative word of mouth influence implementation effectiveness. Considering the second factor,
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ambiguity intolerance, this research aims to shed light on the relationship between the perceived ambiguity of an innovation and the communication behavior among employees. Innovations are by definition new and therefore at least to some extent ambiguous. Since individuals are generally ambiguity intolerant (Ellsberg, 1961), ambiguity is considered to be a main driver of word-of-mouth communication (Abrahamson & Rosenkopf, 1997). However, the interrelation between the perceived ambiguity of an innovation and implementation effectiveness remains unclear. Therefore, this research asks how an innovation’s perceived ambiguity influences employees’ communication behavior and thereby implementation effectiveness.

The third factor broaches the issue of cross-border communication among different groups of employees, such as teams or departments. In implementation research the communication ties between organizational compartments have been largely ignored due to the fact that they are relatively weak compared to the communication relations within groups (Damanpour, 1996; Repenning, 2002). However, network research has shown that weak ties between groups serve as important bridges which provide access to otherwise unavailable information (Grannovetter, 1973). Therefore, this dissertation aims to contribute to implementation research by examining how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness. The fourth factor accounts for senior management’s influence on employees. In particular, this research aims at finding a decision rule which tells senior management what groups within the communication network it should concentrate on in order to ensure an effective and efficient innovation implementation.

In order to address these issues, chapter 2 specifies the context of this research by providing a literature review on intra-organizational innovation implementation. Section 2.1 describes on what innovations this research focuses and how the effectiveness of implementation processes is evaluated. Subsequently, section 2.2 reviews and categorizes factors that influence implementation effectiveness. Based on this literature review, chapter 3 derives the four central research questions of this dissertation and elaborates on the choice of system dynamics as the underlying methodology. In chapter 4, the first research question is addressed by introducing and analyzing a basic system dynamics model which accounts for positive and negative word-of-mouth communication. In chapter 5, this model is extended to incorporate the effects of an innovation’s perceived ambiguity on the communication behavior of ambiguity intolerant employees. By means of the resulting model, research question two is analyzed. Subsequently, chapter 6 extends the basic system
dynamics model of chapter 4 to analyze the third research question, concerning
the communication structure among organizational groups and its impact on
implementation effectiveness. Building on the model and the derived findings
of chapter 6, chapter 7 addresses research question 4 by examining senior
management’s influence on the implementation process. The dissertation closes
by summarizing and discussing the main findings of this research.
2. Literature review on the implementation of innovations within organizations

2.1. Innovations and organizational implementation processes

2.1.1. Classification of innovations

In everyday usage, the word *innovation* often describes an object such as a novel robot or an unprecedented pharmaceutical (Slappendel, 1996, p. 107). However, this object-related characterization of innovations is just one of several innovation types. Thus, Damanpour (1991, p. 556) defined the term *innovation* as the “adoption of an internally generated or purchased device, system, policy, program, process, product, or service that is new to the adopting organization.” This definition also emphasizes that the identification of innovations largely depends on the beholder. That is, whether something is considered to be novel or not depends on the status quo of the subject that is potentially adopting the innovation (Klein et al., 2001, p. 811). In Damanpour’s (1991) definition, the adopting subject is an organization but it can also be an individual, a town, or a state (Zaltman, Duncan, & Holbeck, 1973, p. 10). Since Rogers’ (2003, p. 36) definition also accounts for different subjects adopting an innovation, it is taken as a basis for this research: “An innovation is an idea, practice, or object perceived new by an individual or other unit of adoption.”

This dissertation focuses on organizations as the unit of adoption. On this level, it is often distinguished between *product* and *process innovations* (Damanpour & Gopalakrishnan, 2001; Utterback & Abernathy, 1975). According to Utterback and Abernathy (1975, p. 642), product innovations are new technologies or new combinations of existing technologies which are commercially introduced to meet customer needs. Process innovations, on the other hand, refer to the introduction of new elements into the task, decision, and information systems of organizations or into their physical production or service operations (Knight, 1967, p. 482). While product innovations are mainly customer driven, process innovations often aim at developing the production process towards higher productivity with regard to work force, material inputs, process equipment, work and information flows, task specifications, and other factors that are employed to produce a product or service (Utterback & Abernathy, 1975, p. 641). Research tends to distinguish between a supply and a demand perspective on product and process innovations (Bhoovaraghavan, Vasudevan, & Chandran, 1996). The demand perspective focuses on potential adopters of an innovation. From an adopter’s point of view, a product innovation represents a new technology or a new combination of existing technologies which is relatively discrete and self-contained. If the adopter is an organization, a product innovation is adopted by
this organization to meet the needs of its customers. A process innovation introduces new elements into already existing routines of an organization or replaces them altogether. It is adopted by an organization in order to improve its internal efficiency (Damanpour & Gopalakrishnan, 2001, p. 48).

On the other hand, the supply perspective concentrates on the creators of a product or process innovation. From a creator’s point of view, the distinction between product and process innovations is more ambiguous due to the fact that “any result that stems from process innovation can still appear to be a new product in the marketplace and be constructed as product innovation” (Bhoovaraghavan et al., 1996, p. 233). For example, flexible displays might only be the result of an upgraded production process for rigid displays. Nevertheless, flexible displays are likely to be framed in the context of product innovations. Therefore, this research suggests that most innovations comprise novel product as well as novel process elements and that product and process innovations in their pure forms represent only the two ends of a continuum (Bhoovaraghavan et al., 1996, p. 234; Noori, 1990, p. 107). Thus, from a supply perspective, the categorization of an innovation as a product or process innovation depends on which of the two types is more dominant.

Even though the distinction between product and process innovations seems to be less ambiguous from a demand perspective, it is by no means always clear as Damanpour and Gopalakrishnan’s (2001, p. 52) study showed. Asking experts to categorize 31 innovations in the banking sector, they stated that on average 85% or 83% of them agreed on the final categorization of product or process innovations, respectively. Nevertheless, the 15% or 17% disagreeing in this study suggest that there are innovations that comprise novel product as well as novel process elements, also from a demand perspective. In fact, the adoption of product innovations—such as, for example, electric engines—requires in many cases organizational process adjustments that are novel to the adopting firm (Amey, 1995; Dijk & Yarime, 2010). On the other hand, the adoption of process innovations—like, for instance, radio-frequency identification (RFID)—often inevitably results in novel products (Bunduchi, Weisshaar, & Smart, 2011; Lee, Fiedler, & Smith, 2008). Thus, novel process elements of an innovation are often inseparably interwoven with novel product elements of that innovation and vice versa, thereby blurring the boundary between product and process innovations (Evangelista & Sirilli, 1998, p. 254). Consequently, the classification of product and process innovations along a continuum seems also feasible from a demand perspective, even though both extremes of the continuum may be more likely than from a supply perspective. Therefore, this research uses the term product-process continuum of innovations to refer to the distinction between product and process innovations, independent of the underlying perspective (see Figure 1).
Innovations also differ with regard to their novelty. Within the literature, it is often distinguished between radical and incremental innovations (Carlo, Lyytinen, & Rose, 2011; Damanpour, 1996; Dewar & Dutton, 1986; Ettlie, Bridges, & O’Keefe, 1984; Leifer, McDermott, O’Connor, Peters, Rice, & Veryzer, 2000; McDermott & O’Connor, 2002; Zaltman et al., 1973). Radical innovations are characterized by a high degree of novelty, whereas incremental innovations enhance the state of the art only slightly. Similar to the product-process continuum of innovations, radical and incremental innovations also differ with regard to the perspective. From a supply perspective, “incremental innovations are typically extensions to current product offerings or logical and relatively minor extensions to existing processes, radical product innovations involve the development or application of significantly new technologies or ideas into markets that are either nonexistent or require dramatic behavior changes to existing markets” (McDermott & O’Connor, 2002, p. 424). Radical process innovations comprise unique and original changes in development tools, methods, teams and their structure, meaning that those changes largely depart from other alternatives at the time of invention (Carlo et al., 2011, p. 94).

From a demand perspective, the adoption of radical product or process innovations produces “fundamental changes in the activities of the organization and represents a large departure from existing practices” (Damanpour, 1996,
Radical innovations are frame-breaking at the time of adoption while incremental innovations result in a smaller deviation from existing organizational practices (Dahlin & Behrens, 2005; Damanpour, 1996, p. 699). Since radical innovations are usually less often adopted than incremental innovations, they are frequently referred to as discontinuous change while incremental innovations are often equated with continuous change. Irrespective of the distinction between demand and supply perspective, innovations run on a continuum from incremental to radical (Carlo et al., 2011, p. 94). Therefore, this research uses the term novelty continuum of innovations to refer to the distinction between radical and incremental innovations (see Figure 1).

Since the central theme of this dissertation is the implementation of innovations within organizations, the focus is on the demand perspective and thereby on organizations that adopt an innovation. From this perspective, the literature further subdivides product as well as process innovations. In the case of product innovations, it can be distinguished between tangible products, which are manufactured, and intangible services, which are produced and consumed simultaneously (Oke, 2007, p. 566; Song, Di Benedetto, & Song, 2000, p. 379; Wischnesky, Damanpour, & Méndez, 2011, p. 134). Process innovations, on the other hand, comprise technical and administrative innovations (Carlo et al., 2011, p. 94; Damanpour, 1996, p. 698; Damanpour & Evan, 1984). Technical innovations pertain to technologies which are used to produce products or render services that are directly related to the basic work activities of an organization (Gopalakrishnan & Damanpour, 1997, p. 19). Administrative innovations affect administrative processes, organizational structures, and human resources. They relate more directly to the management of an organization rather than to its basic work activities (Johns, 1993, p. 572). Even though Bunduchi et al. (2011, p. 506) distinguished between technological and organizational process innovation, their definitions are very similar to technical and administrative process innovations: “The term ‘technological process innovation’ refers to new products (such as new information systems) that are used in the production process, while ‘organizational process innovation’ (such as new management accounting methods) are new ways of organizing business activities.”

With respect to the outlined categorization of innovations, illustrated in Figure 1, the dissertation tends to concern rather radical innovations which comprise more process than product elements because those innovations have a higher impact on the organization as a whole. Besides the examples already pointed out by Bunduchi et al. (2011), a radical technical innovation is, for example, the introduction of an enterprise resource planning system (Hong & Kim, 2002; Umble, Haft, & Umble, 2003). Regarding radical administrative innovations, knowledge management systems (Alavi & Leidner, 2001) or management
information systems (Laudon & Laudon, 2002) are prevalent examples. Such radical process innovations usually impact the organization as a whole, leading to communication across functional and spatial boundaries. The greater the number of organizational members and subunits affected by an innovation, the higher the complexity of the implementation process (Leonard-Barton, 1988, pp. 611-612). Complex innovations entail greater work-related uncertainty and require greater amounts of communication because a successful implementation depends on the acceptance of the innovation within several subunits or groups (Fidler & Johnson, 1984, p. 709; Katz & Tushman, 1979, p. 141). Even though this dissertation tends to concern mainly innovations that entail a high implementation complexity, it is not exclusively focusing on them. In fact, the main focus of this research is not on the innovation itself but on the innovation process, namely the implementation phase of an innovation. The following section specifies the process-oriented distinction between the initiation and the implementation phase of intra-organizational innovation processes.

2.1.2. Evaluating the effectiveness of organizational innovation implementation processes

Schumpeter (1996, pp. 81-86) described innovation as a process of creative destruction which is continuously revolutionizing macro level markets and structures. The widespread sub-categorization of the innovation process into the consecutive phases of invention, innovation, as well as diffusion and imitation can also be attributed to Schumpeter (1939, pp. 84-102; Milling & Maier, 1996, p. 17). The invention phase is characterized by the discovery of a previously unknown solution to a problem. In form of an innovation, the invention is economically used for the first time during the innovation phase. In the subsequent diffusion and imitation phase, the innovation spreads through the market, thereby increasingly realizing the potential technological progress (Milling & Maier, 1996, pp. 17-18).

Within an organizational context, the innovation process is subdivided into two main processes: the initiation process and the implementation process (Rogers, 2003, p. 420; Zaltman et al., 1973, p. 58), which are similar to the stages mentioned in the previous paragraph (see Figure 2). The initiation process comprises the collection of information, the creation of concepts, the planning of the adoption process, and the final decision to adopt or disregard an innovation (Rogers, 2003, pp. 420-430). It consists of the two sub-processes agenda-setting and matching. The former starts with the occurrence of an organizational problem, which could lead to distress. This discrepancy between the desired and expected performance of an organization can initiate the innovation process. Thereupon, the problem is exactly defined. Within the subsequent process matching, an innovation is assigned to the problem in order to solve it.
In contrast to the initiation process, the implementation process comprises all events, activities, and decisions that ideally lead to a routine usage of an innovation (Klein & Sorra, 1996, p. 1057; Rogers, 2003, p. 180). It consists of the sub-processes redefining/restructuring, clarifying, and routinizing. Within the first sub-process of the implementation process, the innovation is adjusted to organizational needs as well as to the organizational structure. During the second sub-process, the innovation is increasingly understood and used by the members of the respective organization. Finally, the innovation loses its autonomous character and becomes fully integrated into the organization in the course of the last sub-process (Roger, 2003, p. 435).

Figure 2 The innovation process on an organizational level

Within the initiation process, Rogers (2003, p. 403) differentiated between three kinds of adoption decisions on an organizational level (organizational adoption decision). These innovation-decisions are either positive or negative, with the former approving the adoption of an innovation and the latter disapproving it. They represent a decision point which connects the initiation and the implementation process. In the case of an optional innovation-decision, an individual decides whether to adopt or disregard an innovation, independent of other members of the respective social system. A collective innovation-decision is based on the consensus of the members of a social system. In the case of an authority innovation-decision, a minority of the social system which is characterized by high social esteem, expert knowledge or power decides in favor of or against an innovation. This decision should then be accepted by all other organizational members.

Even though both, the initiation and the implementation process, have a substantial influence on the successful utilization of an innovation, the dissertation focuses on the internal implementation process of an organization,
as highlighted in Figure 2. Accordingly, this research assumes that the initiation process already occurred. Since the organizational adoption of a radical process innovation usually requires the approval of significant expenditures, the remainder of this dissertation assumes that the implementation process is initiated by an authority innovation-decision, which was made by senior management of an organization (Klein & Sorra, 1996, pp. 1063-1064, Lanzolla & Suarez 2012, p. 841; Rogers, 2003, p. 403). Klein and colleagues (Klein & Ralls, 1995; Klein & Sorra, 1996; Klein et al., 2001) stressed the difference between management’s adoption decision and the implementation of an innovation. While “[i]nnovation adoption refers to an organization’s decision to install an innovation within the organization” (Klein et al., 2001, p. 811), the implementation of an innovation describes “the transition period during which targeted organizational members ideally become increasingly skillful, consistent, and committed in their use of an innovation” (Klein & Sorra, 1996, p. 1057). The implementation of an innovation is by no means the direct consequence of its adoption (Rogers, 2003, p. 402). Instead, “adopted policies may never be put into action and adopted technologies may sit in unopened crates on the factory floor” (Klein & Ralls, 1995, pp. 32-33).

In order to distinguish between successful and unsuccessful implementation efforts, it is necessary to select at least one significant measure of implementation success. Karimi et al. (2007, p. 108) evaluated implementation success by measuring the effectiveness, efficiency, and flexibility of business processes, arguing that the first-order effects of an implemented innovation occur at the operational level of an organization. Since this dissertation does not empirically measure the implementation success within organizations, it evaluates the performance of the implementation process by using implementation effectiveness as a proxy measure (Helfrich, Weiner, McKinney, & Minasian, 2007; Klein & Sorra, 1996). This measure implies that there is a strong positive correlation between implementation effectiveness and implementation success which has been confirmed by empirical studies (Choi & Chang, 2009, p. 251; Klein et al., 2001, p. 821). The higher implementation effectiveness, the greater implementation success, which is, among others, characterized by visible benefits from the innovation as well as by the routinization of the innovation among employees (Choi & Chang, 2009, pp. 249-251).

After selecting implementation effectiveness as a measure of implementation success, implementation effectiveness itself needs to be characterized. In implementation research, there has been a general consensus that the effective implementation of an innovation largely depends on its quality of use by targeted end-users (e.g., Douglas & Judge Jr., 2001, p. 165) Hence, Rogers (2003, p. 20) stated that “[i]mplementation takes place when an individual puts an
innovation into use.” Similarly, Leonard-Barton (1988, p. 611) and Leonard-Barton and Deschamps (1988, p. 1252) pointed out that an innovation must be accepted and used by targeted employees in order to be successful. Therefore, implementation effectiveness and innovation use have often been used synonymously (Choi & Chang, 2009; Damschroder et al., 2009; Helfrich et al., 2010). This suggests that the implementation effectiveness is higher, the greater the percentage of targeted employees that use the innovation. Another aspect was introduced by Aiman-Smith and Green (2002, p. 422) who evaluated organizational implementation effectiveness by means of user speed to competence and user satisfaction. Thus, implementation effectiveness is higher, the sooner an innovation can be productively used and the more satisfied its users are. In addition, Klein and Sorra (1996, p. 1059) highlighted the importance of a sustainable implementation by describing implementation effectiveness as “the quality and consistency of the use of a specific innovation within an organization as a whole.”

From these approaches, this research derives a definition of implementation effectiveness. Since this dissertation focuses mainly on complex innovations that must be used by several employees across multiple organizational subunits, the first characteristic of implementation effectiveness considered in this research is the percentage of targeted employees that actually use the respective innovation. The spread of an innovation among targeted employees is a process of internal diffusion (Leonard-Barton & Deschamps, 1988, p. 1253). Therefore, the percentage of employees using an innovation can also be referred to as the level of diffusion. Hence, this research uses the level of innovation diffusion and the level of innovation implementation synonymously to describe the percentage of targeted employees that already adopted and use an innovation. The second characteristic of implementation effectiveness is the speed by which the innovation diffuses within the organization. The third characteristic considered in this research is the sustainability of the diffusion level. In summary, this research assumes that the implementation effectiveness of an innovation is higher, the quicker this innovation reaches a certain level of diffusion among targeted end-users and the longer this level is maintained. Thereby, the level of diffusion is specified as the percentage of targeted employees that adopted and use an innovation (Klein et al., 2001; Rogers, 2003). Since this research focuses exclusively on employees that are supposed to adopt and use an innovation, the terms targeted employee(s) and employee(s) are used interchangeably hereafter.

2.1.3. The individual innovation-decision process of employees
Considering that the implementation effectiveness of an innovation is characterized by its sustained usage among employees, it is crucial for the success of implementation
efforts that employees decide to adopt and use the innovation. In fact, Kim and Kankanhalli (2009, p. 567) mentioned a world-wide survey of 375 organizations which found that “user resistance is the first-ranked challenge for the implementation of large-scale IS [information systems], such as enterprise resource planning (ERP) systems.” Even though the management of an organization can try to force employees to use the new system, it cannot ensure that employees use it to its full potential due to asymmetric information between the management of an organization and its employees. Thus, Leonard-Barton and Deschamps (1988, p. 1253) stressed that the actual usage of an innovation is an internal diffusion process that depends on “numerous individual ‘secondary’ adoption decisions by target users even after successive layers of management have passed along the ‘authority decision’.” In those cases the attitude and commitment of employees essentially determine the extent and quality of use of an innovation, even if an authority, such as senior management, made the primary adoption decision and mandated employees to use the innovation (Choi & Chang, 2009, p. 252; Leonard-Barton & Deschamps, 1988, p. 1253). Therefore, “[s]uccessful innovation implementation depends upon acceptance by organizational members targeted as end-users of the innovation” (Leonard-Barton & Deschamps, 1988, p. 1252). Greenhalgh, Robert, MacFarlane, Bate, and Kyriakidou (2004) explained this significant role of end-users:

People are not passive recipients of innovations. Rather […], they seek innovations, experiment with them, evaluate them, find (or fail to find) meaning in them, develop feelings (positive or negative) about them, challenge them, worry about them, complain about them, ‘work around’ them, gain experience with them, modify them to fit particular tasks, and try to improve or redesign them—often through dialogue with other users. (p. 598)

In the implementation literature, the secondary adoption decision of each targeted employee has been described as one out of five phases within their individual innovation-decision process. The five phases are knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003, p. 170). According to Rogers (2003), the knowledge phase begins when an individual becomes aware of an innovation and gains a basic understanding of how it works. Provided that an individual perceives the innovation to be relevant and acquired enough information about it, the individual seeks social reinforcement from others during the persuasion phase and develops either a favorable or unfavorable attitude towards the innovation. By seeking information from others, an individual tries to reduce uncertainty about an innovation’s profitability. After an individual developed an attitude towards the innovation, that person
continues to seek and process innovation-related information in order to arrive at a decision whether to adopt or reject the innovation. This process is referred to as the decision phase. In case of a positive adoption decision, the individual puts the innovation into use during the implementation phase. In case of a negative adoption decision, the individual disregards the innovation. In the subsequent confirmation phase, the individual seeks reinforcement for the previously made adoption decision. If this individual encounters contradicting information, the previously made decision might change, resulting in the implementation of the updated adoption decision.

It is assumed that the individual innovation-decision process is iterative. That is, after an individual confirmed or disconfirmed a previous decision and implemented an updated decision, this person continues to be susceptible to contradicting information which challenges this person’s updated innovation decision. This implies that the updated innovation decision is not final and might change in the future, thereby accounting for individuals who alternate between using the innovation and other alternatives. The five phases of the individual innovation-decision process and their interplay are depicted in Figure 3.

The previous section briefly outlined the process of organizational innovation implementation which can be sub-divided into an initiation phase and an implementation phase. The organizational innovation-decision marks the end of the former and the beginning of the latter (see Figure 2). Within this dissertation, the focus is on the implementation phase, which is assumed to be
initiated by management’s authority decision to adopt an innovation within an organization. Implementation effectiveness is used to evaluate the success of organizational implementation processes. It is the higher, the greater the percentage of employees using the innovation, the quicker this level is reached, and the longer it is maintained.

This section contrasted management’s innovation-decision with the individual innovation-decision of employees. Even though senior management makes the initial adoption decision for the organization as a whole, the innovation still needs to be used by employees in order to be profitable for the organization (Klein & Sorra, 1996, p. 1058). However, the resistance of employees to use an innovation has been found to be the first-ranked challenge for its implementation within the respective organization. Whether an employee uses an innovation or not depends on the individual innovation-decision which is a process that comprises five phases: knowledge, persuasion, decision, implementation, and confirmation. Thus, the organizational innovation implementation process, as depicted in Figure 2, can be disaggregated into numerous individual innovation-decision processes, as depicted in Figure 3. If these individual innovation-decision processes result in a widespread and routine usage of an innovation on an organizational level, the implementation process has been successful. The following section focuses on factors that have an impact on the effectiveness of organizational implementation processes because they influence the individual innovation-decisions of employees.

2.2. Determinants of implementation effectiveness and implementation success

2.2.1. Theories comprising determinants of implementation effectiveness

Organizations regularly innovate internally. For instance, they introduce new IT systems, establish Total Quality Management (TQM) in manufacturing plants, or implement regulations to counter fraud and other professional misconduct. Such intra-organizational innovations, no matter whether they concern products or processes, are for many companies as important as a new product launch because a company can remain competitive only if it implements innovations that create value efficiently.

The success of such intra-organizational implementation processes depends on the continuous decisions of organizational members to use the innovation (Choi & Chang, 2009; Venkatesh, Morris, Davis, & Davis, 2003). However, the implementation of innovations in organizations frequently fails. That is, new products and processes are often not used as desired by management. As pointed out in chapter 1, Aiman-Smith and Green (2002, p. 421) stated that a 47%
failure rate of new technology implementations “is a major concern of U.S. manufacturing managers and researchers.” Similarly, Chen et al. (2009) mentioned a survey which found that 40% of enterprise resource planning projects failed to meet the business case. For some types of change projects, failure rates of two-thirds and more are common (Burnes, 2004, p. 886). As mentioned earlier, unsuccessful implementation efforts not only waste time and resources, but might even jeopardize organizational survival. In order to remain competitive, implementing new practices successfully and promptly is crucial for organizations, especially in rapidly changing industries.

In implementation literature, several factors which influence an employee’s attitude towards an innovation, and thereby its effective usage and implementation in the respective organization (Choi & Chang, 2009, p. 251), have been identified. Certainly, innovation-related characteristics, as introduced in section 2.1, are among them. However, most of those factors are already considered within the initiation phase (see Figure 2). If the benefit of the respective innovation is doubted within the initiation phase, the organizational innovation-decision will often be negative so that the innovation will not even reach the implementation phase. However, it could be argued that senior management, who makes the organizational innovation-decision, assesses the innovation differently from employees. Despite the possibility of such a discrepancy, several studies have shown that an organization’s failure to benefit from an adopted innovation can often be attributed to an inadequate implementation process rather than to the innovation itself (Gary, 2005, p. 644; Aiman-Smith & Green, 2002, p. 421; Karimi et al., 2007, p. 123; Klein & Sorra, 1996, p. 1055). Therefore, the dissertation focuses mainly on factors, which influence the implementation phase and are largely independent of innovation-specific characteristics.

In implementation research, there are several theories and frameworks which combine and categorize numerous factors that influence the implementation process of an innovation (Greenhalgh et al., 2005; Klein & Sorra, 1996; Meyers, Durlak, & Wandersman, 2012; Rogers, 2003; Stetler, Damschroder, Helfrich, & Hagedorn, 2011). With regard to specific determinants of implementation effectiveness, the Promoting Action on Research Implementation in Health Services (PARIHS) framework conceives of three categories of factors that determine the success of implementation efforts (Helfrich et al., 2010). First, the category evidence comprises factors related to the quality of codified and non-codified sources of knowledge. Second, the category context concerns factors regarding the quality of the environment in which an innovation is implemented. Third, the category facilitation includes factors which assist and enable others to implement the innovation by changing their attitudes, ways of thinking, habits, skills, and ways of working (Helfrich et al., 2010).
Similar to the PARIHS framework, the Consolidated Framework for Implementation Research (CFIR) provides an overarching typology which is meant to promote the development of implementation theory (Damschroder et al., 2009). Starting with Greenhalgh et al.’s (2004) conceptual model, the CFIR was developed by consolidating 19 different conceptual frameworks, including the PARIHS framework. It consists of five major categories: intervention—which comprises innovation-related factors, such as relative advantage, support, adaptability, trialability, and complexity; outer setting—focusing on factors with regard to the economic, social, and political context of the organization, such as incentives, user needs and resources, peer pressure, organizational connectedness and external policy; inner setting—including factors that influence the structural, cultural, and political context of the implementation, such as structural characteristics, networks and communications, implementation climate and culture; individuals—comprising personal attributes of actors, such as knowledge and beliefs about the innovation, tolerance of ambiguity and individual commitment; and implementation process—which refers to factors related to essential activities, such as the degree to which schemes and methods of behavior are developed, the extent to which individuals are attracted and involved, the quality of executing the implementation plan, and the extent and quality of feedback regarding the implementation (Damschroder et al., 2009; Powell et al., 2012, p. 130).

This research has been very valuable in combining and unifying the multiple terms and definitions used for similar elements of the implementation process. However, PARIHS and CFIR have their main focus on health services and have been developed against this background. Therefore, factors which are important in other domains might be missing (Meyers et al., 2012). In addition, both frameworks have been criticized for being of limited practical value. Stetler et al. (2011, “PARIHS limitations and related issues”, para. 1) stated that PARIHS provides a basic “to-do” list but that it lacks well-developed instrumentation and evaluation measures. Therefore, they reworked PARIHS and developed a guide that intents to optimize and enhance efforts of using PARIHS as a theoretical framework. Similarly, Powell et al. (2012, p. 130) enriched the CFIR framework by extracting and defining active implementation strategies from numerous studies in the health and mental health literature. Nevertheless, the focus of both frameworks is still on the health service domain.

Meyers et al. (2012, p. 462) reviewed literature (including literature on the PARIHS and the CFIR framework) from multiple domains and focused “on specific actions (i.e., the ‘how to’) that can be employed to foster high quality implementation.” They identified 14 critical steps that comprise four phases which form the Quality Implementation Framework (QIF). These four phases are: Initial Considerations Regarding the Host Setting, Creating a Structure for
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Implementation, Ongoing Structure Once Implementation Begins, and Improving Future Applications. Meyers et al. (2012, p. 471) tested their framework and found that the “strongest support, in terms of the quantity and quality of empirical studies, exists for the importance of training and on-going technical assistance.” The authors discussed the practical implication of QIF by applying its elements to the three systems of the Interactive Systems Framework for Dissemination and Implementation (ISF): the Synthesis and Translation System—which distills information about an innovation and prepares it for users and potential users; the Delivery System—which comprises those users and potential users; and the Support System—which provides on-going assistance to build and maintain the necessary capacities in the Delivery System (Wandersman et al., 2008). However, the QIF framework is less detailed than, for example, the CFIR framework and focuses more on critical questions that should be asked during each phase than on specifying determinants of implementation effectiveness (Meyers et al., 2012, pp. 469-470).

Despite recent advancements in combining and unifying implementation literature, there is still a lack of consistency in the terminology, especially in the health literature (Tabak, Khoong, Chambers, & Brownson, 2012, p. 347). In addition, implementation research has mainly focused on identifying factors that correlate with implementation effectiveness. Even though Damschroder et al. (2009, Results section, para. 1) stated that these factors “interact in rich and complex ways to influence implementation effectiveness”, the relationships between these factors has rarely been considered. Therefore, many authors have called for multidimensional models that take into account multiple and to some extent interrelated drivers of implementation success (Dean Jr. & Bowen, 1994, p. 393; Klein et al., 2001, p. 811; Klein & Sorra, 1996, p. 1056; Repenning, 2002, p. 110). As mentioned before, Greenhalgh et al. (2005, p. 135) criticized that much literature implicitly assumes that “the determinants of innovation can be treated as variables whose impact can be isolated and independently quantified.” However, more recent work suggests that “in reality the different determinants of organizational innovativeness interact in a complex way with one another” (Greenhalgh et al., 2005, p. 135).

Within literature, one of the few studies that accounts for the interactions between several factors is Choi and Chang’s (2009) innovation implementation research in the public sector. Choi and Chang (2009) argued that most implementation studies tend to focus either on employee-related factors, examining employees’ beliefs and reactions with regard to an innovation, or on institutional factors, focusing on the senior management, structure, and resources of the implementing organization. By combining employee-related and institutional factors, Choi and Chang (2009, p. 251) showed that the institutional factor
management support significantly improves the implementation effectiveness as well as the innovation effectiveness by strengthening the employee-related factor collective implementation efficacy, which was defined as “employees’ collective perception of the extent to which agency members as a group are capable of implementing the innovation.” The collective implementation efficacy, in turn, was found to increase the collective innovation acceptance of employees.

Following Choi and Chang (2009), this dissertation aims to contribute to existing implementation research by examining several employee-related and institutional determinants of implementation effectiveness. As illustrated in Figure 4, the dissertation aims to achieve this goal by combining the employee-related factors peer influence and ambiguity intolerance of employees with the institutional factors management influence and structural characteristics of the organization in order to analyze their interrelated influence on implementation effectiveness. In contrast to Choi and Chang (2009), the dissertation does not focus on the strength of causal relationships among these factors. Instead, the dynamics between several institutional and employee-related factors are of particular interest. Thus, it is not the goal of this dissertation to establish an all-encompassing theory or framework which comprises a comprehensive enumeration of factors influencing implementation success and effectiveness.

**Figure 4** Evaluating implementation success and implementation effectiveness by analyzing the combined influence of employee-related and institutional factors
and categorization of factors that influence the effectiveness of innovation implementation. Instead, only a limited set of well-established factors is chosen whose influences on the implementation process have been analyzed by empirical studies. The dynamics among those factors and their resulting impact on implementation effectiveness are the main interests of this dissertation.

This section reviewed literature with regard to factors that influence implementation effectiveness. Since implementation effectiveness is characterized by the percentage of targeted employees that use an innovation, factors that influence an employee’s innovation-decision process come to the fore. Recent studies have attempted to unify the large body of research that identified numerous such factors. Thereby, the focus of those frameworks has either been on comprehensiveness (e.g., Damschroder et al., 2009) or practicability (e.g., Meyers et al., 2012). However, in order to understand implementation processes better, it is necessary to not only analyze the impact of each factor by itself, but also consider the interrelation between multiple factors and their combined influence on an employee’s decision to use an innovation (Greenhalgh et al., 2004). Among the few studies that have considered the impact of and interrelation between several factors is Choi and Chang’s (2009) implementation study. Distinguishing between employee-related and institutional factors, they found that employees’ collective efficacy and innovation acceptance are mediators between institutional factors and implementation outcomes (Choi & Chang, 2009, p. 251). As depicted in Figure 4, this research follows Choi and Chang (2009) by simultaneously analyzing the influence of two employee-related (peer influence and ambiguity intolerance) and two institutional factors (management influence and structural characteristics of the organization) on an employee’s decision to use an innovation. In the following section, these factors are briefly introduced.

2.2.2. Social influence on implementation effectiveness

In order to identify factors that influence the effectiveness of an organizational implementation processes, previous sections have stressed the importance of an employee’s secondary adoption decision which describes a phase in the individual innovation-decision process. In contrast to the organizational implementation process, which is initiated by the decision of an authority to adopt an innovation within an organization (see Figure 2), the individual innovation-decision process is initiated when an individual comes to know the innovation (see Figure 3). Assuming that senior management is the authority that decides to implement an innovation within an organization, the knowledge phase of the individual innovation-decision process of an employee usually begins when senior management introduces the innovation to that employee. If
senior management did not address all targeted employees, the innovation-decision process of a targeted employee might also be initiated by hearing about the innovation from peers.

Rogers (2003, p. 172) stated that “[t]he innovation-decision process is essentially an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation.” Thus, after getting to know an innovation, an employee gathers and processes information in order to form an attitude towards it during the persuasion phase. Information is also sought and processed during the confirmation phase. Even though the persuasion phase and the confirmation phase differ in that the former describes the initial formation of an attitude while the latter describes its validation, they are similar in that each of the two phases forms the basis for the subsequent decision phase during which an employee decides whether to adopt or disregard the respective innovation (see Figure 3).

The decision of an employee to adopt or disregard an innovation is often also described as the individual’s intention, which may deviate from that person’s actual usage of the innovation. The actual usage of an innovation depends on the implementation phase of the individual innovation-decision process. Nevertheless, research has found a strong correlation between the intention to use and the actual usage of an innovation (Davis, Bagozzi, & Warshaw, 1989, p. 997; Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). Thus, on an individual level, a positive decision to adopt the innovation is often accompanied by a successful implementation phase. Therefore, the remainder of this research assumes that an employee’s actual behavior corresponds to the intended behavior. That is, an employee who decided to adopt an innovation actually uses it, while an employee who decided not to adopt an innovation does not use it. If the adoption decision changes in the course of the confirmation phase, the behavior of the respective employee also changes.

Since the outcome of each individual innovation-decision depends on the information the respective employee seeks and processes during the persuasion phase and the confirmation phase, this information might have a decisive impact on the effectiveness of intra-organizational implementation processes. Employees often seek such information from their social environment because the subjective opinions of others are more convincing and accessible than scientific evaluations of an innovation (Rogers, 2003, pp. 175-176). In addition, Wood and Bandura (1989, p. 362) pointed out that “virtually all learning phenomena resulting from direct experience can occur vicariously by observing people’s behavior and the consequences of it.” Thus, employees seek information from their social environment in order to learn from other employees’
experiences with the innovation. On the basis of the information obtained from an employee’s social environment, this person decides whether to adopt or disregard the respective innovation. For example, Rice and Aydin (1991, p. 238) found “that social information processing influences one’s attitudes toward a new organization information system, over and above traditional sources such as use of the system and occupational membership.” Thus, the social influence of others is a major predictor of an employee’s individual innovation-decision which determines the overall degree of diffusion within an organization and thereby the effectiveness of the respective implementation process.

Several studies have examined the social influence of others on the individual innovation-decision process of employees. It has been found that an individual’s search for information among others is not only spurred by the need to reduce uncertainty about an innovation’s profitability, as mentioned above, but also by the need to reduce uncertainty with regard to social norms. The perception of those norms by an individual is often described by the concept of subjective norm (e.g., Davis et al., 1989; Venkatesh & Davis, 2000). It has been argued that the subjective norm influences an individual’s decision in that it shapes that person’s perception of what behavior is expected from this individual by most other people who are important to him or her (Fishbein & Ajzen, 1975, p. 302). Karahanna, Straub, and Chervany (1999, p. 196) found that subjective norm is a significant predictor of an individual’s intention to adopt an innovation during the persuasion phase. Similar to subjective norm, the influence on an adopter’s image, defined as “the degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system” (Moore & Benbasat, 1991, p. 195), was also found to have a significant influence on the decision to adopt an innovation. However, the influence of image was only significant in the confirmation phase (Karahanna et al., 1999, p. 197).

Venkatesh et al. (2003, p. 451) comprised subjective norm and image under the category social influence, which was defined as the degree to which an employee perceives that important others think he or she should use the innovation. In their analysis they found that social influence is significant only when use is mandated (Venkatesh et al., 2003, p. 451). That is, the opinions and beliefs of others have a significant influence on an employee’s individual innovation-decision when that person is obligated to use the innovation. Since this research focuses on mandatory settings in which senior management made an authority decision to implement the innovation, the social influence of others is likely to play a key role in their individual innovation-decision processes.

When considering the social influence of others on the individual innovation-decision processes of employees, it is often distinguished between the influence of senior management and the influence of peers (Choi & Chang, 2009;
Karahanna et al., 1999; Repenning, 2002). Due to senior management’s power over employees, a senior manager has a higher influence on subjective norm than a regular employee, especially during the persuasion phase (Karahanna et al., 1999). In fact, “[t]op management is mostly considered the main driver of discontinuous change” (Raisch & Birkinshaw, 2008, p. 379). This is the case because senior management can effectively manipulate the institutional environment and thereby the behavior of employees by, for example, “instituting reward systems based on usage, and promoting compliance via direct surveillance” (Repenning, 2002, p. 113).

In addition, research has shown that senior management can improve the climate for implementation by supporting the innovation and by communicating a clear message to employees that using the innovation is important for the success of the organization, that it is normatively expected, and that it is rewarded (Choi & Chang, 2009, p. 246; Klein & Sorra, 1996, p. 1060; Klein et al., 2001, p. 822). If senior management succeeds in improving the implementation climate, implementation effectiveness is also likely to increase (Klein et al., 2001, p. 821). Similarly, Choi and Chang (2009, p. 247) found that management support improves the collective implementation efficacy which is defined as “employees’ collective perception of the extent to which agency members as a group are capable of implementing the innovation.” Collective implementation efficacy, in turn, is a meaningful predictor of employees’ innovation acceptance (Choi & Chang, 2009, p. 251), which is one of the three above-mentioned characteristics of implementation effectiveness.

Besides senior management, an employee also interacts with other employees in order to reduce uncertainty with regard to an innovation’s profitability, the social norm regarding its usage, and the impact of using the innovation on this person’s image (Karahanna et al., 1999; Rogers, 2003). The influence of peers on the individual innovation-decision process is especially distinct during the confirmation phase (Karahanna et al., 1999, p. 197). Similar to the interaction among consumers in a market, the interaction among employees can induce an epidemic-like diffusion of an innovation within an organization. Accordingly, Leonard-Barton and Deschamps (1988, p. 1253) described the intra-organizational implementation of an innovation as a process of internal diffusion. In general, the greater the number of adopters, the greater their social impact on the individual innovation-decision processes of non-adopters. As a result, some non-adopters convert to the adopter camp which increases the social impact of adopters even further, thereby creating a reinforcing feedback loop. The social impact of others on the individual innovation-decision process of targeted users has often been described as bandwagon pressure (Abrahamson & Rosenkopf, 1993), social contagion (Burt, 1987), imitation (Bass, 1969), learning (Abrahamson &
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Rosenkopf, 1997), interpersonal communication (Mahajan, Muller, & Bass, 1990), or word of mouth (Bass, 2004).

As mentioned above, the social influence of senior management and peers on the individual innovation-decision process of an employee is to a large extent driven by the innovation-related uncertainty of this employee. That is, an employee interacts with senior managers and other employees in order to reduce the perceived uncertainty surrounding the innovation (Karahanna et al., 1999; Rogers, 2003). In decision theory, a condition is defined as uncertain if possible outcomes of a decision and their respective probabilities are known to a decision-maker. However, if the probability of outcomes is uncertain, the context of decision-making is referred to as ambiguous (e.g., Camerer & Weber, 1992). Thus, Camerer and Weber (1992, p. 330) defined ambiguity as the “uncertainty about probability, created by missing information that is relevant and could be known.” With regard to the individual innovation-decision process of an employee, possible alternatives to the innovation are known, namely the status quo. Possible outcomes of the innovation-decision process are also known: the innovation is either more, equally, or less profitable than the status quo. However, since an innovation is by definition new, the likelihood of each outcome is at least to some extent uncertain. Therefore, the profitability of an innovation is often ambiguous. Research has shown that people are generally ambiguity intolerant (e.g., Ellsberg, 1961). Therefore, the more ambiguous they perceive an innovation to be, the more they try to reduce the perceived ambiguity by seeking additional information from their social environment (Ashford & Cummings, 1985; McPherson, 1983).

2.2.3. Organizational structure and complexity of social interaction processes

The previous section stated that employees communicate with senior management as well as with other employees to reduce the perceived ambiguity surrounding an innovation’s profitability and the related social norms. However, due to its superior organizational position, senior management’s influence on employees is mostly one-directional, depending only on the degree to which senior management’s goal has already been realized. That is, senior management approaches employees rather than employees approaching senior management. Instead, employees prefer to communicate with people that are similar to them, as will be shown in the following. Therefore, this section introduces the basic mechanisms that govern the interaction among employees. They are specified and analyzed in detail in chapter 4 of this research. The communication between senior management and employees is described and examined in chapter 7.

The likelihood that an employee interacts with another employee in an organization is not equal for everyone (Bohlmann, Calantone, & Zhao, 2010, p. 742). Instead, it depends on the social proximity between employees, which has
been defined as “the extent to which one could be exposed to social information in a given social system” (Rice & Aydin, 1991, p. 221). Rice and Aydin (1991) distinguished between relational, positional, and spatial proximity. Relational proximity refers to the extent to which individuals communicate with each other. The stronger the communication relation between two employees, the more proximate they are to each other. Positional proximity describes the extent to which individuals occupy the same roles. According to this view, employees do not need to communicate with each other in order to be proximate. Instead, the positional proximity between two employees increases with the similarity of their jobs. Finally, spatial proximity describes how close employees are to each from a physical point of view. For example, an employee in the same room is spatially more proximate than an employee in another room. Rice and Aydin (1991, p. 238) found that relational and positional sources have a greater influence than spatial sources. In line with previously mentioned research, they stated that “[t]he two primary sources of social information are those with whom one communicates frequently and one’s supervisor” (Rice and Aydin, 1991, p. 239).

According to these proximity measures, relevant others can be identified and grouped. In an organization, such a group of proximate others can, for example, be a team or department whose members usually communicate a lot with each other (relational proximity), have more or less similar job roles (positional proximity), and are often also located in the same area (spatial proximity). Hence, proximity describes to what extent individuals are similar to each other with regard to certain attributes. “People belong to the same groups because they have things in common” (Greenhalgh et al., 2005, p. 114). For example, the more two employees of a marketing department communicate with each other (relational proximity), the greater the similarity of information they are exposed to. In addition, they both work on projects which concern the marketing of a product or service and have therefore a similar set of obligations (positional proximity). Consequently, they often share the same office space (spatial proximity). Therefore, employees within the same team or department are usually very proximate to each other.

The degree to which interacting individuals are similar in certain attributes is often also referred to as homophily (Rogers, 2003, p. 19). For example, employees’ homophily is greater, the more they share the same values (Klein & Sorra, 1996, p. 1063). The more homophilous individuals are, the more likely they are to communicate with each other because homophily increases the effectiveness and perceived profitability of their communication (Greenhalgh et al., 2005, p. 115; Rogers, 2003, p. 19). Hence, homophily is also an indicator for the relational proximity between them. Similar to positional and spatial proximity, “homophily occurs when similar individuals belong to the same groups, live or work near
each other, and share similar interests” (Rogers, 2003, p. 19). Therefore, employees within the same team or department are often also homophilous.

On the one hand, the high relational proximity between members of the same team or department implies that communication ties within such a group are usually strong. On the other hand, employees of the same group are also homophilous because they work towards the same goal. Both concepts describe the resemblance among employees of the same group. A high homophily among organizational members of the same team or department entails a high relational proximity in terms of strong communication ties within a group (Goldenberg, Libai, & Muller, 2002; Granovetter, 1973, p. 1362; Rogers, 2003). The strong connection between members of the same group has a profound influence on an individual’s values, norms, and behavior by rewarding concordant and by penalizing deviant behavior (Rice & Aydin, 1991, p. 225). Therefore, the own group serves as a reference point for each member. The more proximate and homophilous employees of the same group are, the more effective the communication of new ideas with regard to “knowledge gain, attitude formation and change, and overt behavior change” (Rogers, 2003, p. 19). Consequently, the social influence of others is especially strong within groups. Hence, an employee is more likely to adopt and use an innovation if other group members are already adopters.

Similar to the diffusion across different countries (Putsis, Balasubramanian, Kaplan, & Sen, 1997), employees from different groups may also interact or mix. However, “individuals are often influenced more by within-segment than cross-segment communications” (Bohlmann et al., 2010, p. 745). One of the reasons is that employees from different groups are less similar (i.e., less proximate and/or homophilous) to each other and therefore less suitable reference points. For example, groups can differ with regard to their roles in the organization, their distinct backgrounds and traits, and their common interactions and experiences (Klein & Sorra, 1996, p. 1063). Consequently, the communication with other groups influences norms, values, and behavior to a lesser extent. Another reason for relatively weak ties between groups is the necessity to spend time cultivating relationships with other groups and processing the information received from them (Hansen, 1999, p. 85). Maintaining intergroup relations is generally more costly than cultivating intragroup relations (Boorman, 1975, p. 242). The additional costs of group-spanning communication may, for example, be the result of a less efficient communication due to the geographical distance and/or lower homophily between members from different groups (Rogers, 2003).

Even though connections between groups are less strong than within groups, weak ties serve as important bridges between groups because they are critical for a quick and complete diffusion (Brown & Reingen, 1987; Granovetter, 1973; Levin & Cross, 2004). That is, the removal of a weak tie bridging two groups
is more likely to limit communication possibilities within an organization than the removal of a strong tie within a group (Granovetter, 1973, p. 1366). In addition, it is more likely to receive non-redundant information when interacting with individuals from other groups than interacting with members of the same group. This is the case because members of other groups are less proximate and less homophilous than fellow group members (Burt, 1992, p. 29; Hansen, 1999, p. 85). Therefore, the communication network among organizational groups can decisively influence the implementation effectiveness of an innovation. For example, Bohlman et al. (2010, p. 751) found that “[t]he more difficult an innovation diffusion becomes […], the more significant the effect of the network structure on the diffusion process.”

Rogers (2003, pp. 5-6) defined diffusion in the seminal work Diffusion of Innovations as a process by which information is exchanged over certain communication channels between members of a social system. Innovations diffuse among actors of a social system or an organization through an existing or emerging set of relationships (Allen, 1977, pp. 234-265; Rogers, 2003, p. 5). Such a set of relationships forms a communication network. As outlined above, the communication network among groups is especially important since those rather weak ties are critical for the successful implementation of an innovation within an organization. Therefore, organizational change processes should always be placed within a context of communication in order to understand them better (Ford & Ford, 1995, p. 561). Kraatz (1998, p. 638), for example, stated that communication within social networks results in an adaptation of behavior among its members. As an example, he discussed that colleges organized in a network show the tendency to implement a particular bachelor program if a network partner successfully implemented it beforehand (Kraatz, 1998, p. 632). Kraatz (1998, p. 634) called this effect social learning through networks. Such indirect learning processes are characterized by learning from experiences of others. They do not only take place between organizations but also within them (Tsai, 2001, p. 996; Wood & Bandura, 1989, p. 362). As a result, communication networks also influence the individual innovation-decision processes of employees (Abrahamson & Rosenkopf, 1997, p. 293).

In implementation research, factors pertaining to the structure among intra-organizational groups have often been comprised in the category structural characteristics (Damschroder, 2009). The complexity of an organization, for example, has often been mentioned in implementation literature (Damanpour, 1996; Duncan, 1976). According to the ambidextrous model, a high complexity of an organization is promoting the initiation phase of an innovation, whereas a lower complexity is positively influencing the implementation phase (Damanpour, 1996, p. 699; Raisch & Birkinshaw, 2008, p. 380). This is the case because a higher
organizational complexity brings about a bigger variety and diversity of accessible information and proposals which facilitate the initiation of an innovation. However, a high organizational complexity also entails many different opinions. The resulting conflicts can therefore hamper the implementation of an innovation (Damanpour, 1996, p. 700).

In contrast to the ambidextrous model, Damanpour’s (1996, p. 712) multivariate meta-analysis identified an exactly opposite effect of organizational complexity on the innovation process, finding that “organizational complexity influences the implementation of innovations more positively than it influences the initiation of innovations.” The results also indicate that the innovation process is substantially influenced by the structural complexity of the organization. However, in contrast to the ambidextrous model, Damanpour’s (1996, p. 694) meta-analysis was not able to explain this counter-intuitive influence of organizational complexity, which was characterized by the extent of organizational subdivision into structural components and by the variety of specialists within an organization. Therefore, Damanpour (1996, p. 712) suggested that future studies should control for specific innovation types, use more elaborate stage models, or focus more on the process of innovation within each stage.

Damanpour’s (1996, p. 695) meta-analysis focused on the extent of horizontal complexity which was characterized by the degree of functional “departmentation” and by the extent of role specialization. That is, organizational complexity increases with the number of departments or teams within an organization. However, organizational complexity depends not only on the number of subunits or groups within an organization, the so-called variety of a complex system (Milling, 2002, p. 85). Besides the number of groups, the interrelatedness of the system, which rises with the complexity of the innovation itself (Black, Carlile, & Repenning, 2004), also defines the complexity of an organization. That is, organizational complexity increases also with the number of connections among groups. According to Milling (2002, p. 85), the degree to which groups are interconnected is called connectivity. Besides the variety and connectivity, the third dimension of complexity is the functionality of a system which describes the way elements are connected to each other (Milling, 2002, p. 85). Thereby, the complexity of the system increases exponentially as the connections among elements become more dynamic and nonlinear. This definition of complexity is in line with Sterman (2001, pp. 10-11) who described the connectivity of a system as combinatorial complexity and its functionality as dynamic complexity.

Even though this dissertation focuses on the implementation (demand perspective) and not on the initialization of innovations (supply perspective), it is worth noting that similar definitions of complexity are used with regard to the processes by which innovation occurs in an organization. Garud, Gehman,
and Kumaraswamy (2011, p. 738) suggested that innovation processes are complex because “innovation implicates actors across multiple levels of the organization […] who interact with one another […] across networks of practice communities.” They stated that most definitions of complexity attribute its emergence to the relational complexity of a system, which is characterized by combinations or interactions among heterogeneous elements. In addition, Garud et al. (2011, p. 739) named three other kinds of complexities: temporal, manifest, and regulative complexity. Temporal complexity describes the inherently dynamic nature of nonlinear and often imbalanced processes, which are driven by time delays, lags and differences in rhythms. Manifest complexity describes the difficulty of categorizing “the range of products and services that emerge from research, development and commercialization activities undertaken by the organization” (Garud et al., 2011, p. 739). Manifest complexity is higher, the greater the diversity of products and services. Such a diversity of forms can also emerge from the set of organizational rules or routines that govern how elements may be combined or used. Garud et al. (2011, p. 739) used the term regulative complexity to describe this meaning of complexity.

Comparing Garud et al.’s (2011) to Milling’s (2002) description of complexity, Garud et al.’s (2011) concept of relational complexity more or less comprises the variety and the connectivity dimension of Milling’s (2002) concept. Likewise, the combination of temporal and regulative complexity is similar to Milling’s (2002) definition of the functionality dimension. Assuming that there are two categories of elements within a system, one containing the actors and the other comprising different versions of an innovation, Garud et al.’s (2011, p. 739) concept of manifest complexity is immanent in all three dimensions of Milling’s (2002) conceptualization of complexity.

The preceding paragraphs show that most implementation studies consider structural aspects of an organization only in a very simplified manner. Damanpour (1996, p. 695), for example, examined the influence of organizational complexity on the innovation process. However, only the extent of horizontal complexity, characterized by the degree of functional departmentation and the extent of role specialization, was used as an indicator for organizational complexity. Dynamics among the horizontal elements of an organization were not considered. Similarly, Repenning (2002, p. 122) excluded interactions among organizational groups in his analysis of implementation-specific dynamics, arguing that “the interaction between functions (e.g., manufacturing operators and product development engineers) is likely to be relatively minor when compared to the within-group interactions.”

However, even though ties between groups might be weak, Granovetter (1973) and others have shown that weak ties function as important bridges
which provide access to otherwise unavailable information. Brown and Reingen (1987, p. 352) stated: “If weak ties did not exist, a system would consist of disjointed subgroups, inhibiting the widespread diffusion of information.” In addition, Hansen (1999, p. 85) found that weak ties between groups are a cost-efficient way to facilitate a project team’s search for useful non-redundant information in other groups, while at the same time remaining relatively autonomous by “escaping the penalties of being strongly enmeshed in a network.” Consequently, the intra-organizational communication network among groups is an important factor influencing the effectiveness of innovation implementation. Communication networks do not only comprise the number of organizational groups (i.e., the variety of a complex system), but also their interrelatedness (i.e., the connectivity) and the way they are interrelated (i.e., the functionality of a complex system). Therefore, this research suggests that the analysis of communication networks is more likely to yield insights which improve the implementation of innovations than, for example, the degree of functional departmentation, which only focuses on the variety of a complex system, such as an organization. This is especially the case for the implementation of complex innovations which necessitate the communication across functional borders in order to be effective.

While the connections and interactions among different organizational groups have been largely neglected in implementation research, they have been considered essential in diffusion research. Abrahamson and Rosenkopf (1997, p. 307), for example, investigated the effects of randomly generated network structures on the diffusion process of innovations within social networks. Thereby, they focused on the bandwagon pressure of adopters. That is, the higher the number of adopters, the greater the pressure on non-adopters to also adopt the respective innovation. However, the implicit assumption of this diffusion mechanism is that adopters, unlike non-adopters, never change their opinion about an innovation. They stay adopters forever. Gibbons (2004) analyzed the impact of innovation networks, which change over time, distinguishing between clearly beneficial and ambiguous innovations. In contrast to this dissertation, the focus of Gibbons (2004) was on networks among organizations and not on networks within them. In addition, Gibbons (2004, p. 943) also assumed that once an organization adopted an innovation, it will not discard it. The number of adopters within the network only decreases when organizations fail. Similar to Gibbons (2004) and Abrahamson and Rosenkopf (1997), Bohlmann et al.’s (2010, p. 749) market-level study of different network topologies also assumed that only non-adopters reconsider their attitude towards an innovation due to the positive word of mouth or bandwagon pressure of adopters.
Even though diffusion research has considered the influence of communication networks, Mahajan, Muller, and Kerin (1984, p. 1401) criticized that “[m]ost existing innovation diffusion models […] assume that individual experience with the product is always communicated positively through word-of-mouth.” However, “[f]or certain innovations, this assumption is tenuous since communicators of the product experience may transfer favorable, unfavorable, or indifferent messages through word-of-mouth” (Mahajan et al., 1984, p. 1401). In opposition to the sole inclusion of positive word of mouth, the additional consideration of negative word of mouth also takes into account that adopters might revoke their adoption decision and become non-adopters. Krackhardt (1997), for example, examined the dynamics between adopters and non-adopters of an innovation on an organizational level, not making the restrictive assumption that adopters never change their opinions about an innovation. Due to the explicit consideration of negative word of mouth, the communication between adopters and non-adopters can also result in a conversion of adopters by non-adopters causing adopters to discontinue an innovation.

2.3. Summary of this research’s context

Without introducing any additional information, this section briefly summarizes the preceding literature review, which sets the context of this dissertation. In particular, this chapter reviewed literature on the classification and implementation of innovations within organizations. An innovation was defined as an idea, practice, or object which is new in the eyes of the adopting organization. While incremental innovations describe only minor enhancements of the status quo, radical innovations are characterized by a high degree of novelty. Consequently, each innovation can be placed along a novelty continuum, ranging from incremental to radical. Besides the degree of novelty, innovations can also be classified into product and process innovations. However, they rarely occur in their pure form. Instead, an innovation can be placed along a continuum between product and process innovation, depending on the extent to which product or process elements dominate its nature.

From an adopter’s point of view, a product innovation is a new technology or combination of existing technologies which is relatively discrete and self-contained. Product innovations can be tangible products that can be stored or intangible services which are produced and consumed simultaneously. Process innovations, on the other hand, introduce new elements into already existing routines of an organization or replace them altogether. They comprise technical innovations, which relate to the core activities of an organization, and administrative innovations, which affect supporting activities. This research
tends to concern complex innovations which are rather radical and comprise more process than product elements because those innovations have a higher impact on the organization as a whole. However, the main focus of this research is not on the type of innovation but on the innovation process within an organization.

The innovation process of an organization can be subdivided into the initiation process, which comprises all activities that lead to a decision whether the respective innovation is adopted or not, and the subsequent implementation process, which comprises all activities that aim at fully integrating the innovation into the organization. The innovation decision marks the end of the former and the beginning of the latter. This research focuses on the implementation process. It is assumed that senior management decides whether an innovation is implemented or not. However, the decision to adopt an innovation on an organizational level does not necessarily result in its adoption on an individual level. That is, even though senior management decided to implement an innovation within the organization, employees that are supposed to use it (i.e., targeted employees) may resist changing their working routines, leading to implementation failure (e.g., Kim & Kankanhalli, 2009). This research uses implementation effectiveness as a measure for implementation success. Implementation effectiveness is higher, the quicker and further an innovation spreads among targeted employees and the more sustainable this diffusion is. The level of diffusion is specified as the percentage of targeted employees that adopted and use the respective innovation.

From an organizational perspective, the sustained and widespread usage of an innovation among targeted employees is decisive for the success of implementation efforts. Even though senior management makes the initial adoption decision for the organization as a whole, the innovation still needs to be used by employees in order to be profitable for the organization. Thus, a successful innovation implementation depends on the individual innovation-decisions of targeted employees. The higher the percentage of targeted employees that decided to use the innovation, the higher the effectiveness of the implementation process. The individual innovation-decision process of an employee comprises five consecutive phases: knowledge, persuasion, decision, implementation, and confirmation. After getting to know an innovation (knowledge), an employee develops either a favorable or unfavorable attitude towards it (persuasion) which determines this person’s innovation-decision (decision). The individual innovation-decision is then implemented (implementation) and, if necessary, changed (confirmation). The last three phases of this process can be iterative, depending on whether or not an employee encounters contradicting information during the confirmation phase. If this is the case, the
employee’s previous decision might change, causing the implementation of an updated decision.

The fact that targeted employees may reject an innovation raises the question of what factors influence an employee’s individual innovation-decision. In implementation research, there are several theories which intend to unify and categorize numerous determinants of innovation implementation processes. In order to promote the development of implementation theory, frameworks like PARIHS, CFIR, and QIF often build on each other. Despite these advancements, many of these studies treat the identified factors separately, neglecting interrelations between them. Therefore, many authors have called for multi-dimensional models that take into account multiple and to some extent interrelated drivers of implementation success. Focusing on determinants of employees’ individual innovation-decisions, this research follows Choi and Chang (2009), whose study is one of the few that accounts for the interactions among several factors. In particular, this research intends to contribute to existing implementation research by combining employee-related factors (i.e., peer influence and ambiguity intolerance of employees) and institutional factors (i.e., management influence and structural characteristics of organizations) in order to analyze their interrelated influence on employees’ individual innovation-decision processes. In contrast to many other implementation studies, it is not the goal to establish an all-encompassing theory or framework of factors influencing implementation effectiveness. Instead, the focus is on the dynamics among those four well-established factors.

The individual innovation-decision process of an employee is essentially an information-seeking and information-processing activity to reduce the perceived uncertainty about an innovation’s profitability. Employees also seek and process information about social norms to learn which behavior is accepted, expected, or admired. Information about an innovation’s profitability and social norms is mainly acquired during the persuasion and confirmation phases which prepare the individual innovation-decision. Therefore, this information has a potentially decisive impact on implementation effectiveness. Employees obtain information about an innovation and social norms by communicating with senior management and peers. Senior management’s influence on the individual innovation-decision of employees is ascribed to its influence on implementation climate and employees’ innovation acceptance. In addition, senior management has the power to manipulate the institutional environment, which alters employees’ perception of the social norm, also referred to as subjective norm. Similar to senior management, peers also influence the subjective norm and exert social pressure by providing information about their personal innovation usage. A third factor influencing the individual innovation-decision process is
the perceived ambiguity surrounding an innovation's profitability. Since employees are usually ambiguity intolerant, they try to reduce the perceived ambiguity of an innovation by seeking additional information from their social environment. Consequently, the social influence of managers and peers increases with employees’ ambiguity intolerance.

Besides the social influence of senior management and the social influence of peers, which depend on the ambiguity intolerance of employees, the structural aspects of the communication among organizational members constitute the fourth factor which influences the individual innovation-decision and is analyzed in this research. The organizational communication structure describes who is communicating with each other. Thereby, this research distinguishes the communication between senior management and targeted employees from the communication among targeted employees. With whom a senior manager communicates depends largely on the implementation strategy and decision-making process of senior management, which are specified in chapter 7. However, with whom an employee communicates depends largely on the similarity between this person and others. The more similar (i.e., homophilous and proximate) potential communication partners are, the more likely and effective the communication between them. Employees within the same organizational team or subunit are usually more homophilous and proximate to each other than employees from different groups. Therefore, other employees’ influence on the innovation-decision of an individual is especially strong if they and the individual are members of the same group.

Even though connections between groups are less strong than within groups, weak ties between groups are important because they ensure the widespread diffusion of information which would otherwise be unavailable to some groups. The connections among groups form an intra-organizational communication network which comprises all three dimensions of complexity. In contrast to most implementation studies, such a network does not only consider the number of groups (i.e., the variety of a complex system) but also the number of connections among them (i.e., the connectivity of a complex system) as well as the nature of these ties (i.e., the functionality of a complex system). Since this research focuses on the implementation of complex innovations which affect several organizational groups, the consideration of the communication among these groups is essential for a realistic depiction of intra-organizational diffusion processes. In diffusion literature, the influence of such communication networks on innovation diffusion has been recognized. However, most diffusion studies assume that only non-adopters of an innovation might change their individual innovation-decision due to positive word of mouth. That is, the number of adopters can only increase but never shrink. In an organizational
context, however, the resistance and social pressure of non-adopters might also change the individual innovation-decision of adopters. By considering the negative word of mouth of non-adopters, this research accounts for the possibility that adopters might revoke their individual innovation-decision and discontinue an innovation.
3. Research questions and methodology

3.1. Research questions

This research focuses on the implementation of complex innovations within organizations. As pointed out before, the organizational implementation phase, as the critical period between the decision to adopt and the routine usage of an innovation (Klein & Sorra, 1996, p. 1057; Rogers, 2003, p. 435), has received increasing attention by scholars. Research has identified inadequate implementation processes as a major reason for organizations’ failure to benefit from adopted innovations (Aiman-Smith & Green, 2002, p. 421; Gary, 2005, p. 644; Karimi et al., 2007, p. 123; Klein & Sorra, 1996, p. 1055). Despite the growing number of studies that have identified multiple causes of unsuccessful implementation processes, literature lacks multidimensional models that explain the difference between successful and unsuccessful implementation efforts. As mentioned earlier, such models should take into account multiple and to some extent interrelated drivers of implementation success (Dean Jr. & Bowen, 1994, p. 393; Klein et al., 2001, p. 811; Klein & Sorra, 1996, p. 1056; Repenning, 2002, p. 110). However, existing implementation studies barely focus on the interactions among several determinants, in particular with regard to determinants on different organizational levels. Mostly, they focus either on employee-related processes, examining “employees’ affective and behavioral responses to an innovation,” or on organizational/institutional processes, focusing on the management support, structure, and resources of the implementing organization (Choi & Chang, 2009, p. 245).

In response to the call for multidimensional models, the overarching research question of this dissertation asks how several determinants of implementation effectiveness are interrelated and how combinations of these factors influence the intra-organizational implementation of an innovation. However, as stated before, it is not the goal of this research to uncover and quantify empirical correlations. Neither is the goal to establish an all-encompassing theory or framework of factors influencing implementation effectiveness. Instead, this research focuses on the dynamics among a few well-established factors and their combined influence on implementation effectiveness in order to improve the understanding and effectiveness of intra-organizational implementation processes. To achieve this goal, the dissertation builds on empirical studies by combining their findings within a dynamic simulation model.

Organizational change processes, like the implementation of an innovation, are “created, sustained, and managed in and by communications” (Ford & Ford, 1995, p. 560). Donnellon (1986), for example, argues that the actual implementation of change is all about communication. Therefore, the dissertation focuses on
factors that pertain to the innovation-related communication within an organization. In the previous chapter, the four central factors of this research have already been introduced (see Figure 4). According to Choi and Chang’s (2009) categorization, two of them are employee-related (i.e., peer influence and ambiguity intolerance of employees) and two are institutional determinants of implementation effectiveness (i.e., management influence and structural characteristics of organizations). Against a communication background, structural characteristics of an organization determine with whom targeted employees can communicate, ambiguity intolerance of employees describes how much they engage in communicating with others, and peer influence and management influence specify how this communication affects the individual innovation-decision of targeted employees and thereby implementation effectiveness.

Besides these four central determinants, other factors, such as an innovation’s perceived relative advantage, are assumed to influence implementation effectiveness only indirectly by altering the nature and/or amount of available information. That is, whether or not an employee decides to adopt and use an innovation depends solely on the information that is communicated to this person. Abstracting from the actual content of a message, it is assumed that the type of information is either advocating or opposing an innovation, depending on whether the sender of this information is senior management (proponent), an adopter (proponent), or a non-adopter (opponent). Thus, receivers of an innovation-related message base their individual innovation-decisions solely on the information of their communication partners. Interpreting the implementation of an innovation as a process of communication is congruent with the Bass diffusion model and many other diffusion models that build on it (Bass, 1969; 2004). In addition, it coincides with the Communication Constitutes Organizations (CCO) perspective which argues that “organizations can be conceptualized as fundamentally shaped by discourse” (Blaschke et al., 2012, p. 880). In other words, organizational change processes are essentially driven by the dynamics of communication among organizational members (Kuhn, 2008).

Specifying the overarching research question with regard to the influence of peers, the first research question addresses the issue that most diffusion models focus on the influence of adopters on non-adopters, thereby neglecting the influence of non-adopters on adopters. Defining an adopter (non-adopter) as a targeted employee who uses (rejects) an innovation and has a positive (negative) attitude towards it (Choi & Chang, 2009; Venkatesh et al., 2003, p. 461), this research assumes that adopters spread positive word of mouth while non-adopters spread negative word of mouth. By considering non-adopters’ negative influence on the individual innovation-decision processes of adopters, this research accounts for the possibility that adopters reject an innovation during
the confirmation phase. Even though some studies have accounted for the discontinuance of an innovation by adopters due to non-adopters’ negative word of mouth (e.g., Krackhardt, 1997; Ulli-Beer, Gassmann, Bosshardt, & Wokaun, 2010), none of them analyzed how differences in the strength of positive and negative word of mouth impact the effectiveness of intra-organizational implementation processes. In light of the current debate whether positive or negative word of mouth has a stronger impact on decision-makers (e.g., Berger & Milkman, 2012; Park & Lee, 2009), such an analysis might yield further insights which help to resolve this question. Therefore, this research aims to answer the question how different strengths of positive and negative word of mouth influence implementation effectiveness.

With regard to the ambiguity intolerance of employees, this research aims to shed light on the relationship between an innovation’s perceived ambiguity and the communication behavior among employees. Ambiguity intolerance is considered to be one of the main drivers of diffusion processes. Since an innovation’s profitability is often ambiguous and individuals are usually ambiguity intolerant, the influence of peers is greater, the more ambiguous the innovation is perceived to be (Abrahamson & Rosenkopf, 1993; 1997; Tidd, 2010). Thus, the influence of peers is greater, the higher an individual’s ambiguity intolerance and the greater the perceived ambiguity of an innovation. Even though most studies have focused exclusively on the influence of peers as the main driver of diffusion processes (Bohlmann et al., 2010, p. 749; Gibbons, 2004, p. 943; Goldenberg, Libai, Moldovan, & Muller, 2007, p. 189), only a few have considered that this influence actually depends on an innovation’s perceived ambiguity (Abrahamson & Rosenkopf, 1993; 1997). With regard to the influence of individuals’ ambiguity intolerance on the diffusion process of an innovation, no study at all was found. Therefore, the second research question of this dissertation asks how an innovation’s perceived ambiguity and employees’ ambiguity intolerance influence the intra-organizational communication behavior among peers and thereby the effectiveness of implementation processes.

Structural characteristics of an organization influence implementation effectiveness by determining with whom organizational members can communicate. Due to the proximity and homophily of employees within the same team or department, communication ties within groups are stronger than between groups. Nevertheless, weak ties among groups serve as important bridges which have a major influence on implementation effectiveness. Even though diffusion studies have recognized the importance of intergroup communication, it has been largely ignored in implementation research (Damanpour, 1996; Repenning, 2002). Therefore, the dissertation aims to enrich implementation research by incorporating elements of diffusion research which
enable the examination of the communication structure among groups. What makes this research’s analysis of intra-organizational communication networks unique is the consideration that adopters might discontinue an innovation due to the negative word of mouth of non-adopters (see first research question). In particular, the third research question of this dissertation asks how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness.

Regarding the fourth central determinant of implementation effectiveness, this research also focuses on senior management’s influence on the implementation process. Similar to the influence of peers, senior management can also exert normative pressure on employees. Since peers can either be adopters or non-adopters, their social pressure and word of mouth either promote or impede innovation implementation. Senior management, however, initiated the implementation process and is therefore trying to promote the adoption of an innovation. Due to senior management’s superior hierarchical position, a senior manager has a stronger influence on an employee's individual innovation-decision than a peer. However, senior management’s resources are often limited and do not suffice to influence all employees. Therefore, this research examines the effectiveness and efficiency of different management strategies. Even though some implementation studies have analyzed senior management’s influence on implementation effectiveness (e.g., Choi & Chang, 2009; Repenning, 2002), none of them has considered the communication network among groups of targeted employees. Therefore, building on the third research question, the fourth research question asks what characterizes an effective and efficient management strategy in light of different communication structures among groups. In particular, this research aims at finding a decision rule which tells senior management what groups within the communication network it should concentrate on in order to ensure an effective and efficient innovation implementation.

Figure 5 illustrates the interlocking of the overarching research question, asking—how several determinants of implementation effectiveness are interrelated and how combinations of these factors influence intra-organizational innovation implementation—and the four central research questions. While the second and the third research question are largely independent from each other, they both build on the findings of the first research question. The fourth research question, in turn, builds on the findings of the first and the third research question. The findings of all four central research questions contribute to answering the overarching research question. The following section outlines how the dissertation addresses the four above-mentioned research questions methodologically.
3.2. Methodology

This research uses a formal modeling and simulation technique for theory building in the sense of Davis, Eisenhardt, and Bingham (2007). Formal modeling provides clarity, ease of comparability, logical power, and transparency (Kreps, 1990, p. 6). Simulation allows the deduction of dynamic effects from formal models (Harrison, Lin, Carroll, & Carley, 2007). In particular, this section outlines why computer modeling and simulation techniques—and system dynamics in particular—are suitable for analyzing and answering the four central research questions that have been specified in the previous section.

Computer models are substitutes for real systems. They are used when experiments in real systems are too expensive, too dangerous, or simply impossible. Simulating computer models reduces the time delay between cause and effect which is present in real systems, allowing users to obtain knowledge more quickly than in real systems (Forrester, 1961, p. 49). “The value of a model arises from its improving our understanding of obscure behavior characteristics more effectively than could be done by observing the real system” (Forrester, 1961, p. 49). Therefore, a model should not be too complex, ensuring that it is still possible to understand its output and derive policies for real systems (Lyons, Adjali, Collings, & Jensen, 2003, p. 11). Furthermore, models can simulate conditions which have not yet been observed in real life. This enables, for example, policy makers to prepare for complex and unprecedented situations by evaluating the effectiveness of several responses before these situations actually occur. Thus, the main benefit of computer modeling and simulation techniques is the relatively quick deduction of insights about complex systems at relatively low costs.
With regard to implementation process, it is very hard to observe innovation-related communication in real systems, such as organizations. Lazer and Friedman (2007, p. 672) pointed out that “[e]mpirical analysis, though essential, is constrained by the expense and practical challenges of studying real-world systems.” For example, it is almost impossible to keep track of the interactions among organizational members. Besides, it is very expensive, if not impossible, to set up an experiment which controls for the environment of an organizational implementation process. On the one hand, the internal validity of such an experiment may suffer if too many factors are taken into account. On the other hand, if too few factors are considered, the experiment may not be complex and realistic enough to yield insights which improve the understanding of implementation processes. In addition, Klein et al. (2001, p. 823) called for future research that examines the implementation process over time. Since it can take quite some time till an innovation becomes an organizational routine, real world observations can be very time-consuming and costly. For those reasons, experiments are less suitable to analyze intra-organizational implementation processes.

Computer models, however, can simulate the communication behavior and attitude changes of organizational members based on empirical indicators, such as the proximity and differences of opinion between communication partners. In addition, building and analyzing a computer model of intra-organizational implementation processes is far cheaper and quicker than conducting a comparable experiment. Computer models are also capable of considering a multitude of factors and of simulating their effects on implementation processes without having irreversible effects on the real world. On the other hand, computer models have a lower validity than experiments. However, various tests of internal and external model validity can at least partially neutralize this drawback (Barlas, 1989; Barlas, 1996; Barlas & Carpenter, 1990). Therefore, this research argues that computer modeling and simulation techniques are especially useful to analyze intra-organizational innovation implementation processes.

This dissertation uses system dynamics as a methodology for answering the aforementioned research questions. Jay W. Forrester, who has pioneered digital computers, is considered to be the founder of system dynamics (Forrester, 1961; Lane, 2007). System dynamics is a structural theory of social systems, which is characterized by feedback loops, accumulation processes, and temporal delays (Forrester, 1961; Größler, Thun, & Milling, 2008, p. 375). Thereby, system dynamics differentiates between stock variables, flow variables, information variables or auxiliaries, and parameters. Stock variables, such as “Fraction of Adopters”, describe the state of a system. Flow variables represent the change of stock variables over a certain period of time. Information variables and
parameters determine the values of flow variables, other information variables, and the initial states of stock variables. Based on empirical cause-and-effect relations, those variables and parameters are functionally linked together by means of computer software in order to build a simplified but relevant version of a real system. Whether elements of the real system are relevant for the model or not, depends on the purpose of the model (Forrester, 1961, p. 115). The resulting computer model of the real system can then be simulated over time.

System dynamics is considered to be an appropriate methodology because the literature review in chapter 2 identified feedback loops, accumulation processes, and temporal delays as essential elements of implementation processes. With regard to feedback loops, the literature review outlined that the fraction of adopters determines the social pressure on non-adopters: The higher the number of adopters, the greater the pressure on non-adopters to also adopt an innovation. When some non-adopters become adopters, the pressure on the remaining non-adopters increases even more, thereby creating a reinforcing feedback loop (Lane & Husemann, 2008). The number of adopters can also be understood as an accumulation or stock of employees which increases with the number of non-adopters that become adopters and decreases with the number of adopters that revoke a previously made adoption decision. Considering temporal delays, previous research has shown that “time is required for senior members to develop and implement actions targeted at creating normative pressure” (Repenning, 2002, p. 115). In addition, this research touches a variety of different fields, such as innovation diffusion, psychology, and decision-making. System dynamics models are able to capture these phenomena, blend them into an integrated formal representation, and derive the logical consequences over time. However, this occurs at the cost of aggregation and abstraction.

Within the literature, simulation models can be categorized along several dimensions: empirical versus axiomatic, descriptive versus normative, static versus dynamic, and linear versus nonlinear, to name only four (Bertrand & Fransoo, 2002; Forrester, 1961, pp. 50-51; Größler et al., 2008, p. 378). Concerning the first dimension, system dynamics models are empirical by nature. In contrast to axiomatic models, they are driven by empirical evidence rather than abstract concepts. In other words, the cause-and-effect relations between variables are based on empirical research. With regard to the second dimension, system dynamics models are rather descriptive than normative. That is, system dynamics focuses more on investigating a system and its inherent complexity than on deducing analytically solvable models (Akkermans, 1993; Größler et al., 2008, p. 378). A drawback of normative models is that optimal solutions can only be achieved “in either low-complex artificial situations or when agents possess perfect rationality” (Größler et al., 2008, p. 378). Both aspects are rather unrealistic
with regard to innovation implementation systems. In such complex real-world systems, “analytic modeling often cannot handle the combinatorics of system dynamics” (Lazer & Friedman, 2007, p. 672). Therefore, normative mathematical models can analyze innovation implementation systems only to a limited extent. In this regard, the descriptive nature of system dynamics models seems to be more suitable.

Regarding the third dimension, it can be distinguished between static models, which are describing relationships that do not change over time, and dynamic models, which refer to interactions that do vary with time (Forrester, 1961, p. 50). As the name already suggests, system dynamics models are clearly dynamic. The intra-organizational implementation of an innovation also represents a dynamic system because the exchange of innovation-related information is continuously changing over time, even if the triggering impulse is no longer affecting the system. The fourth dimension differentiates between linear and nonlinear models. “In a linear system the response to every disturbance runs its course independently of preceding or succeeding inputs to the system; the total result is no more nor less than the sum of the separate components of system response” (Forrester, 1961, p. 50). A nonlinear model, however, accounts for temporal interdependencies among system inputs. Intra-organizational implementation systems are nonlinear in nature because they consider the combined impact of earlier and later inputs on system behavior. A typical example is the aforementioned feedback loop between the pressure of adopters, the number of converting non-adopters, and the number of adopters. Regarding all four dimension, system dynamics models are empirical, descriptive, dynamic, and nonlinear. Since these properties match the characteristics of intra-organizational innovation implementation systems, this research advocates a system dynamics approach.

System dynamics models belong to the class of nonlinear differential equation models, also known as compartmental models. Recently, agent-based modeling has been increasingly applied to problems which have previously been modeled with nonlinear differential equation models (Nan, 2011; Rahmandad & Sterman, 2008, p. 998; Zhang, Gensler, & Garcia, 2011). Both approaches yield the benefits of empirical, descriptive, dynamic, and nonlinear models. However, there are several distinct differences between differential equation (DE) and agent-based (AB) models. DE models generally define the behavior of the global system, whereas AB models define behavior at an individual level. Thus, the global behavior of AB models is a result of many individual entities, the so-called agents, who follow their own behavior rules (Borschchev & Filippov, 2004). This bottom-up approach facilitates the implementation of heterogeneous characteristics, as for example different agent- and time-specific probabilities to adopt an
innovation (Mahajan et al., 1990, p. 6). However, as Rahmandad and Sterman (2008) point out, the granularity of AB models also has its downsides:

First, the extra complexity significantly increases computational requirements, constraining the ability to conduct sensitivity analysis. A second cost of agent-level detail is the cognitive burden of understanding model behavior. Linking the behavior of a model to its structure becomes more difficult as model complexity grows. Finally, limited time and resources force modelers to trade off disaggregate detail and the breadth of the model boundary. (p. 999)

DE models, on the other hand, aggregate a population into a relatively small number of compartments, such as adopter and non-adopter compartments. In system dynamics, such compartments are called *stocks*. Thereby, DE models abstract from single events and entities and focus on policies (Borshchey & Filippov, 2004, p. 4). However, within each compartment, people in DE models “are assumed to be homogeneous and well mixed; the transitions among states are modeled as their expected value, possibly perturbed by random events” (Rahmandad & Sterman, 2008, p. 998).

Whether AB models or DE models should be used, depends on the purpose of the model (Forrester, 1961, p. 60; Rahmandad & Sterman, 2008, p. 998). The dissertation concentrates on implementation processes, in particular on four communication-related factors which influence implementation effectiveness: peer influence, management influence, ambiguity intolerance, and structural characteristics of organizations. In doing so, the dissertation intends to contribute to a better understanding of implementation processes and their underlying dynamics. In a second step, this knowledge can then be used to enable decision-makers to derive better policies which ultimately improve implementation effectiveness.

Considering that this research focuses on understanding implementation systems by linking their modeled behavior to the underlying structure, the resulting complexity of an AB model might be cumbersome. A DE model, on the other hand, would be far less complex due to its aggregated nature. Therefore, it is much easier to keep the model complexity manageable when extending the boundary of a DE model, for example, when combining employee-related and institutional factors of implementation effectiveness. In addition, senior management usually monitors and controls the implementation process of an innovation based on aggregated data. Therefore, analyzing organizations on a more aggregated level might be more useful, especially when the focus is on the deduction and implementation of effective management strategies. Research has
shown that the outcomes of granular, individual-based diffusion models are very similar to the results of clustered and aggregated diffusion models as long as the assumptions of homogeneity and perfect mixing are not violated (Edwards, Huet, Goreaud, & Deffuant, 2003; Riley, 2007, p. 1300; Rahmandad & Sterman, 2008, p. 1011). This is in line with the previously made assumption that employees of the same group are largely homophilous. Hence, with regard to the research questions of this dissertation, DE models—such as system dynamics models—seem to be more appropriate than AB models.

3.3. Research design

Changes in the social, political, or economic environment require every organization to adapt sooner or later, for example, by upgrading its production processes to retain its competitive advantage, by adjusting its product and service portfolio to meet changing customer demands, or by responding to new government regulations. Without such innovations, the long-term survival of an organization is seriously jeopardized. Even though most organizations are aware of the need to implement innovations, the actual implementation process frequently fails. Unsuccessful implementation efforts do not only jeopardize organizational survival by wasting time and resources, but also by discouraging senior management from engaging into future change processes because the apparent risk of failing looms large. Even though organizations could learn from unsuccessful implementation efforts, many draw the curtain over necessary changes, thereby leaving them even worse off in the long-run. Therefore, the overarching research question of this dissertation is how several determinants of implementation effectiveness are interrelated and how combinations of these factors influence the intra-organizational implementation of an innovation. By answering this question, the dissertation aims to contribute to a higher success rate and better understanding of implementation processes.

In order to specify the overarching research question, this chapter has deduced four central research questions from the literature review in chapter 2. The first research question focuses on the influence of peers on implementation effectiveness. In light of the outlined lack of studies considering the impact of negative word of mouth on adopters’ individual innovation decision, the first research question asks how different strengths of positive and negative word of mouth influence implementation effectiveness. As illustrated in Figure 5, the second research question builds on the first one by asking how the ambiguity of an innovation and employees’ ambiguity intolerance influence the communication among peers and thereby implementation effectiveness. While the first two research questions focus on employee-related determinants of implementation
effectiveness, the other two research questions concentrate on the combined influence of employee-related and institutional factors. Considering the findings of the first research question, the third research question asks how structural characteristics of the communication network among groups affect peer influence and implementation effectiveness. Building on the third research question, the fourth research question then asks: What structural characteristics of groups within a communication network determine on which of those groups senior management should concentrate its limited resources to ensure an effective and efficient innovation implementation? Table 1 provides an overview of the four central research questions and the corresponding determinants of implementation effectiveness.

This chapter has proposed a computer modeling and simulation approach as the underlying methodology to answer the research questions of this dissertation. In order to justify this choice, the previous section compared the challenges of innovation implementation research to the characteristics of computer modeling and simulation techniques. In implementation research, many authors have called for multidimensional models which consider several determinants of implementation effectiveness as well as how these factors are interrelated. There have also been calls for longitudinal studies of implementation research. However, in real-world settings, it is very expensive, if not impossible to control for the environment of the examined innovation implementation process, especially when conducting longitudinal field research. Analyzing intra-organizational implementation processes against a communication background is especially difficult because keeping track of the formal and informal communication among employees is often impossible. Another complicating factor is the limited ability to test the effectiveness of different management

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Table 1 Composition of further research with regard to the central research questions
strategies in real-world settings. Due to these challenges, the dissertation proposes computer modeling and simulation techniques as appropriate methodologies to analyze innovation implementation processes.

As discussed in the previous section, the main advantage of computer models is the relatively quick deduction of insights about complex systems at relatively low costs. For example, they can simulate communication processes among employees based on empirical indicators and analyze different management strategies without having irreversible effects on the implementation process of real organizations. In particular, this research employs system dynamics, which is based on sets of differential equations (Forrester, 1961; Sterman, 2000) and which has been identified as an appropriate way for theory building in management (Größler et al., 2008). As a rather high-level modeling and simulation technique, system dynamics abstracts from the behavior of individual agents for the sake of clearly identifying and describing causal relationships among variables and relating the resulting behavior of the system to its structure. Therefore, this research uses a system dynamics model to shed light on the deduced research questions.

With regard to implementation processes, systems dynamics is especially suitable because it is able to account for feedback processes among the four considered determinants of implementation effectiveness. In addition, a system dynamics model can account for the long time period of implementation processes by simulating the behavior within the respective organization over time, thereby accounting for temporal delays among factors of influence. System dynamics models are empirical, descriptive, dynamic, and nonlinear in nature. Regarding the level of aggregation, system dynamics models simulate the behavior of groups. Since this research aims to improve the understanding of implementation processes, such an aggregated view is beneficial because it is easier to link the behavior of a model to its underlying structure. Focusing on a more aggregated level is also advantageous because the goal of this research is to support senior management’s decision-making by analyzing different implementation strategies. In line with system dynamics, these strategies usually target groups of employees instead of individuals.

Other studies in the organizational sciences using system dynamics are, for instance, Sastry (1997), Repenning (2002), and Rudolph and Repenning (2002), which also provide more extensive discussions on the usefulness and limitations of simulation modeling. Concerning the implementation of business strategies, Strohhecker and Größler (2012) employed system dynamics to uncover common management fallacies. Snabe and Größler (2006) showed that system dynamics modeling can support the implementation of business strategies. Since a business strategy might also be an innovation, provided it is new to the organization
implementing it, these studies suggest that system dynamics is also an appropriate methodology to analyze innovation implementation processes in general. With regard to innovation diffusion, Milling (1996) and Maier (1998) demonstrated the capability of system dynamics to merge and examine different aspects of innovation diffusion processes.

In line with these studies, this research intends to shed light on change processes by introducing and analyzing a system dynamics model which focuses on intra-organizational innovation implementation processes. Even though the intra-organizational implementation of an innovation resembles a diffusion process among employees, it differs from market-level diffusion processes in that employees might alternate between adopting and discontinuing an innovation (Rogers, 2003; Ulli-Beer et al., 2010). In addition, intra-organizational diffusion processes are characterized by senior management's normative influence on the individual innovation-decisions of employees (Choi & Chang, 2009; Repenning, 2002). Among others, these two aspects are considered in the four central research questions of this dissertation.

As illustrated in Table 1, this research addresses the four central research questions in a consecutive order. Concerning the first research question, the following chapter broaches the issue of adopters discontinuing an innovation due to the pressure and negative word of mouth of non-adopters. A basic system dynamics model is introduced which incorporates positive as well as negative word of mouth to analyze their interrelation and impact on implementation effectiveness. Chapter 5 extends this model by incorporating an innovation's perceived ambiguity and employees' ambiguity intolerance. By means of the extended model, it is analyzed how different degrees of employees' ambiguity intolerance and an innovation's perceived ambiguity influence the communication behavior among peers (research question two). The third research question is addressed in chapter 6. Neglecting the influence of ambiguity, this chapter extends the basic system dynamics model of chapter 4 to analyze the dynamics resulting from the communication structure among several groups of employees. Based on those insights, chapter 7 extends the model of chapter 6 even further to incorporate management's influence on the implementation process (research question four). Depending on the position of groups within a network, chapter 7 analyzes on which groups senior management should focus to ensure an effective and efficient innovation implementation.

An adjusted version of chapters 6 and 7 has been published in the *System Dynamics Review* (Wunderlich, Größler, Zimmermann, & Vennix, 2014). Section 6.2 is largely missing in this publication. A German version of that section was published as a chapter in an edited volume (Wunderlich, Zimmermann, & Größler, 2014). Several parts of chapters 4, 6, and 7 were also presented at the
International System Dynamics Conference (Wunderlich & Größler, 2011; 2012b), at the conference of the European Academy of Management (Wunderlich & Größler, 2012a), and at the Sunbelt Social Networks Conference of the International Network for Social Network Analysis (Wunderlich & Größler, 2013).
4. A basic implementation model accounting for the discontinuance of innovations due to negative word of mouth

4.1. The influence of social communication on the discontinuance of innovations

4.1.1. Purchase versus usage of innovations

In the diffusion literature, the social influence of peers has always been considered to be a key determinant of successful innovation diffusion processes. In particular, the Bass diffusion model spawned interest in analyzing how social pressure created between adopters and non-adopters of an innovation can explain its diffusion process (Bass, 1969; 2004). While Bass (1969) used the term imitation to describe the interaction between adopters and non-adopters, other terms such as word of mouth, learning, and contagion have also been used (Bass, 2004, p. 1834). These interactions among peers have often been described by bandwagon models (e.g., Abrahamson, 1991; Abrahamson & Rosenkopf, 1993). According to Abrahamson and Fairchild (1999, p. 731), bandwagons are diffusion processes which are characterized by “a positive feedback loop in which increases in the number of adopters create stronger bandwagon pressures, and stronger bandwagon pressures, in turn, cause increases in the number of adopters.” In principle, this pressure can be economic, knowledge-based, or social in nature. These three forms of pressure are similar in that they are essentially driven by the number of already existing adopters of an innovation.

As stated earlier, a restriction of many diffusion models is that only adopters exert pressure on non-adopters, whereas non-adopters are assumed to have no influence on adopters at all. Therefore, adopters never revise their adoption decision and reject a previously adopted innovation, whereas non-adopters reconsider adopting it at frequent intervals (Abrahamson & Rosenkopf, 1997; Bohlmann et al., 2010, p. 749; Gibbons, 2004, p. 943; Yücel & van Daalen, 2011, p. 361). The assumption “once an adopter always an adopter” is justifiable if one is interested in the purchase of an innovation, as is often the case in the marketing literature. The prime example is that of durable goods (Bass, 1969; Mahajan et al., 1990). By purchasing a durable good, the potential adopter becomes and stays an adopter until s/he leaves the respective system, no matter whether s/he is satisfied and keeps using the innovation or not (e.g., Gibbons, 2004, p. 943; Goldenberg et al., 2007, p. 188).

In an organization, however, “[s]enior managers tend to be responsible for the decision to adopt a new technology because adoption requires the approval of significant capital expenditures” (Lanzolla & Suarez, 2012, p. 841). Leonard-Barton and Deschamps (1988, p. 1253) stressed that the actual usage of an
innovation is an internal diffusion process that depends on "numerous individual 'secondary' adoption decisions by target users even after successive layers of management have passed along the 'authority decision'." Thus, in an intra-organizational context, an adopter is someone who uses an innovation, and not necessarily the one who purchased it. In order to accrue benefits from an innovation on an organizational level, the most crucial issue is hence not senior management's adoption decision to purchase and implement an innovation, but rather the individual innovation-decision of each employee to use the innovation (Choi & Chang, 2009, p. 252; Lanzolla & Suarez, 2012, p. 853; Leonard-Barton & Deschamps, 1988, p. 1253; Venkatesh et al., 2003, p. 461). The importance of using an innovation as compared to purchasing it becomes even clearer when one considers the implementation of process innovations in an organization (Ettlie & Reza, 1992). The diffusion of innovative processes depends exclusively on organizational members following new routines and procedures instead of old ones (Labatut, Aggeri, & Girard, 2012).

In contrast to the decision to purchase an innovation, the decision to use it is often subject to reconfirmation which can result in discontinuance (Abrahamson & Rosenkopf, 1993, p. 505; Rogers, 2003, p. 191). "In many industries, new technologies are sometimes adopted and then used very little or not at all" (Lanzolla & Suarez, 2012, p. 837). The rejection of an innovation can be the result of "further information that persuades him or her that s/he should not have adopted" (Rogers, 2003, p. 189). Thus, this research argues that the individual innovation-decision of employees to use an innovation is by no means set in stone but may change in the course of the diffusion process due to additional information. As pointed out in the first chapter, the focus of this dissertation is on information from an employee's social environment. In order to account for the importance of actually using an innovation in an organization, this research not only considers that non-adopters revise their innovation-decision due to the social pressure of adopters, but that also adopters revise their innovation-decision due to the social pressure of non-adopters, possibly persuading some adopters to stop using the innovation.

Since the purchase of an innovation is often irreversible, most diffusion models implicitly assume that adopters are immune to the social pressure of non-adopters. However, when implementing an innovation within an organization, its usage, and not its purchase, signals its adoption among employees. Unlike the purchase of an innovation, its usage might decrease, depending on the nature and extent of social pressure. The following section elaborates on the possibility to discontinue an innovation due to social pressure. In section 4.1.3, the concept of social pressure is compared to word of mouth. Section 4.2 introduces a simplified version of Krackhardt's (1997) diffusion model, which
resembles the model of Jackson and López-Pintado (2013) and is capable to illustrate the dynamics between the social pressure of adopters and the social pressure of non-adopters. In the subsequent section, this model is then analyzed with regard to research question one, examining how different strengths of positive and negative word of mouth influence implementation effectiveness. The resulting findings and implications are summarized and discussed in the last section of this chapter.

4.1.2. Adoption and discontinuance of innovations

According to Rogers (2003, p. 335), “[t]he diffusion of an innovation and the spread of an epidemic have much in common, and similar mathematical models have been used to understand these processes.” Against this background, the Bass (1969) diffusion model and many others are similar to SI models, whereby $S$ denotes susceptible and $I$ infective (Dorogovtsev, Goltsev, & Mendes, 2008, p. 1294). Driven by the interaction between susceptible and infected people, diseases spread among a population much like innovations diffuse via the interaction between non-adopters and adopters (Sterman, 2000, p. 324). SI models assume that a person who has been infected stays infected forever. Similarly, most innovation diffusion models assume that an adopter stays an adopter forever. However, among epidemic models, SIS models account for the fact that not all diseases cause permanent infection and that people who were once infected can become susceptible again. In the innovation diffusion literature, analogous models are largely missing. However, similar to an infected person recovering from a disease, an adopter may reject an innovation due to information which causes him or her to reconsider the previously made innovation-decision (Rogers, 2003, p. 189). Rogers (2003, p. 190) also stated that a “rather surprising high rate of discontinuance has been found for certain innovations.”

If one assumes that an adopter is an individual that purchased an innovation which s/he cannot return, discontinuance does not play a role. However, in intra-organizational contexts, not the purchase of an innovation but its continuous use is of paramount importance (Choi & Chang, 2009, p. 252; Lanzolla & Suarez, 2012, p. 853; Leonard-Barton & Deschamps, 1988, p. 1253; Venkatesh et al., 2003, p. 461). The percentage of innovation users might be irrelevant for organizations that focus on selling an innovation to others. However, for organizations that bought and intend to implement an innovation, the percentage of innovation users is essential to accrue benefits from the innovation. Therefore, this research defines an adopter as an employee who is convinced by the innovation and also uses it (Choi & Chang, 2009; Venkatesh et al., 2003, p. 461), whereas a non-adopter is an employee who prefers an alternative, like the status quo, over the innovation and uses that alternative instead.
Adopters “seek reinforcement for the innovation-decision already made, and may reverse this decision if exposed to conflicting messages about the innovation” (Rogers, 2003, p. 189). According to the aforementioned definition of an adopter, adopters who reverse their individual innovation-decisions and do not use the innovation anymore become non-adopters. If more adopters stop using an innovation than non-adopters start using it, the overall fraction of adopters declines, thereby decreasing implementation effectiveness. Therefore, this research argues that marketing-oriented diffusion models which focus on the purchase of an innovation are less suitable when analyzing intra-organizational diffusion processes where not the purchase but the usage of an innovation is crucial. Instead, similar to SIS models, innovation diffusion models are needed which consider that adopters may potentially stop using an innovation, thereby negatively affecting implementation effectiveness.

One of the few innovation diffusion models that accounts for the discontinuance of adopters is introduced by Abrahamson and Rosenkopf (1993). Similar to SIS models—which generally assume that a certain fraction of infected people recovers and becomes susceptible again, provided they do not meet any other infected person within a certain period (e.g., Jackson & López-Pintado, 2013, p. 53)—Abrahamson and Rosenkopf (1993) assumed that a fixed fraction of adopters rejects an innovation after a given time period. However, the number of discontinuing adopters was independent of the number of non-adopters. While the assumption that an infected individual is only sick for a fixed period of time is reasonable, it is less convincing that an adopter’s use of an innovation is only a function of time. Instead, research suggests that adopters stop using an innovation for the same reasons they adopted it in the first place (Abrahamson, 2011; East, Hammond, & Lomax, 2008, p. 221).

First, adopters may discontinue an innovation, if the social pressure, which initially caused its adoption, decreases because the innovation’s “faddish appeal dissipates” (Abrahamson, 1991, p. 599). If the social pressure decreases beyond a certain threshold, so-called counter-bandwagons might be triggered, exerting social pressure on adopters to reject an innovation. Counter-bandwagons are diffusion processes which are characterized by a positive feedback loop in which increases in the number of non-adopters create stronger bandwagon pressures, and stronger bandwagon pressures, in turn, cause increases in the number of non-adopters (Abrahamson & Rosenkopf, 1993). Thus, discontinuance of an innovation is not just a function of time but also a function of the number of non-adopters. Second, adopters may also discontinue an innovation because by using it they learn that “the innovation is inappropriate […] and does not result in a perceived relative advantage over alternatives” (Rogers, 2003, p. 190). Thus, the economic pressure which initially prompted them to adopt the
innovation may change its direction, provided that the perceived relative advantage changes in the course of the diffusion process. This might persuade adopters to reject the respective innovation. Therefore, this research argues that social and economic pressures do not only drive the adoption but also the discontinuance of innovations. Within this chapter, the focus is on the social pressure of peers. The influence of economic pressure will be considered in chapter 5.

Krackhardt (1997) introduced a simple diffusion model which accounts for the dual nature of social pressure by considering adopter-driven bandwagons, which spur the adoption of an innovation, and non-adopter-driven counter-bandwagons, which promote its rejection and discontinuance. Krackhardt (1997, p. 177) proposed this model for controversial innovations “whose value (and subsequent adoption) is socially determined and not rationally determined – that is, there is no exogenous superior or inferior quality to the innovation that determines its eventual adoption.” By stressing the importance of social influence on the diffusion process, Krackhardt’s (1997) definition of a controversial innovation coincides with fad theories of bandwagons. According to fad theories of bandwagons, the diffusion process is driven by information about who has already adopted the innovation, which results in an increased social pressure to conform as the number of adopters rises. Before introducing a simplified version of Krackhardt’s (1997) model, the following section elaborates on the dual nature of social pressure and word of mouth which may both result in the adoption or discontinuance of an innovation.

4.1.3. Positive and negative word of mouth

The social interaction between adopters and non-adopters of an innovation is often referred to as imitation or word of mouth (Bass, 2004, p. 1834). Assuming that adopters are employees who prefer and use the innovation and non-adopters are employees who prefer and use an alternative (Choi & Chang, 2009; Venkatesh et al., 2003, p. 461), the social pressure exerted by adopters is similar to positive word of mouth (WOM), whereas the social pressure exerted by non-adopters is comparable to negative WOM. Both, social pressure and WOM are the result of the social interaction between adopters and non-adopters and both can initiate bandwagon-like diffusion processes (Geroski, 2000). As Goldenberg et al. (2007, p. 187) stated: “While the internal influence parameter of aggregate diffusion models is often interpreted to represent word-of-mouth, it can also capture imitation effects such as social learning, social pressures, or network effects.” Therefore, their effect on the diffusion process is usually modeled in the same manner (Bass, 2004). Similar to the social pressure of adopters and the social pressure of non-adopters, positive WOM and negative WOM can initiate regular
bandwagons and counter-bandwagons, respectively. Nevertheless, there has been a bias in literature towards positive WOM, focusing on the adoption of innovations, whereas the discontinuance of innovations due to negative WOM has largely been ignored (Mahajan et al., 1984, p. 1401; Goldenberg et al., 2007; Rogers, 2003, p. 190).

However, a main difference between social pressure and WOM is that the former simply requires that adopters and non-adopters can observe and imitate each other’s behavior, while the latter requires some sort of direct communication between adopters and non-adopters. The observation of another individual can be directed, meaning that only the observing individual is influenced by the person s/he observes. However, the communication between two individuals is undirected, meaning that both communicating individuals influence each other (Wasserman & Faust, 1997). While social pressure can be exerted by the sheer number of adopters or non-adopters, WOM requires that both parties communicate (Abrahamson & Eisenman, 2008, p. 721).

Despite the fact, that the Bass diffusion model (Bass, 1969) and many other models have focused only on adopters’ positive WOM, disregarding non-adopter’s negative WOM, they have modeled positive WOM in the same way as social pressure by describing it as a direct function of the number of adopters. However, since WOM requires some sort of direct communication, messages are exchanged between adopters and non-adopters. Therefore, in addition to the information about the perceived number of adopters, receivers of the message are able to evaluate its persuasiveness. With more recent research emphasizing the importance of negative WOM, the question has been raised whether negative WOM is more persuasive than positive WOM or vice versa (Berger & Milkman, 2012; East et al., 2008; Fiedler, 2007, p. 15; Mizerski, 1982; Park & Lee, 2009).

Regarding the strength of positive and negative WOM, the widely held belief has been that unfavorable or negative information has a stronger impact on decision-makers than favorable or positive information (e.g., Mizerski, 1982). Also in the current era of digital communication, research has found that the effect of WOM is greater for negative electronic WOM than for positive electronic WOM, especially if the outcome of a decision cannot be known in advance (Park & Lee, 2009, pp. 62, 65). Park and Lee (2009, p. 65) argued that “negative eWOM [electronic word of mouth] information magnify consumers’ prevailing uncertainty and fear.” In a similar vein, Fiedler (2007, p. 15) suggested that negative information is more convincing than positive information, because negative characteristics are easier to recognize and prove than positive characteristics. For example, “to be a dishonest person, it is sufficient to lie or deceive one or two times;” whereas to be an honest person “one has to behave honestly all the time” (Fiedler, 2007, p. 15). Following this line of reasoning, it could be
argued that it is easier to demonstrate that an innovation is disadvantageous (by proving its inferiority once) than to demonstrate that it is advantageous (by proving its superiority consistently). Mizerski (1982, p. 308) tested and partially found support for the hypothesis that receivers of a message tend to attribute negative information to the object’s true characteristics, while positive information tends to be attributed to the personal feelings of the sender’s message. Therefore, negative information tends to have a greater impact on their cognitions and feelings.

However, other studies have questioned the dominance of negative word of mouth. For example, East et al. (2008) examined the impact of positive and negative word of mouth on brand purchase probability. They concluded: “It is our understanding that both academic and practitioner marketers believe that NWOM [negative word of mouth] has more impact on brand purchase than PWOM [positive word of mouth]. Our evidence indicates that this belief is mistaken” (East et al., 2008, p. 221). Instead, they found that positive word of mouth has a greater impact on brand purchase probability than negative word of mouth. Berger and Milkman (2012) analyzed the virality of articles published on the homepage of the New York Times. Similar to East et al. (2008), they found that positive content is more likely to be shared. Thus, Berger and Milkman (2012, p. 201) concluded: “While common wisdom suggests that people tend to pass along negative news more than positive news, our results indicate that positive news is actually more viral.”

Due to the conflicting findings in empirical research, the following section introduces a model which is capable to account for all three scenarios: positive WOM (social pressure of adopters) and negative WOM (social pressure of non-adopters) are equally strong, positive WOM is stronger than negative WOM, and negative WOM is stronger than positive WOM. Even though WOM and social pressure have often been modeled in the same manner (Bass, 2004), this research focuses on WOM in order to account for differences in the persuasiveness of positive and negative WOM. Hence, it is assumed that employees communicate with each other and that this relationship is undirected. That is, if there is a communication relation between individual A and individual B, there is also a communication relation between individual B and individual A. Nevertheless, peers might also exert social pressure on each other via WOM. Against this background, WOM and social pressure are used synonymously throughout the remainder of this research.
4.2. A basic model of intra-organizational diffusion processes considering positive and negative word of mouth

4.2.1. How biases determine the effect of word of mouth

Since intra-organizational innovation implementation depends on employees’ individual adoption decisions (Lanzolla & Suarez, 2012, p. 853; Leonard-Barton & Deschamps, 1988, p. 1253), it resembles the diffusion of a product or service innovation in a market. Therefore, similar methods can be used to analyze these processes. However, section 4.1 showed that the intra-organizational diffusion of an innovation differs from its diffusion in a market in that the usage and not the purchase of the innovation determines its success within an organization. In contrast to the purchase of an innovation, which is often considered to be irreversible (e.g., Bass, 1969), the usage of an innovation might fluctuate over time, depending on the communication among employees. As Greenhalgh et al. (2005, p. 12) stated: “The knowledge that underpins the adoption, dissemination and implementation of a complex innovation within an organization is not objective or given. Rather, it is socially constructed, frequently contested and must be continually negotiated between members of the organization or system.” Thus, depending on the strength of positive and negative WOM, employees might ultimately change their individual innovation-decisions and discontinue an innovation they previously adopted or they might adopt an innovation they previously did not use. Therefore, similar to SIS models, this section describes a theoretical system dynamics model which allows for the adoption and discontinuance of an innovation due to positive and negative WOM, respectively.

In the context of epidemics, Jackson and López-Pintado (2013, p. 54) introduced a generic model of diffusion which embodies, among others, SIS diffusion models, relative threshold diffusion models (decision-makers choose between two competing technologies depending on whether the perceived number of adopters of one of them exceeds a certain threshold or not), and imitation diffusion models. Compared to Abrahamson and Rosenkopf (1997), who assumed that a constant fraction of adopters reject an innovation after a certain time, Jackson and López-Pintado’s (2013, p. 53) rejection rate depends on the fraction of non-adopters. In particular, an adopter becomes a non-adopter if s/he interacts only with non-adopters in a given period of time. Assuming that an employee is either an adopter using an innovation and spreading positive WOM about it or a non-adopter not using it and spreading negative WOM about it, an adopter only becomes a non-adopter and discontinues the innovation if s/he is not exposed to confirming positive WOM during that time period. In other words, an adopter only becomes a non-adopter if s/he only communicates with non-adopters.
On the other hand, Jackson and López-Pintado (2013) assumed that a non-adopter becomes an adopter if s/he is exposed to at least one adopter. Thus, one adopter might be enough to convert a non-adopter, while an adopter only converts to the non-adopter camp if all the employees he interacts with are non-adopters. This imbalance between adoption and discontinuance implicitly assumes that positive WOM is much stronger than negative WOM and/or that positive and negative WOM are different in nature. The former has been discussed above and will be analyzed in the following section. With regard to the latter, East et al. (2008, p. 221) found that positive and negative WOM are similar behaviors of similar origin and with similar measurement biases. Contrary to Jackson and López-Pintado (2003), this suggests that positive and negative WOM are similar in nature (Ulli-Beer et al., 2010). Therefore, in line with Krackhardt’s (1997, p. 184) model, this research assumes that all employees, adopters and non-adopters, change their current belief with probability $P_{AN}$ and $P_{NA}$, respectively, if they cannot find at least one other employee who agrees with them during a time period $t$.

This assumption is supported by Asch (1963, p. 186), who found that the presence of only one other like-minded employee is “sufficient to deplete the power of the majority, and in some cases to destroy it.” In accordance with Asch (1963), Schulz-Hardt, Frey, Lüthgens, and Moscovici (2000, p. 659) stated that “support by a second member gives the minorities additional self-confidence and thus increases their influence on the decision process.” This bias towards a favored or chosen decision coincides with studies which found that information-seeking processes are often not balanced (Schulz-Hardt et al., 2000, p. 655). That is, people prefer confirming over conflicting information (Janis & Mann, 1977; Frey, 1986; Prislin & Wood, 2005, p. 681) and are therefore to a certain extent resistant to change (e.g., Kim & Kankanhalli, 2009).

Similarly, Vennix (1996) stated that people select and interpret information from their environment based on their mental models. As a result, “this selection process is itself guided by the existing mental model and subject to the ‘law’ of looking for confirming evidence” (Vennix, 1996, p. 21). This confirmation bias might be even stronger in public settings because “[h]umans employ defensive routines as a way to protect themselves from losing face when exposing their ideas to others” (Vennix, 1999, p. 386). Consequently, this dissertation assumes that an employee may convert to the opposite camp only if another like-minded organizational member cannot be found. As stated above, isolated adopters convert to the non-adopter camp with conversion probability $P_{AN}$, while isolated non-adopters convert to the adopter camp with conversion probability $P_{NA}$.

Contrary to most diffusion models, this research does not assume that an employee interacts with all other employees to look for like-minded others. According to the concept of satisficing behavior, organizational members do not
strive to obtain all information available (Simon, 1956, p. 129). In line with Simon (1956), De Dreu, Nijstad, and van Knippenberg (2008, p. 25) pointed out that “people can and will choose among a shallow and heuristic versus a deep and deliberate information search-and-processing strategy.” Therefore, it is assumed that employees randomly search for like-minded others only within a certain fraction of their group. Accounting for the fact that within a given time period $t$ employees usually search for and interact with only a limited number of other employees, variable $S_A$ represents the search and interaction intensity of adopters, while $S_N$ represents the search and interaction intensity of non-adopters.

4.2.2. Specifying the influence of word of mouth on implementation effectiveness

This section translates the previous explanations into concrete equations which, in combination, constitute the simulation model. Equation 1a describes the periodical decrease of the overall non-adopter fraction ($N = 1 - A$) due to the conversion of non-adopters to the adopter camp, which is therefore also the periodical increase of the overall adopter fraction ($A$). Equation 1b describes the periodical decrease of $A$ due to the conversion of adopters to the non-adopter camp, which is hence the increase of $N$. Therefore, the periodical net increase of $A$ is the difference between equation 1a and equation 1b (see also Figure 6):

\[
\frac{dN}{dt} = P_{NA} \cdot (1 - A) \cdot A^{SN};
\]

\[
\frac{dA}{dt} = P_{AN} \cdot A \cdot (1 - A)^{SA}.
\]

The term $A^{SN}$ represents the probability that a non-adopter only interacts with adopters in his or her searched fraction of an organization (Krackhardt, 1997). That is, the higher the adopter fraction and the lower the search intensity of non-adopters, the more likely it is that a non-adopter only communicates with adopters. The fraction of all non-adopters who only interact with adopters thus corresponds to the term $(1 - A) \cdot A^{SN}$. Assuming that the unit of time is month(s), these isolated non-adopters convert to the adopter camp with conversion probability $P_{NA}$ within one month. Equation 1b shows that adopters convert to the non-adopter camp in the same manner. The structure of this model is illustrated in Figure 6.

The search and interaction intensities of adopters ($S_A$) and non-adopters ($S_N$) describe with how many other employees an employee on average communicates.
The more colleagues an adopter or non-adopter interacts with, the higher the likelihood that an adopter (non-adopter) interacts with at least one other adopter (non-adopter) and consequently does not change his or her belief that the innovation is advantageous (disadvantageous). Therefore, the higher the search and interaction intensity of adopters ($S_A$), the greater their resistance to convert to the non-adopter camp. Likewise, the search and interaction intensity of non-adopters ($S_N$) can be interpreted as the resistance of non-adopters to convert to the adopter camp. The lower the resistance of adopters and non-adopters, the higher the number of employees switching their allegiance.

Since it is assumed that adopters spread positive WOM and non-adopters negative WOM, the search intensities $S_A$ and $S_N$ are also indicators for the **strength** of positive WOM and negative WOM, respectively. The higher the search intensity of an employee, the more this person communicates with others and the greater the effect of this person’s WOM. Thus, positive (negative) WOM is stronger, the higher the search intensity of adopters (non-adopters). Consequently, the term $A^{SN}$ can be interpreted as the **influence** or **impact** of positive WOM on non-adopters, while the term $(1 - A)^{SA}$ describes the influence or impact of negative WOM on adopters. That is, the impact of positive WOM on the conversion rate of non-adopters (equation 1a) depends on the fraction of adopters and the search intensity of non-adopters. The impact of positive WOM ($A^{SN}$) is stronger, the higher the fraction of adopters ($A$) and the weaker negative WOM ($S_N$). Conversely, the impact of negative WOM ($(1 - A)^{SA}$) is higher, the higher the fraction of non-adopters and the weaker positive WOM.

Similar to the strength of positive and negative WOM, $S_A$ and $S_N$ can also be interpreted as the **extent** of social pressure of adopters and non-adopters, respectively, while the terms $A^{SN}$ and $(1 - A)^{SA}$ can also be interpreted as the
influence or impact of the social pressure of adopters and non-adopters on the respective conversion rates, which are described by equations 1a and 1b. The greater the extent of social pressure of non-adopters \((S_N)\), the lower the impact of social pressure of adopters \((A_S)\) on the conversion rate of non-adopters (equation 1a). Conversely, the higher the social pressure of adopters \((S_A)\), the lower the influence of non-adopters’ pressure \((1 - A)S_A\) on the conversion rate of adopters (equation 1b). Table 2 provides an overview of the key variables of the basic model described in this chapter. A visual representation of this model in form of a complete stock and flow diagram can be found in appendix 1 (Lane, 2008). All variables of the model including equations are listed in appendix 3.

<table>
<thead>
<tr>
<th>Name</th>
<th>Variable</th>
<th>Values</th>
<th>Equation</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adopter fraction</td>
<td>(A)</td>
<td>(0 \leq A \leq 1)</td>
<td>1a, 1b</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Non-adopter fraction (= 1 – A)</td>
<td>(N)</td>
<td>(0 \leq N \leq 1)</td>
<td>1a, 1b</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Conversion probability adopters</td>
<td>(P_{AN})</td>
<td>(0 \leq P_{AN} \leq 1)</td>
<td>1b</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Conversion probability non-adopters</td>
<td>(P_{NA})</td>
<td>(0 \leq P_{NA} \leq 1)</td>
<td>1a</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Search intensity adopters</td>
<td>(S_A)</td>
<td>(S_A \geq 1)</td>
<td>1b</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Search intensity non-adopters</td>
<td>(S_N)</td>
<td>(S_N \geq 1)</td>
<td>1a</td>
<td>Chapter 4</td>
</tr>
</tbody>
</table>

**Table 2** Overview of the key variables used in the basic simulation model

4.2.3. Testing the validity of the basic implementation model

Several validity tests were conducted to gain confidence in the usefulness of the basic implementation model described in this chapter and the following models which are introduced in the subsequent chapters (Barlas, 1996, p. 184). According to Richardson and Pugh (1981, p. 311), “validation is an on-going mix of activities embedded throughout the iterative model-building process.” In other words, if one of the validity tests fails, the model needs to be adjusted and all previously done tests need to be conducted again. This process continues until all tests are passed. Since a complete documentation of this process would go beyond the scope of this dissertation, only the final results of the conducted validity tests are shown.

In order to evaluate the validity of a model, one must consider its purpose (Barlas, 1989; Barlas, 1996; Barlas & Carpenter, 1990). The overarching purpose of this dissertation is to contribute to a better understanding of intra-organizational
innovation implementation processes by shedding light on the interrelations and dynamics among four determinants of implementation effectiveness. By means of the basic implementation model, this chapter examines the influence of peers on implementation effectiveness. As depicted in Table 1, each of the following chapters focuses on one of the other three determinants of implementation effectiveness. Depending on the underlying research question and purpose of the following three chapters, the basic implementation model of this chapter is adjusted, ultimately yielding four different models. Against this background, this research focuses on “a ‘minimum’ most crucial set of formalizable validity tests” (Barlas, 1996, p. 202). This set includes five tests of formal model validation which are in line with the rather theoretical nature of this research (Lane, 1995, p. 117) and which have been mentioned unanimously in several validation frameworks (Barlas, 1996; Forrester & Senge, 1980; Lane, 1995, p. 123; Richardson & Pugh, 1981).

In particular, the five conducted tests for each model in this and the following chapters are: theoretical structure-confirmation test, extreme-conditions test, dimensional consistency test, behavior sensitivity test, and boundary adequacy test. The theoretical structure-confirmation test compares the equations of the respective model with generalized knowledge in the literature (Barlas, 1996, p. 190). This test is passed if “the model structure [does] not contradict knowledge about the structure of the real system” (Forrester & Senge, 1980, p. 9). The extreme-conditions test evaluates the plausibility of simulation results for minimum as well as maximum parameter values (Forrester & Senge, 1980, p. 13). The test is passed if the simulation results are in line with the “knowledge/anticipation of what would happen under a similar condition in real life” (Barlas, 1996, p. 190). The dimensional consistency test is passed if the left-hand side and right-hand side of each equation are dimensionally consistent (Barlas, 1996, p. 191). The behavior sensitivity test examines how sensitive the model behavior is to changes in parameter values (Forrester & Senge, 1980, p. 28). The test is passed “if the real system would exhibit similar high sensitivity to the corresponding parameters” (Barlas, 1996, p. 191). Finally, the boundary adequacy test evaluates “whether or not model aggregation is appropriate and if a model includes all relevant structure” (Forrester & Senge, 1980, p. 14). The test is passed if the model structure satisfies the model’s purpose and if the behavior of the model and the derived policy recommendations are relatively insensitive to further model extensions (Forrester & Senge, 1980).

Concerning the basic implementation model introduced in this chapter, the previous sections justified the structure of the model by deriving it from well-established models (e.g., Bass, 1969; Krackhardt, 1997) and by grounding it in empirical research (e.g., Asch, 1963; Simon, 1956). Therefore, the theoretical structure-confirmation test was passed. With regard to the extreme-conditions
test, all parameter values were tested, finding no inconsistent model behavior. In particular, the search intensities of adopters (SA) and non-adopters (SN) were each assumed to be 1 or 1000 and the conversion probabilities of adopters (PAN) and non-adopters (PNA) as well as the initial adopter fraction (Aini) were each assumed to be 0 or 1. Therefore, the extreme conditions test was also passed. The interested reader can find the simulation results of this test in appendix 7.

Using the automated unit check of Vensim, no dimensional inconsistencies were found, resulting in a positive outcome of the dimensional consistency test. Concerning the behavior sensitivity test, several changes in parameter values were examined. The results of these simulations and an explanation of the respective model behavior are provided in the following section. Even though these results could not be compared to empirical data, they suggest that the sensitivity of the model is reasonable.

When conducting the boundary adequacy test, one must consider the purpose of the basic implementation model introduced in this chapter (Forrester & Senge, 1980, p. 16). The purpose of this model is to answer the first research question, asking how different strengths of positive and negative word of mouth influence implementation effectiveness. Against this background, the boundary of the model seems adequate. In order to examine whether or not the behavior of the model and the derived policy recommendations are valid if the model boundary is extended, the interested reader might be referred to chapters 5, 6 and 7 which introduce extended versions of the basic implementation model. The dynamics and policy recommendations that will be uncovered in the following section of this chapter are also valid for the extended versions of the basic implementation model. Therefore, the model boundary of the basic implementation model also seems adequate when considering the behavior of the model and the derived policy recommendations. Consequently, the boundary adequacy test was also passed.

4.3. Analyzing the impact of word of mouth on implementation effectiveness by means of a basic intra-organizational diffusion model

The previous sections introduced a basic intra-organizational diffusion model which focuses on the usage of innovations within organizations instead of on the purchase of innovations within markets. Therefore, employees who use the innovation are considered to be adopters, while employees who do not use the innovation represent non-adopters. In contrast to most diffusion models, the introduced model accounts for the discontinuance of innovations by allowing adopters to convert to the non-adopter camp due to social pressure and negative
WOM of non-adopters. This happens in the same manner as non-adopters convert to the adopter camp due to adopters’ social pressure and positive WOM (see equations 1a and 1b). However, accounting for conflicting research, the model considers a contingent difference between the strength of positive WOM and negative WOM. In this section, the introduced model is analyzed by running several simulations. Thereby, the focus is on the interaction between adopters and non-adopters. In particular, it is analyzed how the search and interaction intensities of adopters and non-adopters and the relation between positive and negative WOM influence the diffusion process. All simulation runs of this dissertation were conducted using Vensim DSS 6.1c with Euler integration and $dt = 0.03125$, running on a standard PC.

Figure 7 depicts the simulation results of the introduced model for different values of $S_A$ and $S_N$ when $P_{NA} = P_{AN} = 100\%/month$ and when the initial fraction of adopters within the organization ($A_{ini}$) is assumed to be 30%, 50%, or 70%. $A_{ini}$ can, for example, represent the staff of an organization which already uses an innovation and now merges with an organization that does not yet use it ($N_{ini} = 1 - A_{ini}$). It could also represent a so-called greenfield site, which has been established from scratch to ensure dedicated resources and to protect it from the less innovative culture of the organization (Johns, 1993, p. 586). Similar to a greenfield site, the initial adopter fraction could also represent a so-called skunkworks which “is an especially enriched environment that is intended to help a small group of individuals design a new idea by escaping routine organizational procedures” (Rogers, 2003, p. 149). After all employees of such a skunkworks or greenfield site adopted an innovation, the site can then be reintegrated to initiate the diffusion of the innovation throughout the remainder of an organization.

Figure 7b illustrates the equal nature of positive and negative WOM. If the initial fractions of adopters and non-adopters are both 0.5 and $S_A = S_N = 6$ (graph 3 in Figure 7b), both camps are equally strong, resulting in no change of the adopter fraction. However, if $S_A$ is higher than $S_N$ (graph 1: $S_A = 8 > S_N = 4$; and graph 2: $S_A = 5 > S_N = 3$), the innovation diffuses throughout the organization, whereas it gets completely rejected if $S_A$ is smaller than $S_N$ (graph 4: $S_A = 3 < S_N = 5$ and graph 5: $S_A = 4 < S_N = 8$). Figures 7a and 7c depict the diffusion process for the same scenarios with the only difference being that $A_{ini}$ is reduced from 0.5 to 0.4 in Figure 7a, while it is increased from 0.5 to 0.6 in Figure 7c. In any case, an innovation will diffuse completely if $S_A/S_N > 1$ and $A_{ini} ≥ 0.5$. The higher the initial adopter fraction ($A_{ini}$) is, the higher the likelihood and speed of a complete diffusion. In general, a higher ratio between $S_A$ and $S_N$ has the same effect on the diffusion process. For example, a ratio of two (graphs 1 in Figure 7) always leads to a quicker diffusion than a ratio of one (graphs 3 in Figure 7) or a ratio of
one-half (graphs 5 in Figure 7), independent of the initial adopter fraction. Furthermore, in many cases a higher value of \( S_A/S_N \) can compensate for a lower initial adopter fraction, thereby resulting in a successful diffusion even if \( A_{ini} < 0.5 \) (e.g., graph 1 in Figure 7a).

**Figure 7** Influence of the initial adopter fraction (Aini) and the search and interaction intensities (Sa, Sn) on the adopter fraction (A)

However, the ratio between the search and interaction intensities (\( S_A/S_N \)) alone does not describe their influence on the diffusion process sufficiently. Besides their relative values, the absolute values of search and interaction intensities need to be considered as well. It has been argued above that a higher search intensity of an employee increases the likelihood that s/he interacts with a like-mined other employee and hence does not convert to the opposite camp. Therefore, a higher search and interaction intensity of adopters (\( S_A \)) causes them to be more resistant to convert to the non-adopter camp. Likewise, the search and interaction intensity of non-adopters (\( S_N \)) can be interpreted as the resistance of non-adopters to convert to the adopter camp. The lower the resistance of adopters and non-adopters, the greater the number of employees switching their allegiance. Therefore, the impact of the ratio between \( S_A \) and \( S_N \) is greater, the lower the absolute values of \( S_A \) and \( S_N \) are.

This effect is illustrated in Figure 7 where a resistance ratio of 8:4 (graphs 1) between \( S_A \) and \( S_N \) is inferior to a ratio of 5:3 (graphs 2). Even though a ratio \( (S_A/S_N) \) of 2.0 (8:4) suggests a greater dominance of adopters than a ratio of 1.67 (5:3) does, the latter enables a quicker diffusion of the innovation than the former, independent of \( A_{ini} \). This is the case because the lower resistance of
adopters as well as non-adopters (graphs 2) results in an overall higher fraction of employees converting to the respective opposite camp. This effect more than compensates for the lower resistance ratio between adopters and non-adopters ($S_A/S_N$). In other words, since adopters are still more resistant than non-adopters ($S_A/S_N > 1$), a ratio of 5:3 leads to a quicker diffusion than a ratio of 8:4 because, in general, it is easier to persuade employees when the sum of their absolute search and interaction intensities ($S_A + S_N$) is lower ($5 + 3 < 8 + 4$). That is, the net conversion rate—the difference between converted non-adopters (equation 2a) and converted adopters (equation 2b)—is greater for a ratio of 1.67 than it is for a ratio of 2.0.

As pointed out above, the search and interaction intensities of adopters and non-adopters can also be interpreted as the strength of positive and negative WOM, respectively. Compared to the impact of positive WOM which is spread by adopters (i.e., $A^SN$), the impact of negative WOM which is spread by non-adopters (i.e., $(1 - A)^SN$) is practically zero in scenarios where $S_A$ (strength of positive WOM) is much higher than $S_N$ (strength of negative WOM). Therefore, a small initial adopter fraction ($A_{ini}$) suffices to generate the characteristic s-shaped diffusion curve, which is also known from the Bass diffusion model (Bass, 1969). In contrast to the Bass diffusion model, the introduced model focuses on the elementary dynamics of the interaction between adopters (positive WOM) and non-adopters (negative WOM) within an organization. External influence factors, such as advertising, are hence not considered making it necessary to have at least some adopters of the innovation present at the start of the simulation.

The conversion probabilities of adopters ($P_{AN}$) and non-adopters ($P_{NA}$) specify how likely it is that an adopter or non-adopter who could not find another like-minded employee converts to the opposite camp during a time period $t$. Therefore, they can also be interpreted as a measure of resistance: The lower the likelihood that an isolated adopter (non-adopter) converts to the non-adopter (adopter) camp, the higher the resistance of adopters (non-adopters). Consequently, the conversion probabilities have a similar effect on the conversion rates (equations 1a and 1b) as the respective search and interaction intensities. The lower the conversion probability of adopters compared to non-adopters, the higher the likelihood and speed of a complete diffusion. That is, the lower the ratio between $P_{AN}$ and $P_{NA}$, the higher implementation effectiveness. In addition, a lower (higher) conversion probability of adopters (non-adopters) is able to compensate for a lower initial adopter fraction. However, in contrast to the search and interaction intensities, the relative difference between the conversion probabilities sufficiently describes their impact on the conversion process. That is, there is no additional effect on the diffusion process due to the absolute values of the conversion probabilities.
4.4. Summary and discussion of findings with regard to the relative strength of positive and negative word of mouth

This chapter showed that the diffusion of innovations within markets differs from the diffusion of innovations within organizations in that the goal of the former is to sell the innovation to as many actors in the market as possible, while the latter is interested in convincing as many employees as possible to use the innovation. In contrast to the purchase of an innovation, its actual usage is often subject to reconfirmation which may cause employees to discontinue an innovation. Due to the fact that most diffusion models, such as the Bass diffusion model, focus on diffusion processes within markets, they only consider the social pressure or positive word of mouth (WOM) of adopters and disregard the influence of non-adopters which may trigger the discontinuance of an innovation. However, from an organizational perspective, not the purchase of an innovation but its widespread use among employees is essential to generate benefits from it. Therefore, this chapter introduced a simple intra-organizational diffusion model which also considers the social pressure or negative WOM of non-adopters, possibly resulting in the discontinuance of an innovation.

This research defined an adopter as an employee who is convinced by and uses an innovation to its full potential. On the other hand, a non-adopter is an employee who prefers the status quo and does not use the innovation. Consequently, an adopter is assumed to spread positive WOM, while a non-adopter spreads negative WOM. This chapter introduced the search and interaction intensities of adopters ($S_A$) and non-adopters ($S_N$) as an indicator for the strength of positive and negative WOM. Due to the similarity of WOM and social pressure in social communication situations, $S_A$ and $S_N$ can also be interpreted as the extent of social pressure exerted by an adopter and social pressure exerted by a non-adopter, respectively. Since employees only change their individual innovation-decision if they are isolated from like-minded others, the search and interaction intensity can also be interpreted as resistance to change. The higher $S_A$ or $S_N$, the more likely it is that an adopter or non-adopter encounters another like-minded employee and hence does not change his or her individual innovation-decision. Consequently, the search and interaction intensities can also be interpreted as the strength of WOM, the extent of social pressure, or the resistance to change.

The first research question asked how different strengths of positive and negative word of mouth influence implementation effectiveness. In order to answer this question, this chapter analyzed the impact of WOM or social pressure on the diffusion process. The first factor influencing the impact of WOM is of course the strength of WOM, which is characterized by the search
and interaction intensity. The more an employee communicates with others, the less likely it is that s/he does not find another like-minded employee. Therefore, the impact of positive (negative) WOM is the greater the weaker negative (positive) WOM. Besides the strength of WOM, the impact of WOM is also defined by the number of employees that spread it. That is, the higher the fraction of adopters (non-adopters), the greater the impact of positive (negative) WOM. Consequently, the impact of positive WOM (i.e., \( A^{SN} \)) is the greater, the weaker negative WOM (\( S_N \)) and the higher the fraction of adopters (\( A \)). Conversely, the impact of negative WOM (i.e., \( (1 - A)^{SA} \)) is the greater, the weaker positive WOM (\( S_A \)) and the higher the fraction of non-adopters (\( 1 - A \)).

The analysis of this model revealed that the outcome of the diffusion process depends on the absolute and relative strength of positive and negative WOM. The stronger positive WOM is in comparison to negative WOM, the more likely it is that the innovation diffuses completely. In addition, a stronger positive WOM or a weaker negative WOM are able to compensate for a lower initial adopter fraction. Besides this relative strength of positive and negative WOM, implementation effectiveness also depends on the absolute strength of positive and negative WOM. The higher the absolute strength of both positive and negative WOM, the less influential the relative difference between them. That is, if positive and negative WOM are both very strong in absolute terms, a greater relative difference between them is necessary to reach a certain level of implementation effectiveness than if the absolute strengths of both positive and negative WOM were weaker.

Consequently, it might be more beneficial for the management of an organization to support the implementation process by reducing the absolute strength of negative WOM than by increasing the absolute strength of positive WOM. This is not the case because negative WOM is assumed to be more influential than positive WOM. In fact, positive and negative WOM are assumed to be equal in nature. Instead, this strategy is beneficial because a lower absolute strength of negative WOM increases the relative strength of positive WOM while at the same time reducing the absolute strength of both positive and negative WOM. On the other hand, if management focused on increasing the absolute strength of positive WOM, the relative strength of positive WOM would also increase. However, at the same time the absolute strength of both positive and negative WOM would increase, thereby making the relative difference between both less influential. Thus, the analysis of this model suggests that management should concentrate its efforts on limiting the negative impact of employees who do not use the innovation, instead of promoting employees who do already use it. Thereby, this finding challenges the common emphasis on enhancing colleagues’ favorable opinions (e.g., Kim & Kankanhalli, 2009, p. 579). Instead, restricting unfavorable opinions might be more effective.
This chapter introduced a basic communication model between adopters and non-adopters of an innovation in order to analyze the influence of peers on the effectiveness of intra-organizational implementation processes. In particular, it was examined how adopters’ positive WOM and non-adopters’ negative WOM influence the adoption and discontinuance of an innovation. Since individuals are generally ambiguity intolerant (e.g., Ellsberg, 1961), the social influence of peers has been found to be the greater, the higher the perceived ambiguity of an innovation (Abrahamson & Rosenkopf, 1993; 1997; Tidd, 2010). Therefore, the following chapter extends the basic model introduced in this chapter to account for the influence of an innovation’s perceived ambiguity and employees’ ambiguity intolerance on the effectiveness of innovation implementation processes.
5. A model considering innovation discontinuance and employees’ ambiguity intolerance

5.1. Literature review on the ambiguity of innovations

5.1.1. Ambiguity of an innovation in diffusion literature

Chapter 4 pointed out that the influence of peers is often described by bandwagon pressure. Referring to Abrahamson and Fairchild (1999, p. 731), bandwagons were defined as diffusion processes which are characterized by “a positive feedback loop in which increases in the number of adopters create stronger bandwagon pressures, and stronger bandwagon pressures, in turn, cause increases in the number of adopters.” That is, the higher the number of people on a bandwagon, the greater the pressure on others to join the bandwagon as well. In the context of innovation implementation, adopters, for example, exert bandwagon pressure on non-adopters to also use the innovation. In principle, this pressure can be economic, knowledge-based, or social in nature (Abrahamson & Rosenkopf, 1997). All three forms of pressure are similar in that they are essentially driven by the number of people who are already on the bandwagon.

Focusing on the bandwagon pressure of adopters, economic pressure to adopt an innovation is generated if the number of adopters defines an innovation’s profitability. Increasing returns theories assume that the profitability of an innovation increases with the number of its adopters (Arthur, 1994). Thus, the higher the returns are, the greater the economic pressure on non-adopters to also adopt the innovation, which, in turn, causes the number of adopters to increase even further (Abrahamson & Rosenkopf, 1997, p. 292). However, in order to evaluate the profitability of an innovation, its costs and benefits must be known. Even if this information is available, it may be too ambiguous to support the decision-making of non-adopters. Therefore, theories of bandwagons that are based on increasing returns “generally assume that the profitability of innovations is unambiguous” (Abrahamson & Rosenkopf, 1997, p. 292).

However, learning and fad theories of bandwagon diffusion assume that the profitability of innovations is ambiguous (Abrahamson & Rosenkopf, 1997, p. 292). That is, due to missing information, the probability that an innovation outperforms the status quo is unclear (Camerer & Weber, 1992). These theories assume that innovations diffuse mainly due to knowledge-based or social pressure. According to learning theories of bandwagons, the diffusion process is driven by information about an innovation’s profitability. This knowledge increases with the number of adopters who share their experiences with non-adopters. According to fad theories of bandwagons, the diffusion process is driven by information about who has already adopted the innovation, which results in an increased social pressure to conform as the number of adopters rises.
By definition, innovations are new and therefore to a certain degree unknown to potential adopters. Therefore, in most cases, the costs and benefits of an innovation are at least to some extent ambiguous. Thus, an innovation’s ambiguity is not just an underlying assumption of learning and fad theories of bandwagon, but a major driver of most bandwagons. Accordingly, Tidd (2010, p. 18) pointed out that “the critical difference between bandwagons and other types of diffusion is that the former require only limited information to flow from early to later adopters” and that the effect of bandwagons on the diffusion process is the stronger, the more ambiguous the respective innovation. Despite its prevalence and influence on the diffusion process, diffusion research has largely neglected the ambiguity of an innovation’s profitability. The majority of bandwagon models have disregarded information about an innovation’s profitability, arguing that it is ambiguous and therefore of little use to decision-makers. In line with fad theories of bandwagon diffusion, these models have focused exclusively on the social pressure created by the number of adopters as the main driver of diffusion processes (Bohlmann et al., 2010, p. 749; Gibbons, 2004, p. 943; Goldenberg et al., 2007, p. 189).

However, empirical research has shown that individuals generally try to avoid making decisions under ambiguity by adjusting their behavior accordingly (for a review, see Camerer & Weber, 1992). In particular, it is suggested that decision-makers are intolerant of ambiguity and base their adoption decisions to a greater extent on information from their social environment, the more ambiguous an innovation’s profitability (Ashford & Cummings, 1985, p. 77; Burt, 1987, p. 1326; McPherson, 1983, p. 121). By observing the behavior of others and by communicating with them, decision-makers aim to reduce the perceived ambiguity (Ashford & Cummings, 1985, p. 68; McPherson, 1983, p. 121; Rogers, 2003, p. 175). Thus, most bandwagon models have neglected that ambiguous information about an innovation’s profitability—even though objectively, it might be of little use—still influences the adoption decision of individuals and thereby the number of adopters.

Among the few exceptions that consider the influence of an innovation’s ambiguity on the diffusion process are Abrahamson and Rosenkopf (1993, p. 497; 1997, p. 295) who introduced bandwagon models which assume that the social pressure is greater, the more ambiguous an innovation’s profitability and the greater the number of adopters. However, an innovation’s ambiguity—defined as the lack of clarity surrounding the assessment of its profitability—is assumed to be constant over the whole course of the diffusion process. This might be unrealistic in an intra-organizational context where a large part of an innovation’s success depends on the support of employees who are supposed to use the innovation (Choi & Chang, 2009; Douglas & Judge Jr., 2001; Leonard-Barton
& Deschamps, 1988, p. 1252). Choi and Chang (2009, p. 251), for example, found that the extent to which employees accepted an innovation positively correlated with the overall extent to which an organization successfully implemented the innovation. The overall extent of innovation implementation (i.e., the degree of diffusion), in turn, is positively correlated with the accrued benefits from an innovation. Thus, in line with increasing returns theories of bandwagon diffusion, the more accepted and widespread an innovation is within an organization, the higher its effectiveness and profitability.

Research has shown that not an absolute measure of an innovation's profitability, but rather its perceived relative advantage over the status quo influences the individual innovation-decision of employees (Greenhalgh et al., 2005, p. 83; Moore & Benbasat, 1991, p. 195; Rogers, 2003, p. 229; Venkatesh et al., 2003, p. 219). Therefore, this research uses the perceived relative advantage of an innovation as a measure for the innovation's profitability. It is suggested that an innovation's perceived relative advantage over the status quo determines the perceived ambiguity of this innovation. That is, the more evident an innovation's superiority or inferiority over the status quo, the lower the perceived ambiguity of the innovation. As an innovation's relative advantage changes with the number of its adopters, the degree of ambiguity also varies in the course of the diffusion process. Therefore, this research argues that by failing to incorporate the notion that an innovation's ambiguity not only influences, but also depends on the number of adopters, previous bandwagon studies have missed an important link which creates a feedback loop that has been largely ignored so far. The perceived ambiguity of an innovation influences the number of adopters, thereby affecting the perceived relative advantage (i.e., the profitability) of an innovation which, in turn, determines the innovation's perceived ambiguity.

Therefore, this chapter aims to extend existing diffusion theory by highlighting the role of an innovation's perceived ambiguity as a dependent variable of the diffusion process. Thereby, the focus is on the effects of ambiguity intolerance on the interaction behavior of employees within groups. In order to identify the causal mechanisms that characterize the feedback between the perceived ambiguity of an innovation and social interaction processes, the following sections review the existing literature. First, section 5.1.2 elaborates on the perceived relative advantage of an innovation from an employee's perspective. Second, section 5.1.3 derives a definition of the perceived ambiguity of an innovation and relates it to its perceived relative advantage. In a third step, section 5.1.4 reviews research that examines the impact of an innovation's perceived ambiguity on the interaction behavior of ambiguity intolerant employees. The subsequent section extends the basic model of the previous chapter by incorporating a part of Repenning's (2002) implementation model to analyze the effects of ambiguity
intolerance. In section 5.3 and section 5.4 the extended model is analyzed with regard to the second research question, asking how the ambiguity of an innovation and employees’ ambiguity intolerance influence the communication among peers and thereby implementation effectiveness. After presenting the simulation-based results of the analysis, this chapter closes by discussing these results and by outlining implications for future research and practice.

5.1.2. Perceived relative advantage of an innovation

Chapter 2 pointed out that, in an organizational context, the planned diffusion of an innovation among employees is often referred to as the implementation process (Rogers, 2003, p. 420; Zaltman et al., 1973, p. 58). Assuming an innovation-decision made by an authority (Lanzolla & Suarez, 2012, p. 841; Rogers, 2003, p. 403), the implementation process begins with the decision of senior management to adopt an innovation within the organization and ends with the innovation becoming a routine among employees (e.g., Klein & Sorra, 1996, p. 1057). Even though the organizational adoption decision is made by senior management, the success of the implementation process depends on “numerous individual ‘secondary’ adoption decisions by target users” (Leonard-Barton & Deschamps, 1988, p. 1253). That is, an innovation’s effectiveness within an organization increases with the number of targeted employees using the innovation (Leonard-Barton & Deschamps, 1988, p. 1252; Repenning, 2002).

An innovation’s effectiveness not only depends on the individual innovation-decisions of employees, it indirectly affects their decision-making as well. As will be shown in this and the following sections, employees perception of an innovation’s effectiveness influences their communication behavior and thereby their individual innovation-decisions. However, “there is a well-recognised difference between objective advantage (the research evidence as evaluated by experts) and perceived advantage in the eyes of practitioners” (Greenhalgh et al., 2005, p. 83). Therefore, this research distinguishes between the actual effectiveness of an innovation and its perceived effectiveness (Davis, 1989, p. 335). The actual effectiveness describes the objective advantage of an innovation which is based on complete and objective information. However, since this information is rarely available, it could be argued that the actual effectiveness is a rather theoretical construct which does not occur in reality, at least not in its pure form. Therefore, this research defines an innovation’s actual effectiveness as an innovation’s advantage based on research evidence and expert evaluations. On the other hand, the perceived effectiveness describes employees’ beliefs that are derived from limited objective information about an innovation’s effectiveness. Thus, an innovation’s perceived effectiveness describes the perceived advantage of an innovation in the eyes of practitioners.
Burt (2000, p. 1) pointed out that “[a]s much as change is about adapting to the new, it is about detaching from the old.” Building on knowledge about the status quo, employees form expectations about the innovation’s effectiveness. This knowledge serves as a benchmark which determines the expected effectiveness of an innovation. Therefore, employees compare an innovation’s perceived effectiveness to the effectiveness of the status quo when deciding whether to adopt or reject an innovation. The degree to which an employee perceives an innovation to be better than the idea it supersedes is referred to as the perceived relative advantage (Greenhalgh et al., 2005, p. 83; Moore & Benbasat, 1991, p. 195; Rogers, 2003, p. 229; Venkatesh et al., 2003, p. 219). The perceived relative advantage of an innovation has been found to be the most significant and consistent attribute of an innovation determining its adoption (Greenhalgh et al., 2005, p. 84; Rogers, 2003, p. 233). Thus, employees do not simply base their adoption decision on an absolute measure of an innovation’s effectiveness, but rather on its perceived relative advantage ($R$) over the status quo (Repenning, 2002, p. 116):

$$ R = \frac{\text{Perceived Effectiveness}}{\text{Expected Effectiveness}}. \quad (2) $$

The higher the perceived relative advantage of an innovation, the more likely employees are to adopt it. However, if an innovation’s perceived effectiveness is similar to its expected effectiveness (i.e., its perceived relative advantage is close to one) employees are uncertain whether they should use the innovation or keep using the status quo (Abrahamson & Rosenkopf, 1993, p. 490). In this research, the lack of clarity surrounding the choice between an innovation and the status quo constitutes the definition of an innovation’s ambiguity. That is, the closer the perceived relative advantage is to one, the higher the ambiguity surrounding an innovation. If $R$ is close to one, the innovation’s perceived effectiveness is similar to the effectiveness of the status quo (expected effectiveness). If the perceived relative advantage of an innovation ($R$) is either close to zero or substantially bigger than one, this innovation is unambiguously inferior or superior to the status quo. The relation between the perceived relative advantage of an innovation and its perceived ambiguity will be specified and illustrated in section 5.2. The following section deduces a more detailed definition of ambiguity and distinguishes it from uncertainty.

5.1.3. Perceived ambiguity of an innovation

In decision theory, a condition is defined as risky or uncertain if possible outcomes of a decision and their respective probabilities are known to a decision-maker.
On the other hand, if the probability of outcomes is uncertain, the context of decision-making is referred to as ambiguous (e.g., Camerer & Weber, 1992). Thus, Camerer and Weber (1992, p. 330) defined ambiguity as the “uncertainty about probability, created by missing information that is relevant and could be known.” In their review of subjective expected utility theory, Camerer and Weber (1992, p. 326) also mentioned that the distinction between known and unknown probability goes by many names, such as risk vs. uncertainty (Knight, 1921), precise/sharp vs. vague probability (Savage, 1954) or unambiguous vs. ambiguous probability (Ellsberg, 1961). This dissertation distinguishes between risk or uncertainty (known probability) and ambiguity (unknown probability).

Milliken (1987, p. 136) did not explicitly discriminate between uncertainty and ambiguity, but identified three different kinds of “perceived inability[s] to predict something accurately”: (1) state uncertainty, describing an individual’s uncertainty about possible future states of the environment; (2) effect uncertainty, denoting an individual’s inability to predict the consequences of future environmental states; and (3) response uncertainty, defining an individual’s uncertainty about possible choices and/or their outcomes. Drawing on Milliken’s (1987) description of response uncertainty, Abrahamson and Rosenkopf (1997, p. 291) defined response ambiguity as “a lack of clarity about the outcomes of choices in response to environmental states, regardless of their clarity.” The concept of response ambiguity comes closest to the ambiguity definition prevalent in decision theory (Camerer & Weber, 1992, p. 330) and to the situation an employee faces when deciding whether to adopt or reject an innovation.

Note that Camerer and Weber (1992, p. 331) stressed that the ambiguity about outcomes (i.e., risk or uncertainty) is fundamentally different from the ambiguity about the probability of outcomes (i.e., ambiguity). If decision-makers would rather avoid the former, they are considered risk averse, while if they dislike the latter, they are considered ambiguity intolerant. Therefore, they argued that “[a]mbiguity about which outcome will occur is too coarse a category, because risk […] and ambiguous probability […] both exhibit ambiguity about outcomes” (Camerer & Weber, 1992, p. 331). With regard to innovations, Abrahamson and Rosenkopf (1997, p. 292) also distinguished between uncertainty and ambiguity, stating that under conditions of ambiguity, the range of alternatives to the innovation, the range of outcomes for each of those alternatives, the probability of every outcome, or all three of them are unclear, while under conditions of uncertainty all three of them are clear.

With respect to organizational innovation implementation processes, possible alternatives to the innovation are known, namely the status quo. Also the possible outcomes of an employee’s decision to adopt an innovation are known: the innovation is either more, equally, or less profitable than the status quo and
thus either advantageous, neutral, or disadvantageous for the employee. However, the individual innovation-decision is indirectly influenced by the perceived relative advantage of an innovation which is based on incomplete information about an innovation’s actual effectiveness. Since employees do not know the nature and amount of objective information that is unavailable to them, they are uncertain about the probability of each outcome. This uncertainty is greater, the closer the perceived effectiveness of an innovation to the expected effectiveness, which is determined by the status quo. Thus, in line with Camerer and Weber’s (1992) definition of ambiguity, an employee’s individual innovation-decision is made under ambiguity. That is, the decision whether to adopt or reject an innovation is characterized by uncertainty about the probability of outcomes.

Building on the literature mentioned above, this research defines perceived ambiguity of an innovation as the degree to which a decision-maker feels uncertain about the probability that the respective innovation is more effective than the status quo. Thus, it is suggested that the perceived ambiguity of an innovation depends on the perceived lack of objective information and on the difference between an innovation’s perceived and the expected effectiveness. The perceived relative advantage of an innovation is more ambiguous, the greater the perceived lack of objective information and the closer the perceived and expected effectiveness. This research focuses on the influence of the perceived and the expected effectiveness on the perceived relative advantage, while assuming that information asymmetries—created by missing objective knowledge—exist but are constant during the innovation diffusion process.

5.1.4. Impact of ambiguity intolerance on social behavior

Acknowledging that employees need to make decisions under ambiguity when deciding whether to adopt or reject an innovation, raises the question of how the perceived ambiguity influences their decision-making. In psychology and economics, theories of decision-making are primarily built upon the expected utility theory of von Neumann and Morgenstern (1949), which assumes that outcomes and the probabilities of outcomes are known a priori. However, as shown in the previous section, the probabilities of outcomes are often unknown in innovation implementation settings. The subjective expected utility theory of Savage (1954) relaxed the assumption that probabilities are objectively known by allowing them to be formed subjectively. Still, subjective expected utility theory does not allow choices to be influenced by the confidence about those probabilities (e.g., Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005, p. 1680). However, the Ellsberg paradox (Ellsberg, 1961) spurred empirical research which found that decision-makers do prefer less ambiguous outcomes and are willing
to pay premiums of up to 20% of the expected utility in order to reduce ambiguity to uncertainty (for a review, see Camerer & Weber, 1992, pp. 333-337). In other words, they are willing to renounce one fifth of the expected benefits, if, in return, they get to know the probability of outcomes. In decision theory, the preference of uncertainty over ambiguity is widely referred to as ambiguity aversion.

Similarly, in psychology, the term ambiguity intolerance refers to an individual’s tendency to perceive information about ambiguous situations or stimuli as threats or sources of discomfort (Budner, 1962, p. 30; Furnham & Ribchester, 1995, p. 179; Grenier, Barrette, & Ladouceur, 2005, p. 595; Leyro, Zvolensky, & Bernstein, 2010, p. 579). A direct link between decision theory and psychology is established by Sherman (1974, p. 169), who found that the less tolerant individuals are of ambiguity, the more they prefer to know the probabilities of outcomes.

Even though in psychology there is a distinction between ambiguity intolerance and uncertainty intolerance, these two constructs are overlapping to a much greater extent than ambiguity and uncertainty do in decision theory (Grenier et al., 2005; Leyro et al., 2010). Indeed, ambiguity intolerance and uncertainty intolerance seem to have more similarities than differences with both concepts being conceived as cognitive processes in which individuals respond to threatening situations or stimuli with a set of emotional, cognitive, and behavioral reactions (for a review, see Grenier et al., 2005). Nevertheless, ambiguity intolerance tends to refer to situations or stimuli that are perceived to be threatening in the “here and now” while uncertainty intolerance rather pertains to anxiety disorders caused by worries about future events (Leyro et al., 2010, p. 580). Considering the focus of ambiguity intolerance on present ambiguous stimuli and the direct link between ambiguity intolerance and decision theory, this research focuses on ambiguity intolerance to describe employees’ emotional, cognitive, and behavioral reactions in response to an ambiguous innovation.

Since innovations are, by definition, to a certain extent ambiguous and constitute a challenge to existing habits, employees often perceive them as threatening (e.g., Budner, 1962, p. 30; Sheth, 1981, p. 275). Therefore, employees often feel emotions such as uneasiness, discomfort, dislike, anger, and anxiety when deciding whether to adopt or reject an ambiguous innovation (Grenier et al., 2005, p. 594). According to Izard (2009, p. 5), such “discrete emotion feelings cannot be created, taught, or learned via cognitive processes.” Thus, Izard (2009, p. 7) argued that emotion feelings can be conceived as causal processes that are always one of the mediators of cognition or behavior. In particular, he distinguished between feelings in basic emotions, which tend to unconsciously
alter behavior, and feelings in emotion schemas, which affect higher-order cognition and may thus lead to a conscious change of behavior (Izard, 2009, p. 7). Therefore, employees’ emotions during the evaluation of an innovation’s relative advantage influence at least to some extent their individual innovation-decision. Thus, the greater the perceived ambiguity of an innovation with regard to its relative advantage over the status quo, the stronger emotion feelings, such as uneasiness and anxiety, and the stronger their impact on employees’ decision-making. To illustrate the effects of perceived ambiguity on the behavior of employees, this research draws on two ambiguity intolerance studies: McPherson (1983) and Ashford and Cummings (1985).

McPherson (1983, p. 118) analyzed the support-seeking behavior of 110 students who were asked to write an essay about an ambiguous topic. In doing so, individuals could draw on a limited amount of supportive or objective information in the form of other articles. The results indicate that individuals prefer supportive articles, which confirm their currently held opinions, over objective articles in situations which pose a high threat to self-esteem (reading the final essay out loud) and which rely on less useful objective information regarding the topic. This effect was the strongest for individuals who were highly intolerant of ambiguity. When objective information was perceived to be of high utility, individuals tended to seek less supportive information than in cases when objective information was perceived to be of low utility (McPherson, 1983, p. 121). Regarding individual innovation-decisions, objective information is of low utility to employees, if it does not contribute to clarifying whether or not an innovation is advantageous. If it is unclear whether an innovation is advantageous or disadvantageous, the innovation is perceived as more or less ambiguous. Therefore, the findings of that research suggest that a higher perceived ambiguity of an innovation increases an employee’s search for information that supports his or her currently held opinion, independent of whether s/he has a high or low tolerance of ambiguity. However, this behavior is more pronounced, the higher an employee’s ambiguity intolerance (McPherson, 1983, p. 121).

Ashford and Cummings (1985) conducted a survey among 172 employees of a marketing department of a public utility, analyzing their feedback-seeking behaviors. Among others, they predicted and later found that “seeking feedback, information useful in reducing ambiguity, provides one means of coping with the anxiety induced by role ambiguity […] The greater the ambiguity of the job role, the more frequent the use of proactive FSB [feedback-seeking behavior]” (Ashford & Cummings, 1985, p. 69). Feedback seemed to be a particularly valuable resource to individuals who were highly intolerant of ambiguity. Individuals who could tolerate ambiguity also sought feedback for determining
the adequacy of performance but did so less frequently than individuals who could not. The findings of that study illustrate the importance of seeking feedback in order to reduce ambiguity and cope with feelings of anxiety. Since innovations often influence the job roles of employees, an ambiguous innovation entails in most cases an increased ambiguity of the related job role. Therefore, these findings suggest that employees interact with more employees when an innovation, and thereby also the related job role, are perceived to become more ambiguous.

In summary, the literature review of this chapter showed that the number of employees influence the effectiveness of an innovation. However, whether an innovation is perceived to be effective or not depends on its perceived relative advantage which, in turn, determines an innovation’s perceived ambiguity. The clearer it is that an innovation is inferior or superior to the status quo, the lower the perceived ambiguity of the innovation. Ambiguous innovations stimulate feelings in basic emotions and/or emotion schemas, such as anxiety and discomfort. Therefore, employees change their information-seeking behavior in response to changes of the perceived ambiguity. In particular, employees tend to seek more supportive information when objective information about an innovation’s profitability is ambiguous. In addition, they rely more heavily on feedback, the higher the perceived ambiguity of an innovation. Both effects are the stronger, the more ambiguity intolerant individuals are. Thus, it is argued that the ambiguity of an innovation influences an employee’s search for other employees who support his or her own attitude towards the innovation. The more ambiguity intolerant employees are and the higher the perceived ambiguity of an innovation, the more intensely employees search for like-minded others who confirm their currently held beliefs. Figure 8 illustrates these causal relations.

Based on the discussed literature of this chapter, the following section extends the basic model which was introduced in chapter 4 (see Figure 6 and grey box in Figure 8) by accounting for the feedback structure between the adopter fraction, the perceived relative advantage of an innovation, its perceived ambiguity, and the social interaction among employees (see Figure 8). Thereby, the research mainly draws on Repenning (2002) to model the relationship between the adopter fraction and the perceived relative advantage of an innovation. The resulting model and the underlying equations are specified in the following section.
5.2. An intra-organizational diffusion model considering the perceived ambiguity of an innovation

The previous sections of this chapter showed that employees often make decisions under ambiguity when deciding whether to adopt or reject an innovation. Since individuals are generally intolerant of ambiguity, they try to reduce the perceived ambiguity of an innovation by seeking supportive information from their social environment. As Rogers (2003, p. 172) stated, “[t]he innovation-decision process is essentially an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation.” Even though Rogers (2003) only mentioned uncertainty, the studies of Ashford and Cummings (1985) and McPherson (1983) suggest that social interaction is not only a means to reduce the uncertainty about an innovation’s advantageousness, but, in particular, a means to reduce the related ambiguity, which is uncertainty about the probability that the innovation is advantageous. On the basis of the acquired information, employees then make or adjust their individual innovation-decisions which determine the effectiveness of implementation processes.

**Figure 8** Outline of an intra-organizational diffusion model considering the discontinuance of an innovation and employees’ ambiguity intolerance (numbers indicate the corresponding equation; text in italics indicates variable names)
Due to the ambiguity surrounding an innovation’s profitability, diffusion models have generally assumed that the individual innovation-decision of an employee is solely based on information from this person’s social environment. Other factors, such as the perceived relative advantage of an innovation, are assumed to influence the adoption decision only indirectly. Whether or not an individual adopts an innovation depends on the information of the people with whom this person communicates. For example, the higher the number of adopters an individual communicates with, the greater the social pressure on this person to also adopt the innovation. As mentioned before, this approach coincides with the Communication Constitutes Organizations (CCO) perspective which argues that “organizations can be conceptualized as fundamentally shaped by discourse” (Blaschke et al., 2012, p. 880). That is, organizational change processes are driven by the dynamics of communication among organizational members (Kuhn, 2008). Therefore, this chapter assumes that the only factor which directly influences implementation effectiveness by changing employees’ individual innovation-decisions is the communication among employees. Ambiguity intolerance, however, is assumed to influence implementation effectiveness only indirectly by altering the communication behavior of employees.

In order to realize innovation-related benefits on an organizational level, employees need to use the innovation. For example, in a study among US-hospitals, Douglas and Judge Jr. (2001, p. 165) found a positive correlation “between the degree of implementation of TQM [total quality management] practices and overall organizational performance.” Therefore, it is argued that the effectiveness of an innovation increases with the fraction of its adopters (Leonard-Barton & Deschamps, 1988, p. 1252; Repenning, 2002). This dissertation evaluates the effectiveness of an innovation by its capability to reduce inefficiencies or defects ($D$). It is assumed that a higher adopter fraction increases the rate with which they are reduced. However, employees are not aware of that (Repenning, 2002). To calculate the maximum change in inefficiencies, this research draws on Repenning (2002) who used Schneiderman’s (1988, p. 54) half-life model which states that the time to reduce any defect measure to fall by 50% ($T_{hl}$) is constant. Repenning (2002) extended the half-life model by making the improvement rate dependent on the adopter fraction ($A$), so that an improvement rate of 50% within $T_{hl}$ can only be reached if $A = 1$. Equation 3 specifies the monthly decrease of inefficiencies:

$$\frac{dD}{dt} = (D - D_{min}) \cdot \frac{ln(2)}{T_{hl}} \cdot A.$$ (3)
The term $D_{\text{min}}$ describes a theoretical minimum of inefficiencies and the term $\ln(2)/T_{hl}$ represents the actual effectiveness of the innovation, which is unknown to employees. The expected effectiveness, which is based on the experienced effectiveness of the status quo, is described by $\ln(2)/T_{hl}^*$, with $T_{hl}^*$ constituting the expected half-life of an innovation.

Employees are assumed to derive the current effectiveness of an innovation by observing the average change of inefficiencies during the last three months (Repenning, 2002, p. 116). As described in equation 2, this perceived effectiveness is then compared to the expected effectiveness of the status quo in order to determine the innovation’s perceived relative advantage (see Figure 8). It was argued that a perceived relative advantage of one ($R = 1$) maximizes the perceived ambiguity of an innovation ($U$). The more distinct $R$ is from one, the clearer the superiority or inferiority of an innovation. As illustrated in Figure 9, this relationship is described by a bell-shaped function:

$$U(R) = 4(b - a) \cdot \frac{e^{m(R-c)}}{(1 + e^{m(R-c)})^2} + a.$$  

(4)

Figure 9 Illustration of the relationship between an innovation’s perceived relative advantage ($R$) and its perceived ambiguity ($U$) as specified by equation 4
Parameters $a$ and $b$ are the minimum and maximum values of $U$, respectively. Parameter $c$ equals the $R$ which maximizes $U$. That is, $b = U(c)$. Lastly, parameter $m$ describes the slope of the bell-shaped function $U$. As argued above, it is assumed that $U$ reaches its maximum value when $R = 1$. Therefore, $c = 1$. In addition, this research assumes that $a = 0$, $b = 2$, and $m = 10$. Since $b$ also defines the maximum impact of the perceived ambiguity on the search and interaction intensities (see equation 5), it is assumed that employees extend the searched fraction of their group by interacting with two additional employees in their group when the perceived ambiguity reaches its maximum value. Therefore, $b = 2$. A minimum value of zero ($a = 0$) and a slope of ten ($m = 10$) were chosen because they ensure that there is almost no ambiguity if an innovation is perceived to be entirely inferior to the status quo ($R = 0$). In particular, $U(0) = 0.0004$. Since $U(R)$ is a symmetric function with $c = 1$, it yields the same value if $R = 2$. That is, the perceived ambiguity of an innovation is also very low if the innovation is perceived to be clearly superior to the status quo ($R = 2$).

After specifying how the perceived relative advantage ($R$) influences the perceived ambiguity of an innovation ($U$), equations 5a and 5b now describe how the perceived ambiguity ($U$) and the ambiguity intolerance ($I$) influence the intra-organizational interaction behavior of adopters ($S_A^*$) and non-adopters ($S_N^*$), which are used as indicators for the strength of positive and negative WOM:

$$S_N^* = S_N + U \cdot I; \quad (5a)$$

$$S_A^* = S_A + U \cdot I. \quad (5b)$$

The terms $S_N$ and $S_A$ represent the standard search and interaction intensities as they were discussed in equations 1a and 1b, respectively. However, now the product of the perceived ambiguity of an innovation ($U$) and the average ambiguity intolerance of employees ($I$) is added to them. Table 3 provides an overview of the key variables of the basic model described in chapter 4 and the extended model of this chapter. A complete stock and flow diagram of this ambiguity-oriented system dynamics model and all variables including equations can be found in appendix 2 and appendix 3, respectively.

When discussing equation 4, it was argued that the maximum influence of the perceived ambiguity on the search and interaction intensities is two ($b = 2$). That is, if an innovation’s advantageousness is highly unclear, employees will interact with two additional employees in order to find at least one other employee who confirms their current belief (Ashford & Cummings, 1985;
McPherson, 1983). However, the level to which individuals can tolerate ambiguity varies and may depend on the organizational, ethnic and/or national culture of employees (e.g., Hofstede, 1980). The higher employees’ average ambiguity intolerance ($I \in [0 \leq I \leq 1]$), the greater the extent to which $U$ influences $S_A^*$ and $S_N^*$. That is, employees will only interact with two additional other employees if the innovation’s perceived ambiguity reaches its highest value ($b = U(1)$) and if employees are maximally intolerant of ambiguity ($I = 1$). On the other hand, if employees do not mind ambiguity at all ($I = 0$), their search and interaction

<table>
<thead>
<tr>
<th>Name</th>
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<th>Values</th>
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<th>Model</th>
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<tr>
<td>Adopter fraction</td>
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</tr>
<tr>
<td>Non-adopter fraction ($= 1 - A$)</td>
<td>$N$</td>
<td>$0 \leq N \leq 1$</td>
<td>1a, 1b</td>
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<tr>
<td>Conversion probability adopters</td>
<td>$P_{AN}$</td>
<td>$0 \leq P_{AN} \leq 1$</td>
<td>1b</td>
<td>Ch4, Ch5</td>
</tr>
<tr>
<td>Conversion probability non-adopters</td>
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<td>$0 \leq P_{NA} \leq 1$</td>
<td>1a</td>
<td>Ch4, Ch5</td>
</tr>
<tr>
<td>Search intensity adopters (exogenous variable)</td>
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<td>$S_A \geq 1$</td>
<td>1b</td>
<td>Chapter 4</td>
</tr>
<tr>
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<td>$S_N \geq 1$</td>
<td>1a</td>
<td>Chapter 4</td>
</tr>
<tr>
<td>Search intensity adopters (endogenous variable)</td>
<td>$S_A^*$</td>
<td>$S_A^* \geq 1$</td>
<td>5b</td>
<td>Chapter 5</td>
</tr>
<tr>
<td>Search intensity non-adopters (endogenous variable)</td>
<td>$S_N^*$</td>
<td>$S_N^* \geq 1$</td>
<td>5a</td>
<td>Chapter 5</td>
</tr>
<tr>
<td>Defects / Inefficiencies</td>
<td>$D$</td>
<td>$\mathbb{R} \geq 0$</td>
<td>3</td>
<td>Chapter 5</td>
</tr>
<tr>
<td>Actual half-life time</td>
<td>$T_{hl}$</td>
<td>$\mathbb{R} &gt; 0$</td>
<td>3</td>
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</tr>
<tr>
<td>Expected half-life time</td>
<td>$T_{hl}$</td>
<td>$\mathbb{R} &gt; 0$</td>
<td>-</td>
<td>Chapter 5</td>
</tr>
<tr>
<td>Perceived relative advantage</td>
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<td>2, 4</td>
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<td>Perceived effectiveness</td>
<td>-</td>
<td>$\mathbb{R} \geq 0$</td>
<td>2</td>
<td>Chapter 5</td>
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<td>2</td>
<td>Chapter 5</td>
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<td>4</td>
<td>Chapter 5</td>
</tr>
<tr>
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<td>$I$</td>
<td>$0 \leq I \leq 1$</td>
<td>5a, 5b</td>
<td>Chapter 5</td>
</tr>
</tbody>
</table>

Table 3 Overview of the key variables used in the basic simulation model introduced in chapter 4 and the extended ambiguity-oriented simulation model introduced in chapter 5
intensity will not change during the diffusion process. That is, the intensity is independent of the perceived ambiguity.

As described in section 4.2.3, the validity of the ambiguity-oriented model is examined by conducting five validity tests. Since the ambiguity-oriented model builds on the basic implementation model introduced in chapter 4, the theoretical structure-confirmation test focuses on the structure that was added to the basic implementation model. First, the structure describing the causal relations between the adopter fraction and the perceived relative advantage is almost identical to a part of Repenning’s (2002) model. Only variable names and parameter values differ slightly. Second, the connection between the perceived relative advantage and the search intensities of adopters and non-adopters was based on empirical research (e.g., Ashford & Cummings, 1985; McPherson, 1983) and specified by equations 4 and 5. The remainder of the ambiguity-oriented model is identical to the model described and validated in chapter 4. Therefore, the theoretical structure-confirmation test was passed.

With regard to the extreme-conditions test, all parameter values of the ambiguity-oriented model were tested, finding no inconsistent model behavior. Therefore, the extreme conditions test was also passed. The results of this test, focusing on the parameters which have been added to the basic implementation model, are available in appendix 7. The automated unit check of Vensim found no dimensional inconsistencies. Therefore, the ambiguity-oriented model passed also the dimensional consistency test. The results of the behavior sensitivity test—examining changes in parameter values—and an explanation of the respective model behavior are provided in the following section as well as in appendix 7. These results indicate a comprehensible sensitivity of the model.

In order to test whether the boundary of the ambiguity-oriented model is adequate or not, one must consider the purpose of this model (Forrester & Senge, 1980, p. 16). The purpose of the ambiguity-oriented model is to answer the second research question, asking how different degrees of employees’ ambiguity intolerance and an innovation’s perceived ambiguity influence the communication behavior among peers. In light of this research question, the boundary of the model seems adequate. In order to examine whether or not the behavior of the model and the derived policy recommendations are valid if the model boundary is extended, additional structure was added to the model. In particular, the ambiguity-oriented model was extended by accounting for the communication structure among several organizational groups, as is discussed in detail in chapter 6. Even though the resulting model is not described in this dissertation, the dynamics and policy recommendations—which are discussed in the subsequent sections—were also valid for an ambiguity-oriented model which considers the communication structure within an organization. Therefore, the boundary adequacy test was also passed.
5.3. Influence of an innovation’s perceived ambiguity on the diffusion process

The previous section extended the basic intra-organizational diffusion model of chapter 4 to include the influence of an innovation’s ambiguity on the social interaction behavior of employees (see Figure 1). In particular, it was argued that the perceived relative advantage of an innovation depends on its usage by employees and that their search and interaction intensities increase, the more ambiguous its relative advantage is perceived to be. Based on empirical research, this research assumes that the effect of an innovation’s perceived ambiguity on the social interaction behavior of employees is greater, the higher the average ambiguity intolerance of employees (Ashford & Cummings, 1985; McPherson, 1983). In the following, it is specified how an innovation’s perceived ambiguity (U) and employees’ average ambiguity intolerance (I) influence employees’ social interaction behavior (see Figure 8). Thus, the search and interaction intensities are no longer considered to be constant but to vary according to equations 5a and 5b. In order to analyze the influence of U and I, it is assumed that the actual half-life (T_h) is 6 months and that the expected half-life (T_{e-h}) is 9 months (Schneiderman, 1988, p. 52). Thus, if the innovation is used to its full potential (A = 1), it reduces inefficiencies 33% quicker than the status quo or other known alternatives. However, this information is assumed to be unavailable to employees, who instead estimate the innovation’s effectiveness by observing the average change of inefficiencies over three months. In line with Repenning (2002), it is assumed that the innovation can tackle only a limited amount of inefficiencies within an organization. Initial inefficiencies are assumed to be 400 while the minimum inefficiency level that can be reached by using the innovation (D_{min}) is 10. For simplicity, this research also assumes that the only endogenous variable changing the level of inefficiencies is A: the degree to which the innovation is used by employees (see equation 3). As in the previous simulations, both conversion probabilities (P_{NA}, P_{AN}) equal one.

Figure 10 illustrates the influence of different levels of ambiguity intolerance (I) on the adopter fraction (graph 1), on the perceived ambiguity (graph 2), and on the perceived relative advantage of an innovation (graph 3). Similar to the best-performing scenario displayed in Figure 7a, S_A = 5 and S_N = 3. However, in contrast to graph 2 in Figure 7a, the initial adopter fraction (A_{ini}) has been lowered from 0.400% to 0.382%, a value closer to the threshold of a successful diffusion process, in order to highlight the inherent dynamics. Figure 10a depicts the development of A (graph 1), U (graph 2), and R (graph 3) when the average ambiguity intolerance of employees (I) is zero. That is, employees do not mind ambiguity at all. Therefore, similar to the previous simulations of the basic
model illustrated in Figure 7, the perceived ambiguity (U) does not change the interaction behavior of employees (see equations 5a and 5b). Therefore, the innovation diffuses completely within about 30 months. Figure 10b then shows the simulation results of A (graph 1), U (graph 2), and R (graph 3) when I = 0.05. Compared to the previous case where ambiguity played no role, graph 1 in Figure 10b illustrates that the innovation takes about four months longer to successfully diffuse throughout the organization. If ambiguity intolerance is increased to 10%, the innovation does not diffuse successfully but is rejected by all employees (graph 1 in Figure 10c). In the following, the negative impact of ambiguity intolerance is explained.

**Figure 10** Behavior of the adopter fraction (A), the perceived ambiguity (U), and the perceived relative advantage (R) under different degrees of ambiguity intolerance (I)

Graph 1 in Figure 10a shows the characteristic s-shaped growth of the adopter fraction (A). During the first 12 months, the innovation diffuses very slowly because the greater resistance of adopters ($S_A > S_N$) is barely able to offset the initial majority of non-adopters ($A_{ini} < N_{ini}$). However, since the growing number of adopters is able to convert more non-adopters, the fraction of adopters who convert non-adopters increases exponentially, which is visible from month 12 onwards (graph 1 in Figure 10a). This reinforcing feedback loop is only limited by the number of non-adopters who decrease over time. Consequently, the diffusion process starts to slow down at month 24. Finally, the innovation completely diffuses around month 30.

Even though U has no effect on A ($I = 0$), Figure 10a illustrates how A (graph 1) influences R (graph 3) and how R influences U (graph 2). In the beginning, R increases quite rapidly, due to $A_{ini}$. However, the rate of growth declines because only a few new non-adopters are converted during the first 12 months.
After about 26 months, the perceived rate of inefficiency reduction (perceived effectiveness) is as high as the expected effectiveness, causing $R$ to be one (graph 3 in Figure 10a). At this time, $U$ also reaches its maximal value of two ($b = 2$), as is described in equation 4 and shown by graph 2 in Figure 10a. Since the perceived effectiveness depends on the observed improvement rate during the last three months, $R$ is slightly delayed and reaches its maximum about three months after the innovation completely diffused. At this point, $U$ reaches a temporary minimum because the innovation is perceived to be clearly better than the status quo ($R > 1$). However, even though the adopter fraction is maximal ($A = 1$), $R$ starts to decline after month 33. This is the case because the level of inefficiencies approaches $D_{\text{min}}$, thereby causing the perceived effectiveness to decrease. Since the expected effectiveness is assumed to stay constant, $R$ hence decreases (see equation 2). When $R$ approaches one again, $U$ reaches its maximum for the second time at month 44 before it becomes more and more obvious that the innovation cannot reach the expected effectiveness any more. That is, $R$ and $U$ approach zero (graph 2 in Figure 10a). However, those changes do not affect $A$, since employees are assumed to tolerate ambiguity ($I = 0$). That is, employees are completely insensitive to $U$.

Figure 10b illustrates basically the same behavior of $A$ (graph 1), $U$ (graph 2), and $R$ (graph 3) as Figure 10a does. However, the simulation runs depicted in Figure 10b account for the influence of $U$ on $A$ by assuming that employees are to a minor degree ambiguity intolerant ($I = 0.05$). As a result, the complete diffusion of the innovation takes about three months longer than when employees were assumed to not be ambiguity intolerant at all (Figure 10a). The diffusion takes longer because the search and interaction intensities increase when the innovation is perceived to be ambiguous (equations 5a and 5b). Therefore, employees are more resistant to convert to the respective opposite camp. This impedes the diffusion process, especially from month 24 on when $U$ increases rapidly (graph 2 in Figure 10b) because the rising adopter fraction (graph 1) causes $R$ to approach a value of one (graph 3). Due to the slower diffusion, the perceived rate of inefficiency reduction (perceived effectiveness) is smaller than in the previous scenario, which causes $R$ to reach a slightly lower minimum value than in Figure 10a ($R_{\text{max}}: 1.19 < 1.22$). Consequently, the local minimum of $U$ (graph 2 in Figure 10b) is higher than in Figure 10a where $U$ did not influence $A$ ($U_{\text{min}}: 0.902 > 0.733$). When $U$ decreases, due to the fact that $R$ approaches zero, employees adjust their standard search and interaction intensity to a lesser extent (see equations 5a and 5b).

Figure 10c depicts the same scenario as Figure 10b does, with the only difference being that the degree of ambiguity intolerance ($I$) is assumed to be 10% instead of 5%. In contrast to the two previous scenarios, the increased
ambiguity intolerance results in a complete rejection of the innovation (graph 1 in Figure 10c). This is the case because a higher \( I \) results in a greater impact of \( U \) on \( S^*_A \) and \( S^*_N \). The greater \( U \cdot I \) is, the smaller the relative difference between \( S^*_A \) and \( S^*_N \) and the closer \( S^*_A / S^*_N \) is to one. For this reason and because \( S_A > S_N \), the ratio between the search intensities \( (S^*_A / S^*_N) \) is lower for \( I = 0.10 \) than it is for \( I = 0.05 \) (see equations 5a and 5b). For example, if the perceived ambiguity and the ambiguity intolerance were maximal \((U = b = 2, I = 1)\), adopters as well as non-adopters would communicate with two more employees than they would have if they were not at all ambiguity intolerant \((I = 0)\). Given that \( S_A = 5 \) and \( S_N = 3 \) (Figure 10), this would result in \( S^*_A / S^*_N = (5 + 2) / (3 + 2) < 5/3 \). In other words, the relative influence of adopters’ greater resistance is lower, the higher the perceived ambiguity and the greater the ambiguity intolerance. So when \( R \) approaches one (graph 3 in Figure 10c), the perceived ambiguity increases (graph 2 in Figure 10c), thereby causing \( S^*_A / S^*_N \) to decrease. Consequently, adopters’ higher resistance \((S_A > S_N)\) becomes less influential and can hence not compensate for the higher fraction of non-adopters \((A < N)\) any more. Therefore, the adopter fraction decreases, which increases the non-adopter fraction even further (graph 1 in Figure 10c). This process culminates in the complete rejection of the innovation \((A = 0)\) by month 30.

5.4. Impact of an innovation’s actual effectiveness on the diffusion process

Building on the previous findings regarding the influence of an innovation’s perceived ambiguity and of employees’ ambiguity intolerance, the following analysis focuses on the actual effectiveness of an innovation (see Figure 8). In particular, it is examined how different improvement rates influence the perceived ambiguity and hence the interaction behavior of employees.

Adopting Repenning’s (2002) approach, the effectiveness of an innovation is modeled as the number of inefficiencies it reduces during a given time period. In equation 3, the actual effectiveness is defined by the term \( \ln(2)/T_{hl} \) with \( T_{hl} \) constituting the half-life time. The half-life time describes the time it takes to reduce inefficiencies by 50% (Schneiderman, 1988), provided that the innovation is used to its full potential \((A = 1)\). On the other hand, the expected effectiveness is defined by the term \( \ln(2)/T^{*}_{hl} \) with \( T^{*}_{hl} \) constituting the half-life time of the status quo or other known alternatives (Repenning, 2002). In the previous simulations, \( T_{hl} = 6 \) months, while \( T^{*}_{hl} = 9 \) months. That is, the innovation was assumed to be more effective than the status quo because it reduces 50% of the inefficiencies within a shorter time period. However, the actual effectiveness is not known by employees. Instead, they compare the expected effectiveness to
the perceived effectiveness (equation 2). In the following, it is analyzed how the actual effectiveness of an innovation influences the perceived relative advantage (R), the perceived ambiguity (U), and ultimately the adopter fraction (A) and implementation effectiveness.

Figure 11 illustrates the impact of different innovation half-life times (T_{hl}) on A (Figure 11a), R (Figure 11b), and U (Figure 11c). Similar to the underlying simulation settings of graph 4 in Figure 7c, it is assumed that A_{ini} = 0.6, S_A = 3, and S_N = 5. The only difference between the settings of graph 4 in Figure 7c and the settings of graph 1 in Figure 11a is that the former assume that employees are not ambiguity intolerant at all (I = 0), while the latter assume that employees are maximally ambiguity intolerant (I = 1). In comparison to graph 4 in Figure 7c which shows the innovation being completely rejected within 13 months, graph 1 in Figure 11a illustrates that ambiguity intolerance postpones this rejection, causing the innovation to be discarded after 15 months.

In addition, Figure 11a shows how a decreasing half-life time influences the adopter fraction. If inefficiencies are decreased by 50% every five (graph 2) instead of every six months (graph 1), the rejection of the innovation takes a few months longer. This trend continues if T_{hl} is reduced to four months (graph 3). However, if the innovation is even more effective, reducing 50% of all inefficiencies within only three months (graph 4), the innovation is rejected quicker than in the previous case (graph 3). In order to understand the influence of T_{hl} on A (Figure 11a), it is analyzed how T_{hl} indirectly influences R, how R influences U, and how U indirectly influences A (see Figure 8).

Figure 11b illustrates how T_{hl} influences R. If 50% of inefficiencies are reduced every six months, R increases to about 0.7 at month six before it decreases to zero again (graph 1). R increases in the first six months because the high initial adopter fraction results in a quick reduction of inefficiencies (equation 3). However, the actual effectiveness differs from the perceived effectiveness of employees in that the latter is based on employees’ perception of the improvement rate over three months. Therefore, the perceived effectiveness is slightly delayed, causing R to reach its maximum value only around month six. R decreases because the diminishing adopter fraction causes fewer inefficiencies to be eliminated, which decreases the perceived effectiveness. Thus, even though the innovation is actually more effective than the status quo (T_{hl} < T_{id}), the perceived relative advantage remains below one at all times.

The fact that the perceived relative advantage is always smaller one shows that the innovation’s effectiveness is perceived to be inferior to the expected effectiveness of the status quo. If the half-life time is reduced from six (graph 1) to five months (graph 2), the perceived relative advantage (R) reaches a higher maximal value (Figure 11b). A half-life time of four months causes R to be even
greater than one, indicating that during this period the innovation is perceived to be superior to the status quo (graph 3 in Figure 11b). R reaches an even greater value if $T_{hl}$ is reduced to three months (graph 4 in Figure 11b). However, due to the faster rejection of the innovation (graphs 3 and 4 in Figure 11a), the perceived relative advantage decreases quicker than in the previous case (graphs 3 and 4 in Figure 11b). Nevertheless, the more effective an innovation is (i.e., the lower $T_{hl}$ is), the higher the maximal value of $R$ (Figure 11b).

Figure 11c depicts the development of the perceived ambiguity ($U$) for different values of $T_{hl}$. Graphs 1 and 2 show that $U$ increases (Figure 11c) when $R$ approaches one (Figure 11b). A half-life time of four months causes $R$ to increase even above a value of one (graph 3 in Figure 11b), which results in a temporary decrease of $U$ between month 6 and month 10 (graph 3 in Figure 11c). Since an even more effective innovation results in an even higher value of $R$, the temporary decrease in $U$ is even more pronounced when $T_{hl} = 3$ (graph 4 in Figure 11c). This behavior of $U$, in turn, explains the development of $A$ (Figure 11a). The higher the perceived ambiguity of an innovation, the more resistant employees are to convert to the opposite camp. Therefore, the greater resistance of non-adopters ($S_A < S_N$) is less influential when the innovation is perceived to be very ambiguous. That is, a perceived relative advantage close to one ($R = 1$) generates the highest ambiguity, which, in turn, reduces the dominance of non-adopters to the largest extent. Thus, the rejection of the innovation takes the longest when $T_{hl} = 4$ (graph 3 in Figure 11a) because in the other three scenarios the perceived ambiguity never reaches values above 1.5 (graphs 1 and 2 in Figure 11c) or only for short time periods (graph 4 in Figure 11c).
5.5. Summary and discussion of findings regarding innovation ambiguity

Within this chapter, the influence of an innovation's perceived ambiguity on the interaction behavior of employees was investigated. It was argued that the perceived effectiveness of an innovation depends on its actual usage among employees (i.e., the adopter fraction) and that the innovation is perceived to be ambiguous if the perceived effectiveness is similar to the effectiveness of other known alternatives, such as the status quo. The higher the perceived ambiguity of an innovation, the more employees search for information that supports their current belief about the innovation's advantageousness. However, this change in behavior depends on how ambiguity intolerant employees on average are. If they are not ambiguity intolerant at all, their interaction behavior does not change when the perceived ambiguity increases. In such situation the behavior of the model is identical to the behavior described in chapter 4. However, the more ambiguity intolerant employees are, the more they search for and interact with other like-minded employees.

Contrary to common belief (e.g., Abrahamson & Rosenkopf, 1997), the previous analyses suggest that the perceived ambiguity of an innovation negatively influences implementation effectiveness if positive WOM is assumed to be stronger than negative WOM. That is, the more ambiguous an innovation is perceived to be and the more ambiguity intolerant employees are, the lower the speed and probability of diffusion. This effect results from an increase in the search and interaction intensities of employees due to a higher perceived ambiguity (see equations 5a and 5b). Since the search and interaction intensities of adopters and non-adopters increase to the same extent, the relative influence of the camp with the initially higher intensity decreases. Therefore, if positive WOM is assumed to be stronger than negative WOM \((S_A > S_N)\), the relative strength of positive WOM decreases when the perceived ambiguity of an innovation increases.

On the other hand, if the ambiguity intolerance of employees is increased in a scenario where the innovation completely diffuses even though negative WOM is assumed to be stronger than positive WOM \((S_N > S_A)\), implementation effectiveness increases because the relative strength of negative WOM is reduced. However, this is only the case if the initial adopter fraction does not completely outweigh the relatively stronger negative WOM. If the initial adopter fraction is much higher than the initial non-adopter fraction, the positive influence of a decreasing relative strength of negative WOM is outweighed by the negative influence of an increasing resistance of adopters and non-adopters due to an absolute increase of positive and negative WOM. Thus, in these cases an increase in ambiguity intolerance would make employees more resistant to convert to the other camp, thereby slowing down the diffusion process.
The second research question asks how the ambiguity of an innovation and employees’ ambiguity intolerance influence the communication among peers and thereby implementation effectiveness. In line with literature on bandwagon diffusion (Abrahamson & Rosenkopf, 1997; Tidd, 2010), this research finds that employees’ search for like-mined others increases, the more ambiguity intolerant employees are and the higher an innovation’s perceived ambiguity. However, this increase does not necessarily facilitate the diffusion of an innovation. In fact, employees do not extend their search for all kinds of information about an innovation’s effectiveness. Instead, they specifically look for supportive information which confirms their current belief. Therefore, ambiguity intolerant employees are more resistant to convert to the opposite camp, the higher an innovation’s perceived ambiguity. Depending on whether positive or negative word of mouth is stronger, this effect either decreases or increases implementation effectiveness by diminishing the relative strength of the initially stronger camp.

In connection with the findings of chapter 4, these results suggest that management should attempt to restrict the influence of non-adopters by curtailing their search for confirming information. To achieve this, management should try to understand and change the thinking of non-adopters (e.g., Chen et al., 2013, p. 1635). The less driven non-adopters are to confirm their negative attitude, the less resistant they are to adopt the innovation. If the standard search and interaction intensity of non-adopters is much higher than that of adopters (negative WOM is much stronger than positive WOM), another option could be to isolate non-adopters by putting them into relatively small groups which are dominated by adopters. If the size of these groups is smaller than non-adopters’ search and interaction intensity, it caps the number of other employees they can interact with, even when the perceived ambiguity increases.

In a second step, this chapter analyzed the influence of an innovation’s actual effectiveness on the search and interaction intensities of employees. However, employees do not know the actual effectiveness of an innovation. Instead, they adjust their behavior on the basis of the perceived effectiveness, which is derived from observing the decrease in inefficiencies over a certain period of time (i.e., three months in this research). Thus, an innovation which is actually more effective than the status quo might be perceived to be inferior.

As expected, the findings of this analysis show that a greater effectiveness increases the perceived relative advantage of an innovation. The higher the actual effectiveness of an innovation, the quicker it gains on the expected effectiveness of the status quo. Hence, effective innovations reach the point where the perceived relative advantage equals one earlier than less effective innovations. The closer the perceived relative advantage is to one, the higher the perceived ambiguity, causing employees to communicate more with each other.
in order to find like-minded others. It is precisely during such periods that the restricting of non-adopters’ influence benefits the implementation process the most. Knowing that these periods occur earlier, the more effective innovations are, enables senior managers to time their interventions accordingly.

The clearer it is that the innovation is inferior or superior to the status quo, the lower the perceived ambiguity, and hence the lower its effect on the search and interaction behavior of employees. Therefore, an innovation which is perceived to be much less effective than the status quo might cause a similar change in behavior as an innovation which is perceived to be clearly more effective than the status quo. However, only if the effectiveness of an innovation is perceived to be similar to the effectiveness of the status quo, does the perceived ambiguity of an innovation influence the search and interaction behavior of employees. Being aware of those dynamics, allows senior management to correctly interpret the behavior of employees. For example, intense communication among employees might be the result of a high perceived ambiguity, signaling senior management to intervene.

This chapter extended the basic model introduced in chapter 4 to incorporate the influence of employees’ ambiguity intolerance (see Figure 8). The following chapter focuses on research question three by extending the basic model of chapter 4 to analyze how the communication structure within organizations influences implementation effectiveness. Thus, for simplicity, the remainder of this research assumes that employees are not ambiguity intolerant ($I = 0$). Future work could build on this chapter’s analyses by incorporating a network perspective which analyzes the impact of an innovation’s perceived ambiguity against the background of different intra-organizational network structures (Tsai, 2001). In addition, empirical research could test the findings of this study by analyzing, for example, the relationship between ambiguity intolerance and the decision to adopt an innovation. With regard to organizations, future research could focus on management strategies that utilize the described effects of ambiguity intolerance among employees to improve the implementation of innovations.
6. A continuous model considering innovation discontinuance and the communication structure among groups of employees

6.1. Conceptualizing the communication within intra-organizational communication networks

Organizational change—like the implementation of an innovation—“is created, sustained, and managed in and by communications” (Ford & Ford, 1995, p. 560). Donnellon (1986), for example, argues that the actual implementation of change is all about communication. Therefore, this research focuses on communication processes among organizational members. Other factors, such as the relative advantage of an innovation or employees’ experiences (Rogers, 2003), are not considered. The few implementation studies that account for the interaction of employee-related and organizational processes (Damanpour, 1996; Gosselin, 1997; Repenning, 2002; Choi & Chang, 2009) acknowledge the communication among employees as a main driver of organizational change. However, as outlined in chapter 4, most diffusion models make the restrictive assumption that only adopters of an innovation can convert non-adopters and not vice versa (Abrahamson & Rosenkopf, 1997; Gibbons, 2004; Bohlmann et al., 2010). Thus, the percentage of adopters can only grow but never shrink.

Mahajan et al. (1984, p. 1401) point out that this assumption is tenuous since communicators do not only promote an innovation but may also transfer neutral as well as negative information about it through interaction via inter-personal links, the so-called word-of-mouth communication. In opposition to the sole inclusion of positive word-of-mouth information, the additional consideration of negative word-of-mouth information also takes into account the arguments of non-adopters. Chapter 4 introduced a simplified version of Krackhardt’s (1997) model which explicitly accounts for the discussion process between adopters and non-adopters of an innovation. Due to the explicit consideration of non-adopter arguments, the communication between the two parties can also result in a conversion of adopters by non-adopters. Consequently, the converted adopters discard the innovation and become non-adopters by using the status quo instead. Thus, in the basic model introduced in chapter 4, the percentage of adopters cannot only increase but also decrease (see Figure 6).

Accounting for the influence of positive and negative word of mouth simultaneously implies that some individuals might alternate between adopting an innovation and discontinuing it. For example, an employee might use a newly implemented system to manage customer relationships if this person’s team members communicate that they also use it (positive word of mouth). However,
if the team members of the next project tell this employee that they prefer the status quo over the innovation (negative word of mouth) this employee might also decide to stop using the innovation, at least for this particular project. By considering the possibility that some employees might alternate between using and neglecting the innovation, the basic model introduced in chapter 4 resembles SIS models which account for the possibility that individuals become again susceptible (S) to a disease after having been infected (I) with it (e.g., Dorogovtsev et al., 2008).

Even though the model introduced in chapter 4 considers positive as well as negative word of mouth, it does not consider the concrete structure of communication depicting which groups of employees interact with each other. On the other hand, the communication relations among groups, which form an intra-organizational communication network, are considered to be essential in diffusion research (e.g., Abrahamson & Rosenkopf, 1997). Therefore, following Choi and Chang (2009), this chapter brings together employee-related aspects (i.e., peer influence) and organizational aspects (i.e., structural characteristics of organizations) in order to reveal the dynamics caused by intra-organizational communication networks. In particular, this chapter addresses research question three, asking how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness.

To analyze the dynamics caused by intra-organizational communication networks, this chapter builds on Krackhardt’s (1997) model which is able to describe the diffusion process within and across five organizational groups, each consisting of an adopter and a non-adopter camp. In Krackhardt’s (1997, p. 186) model, the communication process between adopters and non-adopters is taking place in two steps. First, there is between-group migration: A certain fraction of adopters as well as non-adopters of a group migrate to the respective camp of all connected groups, for example, adopters from group \( i \) migrate into the adopter camp of group \( j \). Second, similar to the basic model introduced in chapter 4, the adopter and the non-adopter camp within each group interact with each other, resulting in the conversion of a fraction of non-adopters to the adopter camp of that group and vice versa. After conversion took place, the communication process starts again by exchanging a certain fraction of adopters and non-adopters between connected groups. The communication process within and between five organizational groups is illustrated in Figure 12.

Krackhardt (1997) examines under which structural conditions four groups—which in the beginning consist only of non-adopters—can be converted by one initial adopter group. In particular, the influence of the migration rate, the network structure among groups, and the position of the adopter group are analyzed. However, Krackhardt (1997, p. 186) constructed the underlying model
based on the assumption that conversion between the adopter and the non-adopter camp of a group and migration between groups are taking place in an iterative but sequential order. In addition, Krackhardt (1997) only focused on the outcome of diffusion processes. The underlying dynamics that determined these outcomes remained unclear.

Figure 12 Organizational innovation diffusion process within a five-membered chain structure

Building on Krackhardt (1997), the following sections derive a continuous system dynamics model which incorporates positive and negative word of mouth and the communication structure among intra-organizational groups. In a system dynamics environment, section 6.2.1 rebuilds Krackhardt’s (1997) algebraic model. Thereby, the model description focuses on establishing a clear link between the underlying assumptions of the model and the findings of previous research. By means of the derived model, section 6.2.2 replicates and elaborates on Krackhardt’s (1997) findings. Section 6.2.3 of this chapter relaxes Krackhardt’s (1997) restrictive assumption of consecutively alternating migration and conversion by using the temporal dimension of system dynamics, transforming migration and conversion into concurrent and continuous processes. In section 6.2.4, the behavior of this continuous system dynamics model is then analyzed and compared to the behavior of Krackhardt’s (1997) model. In order to understand the behavior of the continuous model better, section 6.3 investigates the underlying dynamic processes and behavior modes, which have not been derived from Krackhardt’s (1997) algebraic model. Hence, in contrast to Krackhardt (1997), the focus is not only on the outcome of the diffusion process but also on the process itself and on its underlying dynamics. The final section of this chapter summarizes and discusses the derived insights.
6.2. Transforming an algebraic innovation diffusion model into a continuous system dynamics model

6.2.1. An algebraic model of intra-organizational innovation diffusion in a system dynamics environment

Since “[a]ll innovations carry some degree of uncertainty for an individual, who is typically unsure of the new idea’s functioning and thus seeks social reinforcement from others of his or her attitude toward the innovation” (Rogers, 2003, p. 175), social communication networks play an important role in the diffusion of organizational innovations. This chapter analyzes the innovation-related communication within intra-organizational networks by distinguishing between five homogeneous and equally large groups of employees. Within each group, there is an adopter camp, consisting of employees who use the innovation, and a non-adopter camp, consisting of employees who neglect the innovation (see Figure 12). These groups can represent, for example, worldwide branch offices of an enterprise or homogeneous departments of an organization which are connected to each other through communication, thereby forming a social network. As Figure 12 illustrates, this chapter focuses on five groups being connected to each other in a chain structure.

Within this network, an innovation diffuses in two steps. First, employees exchange opinions and experiences between groups (Krackhardt, 1997, pp. 186-187). This so-called migration is modeled by exchanging a certain fraction of adopters as well as non-adopters with all connected groups. For example, in the five-membered chain structure depicted in Figure 12, group 2 sends a certain fraction of its adopters to the adopter camps of the connected groups 1 and 3, which, in return, send certain fractions of adopters to group 2. This migration also takes place between the non-adopter camps of connected groups. The fact that both groups influence each other’s adopter and non-adopter fraction indicates that the communication between both groups is undirected. Second, adopters and non-adopters communicate with each other within a group, thereby trying to convince the other party (Krackhardt, 1997, p. 187; Wood, Lundgren, Quellette, Busceme, & Blackstone, 1994, p. 324). In the course of this so-called conversion, a fraction of adopters as well as non-adopters is converted by the opposing party. The degree of diffusion within a group is measured by the proportion of adopters $A_i$ of a group $i$. The term $(1 - A_i)$ represents the proportion of non-adopters because the proportions of adopters and non-adopters within a group $i$ always add up to one.

This section rebuilds Krackhardt’s (1997) algebraic diffusion model within a system dynamics environment. In this dissertation, this system dynamics environment is Vensim DSS 6.1c. To demonstrate the visualization of a system
dynamics model in Vensim, a simplified stock and flow diagram of Krackhardt’s (1997) model is displayed in Figure 13. It depicts the stocks \( \text{Fraction Non-adopters} \) and \( \text{Fraction Adopters} \) and their conversion and migration rates. Since all groups are assumed to be structurally equal, Figure 13 only depicts the model structure for one group, while all other groups are subscripted. The network structure among groups is defined by an adjacency matrix, represented by the parameter \( \text{Is Connected To} \) (see appendices 4 and 6).

![Figure 13: Simplified stock and flow diagram of the migration and conversion processes (the five organizational groups are modeled with subscripts)](image)

In the following, the mathematical formalization of migration and conversion is outlined by replicating Krackhardt’s (1997) model, and thereby also the exact same results, in a system dynamics environment. As in Krackhardt’s (1997) model, migration and conversion are not processes which happen over time but which occur alternately at fixed points in time. More precisely, migration only takes place when the simulation time is even \( (t = 0, 2, 4, \ldots) \). Conversion, on the other hand, only happens when the simulation
time is uneven \((t = 1, 3, 5, \ldots)\). Thus, a single iteration in Krackhardt’s (1997) model, consisting of migration and conversion, equals two time periods in the system dynamics model.

System dynamics simulates models along a temporal dimension consisting of equally large time steps. The size and unit of a time step can be adjusted. This dissertation assumes that one time period consists of 32 time steps and that the unit of time is \(\text{day(s)}\). Thus, one time step equals 0.03125 time periods and thereby 0.03125 days. However, within this section, the temporal dimension of system dynamics is actually not used because the equations, described in the following, are only calculated when the simulation time is even or uneven. Therefore, the size of the time step does not affect the outcome of the model. In section 6.2.3, the assumption that migration and conversion only take place at certain points in time will be relaxed by using the temporal dimension of system dynamics to enable migration and conversion to take place continuously and simultaneously. The temporal dimension will then be distinct from the time step. In these cases, the smaller the value of this technical variable, the higher the numerical precision of calculations.

Whenever migration takes place, a certain fraction of adopters as well as non-adopters migrates into the respective camp of each connected group. The adopter as well as nonadopter fraction that leaves a group \(i\) to migrate into a connected group \(j\) depends on the size of the adopter or non-adopter camp within group \(i\) and on the migration rate between group \(i\) and group \(j\) \((m_{ij})\). Equation 6a specifies the total fraction of adopters emigrating out of group \(i\) into all connected groups \((\text{migration rate } ax\text{ in Figure 13})\). Equation 6b illustrates this emigration loss with respect to the non-adopter camp of group \(i\) \((\text{migration rate } nx\text{ in Figure 13})\):

\[
\frac{dA_{i, \text{emigr}}}{dt} = \frac{\sum_i A_i \cdot m_{ij}}{\text{Time Step}}, \quad (6a)
\]

\[
\frac{dN_{i, \text{emigr}}}{dt} = \frac{\sum_i (1 - A_i) \cdot m_{ij}}{\text{Time Step}}. \quad (6b)
\]

However, while adopters and non-adopters emigrate out of a group \(i\), adopters and non-adopters from the connected groups \(j\) immigrate into group \(i\). Equation 7a specifies the total amount of immigrating adopters \((\text{migration rate } xa\text{ in Figure 13})\), while equation 7b depicts the total amount of non-adopters immigrating into group \(i\) \((\text{migration rate } xn\text{ in Figure 13})\):
With regard to conversion, Krackhardt (1997, p. 183) states that group-internal communication is fueled by employees’ active search for innovation-related information, especially among peers. Prislin and Wood (2005, p. 677) argue that “[t]he views of other people are important in part because they help to structure the cacophony of stimuli to which we are regularly exposed, and thereby help us to operate among those stimuli.” Referring to the work of Eagly and Chaiken (1993), they specify the influence of peers by stating that “others’ attitudes impose structure and make sense out of the world by indicating whether objects are to be evaluated with some degree of favor or disfavor” (Prislin & Wood, 2005, pp. 677-678).

According to the concept of satisficing behavior, organizational members do not strive to obtain all information available from others (Simon, 1956, p. 129). In line with Simon (1956), De Dreu et al. (2008, p. 25) emphasize that “people can and will choose among a shallow and heuristic versus a deep and deliberate information search-and-processing strategy.” Therefore, it is assumed that organizational members randomly search for like-minded others only within a limited fraction of their group. Asch (1963, p. 186) found that the presence of only one other like-minded group member is “sufficient to deplete the power of the majority, and in some cases to destroy it.” As outlined in chapter 4.2, further research confirmed this bias toward a favored or chosen decision. Consequently, this research assumes that an employee may convert to the opposite camp only if another like-minded organizational member cannot be found within the searched group segment. Isolated adopters convert to the non-adopter camp with a daily conversion probability of \( P_{AN} \), while isolated non-adopters convert to the adopter camp with a daily conversion probability of \( P_{NA} \).

In Figure 13, the two flows linking the stock of adopters to the stock of non-adopters represent conversion (Ulli-Beer et al., 2010). Krackhardt (1997, p. 184) assumes that adopters are more likely to convert status-quo oriented non-adopters into adopters than the other way around. Even though chapter 4 mentioned studies that state the opposite, more recent research supports this assumption. For example, East et al. (2008, p. 221) find that positive word of mouth has a bigger impact on brand purchase probability than negative word of

\[
\frac{dA_{immigr}}{dt} = \frac{\sum_j A_j \cdot m_{ji}}{Time\ Step}, \quad (7a)
\]

\[
\frac{dN_{immigr}}{dt} = \frac{\sum_j (1 - A_j) \cdot m_{ji}}{Time\ Step}. \quad (7b)
\]
mouth. In addition, Berger and Milkman (2012, p. 201) stated that, contrary to common wisdom, positive news is more viral than negative news. Regarding the model, the greater influence of adopters’ positive word of mouth translates into a higher search intensity of adopters ($S_A$) than that of non-adopters ($S_N$). Like in the previous chapters, the search intensities describe with how many other employees an employee interacts on average. Assuming that adopters use the innovation and spread positive word of mouth and that non-adopters do not use the innovation but spread negative word of mouth, $S_A$ and $S_N$ also indicate the strength of positive and negative word of mouth. That is, due to the higher strength of positive word of mouth, non-adopters are more easily converted by adopters than the other way around.

Equation 8a describes the proportion of non-adopters of a group $i$ that converts to the adopter camp of that group because those non-adopters could not find any like-minded people within their searched group segment (conversion rate $na$ in Figure 13):

$$\frac{dN_{i\text{conv}}}{dt} = \frac{P_{NA} \cdot (1 - A_i) \cdot A_i^{SN}}{\text{Time Step}}. \tag{8a}$$

The term $A_i^{SN}$ represents the probability that a non-adopter only meets adopters in his or her searched group segment (Krackhardt, 1997, p. 187). The group-internal proportion of all isolated non-adopters that do not find any like-minded organizational members corresponds to the term $(1 - A_i) \cdot A_i^{SN}$. These isolated non-adopters convert to the adopter camp with probability $P_{NA}$ whenever simulation time is uneven. Similarly, equation 8b describes the increase of the non-adopter fraction within a group $i$ due to the conversion of adopters (conversion rate $an$ in Figure 13):

$$\frac{dA_{i\text{conv}}}{dt} = \frac{P_{AN} \cdot A_i \cdot (1 - A_i)^{SA}}{\text{Time Step}}. \tag{8b}$$

This section rebuilt Krackhardt’s (1997) algebraic diffusion model within a system dynamics environment. As outlined above, the diffusion process takes place in two steps: migration and conversion (see Figure 13). Concerning conversion, the argumentation and equations of this section coincide with the basic model introduced in chapter 4 (see Figure 6). That is, equations 1a and 1b are almost identical to equations 8a and 8b. The only difference is that in the basic model in chapter 4 conversion takes place continuously, while in
Krackhardt’s (1997) model it only takes place every second time step. However, this assumption is relaxed in section 6.2.3.

6.2.2. Analysis of Krackhardt’s algebraic model in a system dynamics environment

Krackhardt (1997, p. 188) examines under which conditions a minority of adopters can convince a majority of non-adopters within a five-membered chain structure (see Figure 12). In order to replicate and elaborate on Krackhardt’s (1997) findings, the previous section rebuilt his algebraic model within a system dynamics environment. This section analyzes the resulting system dynamics model. For the following simulations, it is assumed that group 1 initially constitutes the adopter minority within an organization. Thus, group 1 is the mother group (MGr1) which is only composed of adopters, while the other four groups consist of non-adopters only. Such a peripheral mother group can be the result of a greenfield site (Johns, 1993, p. 586), also referred to as skunkworks (Rogers, 2003, p. 149). These are especially supported and enriched groups which are intended to create innovations. Initially, they are often located at the network periphery in order to shield them from other groups’ pressure to conform. The other parameters take the following values: \( S_A = 6 \), \( S_N = 4 \), \( P_{AN} = P_{NA} = 1 \), \( Time\ Step = 0.03125 \).

For each simulation run, the underlying migration rate is assumed to be equal among all five groups in the organization. Figure 14 shows the results of five simulation runs which differ with regard to this underlying migration rate. Figure 14 illustrates that the average adopter fraction over all five groups reacts to an increasing migration rate in a nonlinear way. In case the migration rate is only 7.5% (graph 5 in Figure 14), the average adopter fraction reaches an equilibrium of about 22%. This is only slightly higher than at the beginning of the simulation, when one out of the five groups consisted only of adopters (MGr1), an average adopter fraction of 20%.

If the migration rate increases to 10% (graph 4 in Figure 14), the fraction of adopters migrating from group 1 into group 2 is large enough to convert the non-adopters in group 2. This causes a domino effect in group 3, 4, and 5, resulting in the complete diffusion of the innovation throughout the organization. A further increase of the migration rate to 12.5% and 15% (graph 3 and graph 2 in Figure 14) accelerates this diffusion process. However, if the migration rate is 17.5% (graph 1 in Figure 14), all groups reject the innovation. In this case, the adopter fraction within group 1 is not sustainable because too many non-adopters immigrate from group 2 replacing the adopters that migrated from group 1 into group 2. In summary, only a migration rate between 7.6% and 16.4% results in a total diffusion of the innovation. Lower migration rates lead to an average
adopter fraction of around 20% while higher rates cause a complete rejection of the innovation by converting all adopters of the mother group 1 to non-adopters.

Krackhardt (1997, pp. 190-192) refers to this narrow window of opportunity (a range of 8.8 percentage points) in which an adopter minority wins over a non-adopter majority as the Principle of Optimal Viscosity. Krackhardt (1997, p. 190) finds that this principle is surprisingly insensitive to different conversion probabilities and to changes of the search intensities, provided that the latter take values between 2 and 20 and that $S_A > S_N$. The window of opportunity illustrates that too much communication among groups (i.e., a too high migration rate) can be detrimental to the organization-wide diffusion of an innovation. The mutual reassurance among non-adopter-dominated groups is greater, the higher the communication intensity. In this case, the higher number of united non-adopters quickly converts the minority of adopters, even though positive word of mouth has a higher impact than negative word of mouth ($S_A > S_N$). If the communication intensity among groups is too low, the adopter-dominated group is not able to convert enough non-adopters in the groups it directly communicates with. Only moderately intense communication minimalizes the reassurance effect among non-adopter groups, while maximizing the higher impact of positive word of mouth.

Figure 14 Effects of different migration rates on the innovation diffusion process within Krackhardt’s model and with adopters initially situated in group 1 only
However, the outcome of the model is not only sensitive to the migration rate but also to the position of the mother group within the chain structure (Krackhardt, 1997, p. 194). Figure 15 illustrates the average adopter fraction as a function of the migration rate when the only difference to the previous simulations is that now group 3 is the mother group \((MGr_3)\) composed only of adopters. The simulations depicted in Figure 15 show that the window of opportunity for an adopter minority now completely disappears. Ceteris paribus, there is no migration rate which enables the adopters in group 3 to convert all non-adopters in the other four groups.

In contrast to the mother group being the peripheral group 1 (graph 5 in Figure 14), the centrally located mother group 3 cannot maintain its adopter majority when the migration rate is 7.5\% (graph 1 in Figure 15). Due to the fact that group 3 is connected to two groups instead of to just one, the fraction of emigrating adopters as well as immigrating non-adopters is twice as big. Lowering the migration fraction to 5\% (graph 2 in Figure 15) only delays the extinction of adopters in group 3 but cannot prevent it. In case the migration rate is only 2.5\% (graph 3 in Figure 15), the conversion of the immigrating non-adopters can compensate for the emigration loss of adopters within group 3. Therefore, the adopter fraction of group 3 stays close to 100\%. However, in contrast to the previous simulations depicted in Figure 14, the emigrating

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**Figure 15** Effects of different migration rates on the innovation diffusion process within Krackhardt’s model and with adopters initially situated in group 3 only
adopter fraction is not large enough to survive within the non-adopter dominated groups 2 and 4, let alone to prevail over the non-adopters there. This results in an average adopter fraction of 20%. Krackhardt (1997, pp. 194-196) refers to the increased likelihood and speed of diffusion of a rather isolated mother group as the Principle of Peripheral Dominance.

Besides the Principle of Optimal Viscosity and the Principle of Peripheral Dominance, Krackhardt (1997, p. 196) also finds that it is “almost impossible for the non-adopters to retake control of the organization once adopters have dominated it.” This so-called Principle of Irreversibility is the result of the assumption that the search intensity of adopters is higher than the search intensity of non-adopters. These three principles constituted Krackhardt’s (1997) main findings. After rebuilding Krackhardt’s (1997) diffusion model in a system dynamics environment and after replicating and elaborating on his main findings, the following section uses the temporal dimension of system dynamics to relax the restrictive assumption that migration and conversion take place successively. In particular, a continuous system dynamics model is introduced in which migration and conversion happen simultaneously and continuously.

6.2.3. A continuous system dynamics model allowing for migration and conversion to take place simultaneously

Figure 16 contrasts pure algebraic modeling with system dynamics modeling. The left part of Figure 16 depicts the algebraic equations Krackhardt (1997) uses to calculate the adopter fraction of one iteration. Even though these equations are similar to the system dynamics equations described in section 6.2.1, a key difference between purely algebraic models and system dynamics models is the underlying software of a system dynamics environment. This software not only facilitates the modeling of feedback processes by automating the algebraic calculation of variables across several time steps, it also supports the structuring and visualization of the model by distinguishing between different kinds of variables (e.g., stocks and flows) and by offering a graphical user interface that also permits meaningful variable names (Forrester, 1961, pp. 14-16; Forrester, 1968, chapter 4). The right part of Figure 16 sketches the structure of the model described in section 6.2.1 within the system dynamics environment Vensim. The two stocks Fraction Adopters and Fraction Non-adopters can be identified as boxes in the stock and flow diagram (see Figure 13). The conversion and migration rates that change them are flow variables which are represented by double arrows with a valve in the middle. The causal relations leading to a change of flow variables or information variables are depicted by single arrows.

Figure 16 indicates that both models use the same inputs and are basically capable to produce the same outputs. However, system dynamics models can
generate output values at very short time intervals much more easily than purely algebraic models. To do so, one simply needs to decrease the time step of the respective system dynamics model. However, the model described in section 6.2.1 can only benefit from this increased precision if the temporal dimension of system dynamics is actually used. Up until now, the differential equations described in section 6.2.1 were only calculated during the time steps at even or uneven simulation times for reasons of congruency with Krackhardt’s (1997) original model. Multiplying those differential equations with the time step yields the actual change of the adopter or non-adopter fraction which is caused by the respective flow variable during this time step. In doing so, the time steps in the denominator and numerator of the resulting equations cancel each other out, showing that the output of the model in section 6.2.1 is completely independent from the size of the time step.

In order to allow migration and conversion to take place simultaneously, the increased precision of a smaller time step is needed. It ensures that the fraction of adopters or non-adopters leaving their respective camp does not exceed the fraction of adopters or non-adopters within this camp. Therefore, the temporal

\[
A_i^{t+1} = A_i^{t} \cdot (1 - A_i^{t} \cdot \Delta t) + \sum_j m_{ij} \cdot A_j^{t},
\]

\[
A_{i-}^{t+1} = A_{i-}^{t} \cdot (1 - A_{i-}^{t} \cdot \Delta t) + \sum_j m_{ij} \cdot A_j^{t},
\]

\[
A_{i+}^{t+1} = A_{i+}^{t} \cdot (1 - A_{i+}^{t} \cdot \Delta t) + \sum_j m_{ij} \cdot A_j^{t}.
\]

**Figure 16** Comparison of pure algebraic modeling with system dynamics modeling

\[
S_A, S_N, P_{AN}, P_{NA}, m_{ij}, m_{ji} (MGr_t)
\]

Pure algebraic modeling

Modeling with system dynamics

\[
A_i^{t+1} = A_i^{t}, \ A_i^{t+2}, \ ... \ (t \in M_i)
\]

\[
A_i^{t+1} (t \in Q_i)
\]

\[
S_A = \text{Search intensity of adopters}, \ S_N = \text{Search intensity of non-adopters},
\]

\[
P_{AN} = \text{Probability of becoming a non-adopter}, \ P_{NA} = \text{Probability of becoming an adopter},
\]

\[
m_{ij} = \text{Fraction of adopters or non-adopters of group } j \text{ that migrates to group } i,
\]

\[
m_{ji} = \text{Fraction of adopters or non-adopters of group } i \text{ that migrates to group } j,
\]

\[
MGr_t = \text{Mother group within the network that comprises the initial adopters},
\]

\[
A_i^t = \text{Adopter fraction within group } i \text{ at time } t
\]
dimension of system dynamics is used by redefining the parameters $P_{AN}$, $P_{NA}$, $m_{ij}$ and $m_{ji}$. From now on the conversion probabilities $P_{AN}$ and $P_{NA}$ reflect the likelihood that an adopter or non-adopter converts to the other camp within one day. Similarly, the migration rates $m_{ij}$ and $m_{ji}$ represent the proportion of organizational members that migrate from or to a camp of group $i$ within one day. The adjusted equations of section 6.2.1 of a group $i$ are as follows:

$$\frac{dA_i_{emigr}}{dt} = \sum_j A_i \cdot m_{ij};$$

(6a')

$$\frac{dA_i_{immigr}}{dt} = \sum_j A_j \cdot m_{ji};$$

(7a')

$$\frac{dN_i_{conv}}{dt} = P_{NA} \cdot (1 - A_i) \cdot A_i^SN;$$

(8a')

$$\frac{dA_i_{conv}}{dt} = P_{AN} \cdot A \cdot (1 - A)^SA.$$}

(8b')

Even though not shown here, equations 6b and 7b—representing the migration between non-adopter camps—are adjusted in the same manner. Now the temporal dimension of system dynamics has an effect on the output because it is independent from the time step. It is included in the conversion probabilities and migrations rates whose unit is now percent per day. In doing so, migration and conversion are transformed into simultaneous and continuous processes which take place not just at certain points in time but during the whole simulation period. For example, $P_{NA}$ describes now what fraction of isolated non-adopters convert to the adopter camp within one day. Thus, multiplying $P_{NA}$ by the amount of isolated non-adopters yields the daily decrease of a group’s non-adopter fraction which, in turn, is the daily increase of this group’s adopter fraction due to the conversion of non-adopters (see equation 8a’). Since the adopter fraction of a group $i$ depends on migration and conversion, the total net increase of the adopter fraction of a group $i$ per day, which equals the total net decrease of this group’s non-adopter fraction, is defined as:

$$\frac{dN_i}{dt} = \frac{dA_i_{immigr}}{dt} - \frac{dA_i_{emigr}}{dt} + \frac{dN_i_{conv}}{dt} - \frac{dA_i_{conv}}{dt};$$

(9)
In the continuous system dynamics model, equations 6a’, 7a’, 8a’, and 8b’ describe migration and conversion processes which epitomize the communication processes of the adopter camp of a group $i$. These communication processes result either in an increase or decrease of the adopter fraction in this group. Therefore, in the model they are displayed as inflows and outflows of the stock $\text{Fraction Adopters}$. Figure 13 illustrated Krackhardt’s (1997) algebraic model as a simplified stock and flow diagram in $\text{Vensim}$, a system dynamics modeling and simulation environment (see section 6.2.1). There, the inflows and outflows are represented by double arrows with a valve in the middle. Since only the equations of these flows and not the model structure itself changed, Figure 13 also depicts the main aspects of the continuous system dynamics model introduced in this section.

With the main focus of this chapter being on the communication network among organizational groups, the continuous system dynamics model differs from the basic model, introduced in chapter 4, in accounting for the communication relations between a group $i$ and a group $j$. That is, in the continuous system dynamics model, the communication process is not just defined by conversion, but also by migration processes (see equation 9). Figure 17 outlines the structure of the continuous system dynamics model introduced in this section by depicting the inflows and outflows of two communicating groups. The conversion process between adopters and non-adopters of a group is almost identical to the conversion process of the basic system dynamics model introduced in chapter 4 (see Figure 6). That is, equations 1a and 1b coincide with equations 8a’ and 8b’, respectively. The only formal difference between the conversion processes of both models is that the unit of time is day(s) in the continuous system dynamics model and month(s) in the basic system dynamics model.

The simultaneous and continuous occurrence of migration and conversion allow for a wider interpretation and applicability of the continuous system dynamics model. In particular, the concept of migration can be extended to other forms of group-spanning communication such as making a telephone call or using an instant messenger service. For this purpose, the migration rate between a group $i$ and a group $j$ ($m_{ij}$) can be understood as the daily adopter or non-adopter fraction of group $i$ which initiates interactions with group $j$. Vice versa, the migration rate between group $j$ and group $i$ ($m_{ji}$) represents the daily adopter or non-adopter fraction of group $j$ which initiates interactions with group $i$. Thus, even though members of group $i$ do not need to migrate physically

$$\frac{dN_i}{dt} = \sum_j A_j \cdot m_{ji} - \sum_j A_i \cdot m_{ij} + P_{NA} \cdot (1 - A_i) \cdot A_i^{S_N} - P_{AN} \cdot A_i \cdot (1 - A_i)^{S_A}. \tag{9}$$
to bridge the distance to group $j$, they become part of group $j$ as soon as they start communicating with it. Thus, $m_{ij}$ also contains members of group $i$ that have only temporarily been part of group $j$—for example for the duration of a telephone call—but then terminate their interaction with group $j$ and thereby become members of group $i$ again. Due to the conversion processes within groups, previous adopters of group $i$ might return as non-adopters, after communicating with group $j$. This interpretation of migration is possible because the continuous occurrence of migration and conversion allows organizational members to leave and return to a group within very short time intervals. Therefore, the proposed model is applicable in multiple cases, potentially providing insights into the dynamics of a variety of organizational communication networks that are not limited to physical migration processes between groups.

Figure 17 Outline of a continuous intra-organizational diffusion model considering innovation discontinuance and the communication structure among groups (numbers indicate the corresponding equation; text in italics indicates variable names)

With regard to the validity of the continuous network-oriented model, the same validity tests were conducted as in chapters 4 and 5. Concerning the theoretical structure-confirmation test, the continuous network model is largely based on Krackhardt’s (1997) diffusion model. The only major difference is the continuous occurrence of conversion and migration, which was elaborated on above. In addition, the group-internal conversion process is identical to the basic implementation model which was introduced and validated in chapter 4. Therefore, the theoretical structure-confirmation test was passed. With regard to the extreme-conditions test, all parameter values of the continuous network model were tested, finding no inconsistent model behavior. Therefore, the
As mentioned previously, one must consider the purpose of the continuous network model when conducting a boundary adequacy test (Forrester & Senge, 1980, p. 16). The purpose of this model is to answer the third research question, asking how structural characteristics of the communication network among groups affect peer influence and implementation effectiveness. In contrast to Krackhardt’s (1997) work, the analysis of the continuous system dynamics model does not only examine how variations of the input influence the output of the model. Over and above, the focus is on revealing and describing the inherent dynamics which actually define the output. In the remainder of this chapter, the input of the model is varied and its effect on the output is analyzed in order to make those dynamics more transparent. Against this background, the structural boundary of the model seems adequate. In order to examine whether or not the behavior of the model and the derived policy recommendations are valid if the model boundary is extended, the interested reader might be referred to chapter 7 which introduces an extended version of the continuous network model. The dynamics and policy recommendations that will be uncovered in the remainder of this chapter are also valid for the extended management-oriented version of the continuous network model. Therefore, the model boundary of the continuous network model is also adequate when the model behavior and the derived policy recommendations are taken into account. Hence, the boundary adequacy test was also passed.

### 6.2.4. Comparing the behavior of the Krackhardt and the continuous model

After deriving a continuous system dynamics model of intra-organizational innovation diffusion in the previous sections, this section compares the behavior of the continuous model to the behavior of Krackhardt’s (1997) model, which was rebuilt in an system dynamics environment (see section 6.2.1). In the following, the continuous system dynamics model is simulated using the same parameters as in the prior model: $S_A = 6$, $S_N = 4$, $P_{AN} = P_{NA} = 1$. The only difference to the system dynamics model introduced in section 6.2.1 is that migration and conversion now take place during the entire simulation period, thereby occurring simultaneously.
Figure 18 illustrates the influence of the migration rate on the average adopter fraction of the continuous model, assuming that group 1 constitutes the mother group \((MGr_1)\) within a five-membered chain structure and that the underlying migration rate is equal among all five groups in the organization. In contrast to the previous system dynamics model (Figure 14), Figure 18 shows that the innovation does not diffuse completely when the migration rate is 10% (graph 5 in Figure 18). Instead, it is largely confined to the mother group, as in the case of a 7.5% migration rate (graph 6). If the migration rate is below 10.1%, the average adopter fraction in the continuous model is always between 20% and 23%, with group 1 and group 2 accounting together for over 95% of all adopters. If the migration is slightly above this window’s lower bound of 10.1%, the innovation diffuses in a step-like manner (graph 4 in Figure 18). In fact, these steps become more distinct, the closer the migration rate is to the lower bound of the window of opportunity, provided it is still within this window. Regarding migration rates of 12.5%, 15%, and 17.5% (graphs 3, 2, and 1), the general behavior of the continuous model (Figure 18) is similar to that of Krackhardt’s (1997) model (Figure 14). However, the innovation succeeds (graphs 2 and 3) or fails (graph 1) much quicker than in Krackhardt’s (1997) model.

The continuous occurrence of migration and conversion has a positive as well as a negative effect on implementation effectiveness. On the one hand, the innovation diffuses generally much quicker than in Krackhardt’s (1997) model. On the other hand, only migration rates between 10.1% and 17.1% enable an adopter minority to win over a non-adopter majority, thereby narrowing this window of opportunity from an 8.8 percentage point range in Krackhardt’s (1997) model to a 7 percentage point range in the continuous model. Further simulation runs show that within the shared window of opportunity, comprising migration rates between 10.1% and 16.4%, innovations diffuse quicker in the continuous model than in Krackhardt’s (1997) model as long as the migration rate is higher than 10.5%. The minimal diffusion time in Krackhardt’s (1997) model is around 180 days at a migration rate of 15.2%, while it is 110 days in the continuous model at a migration rate of about 15.7%.

Similar to the analyses in section 6.2.1, further simulation runs within the continuous model confirm that Krackhardt’s (1997) Principle of Optimal Viscosity is surprisingly insensitive to changes of the conversion probabilities and to different search intensities, as long as word of mouth strength \(S_A > S_N\). Since unequal conversion probabilities \((P_{AN}>P_{NA} \text{ or } P_{AN}<P_{NA})\) also cause one camp to be more resistant to conversion than the other, they have a similar effect on the diffusion process. Generally speaking, the window of opportunity is wider, the lower the conversion probability and/or the higher the search intensity of adopters. On the other hand, the window is narrower, the lower the conversion probability and/
or the higher the search intensity of non-adopters. Thereby, a lower conversion probability of a camp (i.e., adopter or non-adopter camp) can to some extent compensate for a lower search intensity of that camp and the other way around. Thus, the general behavior of the model would be the same if $P_{AN} < P_{NA}$ instead of $S_A > S_N$.

The previous analysis shows that the simulation results of the continuous system dynamics model differ only slightly from the simulation results of Krackhardt’s (1997) model in section 6.2.2. Even though numerical values are different, the general behavior of both models is the same. Depending on the migration rate there is a window of opportunity in both models which enables an adopter minority in group 1 to win over a non-adopter majority. If the migration rate exceeds this window, the innovation gets completely rejected. If the migration falls short of this window, the average diffusion degree is around 20%. The closer a migration rate within this window is to its lower bound, the more step-like the diffusion pattern. The resemblance in behavior of both models is due to the fact that their basic structure is the same. Therefore, not only the **Principle of Optimal Viscosity**, but also Krackhardt’s (1997) **Principle of Peripheral Dominance** and the **Principle of Irreversibility** apply in the continuous system dynamics model. To understand this behavior better, the following section analyzes the diffusion process within each of the five groups.

**Figure 18** Effects of different migration rates on the innovation diffusion process within the continuous model and with adopters initially situated in group 1 only.
Chapter 6

The remainder of this chapter focuses on the continuous system dynamics model described in the previous section. Table 4 provides an overview of the key variables of this continuous network model. A complete stock and flow diagram of this model and all variables including equations can be found in appendix 4 and appendix 6, respectively.

### 6.3. Analysis of dynamics within intra-organizational diffusion networks by means of a continuous system dynamics model

The previous sections of this chapter derived a continuous system dynamics model to analyze the influence of intra-organizational communication networks on implementation effectiveness. In order to understand the described behavior of this model, this section analyzes its inherent dynamics. In particular, this section aims to answer research question three by elucidating how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness. As in the previous
section, it is assumed that group 1 is the mother group \( (\text{MGr}_1) \) within a five-membered chain structure and that the other parameters take the following values: \( S_A = 6, S_N = 4, P_{AN} = P_{NA} = 1 \).

Figure 19 depicts the diffusion of an innovation through all five groups within the continuous model if the migration rate is 12.5\% (left) and if the migration rate is 10.4\% (right). In doing so, the left part of Figure 19 disaggregates the diffusion process shown in graph 3 of Figure 18, while the right part of Figure 19 disaggregates the diffusion process shown in graph 4 of Figure 18. Assuming a migration rate of 12.5\%, the left part of Figure 19 shows the characteristic s-shaped growth of the adopter fraction within the initial non-adopter groups (graphs 2, 3, 4, and 5). The fraction of adopters migrating from group 1 into group 2 is big enough to gradually overcome the resistance within group 2 (graph 2) and small enough to ensure that adopters prevail within group 1 (graph 1). The increasing adopter fraction within group 2 induces an exponentially increasing adopter fraction within group 3 which only slows down after the lion’s share of non-adopters within group 3 has been converted (graph 3). This chain reaction continues until group 4 and 5 are also dominated by adopters (graph 4 and 5).

The s-shaped growth of the adopter fraction within non-adopter groups, depicted in the left part of Figure 19, resembles the behavior of the Bass (1969) diffusion model. The underlying dynamics are however more complex. As the previous section has shown (see Figure 18), these dynamics become more evident, the closer the migration rate is to the lower bound of the window of opportunity, provided it is still within this window. Therefore, the right part of Figure 19 illustrates the diffusion of an innovation through five groups organized in a chain structure when the migration rate is 10.4\%, only 0.3\% greater than the window’s lower bound of 10.1\% (see also graph 4 in Figure 18). In this case, the diffusion within group 3, for example, resembles a triple s-shaped growth with points of inflection around day 120, day 180, and day 250 (graph 3 in right part of Figure 19).

In order to identify the dynamics behind the graphs in the right part of Figure 19, the net migration rates and the net conversion rates are calculated within the continuous system dynamics model. In contrast to the migration rate, the net migration rate of a group \( i \) is defined as the difference between the fraction of adopters immigrating into group \( i \) (equation 7a’) and the fraction of adopters emigrating out of group \( i \) (equation 6a’). The net conversion rate of a group \( i \) is defined as the difference between the fraction of non-adopters that are converted to the adopter camp (equation 8a’) and the fraction of adopters that are converted by the non-adopter camp (equation 8b’). Each rate, the net migration rate as well as the net conversion rate, is positive whenever it, by itself, increases the adopter
fraction of the respective group. Since migration and conversion take place continuously and simultaneously, the sum of both rates constitutes the daily net change of the adopter fraction within a group \(i\), which is described by equation 9' (see also Figure 17).

In contrast to the net migration rate of a group \(i\), the net migration rate between a group \(i\) and a group \(j\) describes only the part of the daily net change of the adopter fraction in group \(i\) which results from the migration relation with one specific group \(j\). The net migration rate between a group \(i\) and a group \(j\) is necessary to understand the behavior of the net migration rate of a group \(i\) which is shown in Figure 20. The left part of Figure 20 depicts the net migration rate of all five groups when the migration rate is 10.4% and when group 1 constitutes the mother group (i.e., with the same parameterization as in the right part of Figure 19). The right part of Figure 20 illustrates the respective net conversion rate of all five groups within the model.

In the beginning of the simulation, group 1, the mother group, slightly loses more adopters due to migration (graph 1 in left part of Figure 20) than it gains through conversion (graph 1 in right part of Figure 20) which explains the initial drop of the adopter fraction within group 1 (graph 1 in right part of Figure 19). This drop is greater, the higher the migration rate (graph 1 in left part of Figure 19). From the perspective of group 1, the net migration rate between group 1 and group 2 is negative because the adopter fraction in group 1 is higher than in group 2. But when the adopter fraction in group 2 increases (graph 2 in right part of Figure 19), the proportion of adopters migrating from group 2 into group 1 also grows, thereby increasing the net migration rate of group 1 (graph 1

**Figure 19** Group-internal diffusion within the continuous model, assuming a migration rate of 12.5% (left) and a migration rate of 10.4% (right)
in left part of Figure 20. As a result, the adopter fraction of group 1 is steadily increasing after the initial drop, till it finally reaches 100% again (graph 1 in right part of Figure 19).

Group 2, on the other hand, has a positive net migration rate, due to immigrating adopters from group 1 (graph 2 in left part of Figure 20). Most of those adopters get converted by the dominating non-adopters, resulting in a negative net conversion rate (graph 2 in right part of Figure 20). Since not all of the daily immigrating adopters get converted, the adopter fraction of group 2 still slowly increases (graph 2 in right part of Figure 19). This positive influence of the migration relation with group 1 slowly decreases the negative influence of the conversion process by increasing the net conversion rate of group 2 until it becomes positive around day 105. At this point, the adopter fraction in group 2 reaches a critical threshold of about 41%. In the following, this is referred to as the adopter threshold. From then on, the conversion process supports the positive influence of the migration relation with group 1, resulting in a sharp increase in the adopter fraction of group 2.

Since the conversion probabilities are assumed to be equal ($P_{AN} = P_{NA}$), the adopter threshold of about 41% depends solely on the relation of the two search intensities. For example, if the search intensities of adopters and non-adopters were also assumed to be equal, the adopter threshold would be at 50%. The adopter threshold is a group-internal measure. Therefore, it is only determined by conversion and not by migration processes. In particular, the adopter threshold constitutes the adopter fraction for which the conversion process
results in an equal amount of converted adopters and non-adopters. In other words, the inflow of the adopter fraction (equation 8a’) must equal its outflow (equation 8b’):

\[
\frac{dN_{I,conv}}{dt} = \frac{dA_{I,conv}}{dt},
\]

(10)

(10’)

In the previous simulations, \(S_A = 6\), \(S_N = 4\), \(P_{AN} = P_{NA} = 1\). Therefore, the only unknown is \(A_i\). Solving equation 10’ for \(A_i\) yields three values: 0, 1, and 0.412. Since the first two values represent scenarios with either 0% or 100% adopters, they do not constitute a threshold. Consequently, the adopter threshold equals about 41.2%.

The reinforcing feedback loop between the adopter fraction and the net conversion rate of group 2 is partially inhibited by the net migration rate between group 2 and group 3. From the perspective of group 2, the net migration rate between group 2 and group 3 is negative during that period because the adopter fraction in the connected group 3 is still smaller than in group 2. Despite the negative migration relation with group 3, the overall net migration rate of group 2 (graph 2 in left part of Figure 20) is still positive, due to the positive net migration rate between group 2 and group 1. However, this positive effect becomes much weaker when the gap between the adopter fractions of group 1 and group 2 decreases. The negative influence of the migration relation with group 3, on the other hand, grows stronger because the increasing adopter fraction in group 2 widens the gap between group 2’s and group 3’s adopter fraction.

From day 110 on, this negative effect dominates the self-reinforcing conversion process within group 2 and the positive effect of the migration relation with group 1. Consequently, the net migration rate of group 2 becomes negative (graph 2 in left part of Figure 20), thereby causing the daily net change of the adopter fraction in group 2 to decrease from day 120 on (decreasing slope of graph 2 in right part of Figure 19). The negative influence of the migration relation with group 3 leads to constant drain of adopters which keeps the adopter fraction of group 2 at a level of around 90% (graph 2 in right part of Figure 19). Only when the adopter fraction in group 3 closes the gap to group 2 does the net migration rate of group 2 increase (graph 2 in left part of Figure 20), leading to a complete diffusion of the innovation also within group 2.

From the perspective of group 3, the net migration rate between group 3 and group 2 is positive due to the higher adopter fraction in group 2 (graph 3 and
graph 2 in right part of Figure 19). With an increasing adopter fraction in group 2, a growing proportion of adopters migrate from group 2 into group 3, day after day. Since the non-adopters still dominate group 3, the conversion process has a negative effect on those adopters, converting almost all of them in the beginning of the simulation (graph 3 in right part of Figure 20). However, when the adopter fraction in group 2 grows exponentially, the net migration rate of group 3 also increases, thereby outweighing the decrease of the net conversion rate (graph 3 in left and right part of Figure 20).

From day 130 on, the daily inflow of adopters from group 2 remains more or less constant because group 2’s adopter fraction stalls at around 90% (graph 2 in right part of Figure 19). Nevertheless, group 3’s adopter fraction keeps increasing, albeit with slower speed, because not all of the daily immigrating adopters are converted by the dominating non-adopters (graph 3 in right part of Figure 19). The increasing adopter fraction of group 3, in turn, has a positive effect on the net conversion rate which increases until it becomes positive around day 175 (graph 3 in right part of Figure 20). From then on, the conversion process supports the positive effect of the migration relation with group 2. However, from the perspective of group 3, the net migration rate between group 3 and group 4 is negative. The conversion process within group 3 and the positive migration relation with group 2 cannot compensate for the adopters migrating from group 3 to group 4. Hence, group 3’s adopter fraction levels off at around 90% (graph 3 in right part of Figure 19). Only when group 4’s adopter fraction increases does the negative influence of the migration relation with group 4 decrease, thereby leading to a unanimous adoption of the innovation within group 3.

With regard to group 4 and group 5 (graph 4 and graph 5 in Figure 19 and Figure 20), basically the same dynamics as in group 3 are responsible for the complete diffusion of the innovation within these groups. However, they put up less resistance than previous groups because there are fewer non-adopter groups later in the chain which support them. Thus, the immigrating adopters are split over fewer non-adopter groups which participate in converting them. Therefore, a smaller fraction of immigrating adopters is converted which makes it easier for adopters to gain a foothold in the non-adopter dominated groups and therefore speeds up the conversion process in these groups, which naturally starts at a later time.

Further simulation runs, not displayed here, show that a greater difference between the search intensities of adopters and non-adopters (\( S_A \gg S_N \)) increases the likelihood that a window of opportunity opens up for a certain range of migration rates in which even an adopter minority in group 2 (\( MGr_2 \)) or in group 3 (\( MGr_3 \)) can win over a non-adopter majority. The higher search intensity of adopters results in a lower adopter threshold within groups at which the
influence of the conversion process switches from supporting non-adopters to supporting adopters (see equation 10'). The dynamics of conversion and migration processes, which have been identified above, determine the effectiveness of organizational innovation implementation processes, making them a success or failure.

### 6.4. Summary and discussion of findings regarding communication networks

This chapter analyzed the diffusion of innovations within intra-organizational networks. It focused on system dynamics as the analytical method. In order to illustrate the benefits of system dynamics when analyzing the diffusion of innovations through networks, Krackhardt's (1997) purely algebraic diffusion model was replicated and analyzed in a system dynamics environment. Krackhardt’s (1997) diffusion model was chosen because it does not solely focus on positive word-of-mouth effects but also considers negative word of mouth. However, it assumes that migration and conversion take place consecutively. Thus, after comparing Krackhardt’s (1997) purely algebraic model with its system dynamics replication, the latter was extended by relaxing the restrictive assumption that migration and conversion occur consecutively. Instead, the temporal dimension of system dynamics was used to transform migration and conversion into processes which take place continuously and simultaneously. In contrast to Krackhardt’s (1997) work, the analysis of the continuous system dynamics model did not only examine how variations of the input influence the output of the model. Over and above, the focus was on revealing and describing the inherent dynamics which actually define the output. The input of the model was altered and its effect on the output was analyzed in order to make those dynamics more transparent.

Transforming Krackhardt’s (1997) purely algebraic model into a system dynamics model is beneficial for several reasons. First, Krackhardt (1997) models groups of organizational members that consist of adopters and non-adopters. Within the adopter or non-adopter camp of a group, employees are assumed to be homogeneous and well mixed. This coincides with system dynamics which also assumes that individuals are homogeneous and well mixed within each stock and which also operates on an aggregate level rather than on an individual level (see also section 3.2). The aggregated character of system dynamics facilitates the linking of model behavior to its structure and even permits extending the model while keeping its complexity manageable (Rahmandad & Sterman, 2008, p. 999). Second, the communication between and within groups—represented by migration and conversion—causes complex dynamics and
numerous feedback processes. In contrast to purely algebraic models, system dynamics models promote the simulation of feedback processes by allowing a stock to be an output variable as well as an independent variable. This is possible because system dynamics operates along a temporal dimension consisting of equally large and definable time steps. Therefore, the repeated calculation of a group $i$'s adopter fraction is more convenient than in a purely algebraic model.

A third benefit of using system dynamics for analyzing intra-organizational diffusion processes is the graphical depiction of the model which contributes to a better understanding of the underlying network structure and the dynamics caused by it. This is achieved by distinguishing between stock variables, flow variables, information variables, and parameters, by giving them meaningful names, and by indicating the causal relations between them. Consequently, the dynamics between and within groups become more obvious, making the complex diffusion process easier to grasp and comprehend. Among others, those three points speak for the transformation of Krackhardt's (1997) algebraic diffusion model into a system dynamics model. The analysis in section 6.2.2 shows that the replication of Krackhardt's (1997) model in system dynamics is capable of producing the exact same results. In addition, the characteristics of system dynamics allow the model to be extended so that migration and conversion can take place continuously and simultaneously.

In the previous section, the analysis of the continuous system dynamics model found that the dynamics caused by the interplay between migration and conversion follow a certain pattern for all initial non-adopter groups. It was shown that the net migration rate of a non-adopter group $i$ must be high enough so that not all immigrating adopters get converted immediately. If that is ensured, the adopter fraction of group $i$ slowly increases until it reaches a threshold of about 41%, which depends on the relation of the two search intensities and is the same for all groups independent of their position in the network. At this point the negative influence of the conversion process becomes positive, supporting the adopter camp from then on. However, at one point the increasing adopter fraction and the thereby increasing emigration of adopters negate the formerly positive influence of the migration process because the percentage of adopters leaving group $i$ outweighs the fraction of immigrating adopters, resulting in a negative net migration rate. Only after the adopter fractions in the connected groups increase does the net migration rate of group $i$ also increase, thereby elevating the adopter fraction of group $i$ to 100%.

With this chapter pertaining to research question three, the main focus was on how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness. The
analyses found that the migration processes among groups are driven by balancing dynamics which would distribute the initial adopters evenly across all groups if conversion was turned off. On the other hand, the conversion process within each group is driven by reinforcing dynamics. In case the adopter fraction of a group \( i \) is below the threshold of 41\%, the conversion process would eliminate all adopters within that group if migration did not take place. However, in case the adopter fraction exceeds this threshold, the conversion process would lead to an adopter fraction of 100\% if migration was turned off.

Another finding of the continuous system dynamics model is that the diffusion speed within a group \( i \) increases with the number of other groups being already dominated by adopters and decreases with the number of other groups still being dominated by non-adopters. Thus, the innovation diffuses much quicker in group 5 than in group 2, provided that group 1 is the mother group. This is the case because the balancing character of the migration process distributes the adopters of a group \( i \) over the neighboring groups and their neighbors. The more neighboring groups and their neighbors are dominated by adopters, the higher the net migration rate of group \( i \) and the quicker the innovation diffuses within this group. On the other hand, the more neighboring groups and their neighbors are dominated by non-adopters, the lower the net migration rate of group \( i \) and the slower the innovation diffuses within it.

This finding also suggests that adopter-dominated groups should be connected to each other while non-adopter-dominated groups should be isolated from each other in order to increase implementation effectiveness. Consequently, adopter groups support each other by having a higher net migration rate than if they were surrounded by non-adopter groups. This, in turn, increases the likelihood that the adopter fraction stays above the threshold of 41\%, thereby ensuring that the self-reinforcing dynamics of the conversion process keep working in favor of the adopter camp. Isolating non-adopter groups from each other, increases their net migration rate. This is the case because the ties with adopter groups become more influential. Thus, it is more likely that the negative influence of the conversion process of such a non-adopter group is inverted by increasing the adopter fraction above the 41\% threshold. When this happens, the conversion process starts working for the adopter camp.

The findings of this research have also been tested for very small time steps, finding no major changes in the dynamic behavior of the model. It could be argued that physical migration is not the only form of communication among groups. However, as discussed in section 6.2.3, the concept of migration can be interpreted in a way which also includes other forms of group-spanning communication such as making a telephone call or using an instant messenger service. Therefore, the continuous system dynamics model is applicable in a
multitude of cases potentially providing insights into the dynamics of a variety of organizational communication networks.
7. A management-oriented model considering discontinuance, communication structure, and management influence

7.1. Senior management’s influence on implementation effectiveness

“Senior managers tend to be responsible for the decision to adopt a new technology because adoption requires the approval of significant capital expenditures” (Lanzolla & Suarez, 2012, p. 841). Even though senior management often makes the authority innovation-decision to implement an innovation within an organization, the previous chapters stressed that implementation effectiveness often depends on the individual innovation-decision process of targeted employees. Nevertheless, senior managers have a major influence on the individual innovation-decisions of employees by, for example, “instituting reward systems based on usage, and promoting compliance via direct surveillance” (Repenning, 2002, p. 113).

Senior management’s influence on employees’ individual innovation-decisions has been proven in several studies (Choi & Chang, 2009, p. 251; Kim & Kankanhalli, 2009, p. 578; Venkatesh et al., 2003). For example, Choi and Chang (2009, p. 251) showed empirically that management support significantly improves implementation effectiveness by strengthening employees’ collective innovation confidence and innovation acceptance. Senior managers can also increase implementation effectiveness by improving the implementation climate and by communicating a clear message to employees that using the innovation is important for the success of the organization, that it is normatively expected, and that it is rewarded (Choi & Chang, 2009, p. 246; Klein et al., 2001, p. 822; Klein & Sorra, 1996, pp. 821, 1060). Since all these actions push the adoption of an innovation by exerting normative pressure on targeted employees, they are broadly referred to as management push or management pressure (Repenning, 2002).

The goal of this chapter is to analyze senior management’s influence on the effectiveness of intra-organizational innovation implementation processes. In particular, this chapter focuses on research question four, asking what characterizes an effective and efficient management strategy in light of different communication structures among groups. Building on the analyses of the previous chapter, this chapter aims at finding a decision rule which tells senior management what groups within the communication network it should concentrate on in order to ensure an effective and efficient innovation implementation. In other words: What structural characteristics of groups within a communication network determine on which of those groups senior management should concentrate its limited resources to ensure an effective and efficient innovation implementation?
The previous chapter has identified and described the core dynamics within and between five organizational groups that were organized in a chain structure. Dynamics within organizational groups are mainly driven by the conversion process which is mainly driven by reinforcing dynamics. That is, the higher the adopter fraction of a group, the higher the conversion rate within this group, which again leads to an even higher adopter fraction. These dynamics are only limited by the non-adopter fraction of a group. On the other hand, migration processes between groups are largely driven by dynamics which can be described as balancing feedback loops. Thus, the higher the difference between the adopter fractions of two connected groups, the greater the fraction of adopters migrating from the group with the higher adopter fraction to the group with the lower adopter fraction, which, in turn, decreases the difference between the adopter fractions of both groups. Thereby, migration should be understood as a rather broad concept which is not limited to physical migration. Instead, it comprises all kinds of activities that bridge the distance between two groups, as, for example, calling or e-mailing a member of another group.

Those dynamics led to the suggestion that adopter-dominated groups should be connected to support each other via migration, whereas non-adopter-dominated groups should be isolated from each other to diminish the supporting influence of other non-adopter-dominated groups. With regard to research question four, this suggestion translates into management strategies that focus on connected groups in order to maximize the spillover effect caused by the migration between them. Among others, such strategies are scrutinized in this chapter in order to answer research question four. Thereby, this chapter considers three of the four main factors of this research, namely peer influence, structural characteristics of organizations, and management influence. It builds on the findings of chapter 4, concerning the influence of peers, and on the findings of chapter 6, regarding the dynamics induced by the intra-organizational communication structure (Table 1). However, the main focus of this chapter is on senior management’s influence on employees’ individual innovation-decisions, which ultimately determine the effectiveness of intra-organizational innovation implementation.

In summary, this chapter analyzes ways senior management can influence the network-caused dynamics which were identified and described in the previous chapter to ensure an organization-wide implementation of the respective innovation. Thereby, this research focuses on identifying characteristics of successful management strategies which consider the network structure. Consequently, as illustrated in Figure 21, this chapter extends the common structure of diffusion models by accounting for (1) repeated acceptance and rejection decisions of adopters and non-adopters which might cause employees
to alternate between using the innovation (adopters) and the status quo (non-adopters), (2) the network structure among organizational groups, and (3) management’s normative influence on the organizational diffusion process. Thereby, this chapter goes beyond a mere description of diffusion dynamics in order to explain how management can influence organizational diffusion processes among employees. Thus, the system dynamics model presented in this chapter addresses intra-organizational innovation implementation by combining employee-related and organizational factors (see Figure 4). In contrast to Choi and Chang (2009), this chapter does not focus on the strength of empirical correlations among influencing factors. Instead, it addresses the network-caused dynamics between actors. This allows this research to account for changes of influencing factors and to analyze effective and efficient managerial strategies for implementing innovations in organizations.

Figure 21 Outline of a management-oriented intra-organizational diffusion model considering innovation discontinuance, the communication structure among groups, and management influence (numbers indicate the corresponding equation; text in italics indicates variable names)

To analyze management’s influence on the implementation process and answer research question four, the following section specifies the changes to the continuous system dynamics model introduced in chapter 6. As illustrated in Figure 21, the continuous model is extended by incorporating management’s influence. Thereby, this research draws on Repenning’s (2002) innovation implementation model. In section 7.3, the derived management model is analyzed assuming the five-membered chain structure which has already been the underlying communication structure in the previous chapter. Subsequently,
section 7.4 tests the findings for different networks structures among five organizational groups. Section 7.5 analyzes the influence of the time senior management needs to train and push targeted employees to use an innovation. Finally, section 7.5 summarizes and discusses the findings of this chapter.

7.2. Modeling senior management’s influence on organizational groups

To analyze research question four, this section extends the continuous system dynamics model introduced in chapter 6. Therefore, equations 6a’, 6b’, 7a’, 7b’, 8a’, and 8b’ also apply to the management-oriented model of this chapter. In contrast to previous models of this research, there is no initial adopter fraction, as in chapters 4 and 5, or a mother group (e.g., MGr1), as in chapter 6. Instead, it is assumed that initially all groups consist only of non-adopters and that senior management initiates the diffusion of an innovation by introducing the innovation to a few selected groups (addressed groups). From then on, senior management influences these groups by training the respective employees on how to use it and by exerting normative pressure to actually use it (Repenning, 2002). The binary vector \( \vec{v} \) describes whether or not groups are addressed by senior management. For example, if groups 1 and 4 are influenced, then \( \vec{v} = (1, 0, 0, 1, 0) \). Equation 11 describes senior management’s daily influence on the non-adopter camp of a group \( i \):

\[
\frac{dN_{i \text{mgmt}}}{dt} = \frac{\text{Min}(N_{i}, \text{Max}(A_i^* - A_i, 0))}{T_M} \cdot \vec{v}.
\]  

(11)

The term \( A_i^* - A_i \) describes to what extent senior management pushes non-adopters of an addressed group. It depends on the difference between management’s desired adopter fraction \( A_i^* \) and this group’s current adopter fraction \( A_i \). The greater the discrepancy between senior management’s goal \( A_i^* \) and the group-specific diffusion degree \( A_i \), the higher the pressure senior managers exert on the respective group. In the beginning of the simulation, management’s goal \( A_i^* \) and the adopter fractions of all groups \( A_i \) are zero. Therefore, senior management exerts no normative pressure \( A_i^* - A_i = 0 \). However, when the simulation time equals twelve days, it is assumed that management initiates the implementation process by raising the management goal from zero to one.

The maximum function ensures that senior management’s influence is never negative, even when \( A_i^* < A_i \). This assumption implies that senior management
never exerts pressure on adopters to discontinue an innovation. The minimum function in equation 11 simply guarantees that management’s pressure does not cause the non-adopter fraction of a group to become negative. That is, senior management cannot convert more non-adopters than are in the group. In line with Repenning (2002, p. 115), this chapter also assumes that management needs time to develop and implement actions to convert non-adopters and that non-adopters need time to react, acquire skills, and modify their behavior ($T_M$). The longer it takes until management succeeds in changing non-adopters’ behavior, the smaller the increase of a group’s adopter fraction. Vector $v$ defines which of the five groups senior management influences in this manner. Table 5

<table>
<thead>
<tr>
<th>Name</th>
<th>Variable</th>
<th>Values</th>
<th>Equation</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adopter fraction group $i$</td>
<td>$A_i$</td>
<td>$\mathbb{R} \mid 0 \leq A_i \leq 1$</td>
<td>$6a', 7a', 8a', 8b'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Non-adopter fraction group $i$ $(= 1 - A_i)$</td>
<td>$N_i$</td>
<td>$\mathbb{R} \mid 0 \leq N_i \leq 1$</td>
<td>$6b', 7b', 8a', 8b'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Conversion probability adopters</td>
<td>$P_{AN}$</td>
<td>$\mathbb{R} \mid 0 \leq P_{AN} \leq 1$</td>
<td>$8b'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Conversion probability non-adopters</td>
<td>$P_{NA}$</td>
<td>$\mathbb{R} \mid 0 \leq P_{NA} \leq 1$</td>
<td>$8a'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Search intensity adopters (exogenous variable)</td>
<td>$S_A$</td>
<td>$\mathbb{R} \mid S_A \geq 1$</td>
<td>$8b'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Search intensity non-adopters (exogenous variable)</td>
<td>$S_N$</td>
<td>$\mathbb{R} \mid S_N \geq 1$</td>
<td>$8a'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Migration rate between group $i$ and group $j$</td>
<td>$m_{ij}$</td>
<td>$\mathbb{R} \mid 0 \leq m_{ij} \leq 1$</td>
<td>$6a', 6b', 7a', 7b'$</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Is connected to (adjacency matrix)</td>
<td>$G$</td>
<td>$\mathbb{R}^{5 \times 5} \mid g_{ij} \in {0,1}$</td>
<td>Appendix 4, 5, &amp; 6</td>
<td>Ch6, Ch7</td>
</tr>
<tr>
<td>Addressed groups (binary vector)</td>
<td>$v$</td>
<td>$\mathbb{N}^{5 \times 1} \mid v_i \in {0,1}$</td>
<td>11</td>
<td>Chapter 7</td>
</tr>
<tr>
<td>Management goal for group $i$</td>
<td>$A_i^*$</td>
<td>$\mathbb{R} \mid 0 \leq A_i^* \leq 1$</td>
<td>11</td>
<td>Chapter 7</td>
</tr>
<tr>
<td>Time for mgmt to train</td>
<td>$T_M$</td>
<td>$\mathbb{R} \mid T_M \geq 1$</td>
<td>11</td>
<td>Chapter 7</td>
</tr>
<tr>
<td>Accumulated invested resources</td>
<td>$Q$</td>
<td>$\mathbb{R}^+$</td>
<td>13</td>
<td>Chapter 7</td>
</tr>
</tbody>
</table>

**Table 5** Overview of the key variables used in the continuous simulation model introduced in chapter 6 and the extended management-oriented simulation model introduced in chapter 7
gives an overview of the key variables. A complete stock and flow diagram of this management-oriented system dynamics model and all variables including equations can be found in appendix 5 and appendix 6, respectively.

Compared to the continuous model in chapter 6, the only additional influence on employees’ individual innovation-decisions is management’s normative pressure (see Figure 21). Therefore, in the management-oriented model, the total net increase of the adopter fraction of a group \textit{i} per day, which equals the total net decrease of this group’s non-adopter fraction, is defined as (see also equations 9 and 11):

\[
\frac{dN_i}{dt} = \frac{dA_{i,immigr}}{dt} - \frac{dA_{i,emigr}}{dt} + \frac{dN_{i,conv}}{dt} - \frac{dA_{i,conv}}{dt} + \frac{dN_{i,mgmt}}{dt}. \tag{12}
\]

In order to evaluate the efficiency of different management strategies, the accumulated invested resources of senior management (\(Q\)) are assumed to equal the aggregated amount of exerted pressure. Thus, the accumulated invested resources (\(Q\)) at simulation time \(t\) equal:

\[
Q = \int_0^t \frac{dN_{i,mgmt}}{dt}. \tag{13}
\]

However, for simplicity, the accumulated invested resources only serve as a supplementary variable which does not influence any other variable of the model.

As described in section 4.2.3, the validity of the management-oriented model is examined by conducting five validity tests. Since the management-oriented model builds on the continuous network model described in chapter 6—which itself is based on the basic implementation model introduced in chapter 4—the theoretical structure-confirmation test focused on the structure that was added to the continuous network model. The structure describing management’s normative pressure on non-adopters is almost identical to a part of Repenning’s (2002) implementation model. Only variable names and parameter values differ slightly. The remainder of the ambiguity-oriented model is identical to the model described and validated in chapter 6. Consequently, the theoretical structure-confirmation test was passed.

Concerning the extreme-conditions test, all parameter values of the management-oriented model were tested, finding no inconsistent model behavior. Therefore, the extreme conditions test was also passed. The results of this test, focusing on the parameters which have been added to the continuous network
model, are available in appendix 7. No dimensional inconsistencies were found by the automated unit check of Vensim, resulting in a positive outcome of the dimensional consistency test. With regard to the behavior sensitivity test, several changes in parameter values were examined. The results of these simulations and an explanation of the respective model behavior are provided in the following section. The results of this test indicate a reasonable sensitivity of the management-oriented model.

Also for the management-oriented model introduced in this chapter, one must consider its purpose when testing the adequacy of the model boundary (Forrester & Senge, 1980, p. 16). The purpose of this model is to answer the fourth research question, asking about characteristics of an effective and efficient management strategy in light of different communication structures among groups. With regard to this research question, the model boundary seems adequate. In order to test whether or not the behavior of the management-oriented model and the derived policy recommendations are valid if the model boundary is extended, additional structure was added to this model. In particular, the management-oriented model was extended by accounting for an innovation's perceived ambiguity and employees’ ambiguity intolerance, as is discussed in detail in chapter 5. Even though the resulting model is not described in this dissertation, the dynamics and policy recommendations—which are discussed in the subsequent sections—were also valid for a continuous network model which considers the perceived ambiguity within an organization. As a result, also the boundary adequacy test was passed.

7.3. Analysis of management’s influence on the implementation process

In this section, the management-oriented model of the previous section is analyzed by examining which groups senior management should influence to ensure an effective and efficient diffusion throughout an organization. For the following simulations, it is assumed that the initial adopter fraction of all groups \( A_i \) is zero, that management’s goal \( A_i^* \) increases from zero to one at day twelve, and that it takes on average twelve days until management’s normative pressure causes a change in behavior among non-adopters \( T_M \). As in the previous chapter, this section assumes that the underlying communication structure \( G \) is a chain structure. All other parameters take on the values of chapter 6 \( S_A = 6, S_N = 4, P_{AN} = P_{NA} = 1 \). By changing the value of vector \( \vec{v} \), this section examines which groups are most susceptible to management's influence due to their position within the five-membered chain structure. Section 7.4 then analyzes whether the findings of this section also apply to other network structures.
In principle, senior management has the choice between influencing zero, one, two, three, four, or all five groups. As illustrated in Table 6, this amounts to \(2^5 = 32\) possible strategies. Depending on the underlying network structure, some of those strategies are structural equivalents. For example, in the five-membered chain structure examined in this section, exerting pressure on groups 1 and 2 (strategy A in Table 6) is equivalent to focusing on groups 4 and 5. The simulation results show that senior management’s efforts do not result in a complete diffusion if it exerts normative pressure on only one out of five groups. In case senior management influences two groups, there is a window of opportunity for the innovation to diffuse throughout the whole organization only if management influences group 1 and group 2 or their structural equivalent, group 4 and group 5. If management exerts normative pressure on three or more groups, there is always a certain range of the migration rate which enables the complete diffusion of the innovation, no matter which groups the management team influences. Generally, the more groups are pressured by management, the more likely it is that there is a migration rate for which the innovation diffuses throughout the whole organization. In addition, simulation results show that the innovation diffuses faster, the higher the number of addressed groups.

As described by equation 13, it is assumed that the accumulated amount of exerted pressure represents the total amount of resources senior management invests to develop and implement actions targeted at creating normative pressure. Simulation results show that the greater the number of pressured groups, the higher the accumulated amount of invested resources. However, resources are often scarce. Therefore, it is important to know what groups and what combinations of groups are most susceptible to management pressure and why this is the case. In order to identify and reveal the structural characteristics of the most resource-efficient diffusion strategies, those cases are examined where management successfully influences only two or three groups with the focus being on three groups (Table 6).

If two groups are addressed, as mentioned above, there is only one structurally distinct management strategy within the five-membered chain structure for which the innovation diffuses completely, namely exerting normative pressure on groups 1 and 2 or on groups 4 and 5. In case management influences three groups, there are six structurally distinct strategies which ensure the complete diffusion of the innovation within all five groups. Thus, in order to outline the key structural elements of the five-membered chain structure, this section focuses on the following five strategies: strategy A—exerting pressure on groups 1 and 2; strategy B—influencing groups 1, 2, and 3; strategy C—influencing groups 1, 2, and 5; strategy D—influencing groups 1, 3, and 5; and strategy E—influencing groups 2, 3, and 4. These strategies are also
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The following results are also valid if the two omitted strategies—consisting of groups 1, 2, 4 and groups 1, 3, 4—were included. They have only been omitted for the sake of clarity and brevity.

Since the innovation diffuses throughout the organization for a range of possible migration rates, the migration rate was chosen that minimizes the diffusion time for the respective strategy, thereby assuming optimality for each strategy regarding migration. The underlying migration rate is 17% for strategy A, 24% for strategy B, 16% for strategy C, 7% for strategy D, and 10% for strategy E. The left part of Figure 22 illustrates the development of the average adopter fraction when management employs strategies A to E (indicated by the respective graphs).

Even though strategy A comprises only two groups and requires the most time for the innovation to diffuse completely (graph A in left part of Figure 22), strategy A is not necessarily the worst of the five strategies when taking into account the invested resources (graph A in right part of Figure 22). Depending on the management-specific weighting of diffusion time and invested resources, strategy A may well be preferable over all other strategies because strategy A is most resource-efficient strategy. That is, if the invested resources are much more valuable than a quick diffusion, strategy A (i.e., only exerting pressure on two organizational groups) might be the best choice (right part of Figure 22).

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### Table 6
Overview of possible management strategies with the main focus being on three addressed groups (within the chain structure, the bold strategies are analyzed)

<table>
<thead>
<tr>
<th>Number of Addressed Groups</th>
<th>Possible Management Strategies (Addressed Groups)</th>
<th>Number of Strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$\vec{v}=(0,0,0,0)$</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>$\vec{v}=(1,0,0,0)$; $\vec{v}=(0,1,0,0)$; $\vec{v}=(0,0,1,0)$; $\vec{v}=(0,0,0,1)$</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>$\vec{v}_A=(1,1,0,0)$; $\vec{v}=(1,0,1,0)$; $\vec{v}=(1,0,0,1)$; $\vec{v}=(0,1,1,0)$; $\vec{v}=(0,1,0,1)$; $\vec{v}=(0,0,1,1)$</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>$\vec{v}_B=(1,1,1,0)$; $\vec{v}=(1,1,0,1)$; $\vec{v}_C=(1,1,0,0)$; $\vec{v}=(1,0,1,1)$; $\vec{v}_D=(1,0,1,0)$; $\vec{v}_E=(0,1,1,0)$; $\vec{v}=(0,1,0,1)$; $\vec{v}=(0,0,1,1)$</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>$\vec{v}=(1,1,1,1)$; $\vec{v}=(1,1,0,1)$; $\vec{v}=(1,0,1,1)$; $\vec{v}=(1,0,0,1)$; $\vec{v}=(0,1,1,1)$</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>$\vec{v}=(1,1,1,1)$</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>32</td>
</tr>
</tbody>
</table>
Chapter 7

The simulation results depicted in Figure 22 show that strategies A and B dominate over all other strategies with regard to resource consumption (graph A in right part of Figure 22) and the diffusion time, respectively (graph B in left part of Figure 22). Following Krackhardt (1997), it can be argued that the peripheral position of the influenced groups (groups 1, 2 and 3) causes this dominance. However, strategy C exerts pressure on the three most peripheral groups (groups 1, 2 and 5) but is only third best in terms of diffusion time and fourth best regarding resource consumption (graph C in Figure 22). Therefore, Krackhardt’s (1997) Principle of Peripheral Dominance cannot explain why, for example, strategy B outperforms strategy C.

The previous analysis of the diffusion dynamics revealed that migration is a balancing feedback process. That is, the greater the difference of the adopter fractions between two connected groups, the bigger the negative (positive) impact of the migration process on the adopter fraction of the group with the initially higher (lower) adopter fraction. Consequently, the migration process reduces the gap between the two adopter fractions. If senior management influences groups which are connected to each other, the adopter fractions of those groups resemble each other. This, in turn, decreases the migration process’ negative effect because the influenced groups support each other by exchanging adopters, thereby limiting the impact of neighboring non-adopter-dominated groups on which no pressure is exerted. Thus, strategy B is superior to strategy C because all three groups are connected to each other. For the same reason, strategy E outperforms strategy D (graphs D and E in Figure 22). Thus, this section finds that proximity is an important principle affecting the implementation of innovations.

**Figure 22** Average Adopter Fraction and Accumulated Invested Resources for five different management strategies

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<table>
<thead>
<tr>
<th>Strategy</th>
<th>Groups Influenced</th>
<th>Migration Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1, 2</td>
<td>17%</td>
</tr>
<tr>
<td>B</td>
<td>1, 2, 3</td>
<td>24%</td>
</tr>
<tr>
<td>C</td>
<td>1, 2, 5</td>
<td>16%</td>
</tr>
<tr>
<td>D</td>
<td>1, 3, 5</td>
<td>7%</td>
</tr>
<tr>
<td>E</td>
<td>2, 3, 4</td>
<td>10%</td>
</tr>
</tbody>
</table>
However, even though strategy E focuses on three proximate groups, it is inferior to strategy B. These two strategies differ as the latter influences the three connected groups closest to the periphery of the network while the former exerts pressure on the three most central groups. Therefore, it seems that Krackhardt’s (1997) principle of peripheral dominance complements the principle of proximity in determining a successful diffusion strategy. Generally speaking, it appears that diffusion strategies focusing on groups which are close to each other and located at the periphery of the network lead to a quicker diffusion at lower costs than strategies which exert pressure on groups which are centrally located and “far away” from each other. However, these findings only relate to communication networks that are organized in a five-membered chain structure. In the following section, the derived characteristics of successful diffusion strategies (i.e., peripheral location and proximity of the influenced groups) are tested for other network structures among five groups.

7.4. Impact of different networks structures on senior management’s implementation strategies

This research assumes that all groups are homogenous and that the communication between groups is undirected. Therefore, groups are interchangeable without changing a network’s properties. For example, considering a five-membered chain structure, it makes no difference whether group 3 or another group is situated in the center as long as all five groups are connected in a chain-like structure. The properties of the network stay the same, no matter which group assumes a certain position within the structure. Therefore, such networks only differ from each other with regard to how the five groups are interconnected. According to the Redfiel-Pólya Theorem (Pólya, 1937; Redfield, 1927), there are 34 different network structures among five groups. This research has derived all 34 structures which are illustrated in Figure 23. The 21 structures in the first three rows depict only connected graphs. Those are networks in which every group is reachable from any other group in the network (Wasserman & Faust, 1997, p. 109). Among them, structure I represents the five-membered chain structure which has been analyzed in the previous chapters and sections. The remaining 13 networks (structures XXII* to XXXIV*) are disconnected graphs with groups that are isolated from other groups.

Within the scope of this section, the findings of the previous section are tested for structures I to VI in Figure 23, which contain the most obvious structures like chain, hierarchy, star, and ring. In particular, this section analyzes whether or not management strategies focusing on peripherally located and proximate groups are also successful regarding other network structures among
five groups. For this reason, the location of a group is quantified by calculating its eigenvector centrality (Bonacich, 1972; Bonacich, 2007; Ruhnau, 2000), whereas the proximity of two groups is measured by determining the geodesic distance between both groups (e.g., Wasserman & Faust, 1997).

The concept of eigenvector centrality is chosen to measure the location of a group within a network because it represents “a weighted sum of not only direct connections but indirect connections of every length. Thus it takes into account the entire pattern in the network” (Bonacich, 2007, p. 555). Hence, the centrality of a group \(i\) is higher, the greater number of groups \(j\) connected to group \(i\), and the greater number of groups to which group \(j\) in turn is connected. Consequently, peripherally located groups are characterized by a relatively low eigenvector centrality score. Groups with identical eigenvector centralities have the same influence on the network as a whole and are structural equivalents. For example, group 1 and group 5 in the chain structure have the same eigenvector centrality because they are structural equivalents. In the following, the eigenvector centralities of groups are based on the Euclidean normalization in order to make them comparable across different network structures (Ruhnau, 2000).

To quantify the proximity among influenced groups, the mean geodesic distance of all pairs between influenced groups is determined. That is, if three groups \(i, j,\) and \(k\) are influenced, the geodesic distances between groups \(i\) and \(j,\) groups \(i\) and \(k,\) and groups \(j\) and \(k\) are determined and then averaged. The geodesic distance is defined as the length of the shortest path between two groups (Wasserman & Faust, 1997, p. 110). It equals 1 if both groups are directly connected. If there is no direct connection between both groups, the geodesic distance increases with the number of intermediate groups that connect the two groups along the shortest possible path. With regard to strategy A in the five-membered chain structure analyzed above, group 2 is directly connected to group 1 and group 3. However, group 1 and group 3 are only connected to each other via group 2. Therefore, the geodesic distance is 2 between groups 1 and 3 and 1 between groups 1 and 2 and groups 2 and 3. The mean geodesic distance between groups 1, 2, and 3 is hence 4 divided by 3 which equals 1.33.

Table 7 depicts the eigenvector centralities of all five groups within the first six network structures illustrated in Figure 23. In Table 7, the network structures themselves are ordered according to their degree of centralization (i.e., the network centralization index). It illustrates which groups senior management should target in order to ensure the quickest diffusion of the innovation. By means of the introduced model, the diffusion speed was determined for each of the 10 strategies by measuring the time until the average adopter fraction equals one. Among all strategies, the quickest strategy \((Q)\) was then compared to the strategy which focuses on the three most peripheral groups (i.e., the groups with
the lowest eigenvector centralities). It can be seen that the peripheral strategy \((P)\) not only fails to ensure the quickest diffusion for structure I (chain), which was analyzed in detail above, but also for structures II (hierarchy) and III (star). On the other hand, the proximity of the three influenced groups (i.e., the mean geodesic distance between them) also fails to predict the quickest strategy. That is, in case of structure V, a strategy influencing groups 3, 4, and 5 realizes the lowest possible value of the mean geodesic distance, which is 1. However, focusing on groups 3, 4 and 5 is not the quickest strategy \((Q)\) because these are the most central groups. Thus, the previous suggestions that management needs to consider both centrality and proximity and that it should influence peripheral groups which are proximate to each other also hold for other structures.

As shown in Table 7, the star structure is by definition the network structure with the highest centralization index (Wasserman & Faust, 1997, p. 176). Network structures which are characterized by a high centralization index consist of at least one highly connected group. Such a well-connected group plays a major role in diffusion processes because it acts like a hub for social communication
Chapter 7

within the network (Bohlmann et al., 2010, p. 746). For example in structure III, the most central group is group 3. If group 3 stopped communicating with other groups, all groups would be isolated from each other, thereby resembling network structure XXII* (Figure 23). In structure II, group 2 plays a similar role. Such groups can be identified by their high eigenvector centrality.

The principle of peripheral location suggests that such a central group should not be influenced by senior management because—due to the many other groups it communicates with—it is much harder to convert than peripheral groups. On the other hand, in highly centralized structures, such a group is so central that not influencing it would only leave management strategies that are characterized by a high geodesic distance which violates the principle of proximity. The results depicted in Table 7 suggest that the principle of proximity outweighs the principle of peripheral location for highly centralized structures, such as structures II and III. Since this section focuses on management strategies consisting of three groups, this means that in structures in which a highly central group always separates a combination of three peripheral groups, implementation effectiveness can be increased by exerting pressure on this central group and two connected peripheral groups, instead of focusing on three peripheral but separated groups.

7.5. Summary and discussion of findings regarding senior management’s influence on the implementation process

This chapter analyzed the influence of managerial implementation strategies on the diffusion of innovations within intra-organizational networks by means of a system dynamics model. In contrast to Krackhardt’s (1997) and many others’ work (e.g., Bohlmann et al., 2010; Gibbons, 2004), this research did not only examine how input variations influence the output of the model. Over and above, the focus was on revealing and describing the inherent dynamics which actually define the output. The model’s input was altered and its effect on the output was analyzed in order to elucidate the underlying dynamics. The model extends common formulations of diffusion processes in system dynamics by explicitly accounting for repeated decisions about the daily use of an innovation, for organizational groups organized in particular network structures, and for management’s normative influence on the diffusion process.

This chapter finds that senior management should consider the position of organizational groups in the intra-organizational network when deciding which groups to influence. In particular, this chapter analyzed six different network structures to identify structural characteristics that make some groups more susceptible to management pressure than others. In order to realize a relatively quick and resource-efficient diffusion, it was found that management needs to
<table>
<thead>
<tr>
<th>Network Structure</th>
<th>(IV) Ring</th>
<th>(V) Fully Connected</th>
<th>(V) Partially Connected</th>
<th>(I) Chain</th>
<th>(II) Hierarchy</th>
<th>(III) Star</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Network Diagram" /></td>
<td><img src="image" alt="Network Diagram" /></td>
<td><img src="image" alt="Network Diagram" /></td>
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<td><img src="image" alt="Network Diagram" /></td>
<td><img src="image" alt="Network Diagram" /></td>
</tr>
<tr>
<td>Network Centralization Index</td>
<td>0.00%</td>
<td>0.00%</td>
<td>17.17%</td>
<td>51.76%</td>
<td>80.29%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Eigenv. Centrality Group 1</td>
<td>0.632</td>
<td>0.632</td>
<td>0.451</td>
<td>0.409</td>
<td>0.707</td>
<td>0.5</td>
</tr>
<tr>
<td>Eigenv. Centrality Group 2</td>
<td>0.632</td>
<td>0.632</td>
<td>0.645</td>
<td>0.707</td>
<td>0.923</td>
<td>0.5</td>
</tr>
<tr>
<td>Eigenv. Centrality Group 3</td>
<td>0.632</td>
<td>0.632</td>
<td>0.694</td>
<td>0.816</td>
<td>0.383</td>
<td>1.0</td>
</tr>
<tr>
<td>Eigenv. Centrality Group 4</td>
<td>0.632</td>
<td>0.632</td>
<td>0.645</td>
<td>0.707</td>
<td>0.501</td>
<td>0.5</td>
</tr>
<tr>
<td>Eigenv. Centrality Group 5</td>
<td>0.632</td>
<td>0.632</td>
<td>0.694</td>
<td>0.409</td>
<td>0.501</td>
<td>0.5</td>
</tr>
<tr>
<td>Quickest Strategy (Q)</td>
<td>Groups 1,2,3</td>
<td>Groups 1,2,3</td>
<td>Groups 1,2,4</td>
<td>Groups 1,2,3</td>
<td>Groups 2,4,5</td>
<td>Groups 1,2,3</td>
</tr>
<tr>
<td>Peripheral Strategy (P)</td>
<td>Groups 1,2,3</td>
<td>Groups 1,2,3</td>
<td>Groups 1,2,4</td>
<td>Groups 1,2,5</td>
<td>Groups 3,4,5</td>
<td>Groups 1,2,4</td>
</tr>
<tr>
<td>Mean Geodesic Distance Q</td>
<td>1.33</td>
<td>1</td>
<td>1.33</td>
<td>1.33</td>
<td>1.33</td>
<td>1.33</td>
</tr>
<tr>
<td>Mean Geodesic Distance P</td>
<td>1.33</td>
<td>1</td>
<td>1.33</td>
<td>2.66</td>
<td>2.66</td>
<td>2</td>
</tr>
<tr>
<td>Rank of P when ranking all 10 strategies according to their diffusion time</td>
<td>1st – 10th</td>
<td>1st – 10th</td>
<td>1st</td>
<td>6th – 7th</td>
<td>7th</td>
<td>7th – 10th</td>
</tr>
</tbody>
</table>

**Table 7** Comparison of management strategies across increasingly centralized network structures with senior management exerting pressure on exactly three groups
follow two rules when deciding on which groups it should exert normative pressure: (i) the selected groups need to be shielded from too many non-supporting groups that are dominated by non-adopters (i.e., influenced groups should be peripherally located); (ii) the selected groups should be close enough to each other to mutually stimulate the level of adoptions in them (i.e., they should be proximate to each other). In many cases investigated here, a peripherally located core of influenced groups proved useful to achieve an efficient intra-organizational innovation implementation. Thus, if management’s influence on the diffusion process is considered, Krackhardt’s (1997) Principle of Peripheral Dominance is not valid without restrictions. Instead, both, the peripheral location as well as the proximity between influenced groups need to be considered. The earlier is quantified by calculating the eigenvector centrality of each group, while the latter is measured by determining the mean geodesic distance between three influenced groups.

Influenced groups benefit from a peripheral location because they are only sparsely connected to other groups. Thus, the initially negative influence of balancing migration processes is lower than in groups which are characterized by a higher eigenvector centrality. Therefore, management’s relative influence on peripheral groups is greater than on more centrally located groups (see also equation 12). However, groups that are relatively sparsely connected have a rather low influence on other groups. Hence, the adopters of those groups are less capable of persuading the remaining non-adopter-dominated groups than they would have been if they had been more centrally located.

Besides the peripheral location, this research found that also the proximity of influenced groups plays an important role. Proximate groups support each other by exchanging adopters, thereby limiting the initially negative influence of balancing migration processes. This increases the speed and likelihood that the adopter fraction will rise above the adopter threshold, thereby ensuring that the reinforcing conversion dynamics start working in favor of the adopter camp. However, this effect is weaker, the greater the geodesic distance between two influenced groups. As illustrated in Table 7, neither of the two principles alone—peripheral location and proximity—seems to predict the quickest management strategy for the examined network structures. Instead, the dynamic analysis suggests that both principles need to be considered. Thereby, senior management should consider the centralization of a network. In highly central structures, implementation effectiveness might be higher if the central and therefore most resistant group is also influenced by senior management. In such cases, the principle of proximity outweighs the principle of peripheral location. Future research could further examine under which circumstances one principle is more important than the other.
In summary, this chapter’s analysis has shown that the choices of senior management can determine the success or failure of an innovation. That is, senior management should carefully choose the groups it influences to ensure a timely and resource-efficient implementation. In addition, the analyses of different network structures revealed that senior management should also take into account the communication structure among influenced groups when deciding on a strategy. In particular, this chapter showed that strategies addressing peripherally located and proximate groups facilitate the diffusion process. Depending on the centrality of the network structure, the principle of proximity can be more important than the principal or peripheral location. These findings would not have been possible without extending standard diffusion structures by accounting for employees alternating between using and neglecting the innovation, by considering different organizational network structures, and by including management’s influence on the diffusion process.

While the research presented here has been analyzed for its internal consistency and conceptual fit with reality, it faces limitations that future research can address. This study examines only a limited number of different network structures. Even though the presented findings are expected to hold also for other network structures and other network sizes, additional research is required to confirm this. This study can also serve as a step towards a generic rule which identifies the most effective and/or efficient management strategy for each network structure. Further insights can also be generated by relaxing the assumption that all groups are homogeneous and that the ties between them are equally strong. Concerning network connectivity, effects of individual differences, such as differences in employees’ social capital (Adler & Kwon, 2002), are considered only at the group level. Within groups, this research only accounts for the average connectivity of an employee.

In addition, model assumptions are based on literature on intra-organizational innovation implementation and diffusion processes. Thus, the presented findings relate to the intra-organizational adoption of innovations. However, the principles of peripheral location and proximity also resonate with inter-organizational networks and clusters. Related research has moved away from investigating the geographic or spatial proximity between firms towards concepts similar to those employed in this paper (Porter, 1998). These concepts focus on relational proximity which is based on communication processes between firms (Rice & Aydin, 1991; Torre & Rallet, 2005). In a similar vein, the derived findings might be applied to diffusion scenarios on a market level, such as the roll-out of a new product. Therefore, analyzing communication processes and the resulting dynamics appears promising for understanding how organizations innovate on multiple levels.
8. Summary and discussion of main findings

This dissertation focused on the impact of social communication on the effectiveness of intra-organizational innovation implementation processes. The second chapter specified the context of this research by characterizing innovations and organizational implementation processes. Defining an innovation as an idea, practice, or object which is new in the eyes of the adopting organization, it was shown that innovations can be classified along a novelty continuum, ranging from incremental to radical, and along a product-process continuum, depending on whether the innovation contains more product or process elements. This research concerned complex innovations which are rather radical and which comprise more process than product elements because those innovations tend to entail a greater work-related uncertainty and necessitate the communication across functional boundaries.

Since many organizations fail to benefit from an adopted innovation due to an inadequate implementation process rather than an ineffective innovation, this dissertation’s main focus was on the intra-organizational implementation process. The implementation process was defined as the critical period between senior management’s decision to implement an innovation within the organization and the routine usage of this innovation among employees. Hence, the success of innovation implementation processes depends on employees’ individual innovation-decisions which might change over time. It was assumed that organizational implementation effectiveness is higher, the greater the number of employees using an innovation, the quicker the innovation diffuses among them, and the more sustainable this diffusion is.

Despite a growing number of studies that identify multiple causes of unsuccessful implementation processes, literature lacks multidimensional models that explain the difference between successful and unsuccessful implementation efforts. Such models should take into account multiple and to some extent interrelated drivers of implementation success. Many existing implementation studies barely focus on the interactions among several determinants, in particular with regard to determinants on different organizational levels. Therefore, the overarching goal of this research was to shed light on the interrelations and dynamics between four determinants of implementation effectiveness. In contrast to other implementation studies, the goal was neither to uncover and quantify empirical correlations nor to establish an all-encompassing framework of determinants of implementation effectiveness. Instead, this research focused on four well-established factors and their combined influence on implementation effectiveness in order to improve the understanding and effectiveness of intra-organizational implementation processes.
Following the *Communication Constitutes Organizations* perspective (Blaschke et al., 2012), this dissertation looked at organizational change processes, like the implementation of an innovation, from a communication perspective. Therefore, it focused on four communication-related determinants of implementation effectiveness: (i) the communication among employees (*peer influence*), (ii) the influence of ambiguity intolerance on their communication behavior (*ambiguity intolerance of employees*), (iii) the intra-organizational communication network among groups of employees (*structural characteristics of organizations*), and (iv) the communication between senior management and employees (*management influence*).

To reach the overarching goal of this research, chapter 3 derived four research questions on the basis of the four selected determinants of implementation effectiveness. With regard to the influence of peers, the first research question addresses the issue that most diffusion models only focus on the influence of adopters on non-adopters, thereby neglecting the influence of non-adopters on adopters. Defining an adopter (non-adopter) as an employee who uses (rejects) an innovation and has a positive (negative) attitude towards it (Choi & Chang, 2009; Venkatesh et al., 2003, p. 461), this research assumed that adopters spread positive word of mouth while non-adopters spread negative word of mouth. By considering non-adopters’ negative influence on the individual innovation-decision processes of adopters, this research accounted for the possibility that adopters reject an innovation in the course of the implementation process. In particular, the first research question asked how different strengths of positive and negative word of mouth influence implementation effectiveness.

Considering the second factor, ambiguity intolerance of employees, this research aimed to shed light on the relationship between the perceived ambiguity of an innovation and the communication behavior among employees. Innovations are by definition new and therefore at least to some extent ambiguous. Since individuals are generally ambiguity intolerant (Ellsberg, 1961), perceived ambiguity is considered to be a main driver of word-of-mouth communication (Abrahamson & Rosenkopf, 1997). However, the interrelation between the perceived ambiguity of an innovation and implementation effectiveness remains unclear. Therefore, the second research question of this dissertation asked how an innovation’s perceived ambiguity and employees’ ambiguity intolerance influence the intra-organizational communication behavior among employees and thereby the effectiveness of implementation processes.

The third factor broaches the issue of cross-border communication among different groups of employees, such as teams or departments. In implementation research the communication ties between organizational compartments have been largely ignored due to the fact that they are relatively weak compared to
the communication relations within groups (Damanpour, 1996; Repenning, 2002). However, network research has shown that weak ties between groups serve as important bridges which provide access to otherwise unavailable information (Grannovetter, 1973). Therefore, the third research question of this dissertation asked how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness.

The fourth factor accounts for senior management’s influence on employees. Similar to the influence of peers which was addressed in the first research question, senior management can also exert normative pressure on employees. However, due to senior management’s superior hierarchical position, a senior manager has a stronger influence on an employee’s individual innovation-decision than a peer. Even though some implementation studies analyzed senior management’s influence on implementation effectiveness (e.g., Choi & Chang, 2009; Repenning, 2002), none of them considered the communication network among groups of targeted employees. Therefore, building on the third research question, the fourth research question asked what characterizes an effective and efficient management strategy in light of different communication structures among groups. In particular, this research aimed at finding a decision rule which tells senior management what groups within the communication network it should concentrate on in order to ensure an effective and efficient innovation implementation.

In order to answer these four research questions, this dissertation proposed a computer modeling and simulation approach. The main advantage of computer models is the relatively quick deduction of insights about complex systems at relatively low costs. In particular, this research employed system dynamics, which is based on sets of differential equations (Forrester, 1961; Sterman, 2000) and which has been identified as an appropriate tool for theory building in management (Größler et al., 2008). As a rather high-level modeling and simulation technique, system dynamics abstracts from the behavior of individuals in a system by focusing on their aggregated behavior on a group level. In this way, the causal relationships between variables can be clearly described and the resulting behavior of the system can be related to its underlying structure. Such an aggregated view is also beneficial because the goal of this research was to support senior management’s decision-making by analyzing different implementation strategies. In line with system dynamics, these strategies usually target groups of employees instead of individuals. In addition, systems dynamics is especially suited to analyze implementation processes because it is able to account for feedback processes among several
determinants of implementation effectiveness and for the long time period of implementation processes which can be simulated relatively quickly, thereby accounting for temporal delays between different factors.

With regard to the first research question, examining the influence of peers, the analysis of the respective system dynamics model revealed that the outcome of the diffusion process depends on the absolute and relative strength of positive and negative word of mouth (WOM). The stronger positive WOM is in comparison to negative WOM, the more likely it is that the innovation diffuses completely. In addition, a stronger positive WOM or a weaker negative WOM are able to compensate for a lower initial adopter fraction. Besides this relative strength of positive and negative WOM, implementation effectiveness also depends on the absolute strength of positive and negative WOM. The higher the absolute strength of both positive and negative WOM, the less influential the relative difference between them. That is, if positive and negative WOM are both very strong in absolute terms, a greater relative difference between them is necessary to reach a certain level of implementation effectiveness than if the absolute strengths of both positive and negative WOM were weaker.

Consequently, it might be more beneficial for the management of an organization to support the implementation process by reducing the absolute strength of negative WOM than by increasing the absolute strength of positive WOM. This is not the case because negative WOM is assumed to be more influential than positive WOM. In fact, positive and negative WOM are assumed to be equal in nature. Instead, this strategy is beneficial because a lower absolute strength of negative WOM increases the relative strength of positive WOM while at the same time reducing the absolute strength of both positive and negative WOM. On the other hand, if management focused on increasing the absolute strength of positive WOM, the relative strength of positive WOM would also increase. However, at the same time the absolute strength of both positive and negative WOM would increase, thereby making the relative difference between both less influential. Thus, the analysis of this model suggests that management should concentrate its efforts on limiting the negative impact of employees who do not use the innovation, instead of promoting employees who do already use it. Thereby, this finding challenges the common emphasis on enhancing colleagues’ favorable opinions (e.g., Kim & Kankanhalli, 2009, p. 579). Instead, restricting unfavorable opinions might be more effective.

The second research questions asked how the ambiguity of an innovation and employees’ ambiguity intolerance influence the communication among peers and thereby implementation effectiveness. In line with literature on bandwagon diffusion (Abrahamson & Rosenkopf, 1997; Tidd, 2010), this research found that employees’ search for like-minded others increases, the more
ambiguity intolerant employees are and the higher an innovation’s perceived ambiguity. However, this increase does not necessarily facilitate the diffusion of an innovation. In fact, employees do not extend their search for all kinds of information about an innovation’s effectiveness. Instead, they specifically look for supportive information which confirms their current belief. Therefore, ambiguity intolerant employees are more resistant to convert to the opposite camp, the higher an innovation’s perceived ambiguity. Depending on whether positive or negative word of mouth is stronger, this effect either decreases or increases implementation effectiveness by diminishing the relative strength of the initially stronger camp.

In connection with the findings of chapter 4, these results of chapter 5 suggest that management should attempt to restrict the influence of non-adopters by curtailing their search for confirming information. To achieve this, management should try to understand and change the thinking of non-adopters (e.g., Chen et al., 2013, p. 1635). The less driven non-adopters are to confirm their negative attitude, the less resistant they are to adopt the innovation. If the standard search and interaction intensity of non-adopters is much higher than that of adopters (negative WOM is stronger than positive WOM), another option could be to isolate non-adopters by putting them into relatively small groups which are dominated by adopters. If the size of these groups is smaller than non-adopters’ search and interaction intensity, it caps the number of other employees they can interact with, even when the perceived ambiguity increases.

In a second step, chapter 5 analyzed the influence of an innovation’s actual effectiveness on the search and interaction intensities of employees. However, employees do not know the actual effectiveness of an innovation. Instead, they adjust their behavior on the basis of the perceived effectiveness, which is derived from observing the decrease in inefficiencies over a certain period of time (e.g., three months in this research). Thus, an innovation which is actually more effective than the status quo might be perceived to be inferior. As expected, the findings of this analysis showed that a greater effectiveness increases the perceived relative advantage of an innovation. The higher the actual effectiveness of an innovation, the quicker it gains on the expected effectiveness of the status quo. Hence, effective innovations reach the point where the perceived relative advantage equals one earlier than less effective innovations. The closer the perceived relative advantage is to one, the higher the perceived ambiguity, causing employees to communicate more with each other in order to find like-minded others. It is precisely during such periods that the restriction of non-adopters’ influence benefits the implementation process the most. Knowing that these periods occur earlier, the more effective innovations are, enables senior managers to time their interventions accordingly.
After chapters 4 and 5 analyzed research questions one and two, respectively, chapters 6 and 7 examined research questions three and four, respectively. In contrast to the earlier chapters, chapters 6 and 7 focused on scenarios in which positive word of mouth is stronger than negative word of mouth. In addition, chapters 6 and 7 did not consider an innovation’s perceived ambiguity and employees’ ambiguity intolerance. Instead, chapter 6 extended the basic system dynamics model of chapter 4 to account for the communication structure among organizational groups by converting and extending Krackhardt’s (1997) algebraic diffusion model. With chapter 6 pertaining to research question three, the main focus was on how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within groups and how these effects, in turn, influence implementation effectiveness.

The analyses found that the communication processes between groups (i.e., migration) are driven by balancing dynamics which would distribute the initial adopters evenly across all groups if the communication within groups (i.e., conversion) was turned off. On the other hand, the communication process within each group is driven by reinforcing dynamics. In case the adopter fraction of a group \( i \) is below a threshold, this process would eliminate all adopters within that group if there was no communication with other groups. However, in case the adopter fraction exceeds this threshold, the group-internal communication would lead to an adopter fraction of 100% if there was no group-external communication. The findings of chapter 6 also suggested that in a chain structure, adopter-dominated groups should be connected to each other while non-adopter-dominated groups should be isolated from each other in order to increase implementation effectiveness. This, in turn, increases the likelihood that the adopter fraction stays above the threshold of 41%, thereby ensuring that the self-reinforcing group-internal communication keeps working in favor of the adopter camp. Isolating non-adopter groups from each other, increases implementation effectiveness. This is the case because the ties with adopter groups become more influential. Thus, it is more likely that the negative influence of a non-adopter’s group internal communication is inverted by increasing the adopter fraction above the 41% threshold.

Chapter 7 extended the system dynamics model of chapter 6 by incorporating senior-management’s influence and by accounting for the invested resources. In addition, the findings were tested for other network structures. There was no initial mother group consisting only of adopters. Instead, all groups consisted of non-adopters and senior management initiated the implementation process by exerting normative pressure on selected groups. Confirming the assumption of chapter 6, it was found that management needs to follow two rules when deciding on which groups it should exert normative pressure: (i) the groups
management chooses to influence need to be shielded from groups which are not influenced by senior management and dominated by non-adopters (i.e., influenced groups should be peripherally located); (ii) the chosen groups should be close enough to each other in order to mutually stimulate the level of adoptions within them (i.e., they should be proximate to each other). In addition, the analyses of different network structures revealed that senior management should also take into account the communication structure among influenced groups when deciding on a strategy. In particular, this chapter showed that strategies addressing peripherally located and proximate groups facilitate the diffusion process. However, if network structures are characterized by highly central groups, the proximity of influenced groups can be much more important than their peripheral location.

While the research presented in this dissertation has been analyzed for its internal consistency and conceptual fit with reality, it faces limitations that future research can address. Among others, future research can examine different combinations of the four introduced determinants of implementation effectiveness and/or add other determinants. One could, for example, ask how structural characteristics of an organization interrelate with the ambiguity intolerance of employees and what their combined influence on implementation effectiveness is. In addition, future research could focus on relaxing some of the assumptions of this dissertation, such as considering only five-membered network structures, assuming homogeneous groups, and equally strong ties between groups.
Bibliography


Appendix 1: Stock and flow diagram of basic model
Appendix 2: Stock and flow diagram of ambiguity-oriented model
Appendix 3: Variables and equations included in the basic model and the ambiguity-oriented model

Actual Effectiveness=
\[ \ln(2)/\text{ACTUAL HALF LIFE} \]
\[ \sim \text{Dmnl/Month} \]
\[ \sim \text{monthly amount of reduced inefficiencies if the innovation is used to its full potential (A=1)} \]

ACTUAL HALF LIFE=
\[ 6 \]
\[ \sim \text{Month} \]
\[ \sim \text{period over which inefficiencies decrease by 50\% if the innovation is used to its full potential (A=1); in Repenning (2002) it is assumed to be 9} \]

AMBIGUITY INTOLERANCE=
\[ 1 \]
\[ \sim \text{Dmnl} \]
\[ \sim \text{percentage of the innovation’s perceived ambiguity that affects the normal search intensity; the higher the percentage, the more sensitive employees react to ambiguity, i.e., the higher the ambiguity intolerance; NOTE: Only values between 0 and 1} \]

change in inefficiencies=
\[ (\text{Inefficiencies-MIN INEFFICIENCIES})\times\text{Actual Effectiveness}\times\text{Fraction Adopters} \]
\[ \sim \text{Defects/Month} \]
\[ \sim \text{monthly change (i.e., decrease) in inefficiencies} \]

CONVERSION PROBABILITY A=
\[ 1 \]
\[ \sim \text{Dmnl/Month} \]
\[ \sim \text{probability that an adopter becomes a non-adopter when meeting no other adopter within the searched fraction of the organization; variable in the paper: P_AN} \]
CONVERSION PROBABILITY N=
  1
~ Dmnl/Month
~ probability that a non-adopter becomes an adopter when meeting no other
  non-adopter within the searched fraction of the organization; variable in
  the paper: P_NA

conversion rate an=
  CONVERSION PROBABILITY A*Fraction Adopters *Negative WOM
~ Dmnl/Month
~ adopters becoming non-adopters

conversion rate na=
  CONVERSION PROBABILITY N*Fraction Nonadopters*Positive WOM
~ Dmnl/Month
~ non-adopters becoming adopters

Expected Effectiveness=
  ln(2)/EXPECTED HALF LIFE
~ Dmnl/Month
~ monthly amount of inefficiencies that is expected
to be reduced by the innovation

EXPECTED HALF LIFE=
  9
~ Month
~ period over which inefficiencies are expected to decrease by 50%

Fraction Adopters= INTEG (conversion rate na-conversion rate an, INI FRACTION ADOPTERS)
~ Dmnl
~ fraction of adopters in organization; variable in the paper: A
Fraction Nonadopters = INTEG (conversion rate an-conversion rate na, INI Fraction Nonadopters)
~ Dmnl
~ fraction of non-adopters in organization; variable in the paper: 1 - A
|

Historical Inefficiencies =
SMOOTH(Inefficiencies, INEFFICIENCY SMOOTH TIME)
~ Defects
~ perceived average inefficiencies
|

Inefficiencies = INTEG (-change in inefficiencies, INITIAL INEFFICIENCIES)
~ Defects
~ current level of inefficiencies within a group
|

INEFFICIENCY SMOOTH TIME =
3
~ Month
~ period over which the number of inefficiencies is observed
|

INI FRACTION ADOPTERS =
0.6
~ Dmnl
~ initial fraction of adopters in organization (rest = non-adopters)
|

INI Fraction Nonadopters =
1 - INI FRACTION ADOPTERS
~ Dmnl
~ initial fraction of non-adopters within the organization = 1 - Initial Fraction Adopters
INITIAL INEFFICIENCIES=
  400
  ~ Defects
  ~ number of initial inefficiencies; originally 100 in Repenning (2002)

MAX EFCT OF RESULTS=
  2
  ~ Dmnl
  ~ maximum effect that the ratio perceived vs. expected results has on
  ~ ambiguity (maximum of bell-shaped curve); NOTE: This value should be
  ~ smaller than the minimum of the two normal search intensities!

MIN EFCT OF RESULTS=
  0
  ~ Dmnl
  ~ minimum effect that the ratio perceived vs. expected results has on
  ~ commitment; NOTE: Only values between 0 and “Max Efect of Results”

MIN INEFFICIENCIES=
  10
  ~ Defects
  ~ minimum number of inefficiencies that will remain despite the innovation

Negative WOM=
  Fraction Nonadopters^Search Intensity A
  ~ Dmnl
  ~ impact of negative word of mouth; impact of social pressure of non-adopters

Net Conversion Rate Adopters=
  conversion rate na-conversion rate an
  ~ Dmnl/Month
  ~ net rate of conversion; positive if more non-adopters become adopters than
  ~ vice versa
  ~ :SUPPLEMENTARY
NORMAL SEARCH INTENSITY A =
3
~ Dmnl
~ describes the standard unadjusted intensity with which adopters search for other adopters within the organization (Krackhardt, 1997)

NORMAL SEARCH INTENSITY N =
5
~ Dmnl
~ describes the standard unadjusted intensity with which non-adopters search for other non-adopters within the organization (Krackhardt, 1997)

NORMAL SLOPE RESULTS =
10
~ Dmnl
~ slope with which a change in the ratio perceived vs. expected results affects ambiguity; NOTE: A slope of 10 ensures that f(x) of the bell-shaped curve is close to zero at x=0

Perceived Ambiguity =
4*(MAX EFCT OF RESULTS-MIN EFCT OF RESULTS)
*EXP(NORMAL SLOPE RESULTS *(Perceived Relative Advantage-1))
/(1+EXP(NORMAL SLOPE RESULTS *(Perceived Relative Advantage-1)))^2
+ MIN EFCT OF RESULTS
~ Dmnl
~ perceived ambiguity of an innovation; generates a bell-shaped curve with its maximum at x=1

Perceived Effectiveness =

((Historical Inefficiencies-Inefficiencies)/Historical Inefficiencies)
/INEFFICIENCY SMOOTH TIME
~ Dmnl/Month
~ perceived effectiveness of the innovation
Perceived Relative Advantage =
\[
\text{Perceived Effectiveness/Expected Effectiveness}
\]
\[
\sim \text{Dmnl}
\]
\[
\sim \text{perceived relative advantage of the innovation, comparison of perceived improvement rate (based on actual improvements) and expected improvement rate}
\]

Positive WOM =
\[
\text{Fraction Adopters}^\text{\textcopyright} \text{Search Intensity N}
\]
\[
\sim \text{Dmnl}
\]
\[
\sim \text{impact of positive word of mouth; impact of social pressure of adopters}
\]

Ratio pWOM nWOM =
\[
\text{ZIDZ(Positive WOM, Negative WOM)}
\]
\[
\sim \text{Dmnl}
\]
\[
\sim :\text{SUPPLEMENTARY}
\]

Ratio Sa Sn =
\[
\text{ZIDZ(Search Intensity A, Search Intensity N)}
\]
\[
\sim \text{Dmnl}
\]
\[
\sim :\text{SUPPLEMENTARY}
\]

Search Intensity A =
\[
\text{NORMAL SEARCH INTENSITY A}
\]
\[
+\text{Perceived Ambiguity}^\text{\textcopyright} \text{AMBIGUITY INTOLERANCE}
\]
\[
\sim \text{Dmnl}
\]
\[
\sim \text{adjusted intensity with which adopters search for other adopters within the organization; variable in the paper: S_a; strength of positive WOM; extent of social pressure of adopters}
\]
Search Intensity $N =$
NORMAL SEARCH INTENSITY $N$
 + Perceived Ambiguity $\times$ AMBIGUITY INTOLERANCE

~ $D_{mn}$
~ adjusted intensity with which non-adopters search for other non-adopters within the organization; variable in the paper: $S_n$; strength of negative WOM; extent of social pressure of non-adopters

********************************************************
Control
********************************************************
Simulation Control Parameters

FINAL TIME = 60
~ Month
~ The final time for the simulation.

INITIAL TIME = 0
~ Month
~ The initial time for the simulation.

SAVEPER =
TIME STEP
~ Month [0,?]
~ The frequency with which output is stored.

TIME STEP = 0.03125
~ Month [0,?]
~ The time step for the simulation.
Appendix 4: Stock and flow diagram of continuous network model
Appendix 5: Stock and flow diagram of management-oriented model
Appendix 6: Variables and equations included in the continuous network model and the management-oriented model

Accumulated Invested Resources = INTEG (invested mgmt resources, 0)

~ Dmnl

~ total amount of resources (pressure) exerted on all groups since the introduction of the innovation

~ :SUPPLEMENTARY

AD GR1 =

1

~ Dmnl

~ 0 = group IS NOT addressed by management, 1 = group IS addressed by management

AD GR2 =

1

~ Dmnl

~ 0 = group IS NOT addressed by management, 1 = group IS addressed by management

AD GR3 =

0

~ Dmnl

~ 0 = group IS NOT addressed by management, 1 = group IS addressed by management

AD GR4 =

0

~ Dmnl

~ 0 = group IS NOT addressed by management, 1 = group IS addressed by management
AD GR5 =
0
~ Dmnl
~ 0 = group IS NOT addressed by management, 1 = group IS addressed by management

Addressed Groups[gr1] =
AD GR1 ~| Addressed Groups[gr2] =
AD GR2 ~| Addressed Groups[gr3] =
AD GR3 ~| Addressed Groups[gr4] =
AD GR4 ~| Addressed Groups[gr5] =
AD GR5
~ Dmnl
~ 1 = groups on which management exerts pressure to use the innovation

Adopters in Connected Groups[groups] =
SUM(IS CONNECTED TO[groups,groups!]*Fraction Adopters[groups!])
~ Dmnl
~ the total amount of adopters in the groups that are connected to the respective group

Average Adopter Fraction =
SUM( Fraction Adopters[groups!] ) / ELMCOUNT(groups)
~ Dmnl
~ the actual average adopter fraction within the organization
~ :SUPPLEMENTARY
CHANGE IN MANAGEMENT GOAL DUE TO IMPLEMENTATION =
1
~ Dmnl
~ change in management’s desired adopter fraction due to the official launch
of the innovation implementation process

conversion due to mgmt push[groups]=
  Min(Fraction Nonadopters[groups], Mgmt Push per Group[groups])
  / TIME FOR MGMT TO TRAIN
  ~ Dmnl/Day
  ~ daily effect of management push on the conversion process; min function
    ensures that the non-adopter fraction does not become negative

CONVERSION PROBABILITY A =
1
~ Dmnl/Day
~ likelihood that an adopter converts to the non-adopter camp within one
day, provided he/she did not find any other adopter within the searched
fraction of his/her group

CONVERSION PROBABILITY N =
1
~ Dmnl/Day
~ likelihood that a non-adopter converts to the adopter camp within one day,
  provided he/she did not find any other non-adopter within the searched
  fraction of his/her group

conversion rate an[groups] =
CONVERSION PROBABILITY A
  * Fraction of Adopters Interacting only with Nonadopters[groups]
  ~ Dmnl/Day
  ~ daily fraction of adopters converting to the non-adopter camp due to
    communication with other group members
conversion rate na[groups]=
   CONVERSION PROBABILITY N
   *Fraction of Nonadopters Interacting only with Adopters[groups]
   ~ Dmnl/Day
   ~ daily fraction of non-adopters converting to the adopter camp due to
   communication with other group members

Discrepancy Adopter Fraction[groups]=
   Management Goal Adopter Fraction[groups]-Fraction Adopters[groups]
   ~ Dmnl
   ~ discrepancy between desired adopter fraction and the actual adopter
   fraction

Fraction Adopters[groups]= INTEG (conversion due to mgmt push[groups]+conversion rate na[groups]+-
migration rate xa[groups]-conversion rate an[groups]-migration rate
ax[groups],
INI FRACTION ADOPTERS[groups])
   ~ Dmnl
   ~ proportion of adopters within the respective group

Fraction Nonadopters[groups]= INTEG (conversion rate an[groups]+migration rate xn[groups]-conversion due to
mgmt push[groups]-conversion rate na[groups]-migration rate nx[groups],
INI Fraction Nonadopters[groups])
   ~ Dmnl
   ~ proportion of non-adopters within the respective group

Fraction of Adopters Interacting only with Nonadopters[groups]=
   Fraction Adopters[groups]*Fraction Nonadopters[groups]**SEARCH INTENSITY A
   ~ Dmnl
   ~ proportion of adopters that did not find any other adopter within their
   searched fraction of the respective group
Fraction of Nonadopters Interacting only with Adopters[groups]=
Fraction Nonadopters[groups]*Fraction Adopters[groups]*SEARCH INTENSITY N
~ Dmnl
~ proportion of non-adopters that did not find any other non-adopter within
their searched fraction of the respective group

groups:
(gr1-gr5)
~ Dmnl
~ number of groups within the organization

groupscon<->
groups
~ Dmnl
~ mapping of the subscript “groups” in order to enable matrix calculations
of a matrix where the columns label (“groups”) equals the rows label (also
“groups”) as is typical for an adjacency matrix (see variables “is
connected to” and “number of connections”)

groupsconnext:
(gr2-gr5) -> groupsconprev
~ Dmnl
~

groupsconprev:
(gr1-gr4) -> groupsconnext
~ Dmnl
~

groupsnext:
(gr2-gr5) -> groupsprev
~ Dmnl
~
groupsprev:
  (gr1-gr4) -> groupsnext
  ~ Dmnl
  ~

INI FRACTION ADOPTERS[groups]=
  0,0,0,0
  ~ Dmnl
  ~ initial adopter fractions within the groups
  |

INI FRACTION Nonadopters[groups]=
  1-INI FRACTION ADOPTERS[groups]
  ~ Dmnl
  ~ initial non-adopter fractions within groups
  |

INITIAL MANAGEMENT GOAL[groups]=
  0
  ~ Dmnl
  ~ management’s desired adopter fraction before the official start of the
  innovation implementation process
  |

invested mgmt resources=
  SUM(conversion due to mgmt push[groups!] )
  ~ Dmnl/Day
  ~ monthly amount of pressure exerted over all groups is assumed to represent
  the resources management invested during this month to develop and
  implement actions targeted at creating normative pressure
  |

IS CONNECTED TO[groups,groupscon]=
IF THEN ELSE(SWITCH STRUCTURE=1, I CHAIN STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=2, II HIERARCHICAL STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=3, III STAR STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=4, IV RING
STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=5, V PARTIALLY CONNECTED
STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=6, VI FULLY CONNECTED
STRUCTURE[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=7, “VII CHAIN
&14”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=8, “VIII HIERARCHY
&45”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=9, “IX STAR
&45”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=10, “X RING
&14”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=11, “XI PARTIALLY CONNECTED
&24”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=12, “XII FULLY CONNECTED
&13”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=13, “XIII CHAIN
&24”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=14, “XIV CHAIN
&14&13”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=15, “XV CHAIN
&14&24”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=16, “XVI CHAIN
&14&25”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=17, “XVII HIERARCHY
&45&23”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=18, “XVIII RING
&14&13”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=19, “XIX CHAIN
&14&13&24”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=20, “XX CHAIN
&14&24&25”[groups,groupscon],
IF THEN ELSE(SWITCH STRUCTURE=21, “XXI PARTIALLY CONNECTED
&13”[groups,groupscon],

1/0))))))))))))))))))
~ Dnnl
~ 1 = Chain; 2 = Hierarchy; 3 = Star; 4 = Ring; 5 = PartiallyConnected;
6 = FullyConnected; 7 = Chain+Link14; 8 = Hierarchy+Link45;
9 = Star+Link45; 10 = Ring+Link14; 11 = PartiallyConnected+Link24;
12 = FullyConnected-Link13; 13 = Chain+Link24; 14 = Chain+Link14+Link13; 15 = Chain+Link14+Link24; 16 = Chain+Link14+Link25; 17 = Hierarchy+Link45+Link23; 18 = Ring+Link14+Link13; 19 = Chain+Link14+Link13+Link24; 20 = Chain+Link14+Link13+Link25; 21 = PartiallyConnected+Link13

Management Goal Adopter Fraction[groups] =
MIN(1, INITIAL MANAGEMENT GOAL[groups] + STEP(CHANGE IN MANAGEMENT GOAL DUE TO IMPLEMENTATION, TIME OF OFFICIAL INNOVATION IMPLEMENTATION))
~ Dmnl
~ management’s desired adopter fraction

Mgmt Push per Group[groups] =
MAX(Addressed Groups[groups]*Discrepancy Adopter Fraction[groups], 0)
~ Dmnl
~ the pressure management exerts on the addressed groups due to the discrepancy between desired adopter fraction and the actual adopter fraction, max function ensures that management push is only positive (enhancing adoption)

MIGRATION RATE =
0.1
~ Dmnl/Day
~ daily fraction of adopters and non-adopters that migrate from the respective group to each connected group

migration rate ax[groups] =
Number of Connections[groups]*Fraction Adopters[groups]*MIGRATION RATE
~ Dmnl/Day
~ total daily amount of adopters that emigrate out of the respective group into the connected groups
migration rate $n_x[\text{groups}] =$
Number of Connections$[\text{groups}] \cdot \text{Fraction Nonadopters}[\text{groups}] \cdot \text{MIGRATION RATE}$
$\sim \text{Dmnl/Day}$
$\sim$ total daily amount of non-adopters that emigrate out of the respective group into the connected groups

migration rate $x_a[\text{groups}] =$
Adopters in Connected Groups$[\text{groups}] \cdot \text{MIGRATION RATE}$
$\sim \text{Dmnl/Day}$
$\sim$ total daily amount of adopters that immigrate from all connected groups into the respective group

migration rate $x_n[\text{groups}] =$
Nonadopters in Connected Groups$[\text{groups}] \cdot \text{MIGRATION RATE}$
$\sim \text{Dmnl/Day}$
$\sim$ total daily amount of non-adopters that immigrate from all connected groups into the respective group

Net Change$[\text{groups}] =$
Net Conversion Rate$[\text{groups}] + \text{Net Migration Rate}[\text{groups}]$
$+ \text{conversion due to mgmt push}[\text{groups}]$
$\sim \text{Dmnl/Day}$
$\sim$ daily total change of the adopter fraction of the respective group
$\sim \text{:SUPPLEMENTARY}$

Net Conversion Rate$[\text{groups}] =$
conversion rate $n_a[\text{groups}] - \text{conversion rate } a_n[\text{groups}]$
$\sim \text{Dmnl/Day}$
$\sim$ daily change in the adopter fraction of the respective group due to the difference between non-adopters being converted by adopters and adopters being converted by non-adopters
Net Migration Rate[groups]=
    migration rate \( xa[\text{groups}] - migration rate \ ax[\text{groups}] \)
    ~ Dmnl/Day
    ~ daily change in the adopter fraction of the respective group due to the
    difference between immigrating and emigrating adopters

Nonadopters in Connected Groups[groups]=
    \( \text{SUM(IS CONNECTED TO[groups,groups!] \* Fraction Nonadopters[groups!])} \)
    ~ Dmnl
    ~ the total amount of non-adopters in the groups that are connected to the
    respective group

Number of Connections[groups]=
    \( \text{SUM(IS CONNECTED TO[groups,groupscon!])} \)
    ~ Dmnl
    ~ number of other groups the respective group is connected to through
    migration (degree centrality)

SEARCH INTENSITY A=
    6
    ~ Dmnl
    ~ fraction of a group that is searched by adopters for other like-minded
    adopters

SEARCH INTENSITY N=
    4
    ~ Dmnl
    ~ fraction of a group that is searched by non-adopters for other like-minded
    non-adopters
SWITCH STRUCTURE=
  1
  \sim Dmn1
  \sim \text{Switching between different network structures: } 1 = \text{Chain}; 2 = \text{Hierarchy}; 
  3 = \text{Star}; 4 = \text{Ring}; 5 = \text{PartiallyConnected}; 6 = \text{FullyConnected}; 
  7 = \text{Chain+Link14}; 8 = \text{Hierarchy+Link45}; 9 = \text{Star+Link45}; 
  10 = \text{Ring+Link14}; 11 = \text{PartiallyConnected+Link24}; 
  12 = \text{FullyConnected+Link13}; 13 = \text{Chain+Link24}; 
  14 = \text{Chain+Link14+Link13}; 15 = \text{Chain+Link14+Link24}; 
  16 = \text{Chain+Link14+Link25}; 17 = \text{Hierarchy+Link45+Link23}; 
  18 = \text{Ring+Link14+Link13}; 19 = \text{Chain+Link14+Link13+Link24}; 
  20 = \text{Chain+Link14+Link13+Link25}; 21 = \text{PartiallyConnected+Link13}

TIME FOR MGMT TO TRAIN=
  12
  \sim \text{Day}
  \sim \text{this delay parameter aggregates three components: 1. time is required for management to develop and implement actions targeted at creating normative pressure, 2. time is required for participants to react to the new norms, 3. time is required to acquire skills and modify behavior}

TIME OF OFFICIAL INNOVATION IMPLEMENTATION=
  12
  \sim \text{Day}
  \sim \text{official start of the innovation implementation process}

I CHAIN STRUCTURE[groups, groupscon]=TABBED ARRAY(
  \begin{tabular}{cccc}
    0 & 1 & 0 & 0 \\
    1 & 0 & 1 & 0 \\
    0 & 1 & 0 & 1 \\
    0 & 0 & 1 & 0 \\
    0 & 0 & 0 & 1 \\
  \end{tabular}
  \sim Dmn1
  \sim \text{adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure (1)}
II HIERARCHICAL STRUCTURE\[groups,groupscon\]=TABBED ARRAY(
\begin{array}{cccc}
0 & 1 & 1 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
\end{array}
)

\~ Dmnl

\~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a hierarchical structure (2)

III STAR STRUCTURE\[groups,groupscon\]=TABBED ARRAY(
\begin{array}{cccc}
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
1 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
\end{array}
)

\~ Dmnl

\~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a star structure (3)

IV RING STRUCTURE\[groups,groupscon\]=TABBED ARRAY(
\begin{array}{cccc}
0 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
\end{array}
)

\~ Dmnl

\~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a ring structure (4)
V PARTIALLY CONNECTED STRUCTURE
\[\begin{array}{ccccc}
0 & 1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 1 \\
0 & 1 & 0 & 1 & 1 \\
1 & 0 & 1 & 0 & 1 \\
0 & 1 & 1 & 1 & 0 \\
\end{array}\]
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a partially connected structure (5)

VI FULLY CONNECTED STRUCTURE
\[\begin{array}{ccccc}
0 & 1 & 1 & 1 & 1 \\
1 & 0 & 1 & 1 & 1 \\
1 & 1 & 0 & 1 & 1 \\
1 & 1 & 1 & 0 & 1 \\
1 & 1 & 1 & 1 & 0 \\
\end{array}\]
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a fully connected structure (6)

“VII CHAIN &14”
\[\begin{array}{ccccc}
0 & 1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 \\
\end{array}\]
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with one additional link between group 1 and group 4 (Structure 7)
“VIII HIERARCHY &45”[groups,groupscon]=TABBED ARRAY(
0 1 1 0 0
1 0 0 1 1
1 0 0 0 0
0 1 0 0 1
0 1 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through
migration, in this case the five groups form a hierarchical structure with
one additional link between group 4 and group 5 (Structure 8)

“IX STAR &45”[groups,groupscon]=TABBED ARRAY(
0 0 1 0 0
0 0 1 0 0
1 1 0 1 1
0 0 1 0 1
0 0 1 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through
migration, in this case the five groups form a star structure with one
additional link between group 4 and group 5 (Structure 9)

“X RING &14”[groups,groupscon]=TABBED ARRAY(
0 1 0 1 1
1 0 1 0 0
0 1 0 1 0
1 0 1 0 1
1 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through
migration, in this case the five groups form a ring structure with one
additional link between group 1 and group 4 (Structure 10)
“XI PARTIALLY CONNECTED &24”[groups,groupscon]=TABBED ARRAY(
0 1 0 1 0
1 0 1 1 1
0 1 0 1 1
1 1 1 0 1
0 1 1 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form the partially connected structure with one additional link between group 2 and group 4 (Structure 11)

“XII FULLY CONNECTED \13”[groups,groupscon]=TABBED ARRAY(
0 1 0 1 1
1 0 1 1 1
0 1 0 1 1
1 1 1 0 1
1 1 1 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form the fully connected structure with no link between group 1 and group 3 (Structure 12)

“XIII CHAIN &24”[groups,groupscon]=TABBED ARRAY(
0 1 0 0 0
1 0 1 1 0
0 1 0 1 0
0 1 1 0 1
0 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with one additional link between group 2 and group 4 (Structure 13)
“XIV CHAIN &14&13”[groups,groupscon]=TABBED ARRAY(
    0 1 1 1 0
    1 0 1 0 0
    1 1 0 1 0
    1 0 1 0 1
    0 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with two additional links between groups 1 and 4 and groups 1 and 3 (Structure 14)

“XV CHAIN &14&24”[groups,groupscon]=TABBED ARRAY(
    0 1 0 1 0
    1 0 1 1 0
    0 1 0 1 0
    1 1 1 0 1
    0 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with two additional links between groups 1 and 4 and groups 2 and 4 (Structure 15)

“XVI CHAIN &14&25”[groups,groupscon]=TABBED ARRAY(
    0 1 0 1 0
    1 0 1 0 1
    0 1 0 1 0
    1 0 1 0 1
    0 1 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with two additional links between groups 1 and 4 and groups 2 and 5 (Structure 16)
“XVII HIERARCHY &45&23”[groups,groupscon]=TABBED ARRAY(
0 1 1 0 0
1 0 1 1 1
1 1 0 0 0
0 1 0 0 1
0 1 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a hierarchical structure with two additional links between groups 4 and 5 and groups 2 and 3 (Structure 17)
|

“XVIII RING &14&13”[groups,groupscon]=TABBED ARRAY(
0 1 1 1 1
1 0 1 0 0
1 1 0 1 0
1 0 1 0 1
1 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a ring structure with two additional links between groups 1 and 4 and groups 1 and 3 (Structure 18)
|

“XIX CHAIN &14&13&24”[groups,groupscon]=TABBED ARRAY(
0 1 1 1 0
1 0 1 1 0
1 1 0 1 0
1 1 1 0 1
0 0 0 1 0)
~ Dmnl
~ adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with three additional links between groups 1 and 4, groups 1 and 3, and groups 2 and 4 (Structure 19)
|
“XX CHAIN "&14&24&25"[groups,groupscon]=TABBED ARRAY(  
    0 1 0 1 0  
    1 0 1 1 1  
    0 1 0 1 0  
    1 1 1 0 1  
    0 1 0 1 0  
)

\( \sim \text{adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form a chain structure with three additional links between groups 1 and 4, groups 1 and 3, and groups 2 and 5 (Structure 20) } \)

“XXI PARTIALLY CONNECTED &13”[groups,groupscon]=TABBED ARRAY(  
    0 1 1 1 0  
    1 0 1 0 1  
    1 1 0 1 1  
    1 0 1 0 1  
    0 1 1 1 0  
)

\( \sim \text{adjacency matrix stating which groups are connected to each other through migration, in this case the five groups form the partially connected structure with one additional link between group 1 and group 3 (Structure 21) } \)

********************************************************
.Control
********************************************************

Simulation Control Parameters

FINAL TIME = 300

\( \sim \text{Day} \)

\( \sim \text{The final time for the simulation.} \)
INITIAL TIME = 0
~ Day
~ The initial time for the simulation.

SAVEPER = 1
~ Day [0,?] 
~ The frequency with which output is stored.

TIME STEP = 0.03125
~ Day [0,?] 
~ The time step for the simulation.
Appendix 7: Results of the extreme-conditions test for all four models presented in chapters 4, 5, 6, and 7

Figure 24 depicts the simulation results of the extreme-conditions test of the basic implementation model introduced in section 4.2. The scenario depicted by graph 3 of Figure 7b was chosen as a basis. In this scenario the initial adopter fraction is 50% \((A_{ini} = 0.5)\), the search and interaction intensities of adopters and non-adopters are six \((S_A = S_N = 6)\), and the conversion probabilities of isolated adopters and isolated non-adopters are 100% \((P_{AN} = P_{NA} = 1)\). This scenario is also depicted by graphs 1 in the left and right part of Figure 24. Graph 2 in the left part of Figure 24 illustrates a scenario in which \(A_{ini} = 0\). Since there are no adopters which could convert non-adopters, the adopter fraction will always be 0%. The same logic applies to the scenario depicted by graph 3 in Figure 24 in which there are only adopters \((A_{ini} = 1)\).

![Fraction Adopters](image)

**Figure 24** Extreme-conditions test of the basic implementation model of chapter 4

Graphs 4 and 5 in the left part of Figure 24 depict scenarios in which either isolated adopters or non-adopters never revise their individual innovation-decision \((P_{AN} = 0\) or \(P_{NA} = 0)\). Due to their higher resistance, they are able to convert all members of the opposing camp, resulting either in an adopter fraction of 100% (graph 4) or 0% (graph 5 in left part of Figure 24). The right part of Figure 24 illustrates extreme conditions of \(S_A\) and \(S_N\), either being 1 or 1000. In these scenarios, a higher resistance, in form of a relatively higher search and
interaction intensity of one camp, results in an expected dominance of this camp, provided that everything else is equal \((A_{ini} = 0.5; P_{AN} = P_{NA} = 1)\).

Figure 25 illustrates several simulation runs which constitute the extreme-conditions test of the ambiguity-oriented model of chapter 5. The ambiguity-oriented model is an extension of the basic implementation model introduced in chapter 4. Even though all parameters of the ambiguity-oriented model were tested, Figure 25 only depicts the results of the parameters that were added to the basic implementation model. The scenario depicted by graph 1 in Figure 10a was chosen as a basis. In this scenario, the initial adopter fraction is 38.2% \((A_{ini} = 0.382)\), the search and interaction intensity of adopters is higher than the search and interaction intensity of non-adopters \((S_A = 5 > S_N = 3)\), and the conversion probabilities of isolated adopters and isolated non-adopters are 100% \((P_{AN} = P_{NA} = 1)\). In addition, employees are assumed to be ambiguity intolerant \((I = 0)\). The innovation itself is assumed to be more effective than the status quo \((T_{hl} = 6 < T_{hl}^* = 9)\). The initial amount of inefficiencies is 400 \((D = 400)\) and the minimum level of inefficiencies is 10 \((D_{min} = 10)\). This scenario is also depicted by graph 1 in the left part of Figure 25.

Graph 2 in the left part of Figure 25 illustrates basically the same scenario as graph 1 in Figure 25 with the only difference being that adopters are completely ambiguity intolerant \((I = 1)\). As in Figure 10, a higher ambiguity intolerance results in the complete rejection of an innovation (graph 2 in left part of
Figure 25). If the initial amount of defects or inefficiencies is decreased to its minimum level \( D = D_{\text{min}} = 10 \), the innovation cannot reduce any more inefficiencies (graph 3 in left part of Figure 25). Consequently, its perceived relative advantage is always zero, causing the perceived ambiguity to be almost zero as well \( U(0) = 0.0004 \). Therefore, graph 3 is similar to graph 1 (left part of Figure 25). Graph 4 in the left part Figure 25 illustrates a scenario in which inefficiencies amount to 9000. As a result, the perceived relative advantage of the innovation is slightly higher than in graph 2, reaching a value closer to one \( R_{\text{graph 4}} = 0.533 > R_{\text{graph 2}} = 0.532 \). This increases the perceived ambiguity, which, in turn, decreases the relative dominance of positive word of mouth, resulting in a slightly quicker rejection of the innovation in graph 4 than in graph 2 (left part of Figure 25).

The right part of Figure 25 depicts simulation runs in which the effectiveness of an innovation \( T_{\text{hl}} \) and the status quo \( T^{*}_{\text{hl}} \) are minimal and maximal. Among Schneiderman’s (1988, p. 52) observations of half-life times, operations sheet errors have the shortest half-life (0.6 months) and microprocessors have the longest half-life (18.5 months). Based on these times, a minimum half-life of 0.1 months and a maximum half-life of 60 months were chosen for the extreme-conditions test. A comparison between graph 2 in the left part of Figure 25 \( T_{\text{hl}} = 6 \) and graph 1 in the right part of Figure 25 \( T_{\text{hl}} = 0.1 \) illustrates that a more effective innovation—characterized by a shorter half-life time—does not guarantee a higher implementation effectiveness. In fact, it is a much less effective innovation \( T_{\text{hl}} = 60 \) which diffuses successfully (graph 2 in right part of Figure 25). As elaborated on in chapter 5, a slightly superior innovation \( T_{\text{hl}} = 6 < T^{*}_{\text{hl}} = 9 \) causes more ambiguity than an innovation which is clearly inferior to the status quo \( T_{\text{hl}} = 60 > T^{*}_{\text{hl}} = 9 \). A higher perceived ambiguity decreases the relative dominance of the camp with the stronger word of mouth. Regarding the scenarios depicted in Figure 25, the positive word of mouth of adopters is stronger than the negative word of mouth of non-adopters \( S_{A} = 5 > S_{N} = 3 \). For this reason, the implementation effectiveness depicted in the right part of Figure 25 is higher when the innovation is clearly inferior (graphs 2 and 3). The same explanation applies to graphs 3 and 4 in the right part of Figure 25.

Figure 26 illustrates the simulation results of the extreme-conditions test of the continuous network model introduced in section 6.2.3. Like the ambiguity-oriented model, the continuous network model is an extension of the basic implementation model. The scenario depicted by graph 2 of Figure 18 was chosen as a basis for the extreme-conditions test. In this scenario, group 1 constitutes the mother group consisting of 100% adopters \( A_{1 \text{ini}} = 1 \), the search and interaction intensity of adopters is higher than the search and interaction intensity of non-adopters \( S_{A} = 6 > S_{N} = 4 \), and the conversion probabilities of
isolated adopters and isolated non-adopters are 100% \((P_{AN} = P_{NA} = 1)\). In addition, the daily migration rate is assumed to be 15%. The underlying network structure of this scenario is a five-membered chain structure. This scenario is also depicted by graphs 1 in the left and right part of Figure 26. Similar to graph 2 in the left part of Figure 24, graph 2 in the left part of Figure 26 illustrates a scenario in which all five groups consist only of non-adopters \((A_{1-5 ini} = 0)\). Since there are no adopters which could convert non-adopters, the average adopter fraction will always be 0%. The same logic applies to the scenario depicted by graph 3 in Figure 24 in which each group consists only of adopters \((A_{1-5 ini} = 1)\).

Graphs 4 and 5 in the left part of Figure 24 depict scenarios in which either isolated adopters or non-adopters never revise their individual innovation-decision \((P_{AN} = 0 \text{ or } P_{NA} = 0)\). Due to their higher resistance, they are able to convert all members of the opposing camp, resulting either in an average adopter fraction of 100% (graph 4) or 0% (graph 5 in left part of Figure 26). The right part of Figure 26 illustrates extreme conditions of \(S_A\) and \(S_N\) either being 1 or 1000. Also in these scenarios a higher resistance, in form of a higher search and interaction intensity of one camp, results in an expected dominance of this camp, provided that everything else is equal \((A_{1 ini} = 1; P_{AN} = P_{NA} = 1; m_{ij} = 0.15)\).

Graphs 6 in the left and right part of Figure 26 depict scenarios in which the daily migration rate is either 0% (left part) or 100% (right part). If no migration takes place, the adopters of group 1 do not spread to the other four groups, resulting in a constant average adopter fraction of 20% (graph 6 in left part of
Figure 26). If the daily migration rate equals 100%, the adopters in group 1 are overrun by the non-adopters of the other groups, yielding an average adopter fraction of 0% (graph 6 in right part of Figure 26).

Figure 27 illustrates the simulation results of the extreme-conditions test of the management-oriented model introduced in section 7.2. The management-oriented model is an extension of the continuous network model described in section 6.2.3, which itself is an extension of the basic implementation model introduced in chapter 4. Even though all parameters of the management-oriented model were tested, Figure 27 only depicts the results of network and management-related parameters, which were not included in the basic implementation model. The scenario depicted by graphs B in Figure 22 was chosen as a basis. In this scenario, the initial adopter fraction of all groups is 0% \( (\Delta_{\text{ini}} = 0) \), the search and interaction intensity of adopters is higher than the search and interaction intensity of non-adopters \( (S_A = 6 > S_N = 4) \), and the conversion probabilities of isolated adopters and isolated non-adopters are 100% \( (P_{AN} = P_{NA} = 1) \). In addition, starting from day 12, senior management exerts normative pressure on groups 1, 2, and 3, which are part of a five-membered chain structure (see Table 7). The daily migration rate among groups is assumed to be 24%. This scenario is also depicted by graphs 1 in the left and right part of Figure 27.

![Figure 27](image)

**Figure 27** Extreme-conditions test of the management-oriented model of chapter 7

If employees do not migrate between groups, management can convert all non-adopters within the three influenced groups. However, since there is no migration, these adopters do not spread to the other two groups, resulting in a constant average adopter fraction of 60% (graph 2 in left part of Figure 27).
If the daily migration rate equals 100%, immigrating non-adopters convert most of the adopters that senior management successfully persuaded, yielding an average adopter fraction of only 9% (graph 3 in left part of Figure 27). If the communication structure is not a five-membered chain structure (graphs 1-3) but a minimally centralized ring structure (graph 4) or a maximally centralized star structure (graph 5), management’s influence on groups 1, 2, and 3 also results in an average adopter fraction of about 10% (left part of Figure 27). This is the case because the influenced groups 1, 2, and 3 are less peripherally located in structures IV (graph 4) and III (graph 5) than in structure I (graph 1 in left part of Figure 27). This is also illustrated in Table 7.

In contrast to graph 1, graph 2 in the right part of Figure 27 illustrates a scenario in which management needs on average not 12 days but only 1 day to persuade non-adopters to use an innovation. This results in a 50% quicker diffusion. On the other hand, if management’s normative pressure takes on average 1000 days to affect the individual innovation-decision of non-adopters, the innovation will not diffuse at all (graph 3 in right part of Figure 27). The same result occurs if management decides to influence none of the five groups (graph 4 in the right part of Figure 27). However, if senior management exerts normative pressure on all five groups (graph 5), the innovation diffuses much faster than in a scenario in which only groups 1, 2, and 3 are influenced (graph 1 in the right part of Figure 27).
English summary

The capability of an organization to adjust quickly to unforeseen changes in its environment, such as new regulations, shifts in its customers’ preferences, and changes in its supply chain, is essential for its long-term survival. In many cases, an appropriate reaction to changes in an organization’s environment necessitates the implementation of an innovation. An innovation is an idea, practice, or object which is new to the respective organization. However, the failure rate of such innovation implementation processes within organizations often exceeds 40% (Aiman-Smith & Green, 2002; Burnes, 2004; Chen et al., 2009). Several studies have shown that an organization’s failure to implement an innovation successfully can mostly be attributed to an inadequate implementation process rather than to the innovation itself (Aiman-Smith & Green, 2002; Gary, 2005; Karimi et al., 2007; Klein & Sorra, 1996). One of the main reasons for organizational implementation failure is employees’ resistance to change (Kim & Kankanhalli, 2009).

Even though multiple causes of employees’ resistance to an innovation have been identified, literature is lacking multidimensional models that explain why some implementation efforts result in a successful diffusion of an innovation among employees and others do not. Such models should take into account multiple and to some extent interrelated drivers of implementation success (Dean Jr. & Bowen, 1994; Klein et al., 2001; Klein & Sorra, 1996; Repenning, 2002). Greenhalgh et al. (2005, p. 135) criticized that much literature implicitly assumes that “the determinants of innovation can be treated as variables whose impact can be isolated and independently quantified.” They stated, however, that more recent studies suggest that “in reality the different determinants of organizational innovativeness interact in a complex way with one another” (Greenhalgh et al., 2005, p. 135).

In response to the call for multidimensional models, the overarching goal of this dissertation is to shed light on the interrelations and dynamics among four well-established factors that influence the acceptance and usage of an innovation among employees. Similar to studies that model the diffusion of an innovation within a market (e.g., Bass, 1969; 2004), this dissertation models the diffusion of an innovation among employees of an organization by focusing on the communication between adopters and non-adopters of the respective innovation. Therefore, this research concentrates on four communication-related factors that influence the effectiveness of intra-organizational innovation implementation processes: (i) the communication among employees who are supposed to adopt an innovation (peer influence), (ii) the influence of ambiguity intolerance on their communication behavior (ambiguity intolerance of employees), (iii) the intra-
organizational communication network among groups of employees (structural characteristics of organizations), and (iv) the communication between senior management of an organization and its employees (management influence). Thereby, this research aims to improve the understanding and effectiveness of intra-organizational implementation processes. To achieve this goal, the dissertation constructs and analyzes a dynamic simulation model on the basis of empirical studies.

The dissertation aims to make several contributions. First, based on empirical findings, the market-oriented Bass diffusion model (Bass, 1969; 2004) is adjusted in order to be applicable in an intra-organizational context. The diffusion of innovations within markets differs from the diffusion of innovations within organizations in that the goal of the former is to sell the innovation to as many actors in the market as possible, while the latter is interested in convincing as many employees as possible to use the innovation. While the purchase of an innovation is often irreversible, the decision to actually use this innovation is not. From an organizational perspective, not the purchase of an innovation but its widespread usage among employees is essential to generate benefits from it. Therefore, this dissertation introduces a simple intra-organizational diffusion model which not only considers the adoption and usage of an innovation due to positive word of mouth (WOM), but also its rejection and discontinuance due to negative WOM. The analysis of this model suggests that it might be more beneficial for the senior management of an organization to support the implementation process by reducing the absolute strength of negative WOM than by increasing the absolute strength of positive WOM. Thus, senior management should concentrate its efforts on limiting the negative impact of employees who do not use the innovation, instead of promoting employees who do already use it.

Second, this dissertation aims to shed light on the relationship between the perceived ambiguity of an innovation and the communication behavior among employees. Even though the perceived ambiguity of an innovation and employees’ ambiguity intolerance have been considered to be main drivers of word-of-mouth communication, it remained unclear how they affect the communication behavior among employees and thereby implementation effectiveness. The dissertation establishes a link between the perceived ambiguity of an innovation and its relative advantage over the status quo. An innovation is perceived to be more ambiguous, the closer its perceived effectiveness is to the effectiveness of the status quo. The more ambiguous an innovation, the more employees communicate with each other in order to find supportive information which confirms their current belief about which of the two—the innovation or the status quo—is more advantageous. It is precisely during such periods that the restriction of non-adopters’ influence benefits the
implementation process the most. Being aware of this enables senior managers to time their interventions accordingly.

Third, this dissertation broaches the issue of cross-border communication between different groups of employees, such as teams or departments. In implementation research the communication ties between organizational compartments have been largely ignored because they are relatively weak compared to the communication ties within groups (Damanpour, 1996; Repenning, 2002). However, network research has shown that weak ties between groups serve as important bridges which provide access to otherwise unavailable information (Grannovetter, 1973). Therefore, this dissertation examines how structural characteristics of the communication network among groups affect the communication between adopters and non-adopters within these groups and how those effects, in turn, influence implementation effectiveness. The findings of this dissertation suggest that in a chain structure, adopter-dominated groups should be connected to each other while non-adopter-dominated groups should be isolated from each other in order to increase implementation effectiveness.

Fourth, this dissertation explicitly considers senior management’s influence on the implementation process. Similar to the influence of peers, senior management can also exert normative pressure on employees in order to stimulate the usage of an innovation. Even though some implementation studies analyzed senior management’s influence on implementation effectiveness (e.g., Choi & Chang, 2009; Repenning, 2002), none of them considered the communication network among groups of targeted employees. Therefore, this dissertation contributes to current research by examining characteristics of effective and efficient management strategies in light of different communication structures among several groups of employees. The findings illustrate that management needs to follow two rules when deciding on which groups it should exert normative pressure: (i) the groups management chooses to influence need to be shielded from groups which are not influenced by senior management and dominated by non-adopters (i.e., influenced groups should be peripherally located); (ii) the chosen groups should be close enough to each other in order to mutually stimulate the level of adoptions within them (i.e., they should be proximate to each other). In addition, the analyses of different network structures suggest that senior management should also take into account the communication structure among influenced groups when deciding on a strategy. In particular, the findings suggest that strategies addressing peripherally located and proximate groups facilitate the diffusion process. However, if network structures are characterized by highly central groups, the proximity of influenced groups can be much more important than their peripheral location.
202 | Dutch summary
Dutch summary

Het vermogen van een organisatie om snel in te spelen op onvoorziene veranderingen in haar omgeving, zoals veranderingen in de voorkeuren van klanten en veranderingen in haar productieketen, is essentieel om op lange termijn te kunnen overleven. In veel gevallen is het implementeren van een innovatie vereist voor een adequate reactie op veranderingen in de omgeving van de organisatie. Een innovatie is een idee, gebruik, of object dat nieuw is voor een organisatie. Echter het blijkt dat meer dan 40% van dergelijke innovatie-implementatieprocessen in organisaties faalt (Aiman-Smith & Green, 2002; Burnes, 2004; Chen et al., 2009). Diverse studies hebben aangetoond dat het niet slagen van het implementeren van een innovatie meestal veroorzaakt wordt door een inadequaat implementatieproces en niet door de innovatie zelf (Aiman-Smith & Green, 2002; Gary, 2005; Karimi et al., 2007; Klein & Sorra, 1996).

Een van de hoofdredenen voor het falen van het implementatieproces is de weerstand van werknemers tegen verandering (Kim & Kankanhalli, 2009).

Ondanks dat er diverse oorzaken voor weerstand van werknemers tegen een innovatie zijn geïdentificeerd, ontbreken er multidimensionale modellen in de literatuur die uitleggen waarom sommige implementatiepogingen resulteren in succesvolle diffusie van een innovatie onder werknemers en andere niet. Dergelijke modellen moeten rekening houden met diverse en tot op zekere hoogte samenhangende verklaringsfactoren voor implementatiesucces (Dean Jr. & Bowen, 1994; Klein et al., 2001; Klein & Sorra, 1996; Repenning, 2002).

Greenhalgh et al. (2005, p. 135) bekritiseren dat veel literatuur impliciet aanneemt dat de impact van de verklaringsfactoren voor het implementatieproces kunnen worden geïsoleerd en onafhankelijk worden bepaald. Ze zeggen echter dat recentere studies suggereren dat verschillende verklaringsfactoren voor de innovativiteit van een organisatie op een complexe wijze met elkaar interacteren (Greenhalgh et al., 2005, p. 135).

Als reactie op de behoefte aan multidimensionale modellen is het overkoepelende doel van dit proefschrift het belichten van de onderlinge relaties en de dynamiek tussen vier goed gefundeerde factoren die invloed hebben op de acceptatie en het gebruik van een innovatie door werknemers. Net als studies die de diffusie van een innovatie in een markt modelleren (bv. Bass, 1969; 2004), modelleert dit proefschrift de diffusie van een innovatie onder werknemers van een organisatie door te kijken naar de communicatie tussen werknemers die de innovatie wel, en werknemers die de innovatie niet overnemen. Daarom ligt de focus van dit onderzoek op vier communicatiegerelateerde factoren die de effectiviteit van het innovatie-implementatieproces in een organisatie beïnvloeden: (i) de communicatie tussen werknemers die worden geacht de innovatie te
gebruiken door het management (onderlinge invloed), (ii) de invloed van intolerantie voor ambiguïteit op het communicatiegedrag van deze werknemers (ambiguïteit intolerantie van werknemers), (iii) de communicatienetwerken in een organisatie tussen groepen van werknemers (structuureigenschappen van een organisatie), en (iv) de communicatie tussen het hoger management van een organisatie en haar werknemers (managementinvloed). Hiermee probeert dit onderzoek de effectiviteit van innovatie implementatieprocessen beter te begrijpen. Om dit doel te behalen maakt en analyseert dit proefschrift een dynamisch simulatiemodel op basis van empirische studies.

Het proefschrift poogt op verschillende manieren bij te dragen. Allereerst is het marktgeoriënteerde “Bass diffusion model” (Bass, 1969; 2004) aangepast, op basis van empirische bevindingen, zodat dit toepasbaar is op een intra-organisatie context. De diffusie van innovaties in een markt verschilt van de diffusie van een innovatie in een organisatie, omdat het eerste zich het verkopen van de innovatie aan zoveel mogelijk actoren in de markt ten doel stelt, terwijl de tweede geïnteresseerd is in het overtuigen van zoveel mogelijk werknemers om de innovatie te gebruiken. Terwijl de aankoop van een innovatie vaak niet omkeerbaar is, is de beslissing de innovatie te gebruiken dit wel. Vanuit een organisatieperspectief is niet de aankoop van een innovatie, maar het wijdverspreid gebruik onder werknemers essentieel om de voordelen ervan te generen. Daarom introduceert dit proefschrift een eenvoudig diffusiemodel op intra-organisatie niveau dat niet alleen het overnemen en het gebruik van een innovatie via mond-tot-mond communicatie (MMC), maar ook de afwijzing en beëindiging van het gebruik door negatieve MMC in beschouwing neemt. De analyse van dit model suggereert dat het voor het management van een organisatie waarschijnlijk beter is om het implementatieproces te ondersteunen door de negatieve MMC te verminderen dan door de positieve MMC te bevorderen. Kortom, het management dient haar inspanningen te concentreren op het beperken van het negatieve effect van werknemers die de innovatie niet gebruiken in plaats van het aanmoedigen van werknemers dit het wel gebruiken.

Het tweede doel van dit proefschrift is om licht te werpen op de relatie tussen de ervaren ambiguïteit van een innovatie en het communicatiegedrag tussen werknemers. Hoewel de ervaren ambiguïteit van een innovatie en de intolerantie voor ambiguïteit van een werknemer worden beschouwd als de primaire drijfveren voor mond tot mond communicatie, was het onduidelijk hoe zij het communicatiegedrag tussen werknemers beïnvloeden en daarmee de implementatie effectiviteit. Het proefschrift laat zien dat de ervaren ambiguïteit van een innovatie afhankelijk is van het relatieve voordeel ten opzichte van de status-quo. Een innovatie wordt als meer ambigue ervaren wanneer de ervaren effectiviteit dichter bij de effectiviteit van de status-quo ligt. Hoe hoger de
ambiguïteit van een innovatie, hoe meer de werknemers met elkaar communiceren om ondersteunende informatie te vinden die hun huidige beeld over welke van de twee – de innovatie of de status-quo – meer voordelen heeft. Het zijn juist dit soort periodes waarin het beperken van de invloed van werknemers die de innovatie niet overnemen het grootste positieve effect heeft op het implementatieproces. Door zich hiervan bewust te zijn, kan het management haar interventies hierop timen.

Het derde thema dat in dit proefschrift aan de orde komt, is het onderwerp van grensoverschrijdende communicatie tussen verschillende groepen van werknemers, zoals teams en afdelingen. In implementatieonderzoeken worden de communicatieverbindingen tussen organisatieonderdelen genegeerd, omdat zij relatief zwak zijn in vergelijking tot communicatieverbindingen binnen groepen (Damanpour, 1996; Repenning, 2002). Netwerkonderzoek heeft echter laten zien dat zwakke verbindingen tussen groepen als een belangrijke brugfunctie functioneren die toegang geven tot informatie die anders niet beschikbaar komt (Grannovetter, 1973). Daarom onderzoekt dit proefschrift hoe structurele eigenschappen van het communicatienetwerk tussen groepen de communicatie tussen werknemers die innovaties wel, en werknemers die innovaties niet overnemen in deze groepen beïnvloeden en hoe deze effecten op hun buurt de implementatie effectiviteit beïnvloeden. De bevindingen in dit proefschrift suggereren dat in een ketenstructuur groepen waarin werknemers die de innovatie overnemen domineren onderling verbonden dienen te worden terwijl groepen waarin werknemers die de innovatie niet overnemen van elkaar geïsoleerd dienen te worden om de implementatie effectiviteit te bevorderen.

Ten vierde beschouwt het proefschrift ook de expliciete invloed van het hoger management op het implementatieproces. Net zoals bij de onderlinge invloed, kan het hoger management ook normatieve druk uitoefenen op werknemers om het gebruik van de innovatie te stimuleren. Hoewel enkele implementatieonderzoeken de invloed van het hoger management op implementatie-effectiviteit hebben geanalyseerd (bv. Choi & Chang, 2009; Repenning, 2002), heeft geen enkele van deze studies het communicatienetwerk tussen doelgroepen van werknemers beschouwd. Daarom draagt dit proefschrift bij aan bestaand onderzoek door de eigenschappen van effectieve en efficiënte managementstrategieën te analyseren in het licht van verschillende communicatiestructuren tussen verschillende werknemersgroepen. De bevindingen illustreerden dat het management twee regels dient te volgen wanneer zij besluiten om op bepaalde groepen normatieve druk uit te gaan oefenen: (i) het management moet de groepen die ze willen beïnvloeden afschermen van groepen met werknemers die de innovatie nog niet hebben overgenomen (d.w.z. de te beïnvloeden groepen dienen perifeer gelegen te zijn); (ii) de gekozen groepen moeten zodanig dicht
bij elkaar staan dat ze wederzijds elkaar stimuleren om de innovatie te gebruiken (d.w.z. zij dienen naburig gelegen te zijn). Bovendien suggereert de analyse van verschillende netwerkstructuren dat wanneer het management voor een strategie kiest zij ook de communicatiestructuur tussen de beïnvloede groepen moet meenemen. In het bijzonder wijzen de bevindingen erop dat met name strategieën die gericht zijn op perifere gelegen en naburige groepen het diffusieproces faciliteren. Wanneer echter de netwerkstructuur in hoge mate wordt gekarakteriseerd door centrale groepen kan de nabijheid van de beïnvloede groepen nog van veel meer invloed zijn dan hun perifere ligging.
About the author

Philipp Wunderlich was born on April 20, 1984 in Zwickau, Germany. He graduated from the University of Mannheim, Germany, receiving a degree in business administration with an additional intercultural qualification in English. In the course of his academic studies at the University of Mannheim, he spent one semester at the Korea University Business School, Seoul, South Korea, and one semester at the Wilfrid Laurier University, Waterloo, Canada. In 2010, the University of Mannheim awarded him the prize of the Karin-Islinger-Stiftung for his diploma thesis. He has been working as a teaching assistant at the Methodology Department of the Management Science Faculty at Radboud University Nijmegen, the Netherlands, since February 2011. His research interests include innovation management, organizational change, social networks, and system dynamics modeling and simulation.
Innovation Diffusion within Organizations

Word of mouth and the effectiveness of intra-organizational innovation implementation

Philipp Wunderlich

Invitation

for attending
the public defense
of the thesis

Innovation Diffusion within Organizations

Word of mouth and the effectiveness of intra-organizational innovation implementation

On Friday,
March 13th 2015
at 12:30 hrs
in the aula of the
Radboud University Nijmegen,
Comeniuslaan 2 in Nijmegen.

You are very welcome at
the reception after the defense.

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