Association for Information Systems
AIS Electronic Library (AISeL)

Research Papers

ECIS 2016 Proceedings

Summer 6-15-2016

DRIVERS AND EFFECTS OF INFORMATION SYSTEMS ARCHITECTURE COMPLEXITY: A MIXED-METHODS STUDY

Jannis Beese
University of St.Gallen, jannis.beese@unisg.ch

Stephan Aier
University of St. Gallen, stephan.aier@unisg.ch

Kazem Haki
University of St. Gallen, kazem.haki@unisg.ch

Pouya Aleatrati Khosroshahi
Technical University of Munich, p.aleatrati@tum.de

Recommended Citation

Beese, Jannis; Aier, Stephan; Haki, Kazem; and Aleatrati Khosroshahi, Pouya, "DRIVERS AND EFFECTS OF INFORMATION SYSTEMS ARCHITECTURE COMPLEXITY: A MIXED-METHODS STUDY" (2016). *Research Papers*. 74.
http://aisel.aisnet.org/ecis2016_rp/74

DRIVERS AND EFFECTS OF INFORMATION SYSTEMS ARCHITECTURE COMPLEXITY: A MIXED-METHODS STUDY

Research

Beese, Jannis, University of St. Gallen, Switzerland, jannis.beese@unisg.ch

Aier, Stephan, University of St. Gallen, Switzerland, stephan.aier@unisg.ch

Haki, Mohammad Kazem, University of St. Gallen, Switzerland, kazem.haki@unisg.ch

Aleatrati Khosroshahi, Pouya, Technical University of Munich, Germany, p.aleatrati@tum.de

Abstract

Today's organizations deal with a significant complexity of their information systems (IS) architecture—a complex cobweb of heterogeneous IS with tight, mutual interrelations. With the constantly increasing number of IS along with the inherent complexity of the organizational context in which IS are embedded, organizations lose control of their IS architecture's evolution. Through employing a sequential mixed-methods research design, this study investigates the drivers and effects of IS architecture complexity. Based on the extant literature and on focus groups data, at the outset we develop a research model and derive its constitutive hypotheses. We subsequently test the research model following a partial least squares (PLS) approach to structural equation modelling (SEM) with survey responses from 249 IT managers and architects. While differentiating structural and dynamic complexity, this study confirms a high degree of integration, large size, high diversity, strong dynamics, and, in particular, inadequate planning as the main drivers of IS architecture complexity. Further, this study affirms the negative effect of IS architecture complexity on the efficiency, agility, comprehensibility, and predictability of the IS.

Keywords: Complexity drivers, Complexity effects, Exploratory mixed-methods, Information systems complexity, Information systems architecture,

1 Introduction

Over the past decades, we have witnessed an enormous growth of investments in information systems (IS) in organizations. On one hand, constant investments in IS had a significant impact on organizations' performance (Melville et al., 2004; Brynjolfsson and Hitt, 2000). On the other hand, these investments resulted in a significant complexity of the IS architecture, i.e., an organization's fundamental IS components, their relations, and the principles governing their design and evolution (ISO/IEC/IEEE, 2011). This manifests in a large and ever-growing number of heterogeneous IS, which are costly to maintain, mutually interrelated, and lack flexibility with regard to business changes (Schmidt and Buxmann, 2011). In addition to the technical heterogeneity, the organizational context in which IS architectures are embedded reflects the other aspect of their complexity (Avgerou, 2001). As organizations are shaped by the intrinsic flux of human actions (Tsoukas and Chia, 2002), social interactions among different actors (e.g., design decision makers) with diverse, competing, and changing stakes and requirements, bring about uncontrolled and emergent IS architectures.

While taking into account maturing literature on IS complexity, the study at hand lays emphasis on *IS architecture complexity* in terms of the growing number of and the mutual interrelations between IS components as well as their evolution over time. Notwithstanding a plethora of discussions on IS complexity in the extant literature (Boisot, 2006; Boisot and McKelvey, 2010; Cooke-Davies et al., 2007; Merali, 2006), first, there are a few studies that report measurement items for IS complexity (e.g., Xia and Lee, 2005; Schütz et al., 2013; Bosch-Rekveldt et al., 2011; Maylor et al., 2008) and, second, complexity in the specific context of IS architecture is yet underexplored. Thus, we pose the following research question:

RQ: What are drivers and effects of information systems architecture complexity?

Relying on the existing body of knowledge on IS complexity, we answer this question by contributing an empirically validated research model that not only outlines drivers and effects of complexity in IS architecture, but also rigorously develops measurement items for IS architecture complexity, drawing on both technical and social aspects.

This study employs a sequential mixed-methods research design (Creswell and Clark, 2011), comprising both qualitative and quantitative research methods. Supported by our synthesis on the extant literature and through several rounds of focus groups, we first collect qualitative data to develop a research model on the drivers and effects of IS architecture complexity. This research model encompasses two types of IS architecture complexity (*structural* and *dynamic* complexity), five driver constructs (*size*, *diversity*, *integration*, *planning*, and *dynamics*), four effect constructs (*efficiency*, *agility*, *comprehensibility*, and *predictability*), and eventually develops measurement items for these constructs and hypothesizes their relationships.

In the quantitative part of the study, we use both paper-based and online surveys to collect 249 valid responses, and empirically test the research model through a partial least squares (PLS) approach to structural equation modelling (SEM). Our proposed model makes previously hypothesized connections between drivers of IS architecture complexity and related effects explicit and evaluates their strength statistically. Furthermore, we evaluate compounding effects between different driver constructs. Results indicate that a high degree of integration, large size, high diversity, strong dynamics, and, in particular, inadequate planning, significantly contribute to IS architecture complexity. This complexity, in turn, negatively impacts the efficiency, agility, comprehensibility, and predictability of the IS architecture.

2 Research Methodology

In order to develop a conceptual model for studying IS architecture complexity, one needs to take into account the multiple and diverse conceptualizations related to IS architecture complexity as well as related to potential effects and drivers. On the one hand, there is a large body of research on IS complexity in general, and multiple publications discuss what this constitutes on an abstract level (Boisot, 2006; Boisot and McKelvey, 2010; Cooke-Davies et al., 2007; Merali, 2006). On the other hand, there still are only a few publications that explicitly provide measurement scales (e.g., Xia and Lee, 2005; Schütz et al., 2013; Bosch-Rekveldt et al., 2011; Maylor et al., 2008) or formulate relations between different aspects of IS architecture complexity (e.g., Mocker, 2009). We therefore employ the exploratory sequential mixed-methods research design of Creswell and Clark (2011): First, qualitative data is collected in order to derive appropriate conceptualizations of IS architecture complexity, its drivers and its effects, and to link these constructs in the form of hypotheses. For the measurement adaptation and development process we follow the recommendations of MacKenzie et al. (2011) and Churchill (1979). Based on the results of this process, we then design a survey, which allows us to test the hypotheses using structural equation modelling. The overall research design of this study (see Figure 1) follows the suggested four phases of Creswell and Clark (2011 p.88, Figure 3.5).

Phase 1: An initial analysis of literature hinted at the importance of not only analysing the technical, but also the social aspects of IS architecture complexity. However, we found no definite combination of extant measurement scales for drivers of IS architecture complexity in the literature. We thus used focus group workshops to test measurement items that were adopted from different but related contexts, such as IS development project complexity (Xia and Lee, 2005) or application landscape complexity (Schneider et al., 2015). Focus groups allow the simultaneous collection of rich data from multiple participants, thus enabling researchers to make important connections and to identify subtle nuances in expression and meaning, which is important for the development of high-level conceptual models and measurement scales (Stewart et al., 2007).

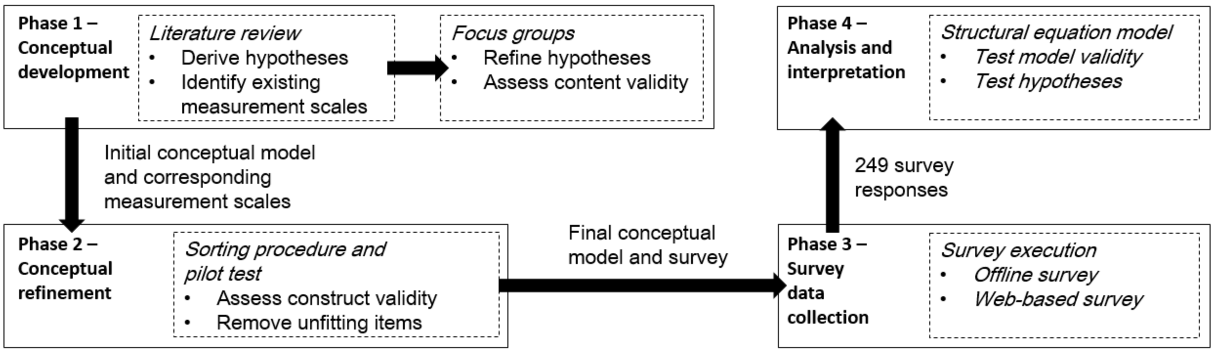

Figure 1. Research design overview

A series of four two-day focus group workshops was conducted during June 2014 and May 2015, involving senior architects and IT managers employed with ten large companies from the banking, insurance, logistics, and utilities sectors (see Table 1 for an overview). Workshop participants were selected by the authors based on their knowledge, their experience within the firm, and their ability to contribute to the topic. The size of the focus groups allowed for the emergence and analysis of different ideas and viewpoints, while still being small enough for an in-depth discussion of more complicated questions. Each workshop was prepared and moderated by two of the authors, following the guidelines of Stewart et al. (2007). During the workshops, two other researchers, in addition to the moderators, took notes, which were analysed later. The aim of the first workshop was to develop a common understanding and conceptualization of IS architecture complexity in large enterprises. Based on this understanding, participants then identified and discussed root causes and drivers of complexity as well as complexity management efforts during the second workshop. The third workshop participants then grouped and positioned the previously identified constructs (drivers, conceptualizations of complexity, and goals of complexity management) in relation to each other and discussed interdependencies. The final workshop was used to validate a preliminary version of the conceptual model that is employed in this research through expert’s opinions.

Date	**Participants**	**Goal**
16./17.06.2014	16	Develop an understanding of IS architecture complexity and its role in organizations.
13./14.10.2014	13	Identify drivers of complexity, as well as common goals of complexity management.
11./12.02.2015	13	Identify relations between the constructs (derive hypotheses).
11./12.05.2015	8	Validate a preliminary version of the conceptual model.

Table 1. Overview of focus group workshops

Phase 2: The open nature of the focus group workshops of phase 1 led to a comprehensive conceptual model with 11 constructs (two types of IS architecture complexity, five drivers, and four effects) and 122 potentially relevant measurement items for these constructs, backed by literature and focus group data. This initial pool of measurement items included items that were controversial during focus group discussions with regard to their importance and applicability, especially with regard to relevant drivers of complexity. In order to select the most relevant subset of items for the design of the subsequent quantitative part, and to further validate its conceptual foundation, a pilot test and a sorting procedure were performed with 12 IS researchers, including 5 senior scholars. The employed process for integrating and developing measurement scales for drivers of IS architecture complexity is based on Churchill (1979), MacKenzie et al. (2011) and Xia and Lee (2005). During the sorting exercise, participants were asked to evaluate the proposed items with regard to their fit to any one of the 11 constructs. Furthermore, participants were encouraged to point out ambiguous or badly phrased items, which were then discarded.

Phase 3: A combined analysis of the notes and results from the focus groups, the results from the sorting procedure, and the data from the pilot test, led to a set of 51 measurement items that were included in the final survey. Following Gefen et al. (2011), we aimed for at least three observable variables per construct, in order to have sufficient degrees of freedom in the model, which strengthens the statistical power and offsets potential bias in parameter estimates (Dijkstra, 2010; MacCallum et al., 1996). We collected data from 106 respondents (86% response rate) from a paper based survey handed out at a European practitioner conference where the research project was introduced by a well-known and respected community member as well as one of the authors. An initial estimate (following Faul et al., 2009) of this dataset indicated that roughly 240 responses in total were required in order to be statistically significant ($p < .01$). Thus, we used the same items in an online survey to collect data from an additional 143 respondents. The online survey was sent to 571 contacts, leading to a 25% response rate. For both surveys, we took care that only relevant people—experienced enterprise architects and IT managers of large enterprises—were targeted.

Phase 4: Data was analysed following Gefen et al. (2011) and Ringle et al. (2012). Since there is no well-developed a-priori theory, which explains the entire phenomenon of interest, we chose PLS-SEM over covariance-based approaches to reduce the risk of overfitting during analysis (Gefen et al., 2011). The tests were performed using SmartPLS version 3.2.1. (Ringle et al., 2015). Missing values were handled through mean replacement and bootstrapping was conducted with a sample size of 5000 to assess path estimate significance.

3 Related Work and Conceptual Model Development

The proposed conceptual model of this research consists of three major parts: five drivers of IS architecture complexity (*size*, *diversity*, *integration*, *planning*, and *dynamics*), two types of IS architecture complexity (*structural complexity* and *dynamic complexity*), and four effect constructs (*efficiency*, *comprehensibility*, *agility*, and *predictability*). This section discusses related work for each construct.

3.1 Drivers of IS architecture complexity

Several studies of IS complexity focus abstract aspects and conceptualizations of complexity itself, often employing concepts from other disciplines such as computational complexity theory or complex systems theory (Cooke-Davies et al., 2007; Dewar and Hage, 1978; Xia and Lee, 2005). In addition, the effects of concrete instantiations of complexity in IS have been studied for selected types of complexity, such as task-complexity (Gupta et al., 2013; Campbell, 1988; Xu et al., 2014), technological complexity (Yayavaram and Chen, 2015), and enterprise architecture complexity (Schütz et al., 2013).

With the aim of integrating insights from these studies, we identified five major drivers of IS architecture complexity: *size*, *diversity*, *integration*, *planning*, and *dynamics*. In the following, we describe each identified driver in more detail and explain which aspects are considered to be relevant and thus included in our measurement model.

Size refers to the overall size of the system and its components, thus referring to both the number of elements as well as the dimensions of a single element. Complexity is conjectured to be partially a result of a large number of computing components and the volume of data processed by these components (Schneberger and McLean, 2003; Mocker, 2009; Schütz et al., 2013). Sharma (2007) emphasizes the effects of extensive and comprehensive tasks. Furthermore, database and network intensity are often included in complexity metrics (Weidong and Lee, 2005; Meyer and Curley, 1991).

Diversity has been conjectured to have an effect on system complexity (Page, 2010). Following Stirling (2007), diversity is a combination of *variety* (the number of different categories), *disparity* (the degree of difference between categories), and *balance* (the evenness in distribution). In particular, the variety of computing components and component interactions has been linked to complexity by Schneberger & McLean (2003). Mocker (2009) also studies the effect of application architecture diversity on costs as an aspect of complexity. While acknowledging the importance of diversity for IS architecture complexity, no direct correlation with application portfolio operation costs is found. The diversity of platforms, technologies, and information sources have been suggested as drivers of complexity (Weidong and Lee, 2005; Meyer and Curley, 1991).

Integration represents the level of interconnectedness: How many interdependencies exist between different components, how strong are these couplings, and how do the components interact with each other? In particular, the degree of system integration and interdependencies between tasks are conjectured to affect system complexity (Sharma and Yetton, 2007; Bosch-Rekveldt et al., 2011). Furthermore, a study of Mocker (2009) on application portfolio complexity discovers a statistical relation between the number of application interfaces and maintenance costs. Systems integration effort is also included in the complexity metric of Meyer and Curley (1991).

Dynamics refers to the rate of change of the overall system or of individual components. Schneberger & McLean (2003) suggest that the overall rate of change in the number and variety of components, and of their interactions contribute to complexity. The rate of change for actors is also included in Meyer and Curley’s complexity metric in the sense that highly complex systems constantly require people to attain new knowledge (Meyer and Curley, 1991). Chen et al. (2014) show environmental complexity and dynamics to affect organizational performance.

Planning in this context means to guide the evolution of the IS in an efficient and effective way, by being aware of the components of IS development and their interdependencies. Literature on complexity management emphasizes that adequate planning will help to reduce and avoid unnecessary complexity, i.e. complexity that is not a direct result of business requirements (Premkumar and King, 1992). In particular, all relevant stakeholders should be included in the decision-making process and system development should be done in a well-defined and structured way (Whitty and Maylor, 2009; Tait and Vessey, 1988; Renn et al., 2011). Furthermore, relying on established principles and guidelines may help to reduce resultant system complexity (Beese et al., 2015).

3.2 Structural and dynamic IS architecture complexity

In order to capture IS architecture complexity itself, we adopt the well-established distinction between structural IS architecture complexity and dynamic IS architecture complexity (Weidong and Lee, 2005; Geraldi, 2009; Geraldi et al., 2011; Whitty and Maylor, 2009; Maylor et al., 2008).

Structural complexity aims at capturing the complexity inherent in a static snapshot of the information system, i.e. the difficulty in understanding all the different elements and their interdependencies. This comprises the variety (Ribbers and Schoo, 2002), multiplicity (Campbell, 1988; Pich et al., 2002; Mocker, 2009), and differentiation (Baccarini, 1996) of system elements as well as their coordination (Wood, 1986), interactions (Pich et al., 2002; Tait and Vessey, 1988) and integration efforts (Ribbers and Schoo, 2002).

Dynamic complexity conversely aims at capturing complexity that is due to changes of the IS over time. This comprises complexity due to uncertainty (Campbell, 1988; McKeen et al., 1994), ambiguity (Meyer and Curley, 1991), variability (Ribbers and Schoo, 2002), and dynamism (Meyer and Curley, 1991; Wood, 1986).

3.3 Effects of IS architecture complexity on organizational performance

IS complexity is hypothesized to negatively affect organizational performance (Kourteli, 2000), comprising both efficiency impacts and competitive impacts, such as an organization’s agility (Melville et al., 2004; Sabherwal and Jeyaraj, 2015). Consequently, complexity management is employed to reduce complexity and to offset its effects, so that businesses can operate in a more agile, efficient, or robust way (Hoogervorst, 2004). In order to understand the impact of IS architecture complexity, we therefore also analyse common goals of IS architecture complexity management.

Efficiency: One common goal of complexity management is the sustained ability of IT departments to keep operations running within strict budget requirements. A central aspect for this is to reduce unnecessary, non-business induced IS architecture complexity in order to reduce costs and uphold efficient operation (Kourteli, 2000). This is supported by a number of studies linking aspects of IS architecture complexity to operating efficiency in terms of costs (Mocker, 2009; Schneider et al., 2015). Efficiency in this context includes avoiding redundancies, i.e., unnecessary overlaps between different IT applications and functional capabilities (Ross et al., 2006).

Comprehensibility: Complexity prevents people from understanding the way a system operates, by making it harder to recognize inconsistencies and to interpret results correctly (Attewell, 1992). According to Paulson (2010 p.202), “complexity is the enemy of transparency”. Complexity management therefore aims at making IS architectures easier to use and comprehend, which is increasingly important for fulfilling regulatory requirements (Gibson and Simpson, 2015; Abdullah et al., 2010). Furthermore, complex IS prevent less skilled users from using the systems and increase training efforts (Premkumar and Roberts, 1999).

Agility: An important goal of IS development is the sustained ability of the organization to react to changing requirements within time and budget constraints (Sambamurthy et al., 2003). Agility in this context means to recognize threats and opportunities quickly and to react accordingly “with ease, speed, and dexterity” (Tallon and Pinsonneault, 2011 p.464). This includes the concepts of adaptivity and sustainability, i.e., aligning IS with constantly changing goals of the organization (Vessey and Ward, 2013; Wieland and Wallenburg, 2012). Enterprises with less complex IS are easier to change, thus a link between IS complexity and agility has been hypothesized (Arteta and Giachetti, 2004).

Predictability: The effects of changes on complex IS architectures are hard to predict, due to the dynamic and emergent nature of IS development (Luna-Reyes et al., 2005; McLeod and Doolin, 2012). Organizations employ complexity management in order to make the effects of changes more predictable and in turn, to reduce uncertainty and risks, both during continuous operation and during IS transformation (Geraldi, 2009; Renn et al., 2011). The necessity to correctly predict the effects of IS design decisions is emphasized by the large number of failed IS development projects (e.g., Howell et al., 2010; Luna-Reyes et al., 2005).

3.4 Hypotheses development

The development of the conceptual model took place in phase 1 and phase 2 (see Figure 1) of this research. Based on the constructs identified through literature, we used focus group discussions to ensure that from an expert’s point of view, no essential aspects were ignored, and that complexity concepts, which originate from different but related contexts (e.g. task or application architecture complexity), are applicable to IS architecture complexity.

Our conceptual model comprises three major parts (Figure 2):

(i) *Size*, *diversity*, *integration*, *planning*, and *dynamics* as common drivers of IS architecture complexity

(ii) Two types of IS architecture complexity, *structural complexity* and *dynamic complexity*

(iii) Four effects, *efficiency*, *agility*, *comprehensibility*, and *predictability*, which are hypothesized to be affected by IS architecture complexity

Although IS complexity is discussed for several years now, there still are only a few scientific and/or practitioner-oriented publications *reporting on specific interactions between different aspects of IS architecture complexity* (e.g., Mocker, 2009; Bosch-Rekveldt et al., 2011). Since there is no a priori theory that explains the precise relations, this paper is of the theory-creating rather than the theory-testing kind. According to Gregor (2006), our theory can be classified as *theory for explaining and* *predicting*. We argue with Iivari and Huisman (2007, p.42) that "even though theory-creating research is sometimes associated with qualitative and interpretive research methods rather than with quantitative ones (Järvinen, 2001), we do not see any philosophical (Chalmers, 1999) or methodological (Dubin, 1978; Wallace, 1983) reasons why this should be so".

In terms of hypotheses (see Figure 2), we expect to find interrelations between different driver constructs (*H1*), as some of these drivers may have compounding effects. However, we did not fix any connections between drivers at the outset of this research, but rather derive these based on the data. Drivers of IS architecture complexity are naturally expected to contribute to IS architecture complexity (*H2*). Furthermore, we expect *structural complexity* to contribute to *dynamic complexity* (*H3*), and both types of complexity should have an overall negative effect on organizational performance (*H4*). We now proceed to further elaborate these relations and to formulate explicit hypotheses for *H1-H4*.

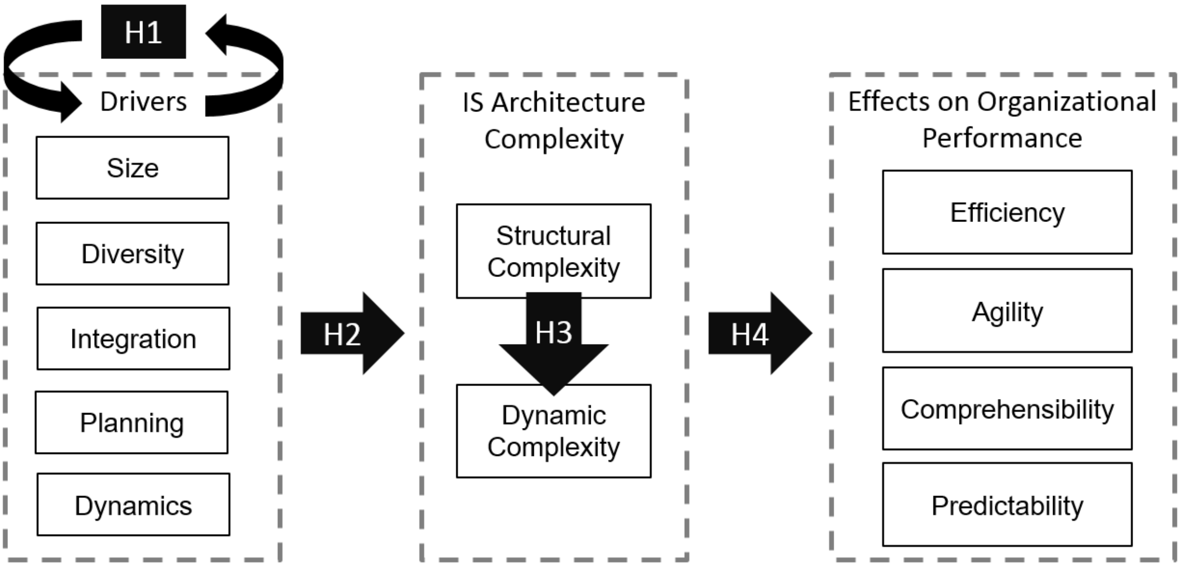

Figure 2. Overview of the initial conceptual model.

S*ize* and *diversity* are expected to augment the effects of other complexity drivers: Discussions in the focus groups indicated that while *size* and *diversity* alone do not cause problems, they compound difficulties that arise for example due to *dynamics* (a larger number of components needs to be changed in a certain timeframe) and *integration* (integrating diverse components is more difficult than integrating similar components). Thus, we hypothesize:

H1: There exist interdependencies between size, diversity, integration, planning, and dynamics as drivers of IS architecture complexity, with some drivers compounding the effects of other drivers.

Based on Mocker (2009) and the definition of *structural complexity* (Xia and Lee, 2005), we expect *integration* to impact *structural complexity*, and, similarly, *dynamics* to impact *dynamic complexity*. Literature also recognizes the importance of adequate planning mechanisms for reducing unnecessary complexity, so we expect *planning* to influence both *structural* and *dynamic complexity* (Bosch-Rekveldt et al., 2011; Remington and Pollack, 2007; Ashmos et al., 2000). Mocker (2009) also finds no simple linear relation between diversity-related complexity and effects of complexity. Schneberger and McLean (2003) even hypothesize a negative relation between *size/diversity* and costs for low levels of complexity. Consequently, we expect an overall increase of IS architecture complexity resulting from increases in the driver constructs:

H2: Size, diversity, integration, planning, and dynamics lead to IS architecture complexity.

In their research on information system development project (ISDP) complexity, Xia and Lee (2005) find structural and dynamic IT complexity to be distinct yet related constructs (cf. Table 5, Xia and

Lee, 2005 p.70). Based on focus group discussions, we expect this link between static and dynamic complexity to be even stronger in the context of IS architecture complexity: if a static snapshot of an IS architecture is already complex, the dynamic system will be even more so.

H3: Structural IS architecture complexity positively influences dynamic IS architecture complexity.

Furthermore, *structural complexity* has been hypothesized to be negatively influence *agility* (Arteta and Giachetti, 2004) as well as *comprehensibility* (Paulson, 2010; Premkumar and Roberts, 1999).

Focus group participants also emphasized the importance of lowering unnecessary *structural complexity* to ensure efficient operation, so we expect *structural complexity* to negatively impact *efficiency*. We do not expect *dynamic complexity* to have a strong negative effect on *efficiency* or *agility*. In fact, focus group discussion suggested that a certain level of *dynamic complexity* might be necessary for maintaining an agile operation. On the other hand, dynamically complex IS architectures are generally harder to comprehend and the effects of changes are harder to *predict*. One participant, responsible for IT complexity management in a global financial service company, stated that “reducing unnecessary complexity is the only sustainable way to reduce cost without losing flexibility and stability”. Overall, we hypothesize a negative effect of IS architecture complexity on organizational performance.

H4: IS architecture complexity has negative effects on organizational performance.

For our study, the effects of IS architecture complexity can be expected to correlate, as they originate from the same source. We do, however, not see a clear causal relation between these constructs, as, for example, no temporal order exists, in which these effects necessarily appear. This is different from the hypotheses related to drivers; as an example, more problems with integration in IS architectures arise, if a large and diverse number of components exists, whereas problems with managing a large size can arise independent of integration issues. Discussions in focus groups also did not indicate any clear causal relations between different effects, thus we refrain from formulating hypotheses for this area.

4 Data Analysis and Results

In presenting our analysis we follow the SEM guidelines of Gefen et al. (2011) by reporting all recommended results. To avoid common method bias, we compared responses from the online and the paper-based survey using Multi-Group-Analysis (MGA) and no significant differences were found, i.e. all p-values were in between 0.230 and 0.793 (Rigdon et al., 2010; Hair Jr. et al., 2014). Harman’s single-factor test leads to 19.4% variance explained, indicating that no single factor accounts for the majority of covariance among the measures (Podsakoff et al., 2003). We did not detect any outliers or particular response patterns in the results. Furthermore, at most three items of the final model are missing for any given respondent, thus allowing us to use all 249 responses during the analysis. Table 2 provides descriptive data (industry, company size, and length of employment) for the sample. As our survey was targeted at experienced senior enterprise architects and IT managers in large enterprises, more than half of our responses come from people working at organizations with more than 5000 employees and 42 percent have been employed by their current company for more than 10 years.

Industry (233 responses)	**Percent**	**Company Size (237 responses)**	**Percent**
Utilities	6,4	<50	2,9
Financial Services	30.0	50-249	8,0
Health care	3.4	250-999	10,2
Retail	4,7	1000-4999	27,8
Information and Communication	13.7	>5000	51,1
Government	5,2	**Length of Employment (212 responses)**	
Manufacturing and Processing	8.6	< 2 years	5,7
Insurance	17,2	2-5 years	27,4
Transport and Logistics	6,4	6-10 years	25,0
Others	4,3	> 10 years	42,0

Table 2. Demographics of survey respondents (249 total responses)

Item-ID		Item(1)	Ld.	t val
Size	Actor	The IT systems support a large number of users.	.65	7.60
	Tech	During day-to-day business, the productive systems require and process large amounts of data.	.54	6.40
	Task1	The IT systems support many different functionalities.	.61	5.84
	Task2	Most IT supported tasks are rather extensive and complex.	.63	7.58
Diversity	Task	The organization's IT systems are often customized to suit individual requirements.	.74	14.20
	Tech1	There is a diverse set of IT platforms which users need for their daily work.	.60	6.32
	Actor2	The expertise and requirements of system users vary considerably.	.70	9.04
	Struct	Diverse IT systems are involved in managing and controlling workflows.	.62	7.34
Integration	Actor	The employees of your company need to network and to coordinate their actions in order to accomplish their tasks.	.56	4.01
	Env	Many IT systems are closely linked to and dependent on external systems.	.70	6.32
	Struct	IT-supported workflows are highly integrated. The successful completion of a work process often depends on processes in other systems.	.69	4.91
	Task1	The successful completion of a task is often interdependent with other tasks and processes.	.59	4.19
	Task2	In your organization many interdependencies between organizational units and many cross-departmental tasks and projects exist.	.73	6.81
Planning	Actor(2)	Roles and responsibilities are assigned through well-defined processes, which include relevant stakeholders from business and IT.	.75	16.37
	Struct(2)	The development of the system landscape follows well-defined and established principles.	.81	24.06
	Task(2)	IT system requirements are developed through well-defined processes, which include relevant stakeholders from business and IT.	.62	8.89
	Tech1(2)	There are established guidelines on what types of tools and technologies are included in the portfolio of the organization.	.76	18.09
	Tech2	Decisions about the use of technologies are made opportunity-driven by individual departments and projects.	.71	16.79
Dynamics	Actor	Employees frequently change their roles and positions, and thus also their area of responsibility.	.71	15.16
	Struct(2)	Most workflows and processes remain stable throughout longer time periods.	.51	5.55
	Task1	System requirements often are short-lived and change rapidly.	.69	14.12
	Task2	The number of different tasks that need to be addressed by the IT rises quickly.	.73	16.34
	Tech	The employed technologies often still receive functional updates, which frequently leads to large system updates.	.65	10.31
Struct. Comp.	SC 1	Coordination and integration of the different systems is a difficult and not yet adequately solved task.	.85	39.50
	SC 2	Coordination between human users, software and hardware is difficult and often leads to problems.	.81	34.89
	SC 3	Interactions and dependencies between individual system components lead to a complex system landscape and are often the cause of problems.	.74	17.63
	SC 4	The number and variety of systems leads to a complex and hard to comprehend information system landscape.	.75	23.41
Dynamic Complexity	DC 1	The development of the IT landscape is characterized by uncertainties, making the impact of individual changes difficult to evaluate.	.79	29.43
	DC 2	The relationships between individual components are unclear, leading to ambiguous results, which are difficult to understand without additional information.	.82	43.16
	DC 3	In the organization there exists a large and rapidly changing range of different systems, technologies and requirements.	.72	16.82
	DC 4	The development of the IT landscape is very dynamic, requiring frequent and often difficult to understand adjustments.	.78	21.31
Effic.	Eff 1	The operating and development costs of the IT landscape are low compared to the scope of performance.	.73	9.56
	Eff 2	The time and costs required to use, operate and develop the system landscape are comparatively low.	.85	21.30
	Eff 3	Redundancies are avoided. There is little overlap between different applications and functional capabilities.	.71	10.74
Comprehen..	Comp1	The system landscape is transparent. Processes and results are understandable for the end-users.	.79	25.42
	Comp2	The development and behaviour of the IT landscape can be explained and communicated easily.	.86	48.08
	Comp3	Use and operation of the system landscape is easy to learn. New employees become acquainted with the systems quickly and without major problems.	.70	14.10
	Comp4	The behaviour of the system landscape is comprehensible. The causes of exceptions and errors can be quickly traced.	.81	28.78
Agility	Agil1	The IT department is able to react with speed and dexterity. Even larger adjustments are implemented in time and quality.	.86	34.88
	Agil2	Foreseeable adjustments are well anticipated and can be implemented without much difficulty.	.86	42.19
	Agil3	The IT department can implement critical updates and bug fixes quickly. There is little time between the decision to change something and the implementation of the change.	.81	26.23
	Agil4	The company is innovative and technologically advanced. New ideas and technologies are quickly adopted and used in production.	.63	11.13
Predictab.	Pred1	The effects of adjustments and changes are predictable. Costs and expenses for developments can be estimated reliably.	.80	27.37
	Pred2	The IT systems operate reliably. Failures and critical errors occur rarely or not at all.	.83	26.60
	Pred3	The IT system landscape is relatively stable. Major changes occur infrequently and affect only few components.	.78	21.60

(1): As the survey was developed and taken in German, the formulations here are the authors' best efforts to translate the original items.
(2): Reverse coded items

Table 3. Measurement items included in the final model

After an initial analysis of all 249 survey responses, four measurement items were dropped due to low loadings on the respective constructs, and, in hindsight, measuring different aspects. For *size* and *diversity*, two items aimed at capturing the number and diversity of external dependencies on the system. These items showed a noticeable correlation with several items from integration, but a low correlation with the intended constructs. Due to the phrasing of these items, emphasizing number and diversity instead of integration, we decided to drop rather than reassign them. For *integration*, one item related to the degree of centralization was dropped because it did not correlate with any of the other items. For *dynamics*, one item that tried to capture the employee fluctuation was dropped because responses were noticeably more positive (i.e. less fluctuation) than for other items and showed almost no variance.

4.1 Measurement model and validity tests

Table 3 provides a list of all measurement items included in the final model and their respective loadings and t-values. Table 4 contains the number of items for each construct during the different stages of this research, as well as general scale information (mean and standard deviation) and standard statistical quality criteria (composite reliability, Cronbach's α, average variance extracted (AVE), and R^2 values from the final SEM).

	Original Items	**Survey Items**	**Final Items**	**Composite Reliability**	**Cronb. Alpha**	**AVE**	**R^2**	**Mean**	**Std. Dev.**
Size	20	5	4	0.825	0.717	0.542	-	3.918	0.858
Diversity	18	5	4	0.802	0.675	0.506	-	4,259	0.706
Planning	18	6	5	0.851	0.788	0.536	-	2.830	0.734
Integration	18	5	5	0.783	0.673	0.433	0.279	3.760	0.609
Dynamics	20	6	5	0.794	0.677	0.441	0.339	3.091	0.582
Structural Complexity	4	4	4	0.866	0.793	0.618	0.208	3.494	1.817
Dynamic Complexity	4	4	4	0.861	0.785	0.607	0.606	3.255	1.940
Efficiency	3	3	3	0.809	0.654	0.586	0.121	2.807	1.357
Comprehensibility	4	4	4	0.868	0.798	0.623	0.285	2.825	2.047
Agility	4	4	4	0.867	0.794	0.623	0.162	3.085	2.213
Predictability	3	3	3	0.844	0.726	0.644	0.257	3.190	1.388

Table 4. Overview of constructs and scales

	Size	**Div.**	**Integration**	**Planning**	**Dynamics**	**Struct. Compl.**	**Dyn. Compl.**	**Efficiency**	**Compr.**	**Agility**
Diversity	.821									
Integration	.675	.607								
Planning	.216	.186	.292							
Dynamics	.815	.585	.461	.229						
Structural Complexity	.335	.295	.257	.473	.444					
Dynamic Complexity	.459	.354	.312	.471	.707	.860				
Efficiency	.421	.355	.227	.269	.322	.464	.406			
Comprehensibility	.283	.213	.243	.542	.350	.633	.564	.740		
Agility	.157	.140	.209	.423	.230	.498	.417	.770	.766	
Predictability	.299	.203	.238	.449	.436	.534	.655	.608	.781	.663

Table 5. Heterotrait-monotrait (HTMT) analysis of discriminant validity

The values for the composite reliability of the constructs (> 0.7) and for Cronbach's α are within acceptable ranges (> 0.6) for exploratory research (Hair Jr. et al., 2014). We performed separate factor analyses for all constructs to ensure unidimensionality of constructs, following Gefen (2003), and Gefen and Straub (2005). In all cases a single component was extracted, on which the items load evenly and which explains most of the variance. Discriminant validity was tested using Heterotrait-Monotrait (HTMT) analysis (see Table 5), and the results are well within the recommended thresholds (< 0.9) of Henseler et al. (2015).

4.2 Testing of hypotheses

Figure 3 shows the final SEM, capturing the relation between drivers and effects of IS architecture complexity. All constructs were measured in reflective mode. The arrows linking the constructs contain the respective path coefficients, the significance level estimates from bootstrapping with 5000 samples, and the effect sizes (f^2) in brackets. The constructs themselves include the determination coefficients (R^2), reflecting the share of an endogenous construct that is explained by the incoming links. Table 6 lists the total effects and significance levels of this model.

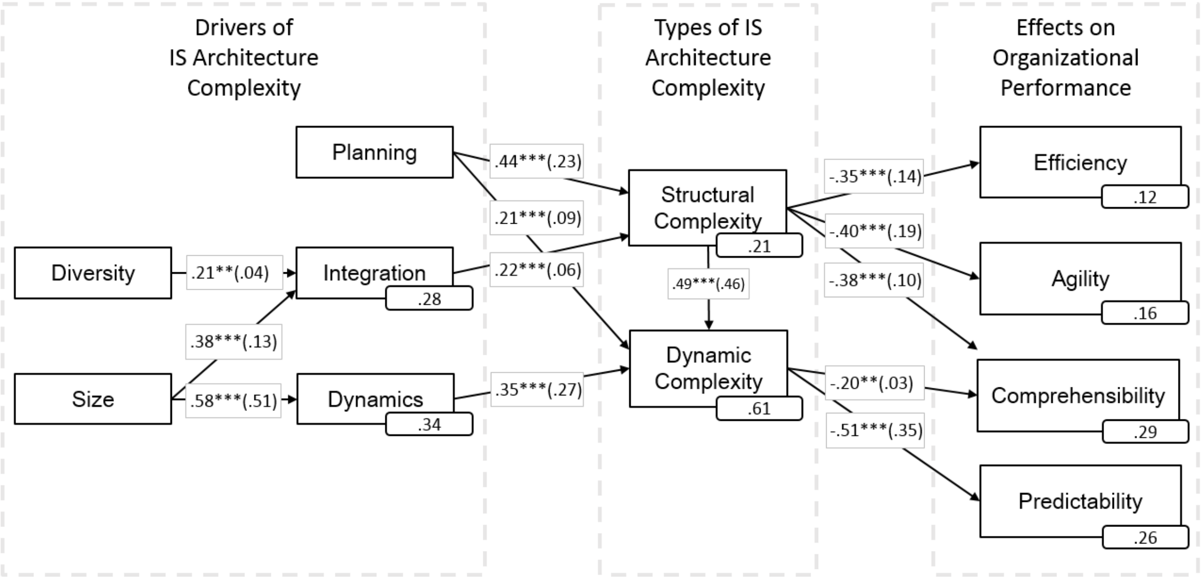

*Figure 3. Final structural equation model (***: $p < 0.01$, **: $p < 0.05$)*

Following the suggestions of Gefen et al. (2011), we compared the effects of the final model with the saturated model, i.e. the model in which nodes from one layer are connected to all nodes from subsequent layers. This is done to ensure that no significant paths have been ignored in the final model. The path coefficients and significance level estimates of the saturated model are displayed in Table 7. A comparison of Table 7 with Figure 3 and Table 6 shows that all relevant paths and effects are included in the final model. In addition, we performed linear regression analysis tests between connected constructs to ensure that the variance inflation factors (VIF) and Durbin-Watson statistics are within acceptable thresholds (Kutner et al., 2005).

Finally, we tested the predictive relevance of the model with the non-parametric Stone-Geisser test by applying a blindfolding procedure with an omission distance of 7 in SmartPLS (Hair Jr. et al., 2014). All Q^2 values (*structural complexity*: 0.120, *dynamic complexity*: 0.357, *efficiency*: 0.064, *comprehensibility*: 0.171, *agility*: 0.097, *predictability*: 0.154) are larger than zero. This indicates that the model has predictive validity, i.e., empirical data can be reconstructed using the model and the PLS parameters (Götz et al., 2010).

	Integration	Dynamics	Structural Complexity	Dynamic Complexity	Efficiency	Comprehensibility	Agility	Predict.
Size	.383***	.582***	.084***	.246***	-.029**	-.081***	-.034**	-.125***
Diversity	.205***		.045**	.022**	-.016*	-.021**	-.018*	-.011**
Planning			.435***	.424***	-.154***	-.248***	-.175***	-.215***
Integration			.220***	.108***	-.076***	-.104***	-.088***	-.055***
Dynamics				.351***		-.070**		-.178***
Structural Complexity				.493***	-.348***	-.474***	-.403***	-.250***
Dynamic Complexity						-.201***		-.507***

*Table 6. Total effects in the final model (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$)*

	Integr.	Dynamics	Planning	Structural Compl.	Dynamic Compl.	Efficiency	Compr.	Agility	Predict.
Size	.389***	.531***	-.050	.042	.003	-.188*	-.085	-.022	-.037
Diversity	.197**	.084	.008	.052	.030	-.089	-.013	-.054	-.044
Planning				.410***	.218***	-.110	-.300***	-.166**	-.223***
Integration				.260**	.084	-.018	-.039	-.128*	-.086
Dynamics				.098	.342***	-.016	-.072	.011	-.100
Structural Complexity					.484***	-.228***	-.308***	-.269***	-.083
Dynamic Complexity						-.008	-.070	-.125	-.291***

*Table 7. Path coefficients of the saturated model (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$)*

In general, the R^2 levels resemble approximately the values that can be expected from similar studies when using only IS architecture complexity as a construct for explaining aspects of organizational performance (see, for example, Mocker, 2009). We now present the findings of our hypotheses testing, based on Figure 3 and Table 6.

H1 is supported and made more precise: Diversity and size influence integration and size influences dynamics. Other interdependencies are not supported by a comparison with paths in the saturated model, thus the final model only includes these links. For both, integration and dynamics, size is a major influence factor, whereas the impact of diversity is comparatively low.

Regarding *H2*, we find that inadequate planning leads to structural complexity and strong dynamics lead to dynamic complexity. To a lower extent, planning also affects dynamic complexity and the level of integration positively influences structural complexity. *H3* is also supported: Structural complexity has a major impact on dynamic complexity.

In terms of complexity effects (*H4*), structural complexity influences efficiency, agility, and comprehensibility, and dynamic complexity influences comprehensibility and predictability. All relations are significant, however the R^2 values of comprehensibility and predictability are noticeably higher when compared to efficiency and agility.

5 Discussion and Conclusion

The contribution of this research is twofold. First, concerning IS architecture, we derived and tested a conceptual model that links identified drivers and effects of IS architecture complexity. In this context, our results suggest that a high degree of integration, a large size, high diversity, strong dynamics, and, in particular, inadequate planning significantly contribute to IS architecture complexity. Structural complexity is mainly driven by inadequate planning, whereas dynamic complexity is mostly the result of a high structural complexity combined with strong dynamics. This IS architecture complexity then negatively impacts the organization's efficiency, agility, comprehensibility, and predictability. Structural complexity is linked to decreases in efficiency, agility, and comprehensibility, whereas dynamic complexity negatively affects predictability and comprehensibility. These results extend previous research on IS architecture complexity (e.g., Mocker, 2009) by not limiting the scope of analysis to costs and purely technical aspects of the IS architecture but instead using a comprehensive research model, including dynamic and social aspects of the IS, which also analyses effects on other important aspects of organizational performance, such as agility, comprehensibility, and transparency.

Second, we contribute to literature on IS complexity by not only conceptualizing and explicitly linking identified complexity drivers and related effects in the context of IS architecture but also quantifying the effects of these relations. This extends previous studies (e.g., Benbya and McKelvey, 2006; Bosch-Rekveldt et al., 2011; Schneider et al., 2015) that have investigated general consequences of complexity in the context of information systems and have hypothesized individual relations between constructs. The proposed integrated model positions all identified constructs in relation to each other and tests these relations. The choice of paths for the final model, while a-priori not obvious, is supported by literature, focus group discussions, and by comparison with the saturated model.

For interpreting our results, it is noteworthy that our model measures the overall complexity of an IS architecture, which is considered independent of underlying business requirements. Research suggests that a certain level of business-induced complexity is expected to benefit the overall organization, since negative effects due to complexity are offset by benefits on the business side (Kourteli, 2000; Schneberger and McLean, 2003). This leads to an important distinction between necessary IS complexity, i.e., IS complexity that is the direct result of business requirements, and unnecessary IS complexity, i.e., IS complexity that cannot be justified by inevitable business complexity (Kourteli, 2000). Below a certain threshold of inevitable IS complexity, an increase in complexity may actually benefit the organization as a whole (Schneberger and McLean, 2003). Thus, our results do not allow to derive a somehow optimal level of IS architecture complexity, as they only quantify the overall negative effects.

With regard to limitations, we note that we cannot claim our sample to be representative of a more general population. We did, however, select survey participants based on their expertise with the IS architecture in their organization and thus expect our results to adequately reflect the state of large real-world enterprises. Furthermore, we tested for invariance between industries and found no significant differences.

Keeping this limitation and the discussion on necessary versus unnecessary complexity in mind, the proposed model allows for a high-level estimate of the consequences of architectural IS design decisions. This provides practitioners with a tool to guide and focus their complexity management efforts: if a specific strategic goal is given, for example an increase in comprehensibility and predictability due to regulatory requirements, the path estimates in Figure 3 and the total effects in Table 6 can be used to evaluate prospective changes to the IS architecture.

Furthermore, we expect the proposed quantitative model to provide a useful basis for a more sophisticated analysis of the underlying generative mechanisms of IS architecture complexity. Our results give researchers a better understanding of the specific relations between drivers of IS architecture complexity, IS architecture complexity itself, and effects of IS architecture complexity. Future efforts may provide more insight into the actions and design choices of the people that guide the evolution of the IS as well as the rationale behind these actions and choices.

References

Abdullah, N. S., S. Sadiq and M. Indulska (2010). Emerging Challenges in Information Systems Research for Regulatory Compliance Management. In Advanced Information Systems Engineering (Pernici, B., Ed),251-265, Springer Berlin Heidelberg.

Arteta, B. M. and R. E. Giachetti (2004). "A measure of agility as the complexity of the enterprise system". *Robotics and Computer-Integrated Manufacturing* 20 (6), 495-503.

Ashmos, D. P., D. Duchon and R. R. Mcdaniel (2000). "Organizational responses to complexity: the effect on organizational performance". *Journal of Organizational Change Management* 13 (6), 557-595.

Attewell, P. (1992). "Technology Diffusion and Organizational Learning: The Case of Business Computing". *Organization Science* 3 (1), 1-19.

Avgerou, C. (2001). "The significance of context in information systems and organizational change". *Information Systems Journal* 11 (1), 43-63.

Baccarini, D. (1996). "The concept of project complexity - a review". *International Journal of Project Management* 14 (4), 201-204.

Beese, J., S. Aier and R. Winter (2015). "On the role of complexity for guiding enterprise transformations". In *5th Enterprise Engineering Working Conference* (Aveiro, D. and Pergl R. and Valenta M., Eds), 113-127, Springer, Prague.

Benbya, H. and B. Mckelvey (2006). "Using coevolutionary and complexity theories to improve IS alignment: A multi-level approach". *Journal Of Information Technology* 21 (4), 284-298.

Boisot, M. (2006). "Moving to the edge of chaos: Bureaucracy, IT and the challenge of complexity". *Journal of Information Technology* 21 (4), 239-248.

Boisot, M. and B. Mckelvey (2010). "Integrating Modernist and Postmodernist Perspectives on Organizations: A Complexity Science Bridge". *Academy of Management Review* 35 (3), 415-433.

Bosch-Rekveldt, M., Y. Jongkind, H. Mooi, H. Bakker and A. Verbraeck (2011). "Grasping project complexity in large engineering projects: The TOE (Technical, Organizational and Environmental) framework". *International Journal of Project Management* 29 (6), 728-739.

Brynjolfsson, E. and L. M. Hitt (2000). "Beyond computation: Information technology, organizational transformation and business performance". *The Journal of Economic Perspectives*, 23-48.

Campbell, D. J. (1988). "Task Complexity: A Review and Analysis". *Academy of Management Review* 13 (1), 40-52.

Chalmers, A. F. (1999) *What Is this Thing Called Science?* 3. Open University Press, Buckingham.

Churchill Jr., G. A. (1979). "A Paradigm for Developing Better Measures of Marketing Constructs". *Journal of Marketing Research* 16 (1), 64-73.

Cooke-Davies, T., S. Cicmil, L. Crawford and K. Richardson (2007). "We're Not in Kansas Anymore, Toto: Mapping the Strange Landscape of Complexity Theory, and Its Relationship to Project Management". *Project Management Journal* 38 (2), 50-61.

Creswell, J. W. and V. L. P. Clark (2011) *Designing and conducting mixed methods research*. 2nd. Sage, Thousand Oaks, CA.

Dewar, R. and J. Hage (1978). "Size, Technology, Complexity, and Structural Differentiation: Toward a Theoretical Synthesis". *Administrative Science Quarterly* 23 (1), 111-136.

Dijkstra, T. K. (2010). Latent Variables and Indices: Herman Wold’s Basic Design and Partial Least Squares. In Handbook of Partial Least Squares (Vinzi, V. E. and Chin W. W. and Henseler J. and Wang H., Eds)23-46, Springer Berlin Heidelberg.

Dubin, R. (1978) *Theory Building*. Free Press, New York.

Energie, B. F. (2014) *Füllungsgrad der Speicherseen 2014, Sonntag 24h, Wochenbericht Speicherinhalt*.

Faul, F., E. Erdfelder, A. Buchner and A.-G. Lang (2009). "Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses". *Behavior Research Methods* 41 (4), 1149-1160.

Gefen, D., E. Karahanna and D. W. Straub (2003). "Trust and TAM in online shopping: An integrated model". *MIS Quarterly* 27 (1), 51-90.

Gefen, D., E. E. Rigdon and D. Straub (2011). "An Update and Extension to SEM Guidelines for Administrative and Social Science Research". *MIS Quarterly* 35 (2), iii-xiv.

Gefen, D. and D. Straub (2005). "A Practical Guide to Factorial Validity Using PLS-Graph - Tutorial and Annotated Example". *Communications of the AIS* 16 (5), 91-109.

Geraldi, J. (2009). "What complexity assessments can tell us about projects: dialogue between conception and perception". *Technology Analysis & Strategic Management* 21 (5), 665-678.

Geraldi, J., H. Maylor and T. Williams (2011). "Now, let's make it really complex (complicated) A systematic review of the complexities of projects". *International Journal of Operations & Production Management* 31 (9), 966-990.

Gibson, A. and D. Simpson (2015). "The Mexican transparency standoff: What will you do ‘next time’?". *Journal of Securities Operations & Custody* 7 (4), 362-369.

Götz, O., K. Liehr-Gobbers and M. Krafft (2010). Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach. In Handbook of Partial Least Squares: Concepts, Methods and Applications (Vinzi, V. E. and Chin W. W. and Henseler J. and Wang H., Eds)691-711, Springer, Heidelberg.

Gregor, S. (2006). "The Nature of Theory in Information Systems Research". *MIS Quarterly* 30 (3), 611–642.

Gupta, A., H. Li and R. Sharda (2013). "Should I send this message? Understanding the impact of interruptions, social hierarchy and perceived task complexity on user performance and perceived workload". *Decision Support Systems* 55 (1), 135-145.

Hair Jr., J. F., G. T. M. Hult, C. M. Ringle and M. Sarstedt (2014) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage, Los Angeles, CA.

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

Hoogervorst, J. a. P. (2004). "Enterprise Architecture: Enabling Integration, Agility and Change". *International Journal of Cooperative Information Systems* 13 (3), 213-233.

Howell, D., C. Windahl and R. Seidel (2010). "A project contingency framework based on uncertainty and its consequences". *International Journal of Project Management* 28 (3), 256-264.

Iivari, J. and M. Huisman (2007). "The Relationship between Organizational Culture and the Deployment of Systems Development Methodologies". *MIS Quarterly* 31 (1), 35-58.

Iso/Iec/Ieee (2011). "Systems and software engineering — Architecture description (ISO/IEC/IEEE 42010:2011).

Järvinen, P. (2001) *On Research Methods*. Opinpajan kirja, Tampere, Finland.

Kourteli, L. (2000). "Scanning the business environment: some conceptual issues". *Benchmarking: An International Journal* 7 (5), 406-413.

Kutner, M., C. Nachtsheim, J. Neter and W. Li (2005) *Applied Linear Statistical Models*. 5th. McGraw-Hill/Irwin.

Luna-Reyes, L. F., J. Zhang, J. Ramón Gil-García and A. M. Cresswell (2005). "Information systems development as emergent socio-technical change: a practice approach". *European Journal of Information Systems* 14 (1), 93-105.

Maccallum, R. C., M. W. Browne and H. M. Sugawara (1996). "Power analysis and determination of sample size for covariance structure modeling". *Psychological Methods* 1 (2), 130-149.

Mackenzie, S. B., P. M. Podsakoff and N. P. Podsakoff (2011). "Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques". *MIS Quarterly* 35 (2), 293-334.

Maylor, H., R. Vidgen and S. Carver (2008). "Managerial complexity in project-based operations: A grounded model and its implications for practice". *Project Management Journal* 39, 15-26.

Mckeen, J. D., T. Guimaraes and J. C. Wetherbe (1994). "The relationship between user participation and user satisfaction: an investigation of four contingency factors". *MIS Quarterly* 18 (4), 427-451.

Mcleod, L. and B. Doolin (2012). "Information systems development as situated socio-technical change: a process approach". *European Journal of Information Systems* 21 (2), 176-191.

Melville, N., K. Kraemer and V. Gurbaxani (2004). "Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value". *MIS Quarterly* 28 (2), 283-322.

Merali, Y. (2006). "Complexity and information systems: The emergent domain". *Journal of Information Technology* 21 (4), 216-228.

Meyer, M. H. and K. F. Curley (1991). "An Applied Framework for Classifying the Complexity of Knowledge-Based Systems". *MIS Quarterly* 15 (4), 455-472.

Mocker, M. (2009). "What Is Complex About 273 Applications? Untangling Application Architecture Complexity in a Case of European Investment Banking". In *42nd Hawaii International Conference on System Sciences, 2009. HICSS '09*.

Page, S. E. (2010) *Diversity and Complexity*. 1st. Princeton University Press.

Paulson, H. (2010) *On The Brink: Inside the race to stop the collapse of the global financial system*. Hachette UK.

Pich, M. T., C. H. Loch and A. De Meyer (2002). "On Uncertainty, Ambiguity, and Complexity in Project Management". *Management Science* 48 (8), 1008-1023.

Podsakoff, P. M., S. B. Mackenzie, J.-Y. Lee and N. P. Podsakoff (2003). "Common Method Biases in Behavioral Research - A Critical Review of the Literature and Recommended Remedies". *Journal of Applied Psychology* 88 (5), 879-903.

Premkumar, G. and W. R. King (1992). "An Empirical Assessment of Information Systems Planning and the Role of Information Systems in Organizations". *Journal of Management Information Systems* 9 (2), 99-125.

Premkumar, G. and M. Roberts (1999). "Adoption of new information technologies in rural small businesses". *Omega* 27 (4), 467-484.

Remington, K. and J. Pollack (2007) *Tools for Complex Projects*. Gower Publishing, Ltd.

Renn, O., A. Klinke and M. V. Asselt (2011). "Coping with Complexity, Uncertainty and Ambiguity in Risk Governance: A Synthesis". *AMBIO* 40 (2), 231-246.

Ribbers, P. M. A. and K.-C. Schoo (2002). "Program Management and Complexity of Erp Implementations". *Engineering Management Journal* 14 (2), 45.

Rigdon, E. E., C. M. Ringle and M. Sarstedt (2010). "Structural modeling of heterogeneous data with partial least squares". *Review of Marketing Research* 7 (7), 255-296.

Ringle, C. M., M. Sarstedt and D. W. Straub (2012). "A Critical Look at the Use of PLS-SEM in MIS Quarterly". *MIS Quarterly* 36 (1), iii-xiv.

Ringle, C. M., S. Wende and J.-M. Becker (2015). "SmartPLS 3. " *Bönningstedt: SmartPLS*.

Ross, J. W., P. Weill and D. C. Robertson (2006) *Enterprise Architecture as Strategy. Creating a Foundation for Business Execution*. Harvard Business School Press, Boston, MA, USA.

Sabherwal, R. and A. Jeyaraj (2015). "Information Technology Impacts on Firm Performance: An Extension of Kohli and Devaraj (2003)". *MIS Ouarterly* 39 (4), 809-836.

Sambamurthy, V., A. Bharadwaj and V. Grover (2003). "Shaping Agility through Digital Options: Reconceptualizing the Role of Information Technology in Contemporary Firms". *MIS Quarterly* 27 (2), 237-263.

Schmidt, C. and P. Buxmann (2011). "Outcomes and success factors of enterprise IT architecture management: empirical insight from the international financial services industry". *European Journal of Information Systems* 20 (2), 168-185.

Schneberger, S. L. and E. R. Mclean (2003). "The complexity cross: implications for practice". *Communications of the ACM* 46 (9), 216-225.

Schneider, A. W., T. Reschenhofer, A. Schütz and F. Matthes (2015). "Empirical Results for Application Landscape Complexity". In: *Proceedings of the 48th Hawaii International Conference on System Sciences (HICSS)*, 4079-4088.

Schütz, A., T. Widjaja and J. Kaiser (2013). "Complexity In Enterprise Architectures - Conceptualization And Introduction Of A Measure From A System Theoretic Perspective". In *Proceedings of the International Conference On Information Systems, ICIS 2013* Association for Information Systems, AIS Electronic Library (AISeL).

Sharma, R. and P. Yetton (2007). "The Contingent Effects of Training, Technical Complexity and Task Interdependence on Successful Information Systems Implementation". *MIS Quarterly* 31 (2), 219-238.

Stewart, D. W., P. N. Shamdasani and D. W. Rook (2007) *Focus Groups: Theory and Practice*. 2. Sage Publications, Thousand Oaks.

Stirling, A. (2007). "A general framework for analysing diversity in science, technology and society". *Journal of the Royal Society Interface* 4 (15), 707-719.

Tait, P. and I. Vessey (1988). "The Effect of User Involvement on System Success: A Contingency Approach". *MIS Quarterly* 12 (1), 91-108.

Tallon, P. P. and A. Pinsonneault (2011). "Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model". *MIS Quarterly* 35 (2), 463-486.

Tsoukas, H. and R. Chia (2002). "On organizational becoming: Rethinking organizational change". *Organization Science* 13 (5), 567-582.

Vessey, I. and K. Ward (2013). "The Dynamics of Sustainable IS Alignment: The Case for IS Adaptivity". *Journal of the Association for Information Systems* 14 (6), 283-311.

Wallace, W. L. (1983) *Principles of Scientific Sociology*. Aldine Publishing Company, New York.

Weidong and Lee (2005). "Complexity of Information Systems Development Projects: Conceptualization and Measurement Development". *Journal of Management Information Systems* 22 (1), 45-83.

Whitty, S. J. and H. Maylor (2009). "And then came Complex Project Management (revised)". *International Journal of Project Management* 27 (3), 304-310.

Wieland, A. and C. M. Wallenburg (2012). "Dealing with supply chain risks: Linking risk management practices and strategies to performance". *International Journal of Physical Distribution & Logistics Management* 42 (10), 887-905.

Wood, R. E. (1986). "Task complexity: Definition of the construct". *Organizational Behavior and Human Decision Processes* 37 (1), 60-82.

Xia, W. and G. Lee (2005). "Complexity of Information Systems Development Projects: Conceptualization and Measurement Development". *Journal of Management Information Systems* 22 (1), 45-83.

Xu, J., I. Benbasat and R. T. Cenfetelli (2014). "The influences of online service technologies and task complexity on efficiency and personalization". *Information Systems Research* 25 (2), 420-436.

Yayavaram, S. and W.-R. Chen (2015). "Changes in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity". *Strategic Management Journal* 36 (3), 377-396.