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Interorganizational Information System Deployment in Supply Chain Triads

Frank Bodendorf
Friedrich Alexander University Erlangen-Nuremberg, frank.bf.bodendorf@bmw.de

Lars Schmidt
Technical University of Munich, lars_schmidt@me.com

Jörg Franke
Friedrich-Alexander-University of Erlangen-Nuremberg, joerg.franke@faps.fau.de

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Completed Research Paper

Frank Bodendorf
Friedrich-Alexander-University Erlangen-Nuremberg
Egerlandstraße 7
frank.bodendorf@fau.de

Lars Schmidt
Technical University of Munich
Arcisstraße 21
lars.schmidt@tum.de

Joerg Franke
Friedrich-Alexander-University Erlangen-Nuremberg
Egerlandstraße 7
joerg.franke@fau.de

Abstract

Interorganizational information systems (IOIS) are valuable tools providing platforms for information flow enabling more efficient and reliable collaboration in digitalized supply chains. An IOIS is subject to influencing factors originating in the company and environment. Inspired by complex adaptive system theory, an agent-based simulation model is designed, exploring factors affecting the integration and efficiency of IOIS. These factors are derived from resource-based view and dynamic capabilities theory. The influence on information system deployment is assessed by merging these factors into exogenous, intercompany climate, and operational dimensions. First, the results indicate that product-specific factors have a greater influence than the environment when deploying an IOIS. Second, deliberate design of IC relationships should be considered during the development of an IOIS. Third, extensive information exchange between supply chain partners might be disadvantageous for IOIS utilization. Fourth, the advantages of IOIS can be lost when completely open systems are used.

Keywords: Interorganizational information systems, complex adaptive systems, agent-based modeling, supply chain management

Introduction

A supply chain can be described as a network of companies where joint value creation takes place. This puts the supply chain at the core of the business of its participants. To optimize management across the chain, collaboration of the involved companies becomes necessary. Efficient information exchange via interorganizational systems within supply chains is essential to gain an advantage over competitors (Mikalef et al., 2020). Using interorganizational systems builds supply chain management capabilities, which positively influence supply chain performance. To generate and sustain this advantage, Grover (1993) and Nidumolu (1995) propose interorganizational information systems (IOIS) as a vital instrument to enhance the information exchange between supply chain partners. IOIS are especially valuable as the variety of customer demands increases and product lifetime decreases, resulting in ever more dynamic challenges in the supply chain. To keep up with the requirements of these increasingly difficult conditions, a higher level of supply chain collaboration is necessary, which can be achieved by deploying IOIS (Q. Zhang

& Cao 2018). IOIS are systems comprising computers and people that process information and allow information exchange between companies. Building IOIS facilitates the pooling and integration of the resources available to supply chain partners. The specification of IOIS ranges from rudimentary workflows to highly complex and integrated ecosystems. Larger companies are most likely to employ an extensive range of information systems (IS), including IOIS, which develop over time (Du et al. 2019).

Research in the field of supply chain management is founded on several management theories. According to van Weele and van Raaij (2014) the resource-based view (RBV) and the dynamic capabilities theory (DCT) are popular candidates used as basic theories for research in the field of IS and supply chain management. This study explores the influencing factors coming from these fundamental theories on IOIS and opens up a promising research avenue. Even though the RBV has been quite present in IS research (Wade & Hulland 2004), the explicit connection of RBV to IOIS is scarce in the existing literature. One rare example is the paper of C. Zhang and Dhaliwal (2009) who examine the influence of RBV and institutional theory on the adoption of technology for intercompany (IC) supply chain management. In the scope of the RBV strategic information technology (IT) alignment in the sense of IOIS can also be seen as a resource (Sabherwal et al. 2019). The DCT receives some more attention in the IOIS literature. In three case studies Holweg and Pil (2008) apply the DCT among other theories to the exploration of supply chain management and IT system usage. They conclude that the DCT has a too narrow perspective towards one firm to explain phenomena in supply chains generally. Rajaguru and Matanda (2013) use the DCT to connect supply chain capabilities with IOIS integration which refers to connecting actors and IT applications across different organizations. Mikalef et al. (2020) introduce the concept of IT-enabled dynamic capabilities as a requirement for better competitive performance. Additionally, Rai et al. (2012) are concerned with DCT and explain how relational value is created by means of IOIS.

Motivated by previously mentioned literature streams this paper takes advantage of RBV and DCT to explore the use of IOIS in supply chains and its economic efficiency which refers to the total payoffs and costs that occur to all actors. This leads us to the following research question addressed in this paper: How are IOIS in supply chain triads influenced by factors originating from the concepts of resources available to the single company (RBV) and adoption in the resource base of involved companies (DCT)? Building on an agent-based model (ABM), this study presents a validated simulation model that enables the integration of RBV and DCT. The approach opens up additional possibilities such as the simulation of supply chain triads as the smallest unit of a supply network existing of three nodes and links connecting them, allowing a more focused analysis of interactions and dependencies. Moreover, the approach enables the independent manipulation of different influencing factors and the analysis of extreme conditions.

Theoretical Foundation

Different influencing factors on IC relations and IOIS integration are identified by a literature review. Following the framework given by Wolfswinkel et al. (2013) axial and selective coding is used to identify second-order themes, which group similar 1st order concepts into higher-level categories that capture overarching ideas, and aggregated dimensions, which classify patterns and connections that exist across the second order themes. These second-order concepts bundle multiple influencing factors and may contradict each other as not all influences identified in the literature are consensual. An overview of those influencing factors is given in Figure 1. The different concepts are discussed in more detail below.

The main dimensions all concepts have been assigned to are called exogenous, relational, and operational dimensions. Each base theory contributes different factors to the model. First, the RBV gives insights into the static resources, including environmental and product-related aspects (Grover 1993; Grover and Saeed 2007; Li and Lin 2006). These factors form one exogenous dimension. Second, the DCT contributes to how resources and competencies can develop in a partnership (Wang et al. 2006). This perspective leads to the collaboration factor, which describes the sharing of profits and risks, as well as to the factor of technical compatibility between parties. The operational dimension is formed by combining collaboration and technical compatibility. Additionally, motivated by Rajaguru & Matanda (2013), the DCT provides the background of IC aspects of the supply chain. These insights are used to synthesize the IC prerequisites and behavior, which describe the initial and pursued relationship between the supply chain partners by means of IOIS. IC prerequisites and behaviors are combined in the relational dimension.

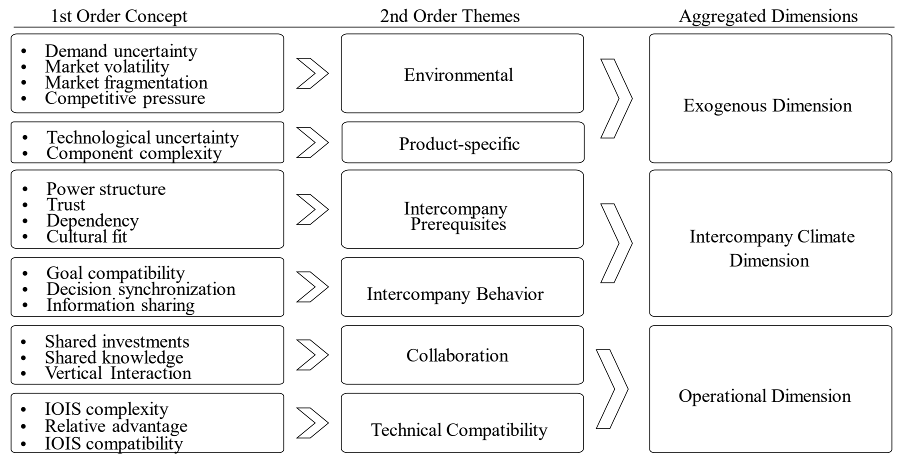


Figure 1. Initial concepts derived from grounded theory analysis

The **exogenous dimension** subsumes all influences that the actors cannot control. It must also hold that the market segment cannot be switched and the product or rather the kind of product is not changeable in its foundation. Thus, the dimension comprises concepts that originate from the environment in which the companies operate and form product-specific properties.

Environmental Factors: Demand uncertainty is the degree to which the customer demand or taste can change (Li & Lin 2006). Grover and Saeed (2007) make the point that IOIS enable faster access to more information across the supply chain. Information systems lead to a more effective and coordinated response to demand uncertainty, which supports the usage of IOIS in such contexts (Wang et al., 2006). *Market volatility* can be defined as ”the rate at which prices and players in the industry change over time” (Choudhury 1997, p. 14). Grover and Saeed (2007) argue that buyers are less willing to restrict themselves to the only source from selected suppliers in volatile environments to ensure continuous service. The concept of volatility is also described as market maturity by Grover (1993). The argument of Grover (1993) is that higher levels of innovation are necessary for mature markets to differentiate the company from competitors and to increase sales. Therefore, maturity has an impact on the integration of IOIS. *Market fragmentation* denotes the variance of prices and products from different companies within one market. Narayanan et al. (2009) distinguish between buyer side and supplier side when analyzing market fragmentation. The authors argue that a consolidated market with only a few buyers leads to an environment in which the adoption of IOIS is mandatory for the suppliers. *Competitive pressure* can be defined as the effects that the development of a specific company experiences from other competing companies (Grover, 1993). Innovation activities are especially affected by competitive pressure due to the need to keep pace with the environment. Innovations that create a competitive advantage in the market can result in increased revenue and market share. This financial success can provide organizations with additional funds to invest in IOIS deployment initiative.

Product-specific Factors: Technological uncertainty is defined by Li and Lin (2006) as the unpredictability of technological development in an industry. Son et al. (2005) argue that IOIS systems are not ideal under high technological uncertainty and conclude that any kind of uncertainty decreases the adoption of IOIS. Similar to competitive pressure, technological uncertainty also influences the IOIS integration according to Grover (1993). *Component complexity* can be defined using the general definition of complexity given by Grover (1993). This complexity requires seamless coordination and the exchange of high amounts of information between the supply chain partners. This high demand for complex products favors the deployment of an IOIS, which makes information more quickly accessible and offers an adequate process for capturing, storing, and organizing information.

The intercompany climate dimension refers to the transactions' aura, which ”describes the sentiments that exist between the dyad members” (Nidumolu 1995, p. 92). In this sense, the IC climate is made up of concepts that are at the core of the relationship and can be influenced by the interacting firms. Unlike the environment dimensions, the IC climate can be changed theoretically in the course of a relationship. However, in practice observations, once an IC climate is established, it tends to become fixed because altering could potentially lead to inefficiencies or conflicts between the partners.

Intercompany Prerequisites: Power itself needs to be described first to define the power balance in the supply chain. Power can be seen as the extent to which one entity can exert influence on another (Bodendorf and Franke, 2022). Power can be balanced unequally, as a powerful buyer may have control over a pool of suppliers. Son et al. (2005) argue that these powerful companies can influence their counterparties to adapt IOIS. *Trust* is defined by Li and Lin (2006) as the willingness to rely on a trading partner. It can also be seen as the acceptance to be vulnerable to the actions of a partner (Klein & Rai 2009). Kembro et al. (2017) find that trust is a crucial factor to enable interorganizational information sharing. Grover and Saeed (2007) argue that trust is necessary when companies engage in IOIS due to the potential abuse of information by the other party. Carr and Smeltzer (2002), on the other hand, conclude that trust does not influence the IT use for collaboration between companies. *Dependency* is a core factor of supply chain collaboration. The need of accessing a partner's resource yields dependency, which naturally has different characteristics depending on the relation of the supply chain partners (Klein & Rai 2009). In the IOIS context *cultural fit* is defined by Kembro et al. (2017) as the willingness of persons involved in supply chain activities to collaborate and share information. Rajaguru and Matanda (2013) go into detail about the culture and the cultural fit. They point out that "cultural fit rests on shared business philosophies, subjective norms, traditions, and values" (Rajaguru & Matanda 2013, p. 3). They derive that successful integration of IOIS is based on a cultural fit between the supply chain participants.

Intercompany Behavior: Goal compatibility is defined by Nidumolu (1995) as the degree to which a company can fulfill its own goals while working on a common task. Rajaguru and Matanda (2013) point out that a higher level of IOIS integration is more likely if the strategic goals of the supply chain partners are aligned. As stated by Q. Zhang and Cao (2018), *decision synchronization* comprises measures to align the activities of all participants in the supply chain. This affects nearly all aspects of the supply chain, such as resource and capacity planning, procurement, and logistics. In comparison to goal compatibility, decision synchronization refers to the joint planning once compatible goals are set (Cao et al. 2010). Muckstadt et al. (2001) point out that true collaboration does not only require the exchange of data but also joint planning of the inventory and production strategy of the supply chain. Wang et al. (2006) conclude that these joint efforts are information-intensive and do therefore promote the virtual integration of the supply chain participants. *Information Sharing* is defined by Cao et al. (2010) as the extent to which a firm shares ideas, plans, and procedures with its trading partners. The importance of data accuracy for information sharing between IT systems is stressed by Rai et al. (2006). According to Rai et al. (2012) this information exchange also leads to fostering business development between the participating parties since learnings can be drawn from the relationship.

Besides environmental and climate-related dimensions, the last dimension comprises all **operational factors**. Those operational elements can be altered by the cooperating companies relatively easily and shape the everyday business of the supply chain.

Intercompany Collaboration: Shared investments can be defined as the process of collaboratively ”investing in capabilities and assets with supply chain partners” (Cao et al., 2010, p. 6620). Kembro et al. (2017) link this to the integration of IOIS since the sharing of information requires mutual investments. The IOIS itself can therefore be seen as a shared investment between the partners of a supply chain. Based on this, Klein and Rai (2009) specify that the degree of IT customization plays a role for the efficiency of information sharing. Better customized systems enable higher levels of information sharing but are also more investment-intensive. *Shared knowledge* refers to the collaboratively created know-how of supply chain participants to operate in their market (Cao et al. 2010). This makes it different from information sharing, which refers to necessary information on an operational basis. With IOIS in mind, Q. Zhang and Cao (2018) suggest that data processing is a valuable instrument for the creation of shared knowledge. *Vertical interaction* is described by Nidumolu (1995) as the scope to which the individual partners of a supply chain are linked. This link is established by the flow of resources, activities, and information - upstream as well as downstream. Grover (1993) points out that the requirement of close coordination characterizes supply chains with high vertical dependencies. The resulting close relationship between the participating companies promotes the integration of IOIS. Nidumolu (1995) also hypothesizes a link between IOIS investments and vertical interactions. This conclusion is due to the higher interaction between the companies that make investments in IOIS necessary in the first place.

Technical Compatibility: IOIS complexity can be defined by referring to the general definition of complexity given by Grover (1993): The level of difficulty, which is met by a user when using the IOIS can be seen as its complexity level. Data is generally more accessible when modern data storage systems are deployed. From this it can be concluded that the deployment of an IOIS generally reduces the complexity to handle data. To the opposite, Rajaguru and Matanda (2013) indicate that complexity of IT systems can slow down or hinder the integration of IOIS. *Relative advantage* can be defined as the property of a particular innovation to contribute a higher benefit compared to the current situation and alternative innovations (Grover 1993). It is imperative to note here that the advantage of a system is a subjective measure as only its users can perceive it. Rai et al. (2012) stress that logistics operations are especially information-intensive and feature complex relationships. New and innovative systems are therefore introduced frequently and need to be evaluated regularly to prevent inefficiencies. Grover (1993) hypothesizes that innovations such as IOIS, which are perceived to have advantages, are more likely to be adopted. Additionally, Narayanan et al. (2009) point out that more advanced information processing systems will reduce information uncertainty and time delays. *IOIS compatibility* is described by Grover (1993) as the degree to which an innovation fits the existing business practice as well as the future needs of a user. Rajaguru and Matanda (2013) say that technical compatibility originates from similar information systems that the supply chain partners deploy. This technical compatibility is vital since Kyu Kim et al. (2011) point out that the real-time exchange of information is not feasible with incompatible information systems. Kembro et al. (2017) remark that different technical systems may lead to difficulties when implementing new structures for information exchange. Rajaguru and Matanda (2013) emphasize that despite advances in electronic systems, technical barriers still exist, which might hinder the successful implementation of IOIS.

Hypotheses Development

Current literature is not conclusively investigating the interrelationships between the above-mentioned factors and IOIS integration. One can identify the following gaps due to limitations in the existing research:

- The proposed factors have not yet been examined in a connected system, but their effect has been determined individually and across multiple studies.
- An aggregation of the underlying first-order concepts, as proposed in this paper, has not been conducted yet. IOIS integration has been examined based on the individual first-order concepts and no second-order themes have been developed.
- The cited studies are either theoretical works or surveys, limited to certain industries. No simulation model has yet been conducted to examine IOIS-integration on an IC level.
- Not all of the proposed factors have been examined concerning IOIS integration. Some of the factors, like IC dependency and decision synchronization, have only been examined for their connection to the general relationship between companies.
- The identified literature focuses mainly on the dyadic relationship between companies in supply chains. A simulation model can explore the IOIS integration in more than dyadic relationships.

This study uses second-order themes to gain insights into the relevance of each effect. These themes, which are displayed in Figure 1, are interpreted as influencing factors on IOIS integration. Following the arguments in the theoretical background section the following hypotheses regarding the exogenous dimensions are derived:

- H1. Environmental factors, which comprise demand uncertainty, market volatility, market fragmentation, and competitive pressure, harm IOIS integration and efficiency in supply chains.
- H2. Product-related factors in the form of technological uncertainty and component complexity have a positive effect on IOIS integration and efficiency in supply chains.

The climate dimensions can also be seen to influence IOIS integration. This leads to:

- H3. Prerequisites in the relationship between the trading partners, represented by trust, power structure, dependency, and cultural fit, have a positive effect on IOIS integration and efficiency in supply chains.
- H4. Behavioral factors, characterized by goal compatibility, decision synchronization, and information sharing between partners, have a positive effect on IOIS integration and efficiency in supply chains.

The last dimension hypothesized to have a direct effect on the integration and efficiency of IOIS is the operational dimension. This leads to the subsequent hypotheses.

- H5. Collaboration, represented by shared investments, shared knowledge, ownership participation, and vertical integration, has a positive effect on IOIS integration and efficiency in supply chains.
- H6. Technical factors, reflected by IOIS complexity, IOIS compatibility, and relative advantage of the technology, have a positive effect on IOIS integration and efficiency in supply chains.

In a real-world scenario, it can be expected that multiple factors change simultaneously. The aggregated dimensions as used above can therefore also affect the integration and efficiency of IOIS by exhibiting a joint movement of the underlying factors. The aggregated dimensions comprise the factors derived from theory as shown in Figure 1. The following hypotheses are therefore formulated to examine the influence of the aggregated dimensions:

- H7. The exogenous dimension, comprising environmental and product-specific factors, has a positive effect on IOIS integration and efficiency in supply chains.
- H8. The climate dimension, comprising IC prerequisites and behaviors, has a positive effect on IOIS integration and efficiency in supply chains.
- H9. The operational dimension, comprising collaboration and technical factors, has a positive effect on IOIS integration and efficiency in supply chains.

Additionally, the IC climate in the supply chain can be seen as a direct influencing factor on the IOIS integration as proposed by Son et al. (2005). The IC climate is defined by Nidumolu (1995) as the attitude prevailing between the trading partners. Bodendorf and Franke (2022) describe a positive IC climate as being beneficial for collaboration and having a positive influence on electronic data exchange. The IC prerequisites, such as power balance, are described by Kembro et al. (2017) as having an influence on the climate in a relationship. The connection of behavioral factors, such as goal compatibility, to the IC climate is pointed out by Nidumolu (1995). From this point of view, another hypothesis can be added to the conceptual model:

- H10. The IC climate has a positive effect on IOIS integration and efficiency in supply chains.

A model of the different factors and their influences on IOIS integration can be created as outlined in Figure 2. As mentioned above, existing research focuses predominantly on dyadic relationships between two supply chain partners and deals with the supplier-buyer relationship as an abstraction of the general structure of the real world.

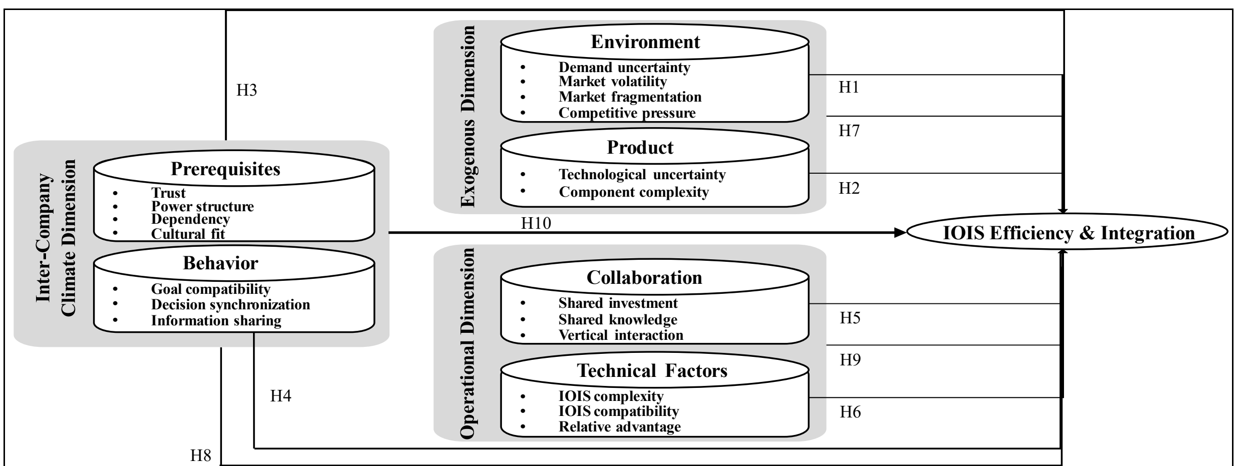


Figure 2. Conceptual model and hypotheses

Research Approach

Computational approaches are a suitable research instrument in organizational sciences as demonstrated by Burton and Obel (2011). Davis et al. (2007) show how simulations can be a valuable approach for theory development and Benbya et al. (2020) emphasize how simulations might help to explore complex systems. To gain insights into the relationships of systems in an organizational context Fioretti (2013) claims that simulations and ABMs are expedient. Especially in the setting of IS, Za et al. (2018) show that simulation experiments are a frequent choice and advocate as an important tool in information systems research. The environment of IOIS across companies can be modeled as a CAS (Haki et al., 2020). With the complexity of this system in mind Hedström and Manzo (2015) highlight that ABM is a critical tool to explore the interactions of the agents in a manipulable environment. ABMs are beneficial for modeling CAS as they allow to replicate complex behavior with a relatively lean program by facilitating the interaction between many agents (Holweg & Pil 2008). Figure 3 depicts the multiple steps to be conducted in a simulation experiment.

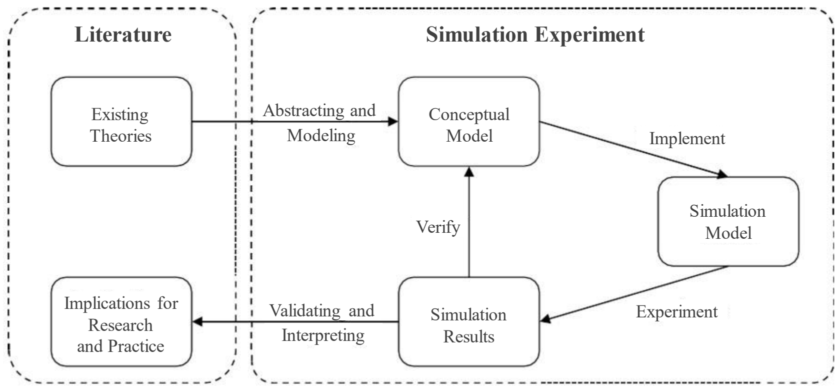


Figure 3. Simulation as part of the research concept (Beese et al. 2019)

Initially, a simulation framework is derived from theory, which is presented in Figure 3. Next, a simulation model is developed using a suitable technical approach. In the case of this study, an ABM simulation is chosen, which is an appropriate approach to information system research according to Beese et al. (2019). The developed model is validated to ensure the reliability and validity of the simulation.

Based on the framework depicted in Figure 3 an ABM simulation model is developed and implemented in Python using the mesa package. The model is created following Beese et al. (2019) with the additional insights of Davis et al. (2009) in mind. The environment sets the stage for all agents and interactions. Next, the agents are described, followed by presenting the possible interactions between them. Finally, to be able to carry out experiments in the simulation environment, the influencing factors (see Figure 2) are incorporated as independent variables (IVs) and the dependent variables (DVs) are defined (Za et al., 2018.). Table 1 summarizes the model's components in more detail.

Component		**Description/Implementation**
Agents	*IT Application*	The IT application vector (AV) is characterized by 10 digits with the special feature of "?", e.g., [010??011?1]. "?" represents features that are subject to improvisation and are realized at the moment the IT application is used. Every "?" will be set to either 0 or 1 with an even chance of 50%. The costs of the deployment of IT applications are also considered. The creation time of the application is used to calculate the age of the IT application.
	Actors	Actors are classified by the tier they belong to in the supply chain. This tier is defined by an integer attribute ranging from 1 to 3. The first tier is defined as being the most upstream in the supply chain and is therefore directly linked to new opportunities. Based on the opportunity an actor receives, it can decide to act according to the scope of its abilities. Possible payoffs gained by the actors and all cost occurred are stored in two separate attributes.
Interactions	*Actor-Actor*	Connections between actors are represented by a graph with a node for each actor. The edges between these nodes represent the relations between the actors. Once the connection is established, an attribute value between 0 and 1 indicates the strength of the relationship. If the connection is strong enough, the edge indicates knowledge exchange, which can be interpreted as a flow on that edge.

	Actor-Application	The graph is supplemented by nodes representing the IT applications in the system. Additional edges can be established between actors and applications and are classified by an attribute value between 0 and 1, indicating the level of knowledge the actor possesses about the application. If this knowledge is sufficient, the application can be used by the actor, which is equivalent to a flow on that edge.
Influence Factors	*Environmental*	The environment is simulated by varying parameters such as velocity, which is defined as the frequency of the arrival of new opportunities, and unpredictability, which determines the extent to which the opportunities differ from each other.
	Product-Specific	This reflects the technological ambiguity and component complexity, whereby complexity represents the number of matches needed between the realized IT application and the opportunity vector and ambiguity describes how likely it is for the actor to misperceive the single manifestations of the opportunity.
	IC Prerequisites	This parameter represents the likelihood of actors to initially execute the connect action, which is available to them every time they are activated.
	IC Behavior	This parameter represents the likelihood of actors to engage in communication. The parameter is checked against a random number every time an actor tries to engage in communication. A prerequisite for this communication is an established connection between the actors.
	Collaboration	Collaboration is represented by the density of communication determining how much knowledge about an application is shared. The actor with less knowledge will learn about the application from the actor with more knowledge. The higher this factor, the more knowledge is transferred.
	Technical Compatibility	Since barriers to using the IOIS are increased if the new system has a high complexity, is incompatible, or offers no advantage, this factor represents the likelihood to engage with an IOIS. This includes the potential deployment of an IOIS but also the communication and connection with other actors regarding IOIS. Therefore, the corresponding parameter determines the chance of an actor to engage with the environment and to use an existing IOIS.

Table 1. Components of the simulation model

The validation of the ABM aims at confirming that the model is in line with the developed theory (Fioretti 2013). Burton and Obel (2011) point out that while creating the simulation model the focus should be on facilitating the validation, instead of building an overcomplicated model. To validate a simulation model, Sargent (1998) proposes a toolbox of different techniques, which are applied here to the model. The experiments are designed to investigate the defined hypotheses which are based on the six influencing factors: environment, product specificity, IC prerequisites, IC behavior, collaboration, and technical compatibility.

These factors are the input factors of the experiments. Initially, the individual effects of each factor are tested. Each experiment varies the factor in the range of 0 to 1 with a step size of 0.01. Each step represents a simulation run and is repeated 10 times to ensure a sufficiently large data set for the analysis. This results in a total of 1010 runs for each experiment. Each run consists of 300 time-steps. The first 100 steps are not considered to allow the run to stabilize. To test the hypothesized joint effects of the aggregated dimensions, additional experiments are conducted in a second step. These experiments vary two parameters at the same time with a step size of 0.025. This leads to 41 steps per parameter and consequently to 1681 runs for each experiment as all 41 values of both parameters are combined with each other. A total of three joint experiments is necessary to explore the proposed hypothesis of relationships between the aggregated dimensions and IOIS integration and efficiency since each of the three dimensions leads to a joint experiment. The runs result in measurements of integration, efficiency, and climate. These DVs are then correlated with the experimental factors, which function as IVs, using linear and non-linear regressions.

Coming back to the validation techniques proposed by Sargent (1998), internal validity is established through a multitude of runs, which ensure the stability of the simulation results. These runs are conducted with all parameters set to their default value. The results of the internal validation are listed in Table 2 and show a stable output of the simulation model.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Integration	200	14.598	0.786	12.970	14.083	15.187	16.909
Efficiency	200	0.208	0.032	0.134	0.184	0.229	0.297
Climate	200	11.119	0.401	10.012	10.830	11.362	12.169

Table 2. Validation of the simulation model

In our experiment the DVs are not standardized and used in their original format. This also leads to the comparability of effects on the DVs between different experiments. Only the comparability of the influences of one IV on two different DVs needs to be sacrificed. This means that, for example, an influence of the environment on integration can have a very different value than the influence of the environmental inefficiency. This is due to integration and efficiency being subject to very different scales. The non-linear regression models are implemented as polynomial regressions, which include the quadratic and cubic form of the input factor. Ordinary polynomial regressions suffer from some disadvantages. Most notably, the different polynomials are not independent of each other. This leads to the potential issue of multicollinearity between the linear, quadratic, and cubic forms of a variable. This is evident since the different forms are just derived by taking the original variable to the power of 2 or 3, which leads to correlations. To solve this problem, orthogonal polynomials are used by applying the poly function of R. This does not only reduce multicollinearity, but also increases numeric stability (Haki et al., 2020). This stability is achieved since regressions of orthogonal polynomials typically adhere to the results of lower-order fittings and add another layer on top. Therefore, the effects of higher-order polynomials are introduced step by step and compared to classical polynomial regressions. Unfortunately, when calculating orthogonal polynomials also the IV of the linear model needs to be altered. This can lead to counter-intuitive results when examining the linear regression models since the values do not necessarily match the regression graph. This property of orthogonal polynomials is prevalent in all degrees but is most apparent in the linear model. Considering this property, the following data analysis uses the original data for all linear regressions and orthogonal polynomials for all non-linear regressions.

The two-way joint experiments are evaluated in a similar fashion. A total of three regression models is used to evaluate the results of each experiment. Since two individual IVs are now present, a multiple regression becomes necessary. The first model is a linear multiple regression using the linear data without interaction effects. The second model is a non-linear multiple regression using the orthogonal quadratic polynomials. This approach is comparable with the analysis of the direct effects. The last experiment also applies the quadratic form and includes the interaction term between the two IVs.

Simulation Results: Direct and Joint Effect Analysis

The ***direct effects*** capture the impact of the six influencing factors on IOIS integration and efficiency. Comparing the effects on integration and efficiency, three different patterns can be identified. First, opposing effects are observed, leading to a trade-off between integration and efficiency. Second, a peak in integration and efficiency is witnessed, which marks an optimum of the observed factor. Finally, integration and efficiency might also jointly increase for higher values of the observed factor.

The influence of the **environmental factor** can be fitted very well to both integration and efficiency effects on the IOIS using the regression models. The linear regression shows a significant positive relationship between the environmental parameter and IOIS integration (10.874; $p<0.01$). A negative relationship towards the IOIS efficiency is also noticed (-0.266; $p<0.01$). Figure 4 illustrates these results and plots the estimator of the best fitting, cubic regression. The effect on integration shows an exponential shape. As the actors integrate more applications, higher levels of the environmental factor are reached. The effect on efficiency is opposed to the effect on integration. The actors find it increasingly difficult to realize profits as the level of the environmental factor increases. This trend is leveling out as high levels of the environmental factor are reached, as seen in Figure 4. The relationship between the environmental factor and efficiency is also much more spread when compared to the relation with integration. *H1 can therefore be partly confirmed* since environmental complexity is found to have a negative relation with the efficiency of IOIS usage in the supply chain. However, the regression with the integration of IOIS shows a positive relation.

	Dependent variable:					
	Integration			Efficiency		
Environmental	10.874***	99.428***	99.911***	−0.266***	−2.490***	−2.477***
	(0.147)	(0.823)	(0.757)	(0.006)	(0.053)	(0.052)
Environmental²		34.543***	33.931***		0.618***	0.602***
		(0.830)	(0.765)		(0.053)	(0.053)
Environmental³			10.438***			0.273***
			(0.771)			(0.053)
Constant	6.329***	11.790***	11.781***	0.421***	0.288***	0.288***
	(0.085)	(0.026)	(0.024)	(0.004)	(0.002)	(0.002)
Observations	1,000	1,000	1,000	1,000	1,000	1,000
R^2	0.846	0.944	0.953	0.658	0.698	0.706
Adjusted R^2	0.846	0.944	0.952	0.657	0.698	0.705
Note:						*p<0.1; **p<0.05; ***p<0.01

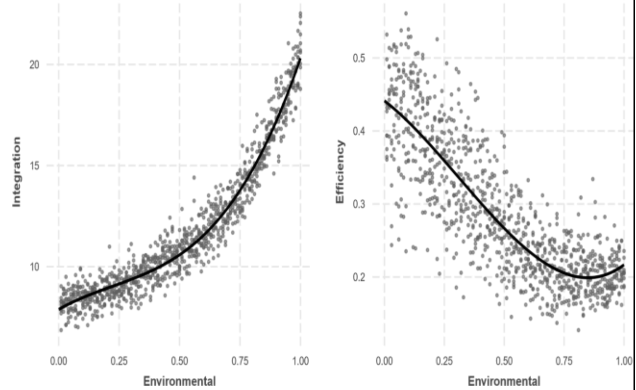


Figure 4. Relation of the environment to integration and efficiency

The relationship between the **product-specific factors** and both integration and efficiency shows a distinct pattern, as seen in Figure 5. These stepwise shapes are due to the complexity parameter which can only take integer values and needs to be rounded. Nevertheless, the regression shows overall suitable fittings. The linear models already fit the relationships of the product-specific factors well, especially to IOIS efficiency. The relation to IOIS integration is positive (89.461; $p<0.01$) and the relation to efficiency negative (-2.386; $p<0.01$). In both cases, a good fit can be achieved by using the cubic polynomials of the factor, which also corresponds to the fit depicted in Figure 5. The results indicate that the value of the product-specific factor represents a compromise between integration and efficiency. As integration goes up, efficiency goes down. The fits are shaped opposite to each other, with both starting at a stationary level. The number of integrated applications is low, and the profit is relatively high for low product-specific levels. These levels are comparatively constant up to a certain level of the product-specific factor. This pivotal level is around 0.5 for the IOIS integration and around 0.25 for the efficiency of the IOIS. When these values of the product-specific factors are reached, the applications' integration increases and efficiency decreases. Once very high levels of the product-specific factor are reached, both values are leveling out. *H2 can, therefore, only be partly confirmed*. Nevertheless, the hypothesis can be confirmed to the extent that product-specific factors do have a positive relationship with IOIS integration.

	Dependent variable:					
	Integration			Efficiency		
Product	89.461***	828.900***	828.900***	−2.386***	−22.106***	−22.106***
	(1.665)	(14.421)	(11.180)	(0.021)	(0.198)	(0.086)
Product²		174.346***	174.346***		0.250	0.250***
		(14.421)	(11.180)		(0.198)	(0.086)
Product³			−289.271***			5.649***
			(11.180)			(0.086)
Constant	−16.175***	28.555***	28.555***	1.044***	−0.149***	−0.149***
	(0.964)	(0.454)	(0.352)	(0.012)	(0.006)	(0.003)
N	1,010	1,010	1,010	1,010	1,010	1,010
R^2	0.741	0.774	0.864	0.925	0.925	0.986
Adj. R^2	0.741	0.774	0.864	0.925	0.925	0.986
Note:						*p<0.1; **p<0.05; ***p<0.01

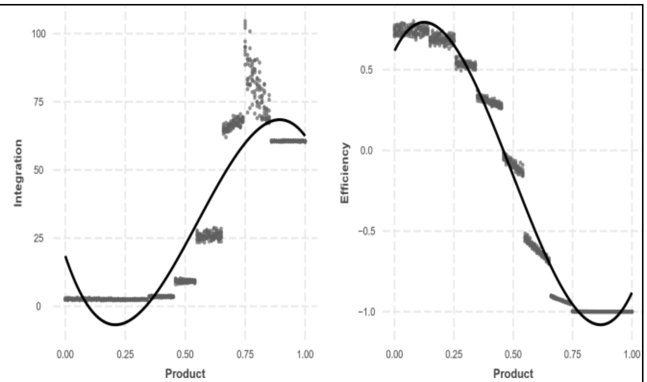


Figure 5. Relation of product-specific factors to integration and efficiency

The relationship with IOIS efficiency, on the other hand, is negative. **IC prerequisites** are hypothesized to have a direct effect on the integration and efficiency of IOIS. Now, both measures show a positive relationship with IC prerequisites. Integration shows a positive relation (19.849; $p<0.01$), which is already a really good fit for the linear model. Figure 6 shows that the non-linear model can only improve the fit slightly. The efficiency can also be fitted with the linear model and shows a positive relation (0.205; $p<0.01$). The non-linear models can, again, improve the fit slightly. The IOIS integration shows a nearly linear relationship to IC prerequisites, which is only flattening slightly for higher levels of IC prerequisites. However, the efficiency of the actors shows a much more distinct pattern. Here, the relation is very steep at first, leading to high gains of efficiency within the first few percent of the range of IC prerequisites. The curve is then flattening for higher IC prerequisite values, leading to a slower increase of IOIS efficiency.

H3 can therefore be accepted since the IC prerequisites show a positive relation to IOIS integration and efficiency.

	Dependent variable:					
	Integration			Efficiency		
Prerequisites	19.849*** (0.104)	183.913*** (0.831)	183.913*** (0.800)	0.205*** (0.004)	1.902*** (0.034)	1.902*** (0.033)
Prerequisites²		−15.395*** (0.831)	−15.395*** (0.800)		−0.505*** (0.034)	−0.505*** (0.033)
Prerequisites³			7.241*** (0.800)			0.317*** (0.033)
Constant	2.410*** (0.060)	12.335*** (0.026)	12.335*** (0.025)	0.073*** (0.002)	0.175*** (0.001)	0.175*** (0.001)
Observations	1,010	1,010	1,010	1,010	1,010	1,010
R²	0.973	0.980	0.981	0.716	0.767	0.787
Adjusted R²	0.973	0.980	0.981	0.716	0.766	0.786
Note:						*p<0.1; **p<0.05; ***p<0.01

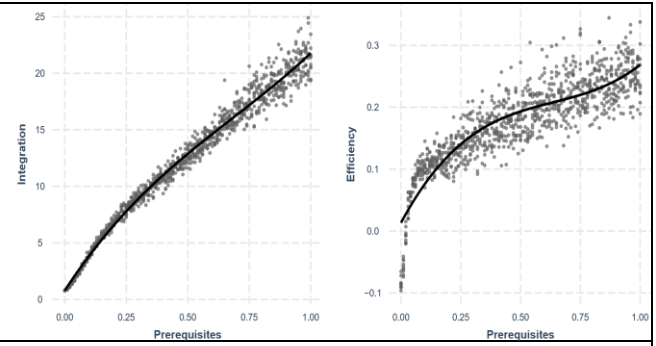


Figure 6. Relation of IC prerequisites to integration and efficiency

The direct relation of **IC behavior** to integration and efficiency is also examined in the following. Then, the analysis of the relation to the IC climate follows. Figure 7 shows that IOIS integration and efficiency each reach a certain maximum for specific values of the IC behavior. The maximum integration can be observed at an IC behavior of 0.433 and the maximum efficiency at 0.496 when the quadratic model is applied. Additionally, the linear regression of the integration shows a significant negative relationship (-6.801; p<0.01) due to the shift of the maximum towards the left. The results reveal that no linear relationship can be established to the IOIS efficiency. Both models are best fitted with the cubic regression model. *H4 can consequentially not be confirmed*.

	Dependent variable:					
	Integration			Efficiency		
Behavior	−6.801*** (0.437)	−63.018*** (1.222)	−63.018*** (0.774)	−0.007 (0.008)	−0.063 (0.047)	−0.063 (0.045)
Behavior²		−122.715*** (1.222)	−122.715*** (0.774)		−1.938*** (0.047)	−1.938*** (0.045)
Behavior³			29.998*** (0.774)			0.488*** (0.045)
Constant	13.997*** (0.253)	10.597*** (0.038)	10.597*** (0.024)	0.158*** (0.005)	0.155*** (0.001)	0.155*** (0.001)
Observations	1,010	1,010	1,010	1,010	1,010	1,010
R²	0.193	0.927	0.971	0.001	0.626	0.666
Adjusted R²	0.193	0.927	0.971	−0.0003	0.625	0.665
Note:						*p<0.1; **p<0.05; ***p<0.01

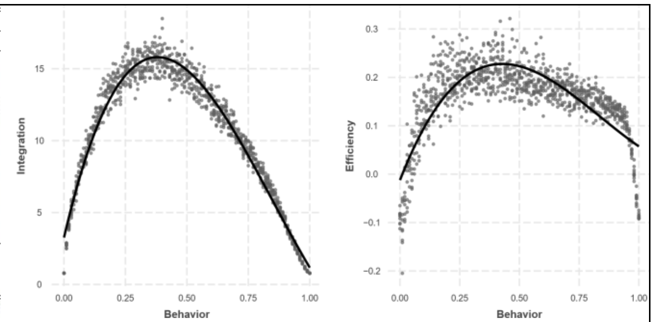


Figure 7. Relation of IC behavior to integration and efficiency

The regression results of the **collaboration factor** show a significant positive relation to IOIS integration (15.788; p<0.01) and efficiency (0.163; p<0.01). The collaboration factor is neither a tradeoff nor does it exhibit a maximum, but both factors of integration and efficiency do constantly rise with higher levels of collaboration. Nevertheless, Figure 8 shows that especially efficiency exhibits diminishing marginal effects. Based on the above-described findings, *H5 can be confirmed*:

	Dependent variable:					
	Integration			Efficiency		
Collaboration	15.788*** (0.181)	146.281*** (0.912)	146.281*** (0.742)	0.163*** (0.007)	1.508*** (0.051)	1.508*** (0.042)
Collaboration²		−44.662*** (0.912)	−44.662*** (0.742)		−1.278*** (0.051)	−1.278*** (0.042)
Collaboration³			16.807*** (0.742)			0.909*** (0.042)
Constant	5.196*** (0.105)	13.090*** (0.029)	13.090*** (0.023)	0.096*** (0.004)	0.177*** (0.002)	0.177*** (0.001)
Observations	1,010	1,010	1,010	1,010	1,010	1,010
R²	0.883	0.965	0.977	0.349	0.599	0.726
Adjusted R²	0.883	0.965	0.977	0.348	0.598	0.725
Note:						*p<0.1; **p<0.05; ***p<0.01

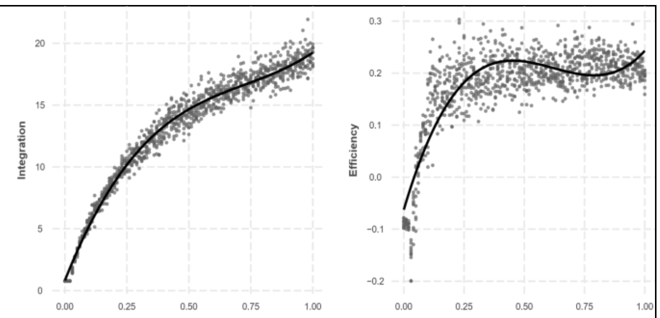


Figure 8. Relation of collaboration to integration and efficiency

The insights gained on **technical compatibility** follow a similar pattern to the previous insights on the collaboration factor. However, there are slight differences that distinguish both results. Both DVs have a strong positive relationship with the technical compatibility. Both relationships are more robust than the ones observed for the collaboration factor. This is especially noteworthy for the IOIS efficiency. As can be seen in Figure 9, both relations can be fitted very well with the cubic regression.

	Dependent variable:					
	Integration			Efficiency		
Technical	19.725*** (0.084)	182.761*** (0.700)	182.761*** (0.571)	0.715*** (0.011)	6.626*** (0.051)	6.626*** (0.034)
Technical^2		10.888*** (0.700)	10.888*** (0.571)		−2.958*** (0.051)	−2.958*** (0.034)
Technical^3			−12.861*** (0.571)			1.209*** (0.034)
Constant	−1.409*** (0.049)	8.453*** (0.022)	8.453*** (0.018)	−0.335*** (0.007)	0.022*** (0.002)	0.022*** (0.001)
Observations	1,010	1,010	1,010	1,010	1,010	1,010
R^2	0.982	0.985	0.990	0.794	0.953	0.979
Adjusted R^2	0.982	0.985	0.990	0.794	0.952	0.979
Note:						*p<0.1; **p<0.05; ***p<0.01

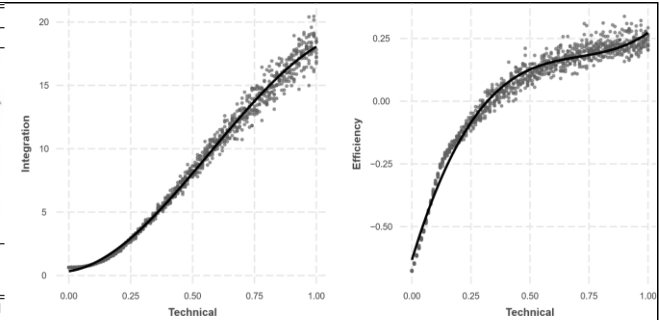


Figure 9. Relation of technical compatibility to integration and efficiency

Additionally, it is observable that the relationship between the technical compatibility and IOIS integration is now of exponential shape. When compared directly to the relations with collaboration it is notable that the spread of both relations is considerably smaller. The shape of the relation of IOIS integration now exhibits an upward curve. IOIS efficiency is also characterized by a less steep incline in the beginning, followed by a more gently flattening of the curve. There is no cluster of values in the diagram as observed before. Consequently, *H6 can be confirmed*. The technical compatibility has a positive relation to both integration and efficiency of IOIS.

Succeeding the analysis of the different factors' impact on the IC climate, the relation of **IC climate** to the **IOIS integration** and **efficiency** is explored. Figure 10 exhibits the regressions computed to gain insights into these relations.

	Dependent variable:					
	Integration			Efficiency		
Climate	−0.217*** (0.004)	−238.402*** (3.966)	−238.402*** (3.951)	−0.002*** (0.0001)	−2.279*** (0.072)	−2.279*** (0.071)
Climate^2		47.789*** (3.966)	47.789*** (3.951)		−0.698*** (0.072)	−0.698*** (0.071)
Climate^3			20.905*** (3.951)			0.448*** (0.071)
Constant	14.963*** (0.101)	10.530*** (0.066)	10.530*** (0.066)	0.195*** (0.002)	0.153*** (0.001)	0.153*** (0.001)
N	3,594	3,594	3,594	3,594	3,594	3,594
R^2	0.492	0.511	0.515	0.216	0.236	0.244
Adj. R^2	0.492	0.511	0.515	0.216	0.236	0.244
Note:						*p<0.1; **p<0.05; ***p<0.01

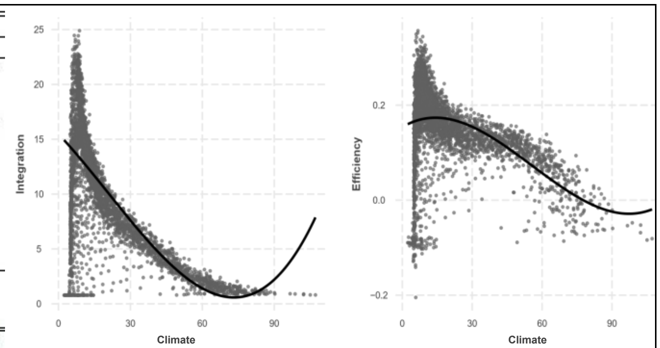


Figure 10. Relation of IC climate to integration and efficiency

Notably, the regressions are fitting the data less well compared to other previously conducted regressions. Nevertheless, all coefficients exhibit high levels of significance. When only considering the linear models, the assumption can be made that the climate dimension has a negative relation (-0.217) to the IOIS integration and a slightly negative relation (-0.002) to the IOIS efficiency. The plots of the two functions in Figure 10 show a more differentiated picture of the correlation between IC climate and both DVs. The IOIS integration starts at low values for low IC climate before it spikes up sharply. After this initial spike the levels of integration reach their maximum before dropping back down again. The IOIS efficiency is subject to a similar development depending on the values for the IC climate. Here, the initial efficiency is even negative before sharply rising to its maximum. In the following, the levels of efficiency are dropping back down towards zero. *H10, therefore, cannot be confirmed*. The IC climate is negatively related to both IOIS integration and efficiency. In the following H7, H8 and H9.are investigated.

The ***joint effect*** of the **exogenous dimension's** environmental and product-specific factors can be fitted well using the non-linear regression. The joint effect of these factors forms the exogenous dimension. It is noteworthy that the most significant IV is the linear product-specific factor. For the relation on integration, only the quadratic polynomial of the product-specific factor has a similar significance. No other significant influences can be measured on efficiency and the linear product-specific factor is the only explanatory variable. Figure 11 visualizes these results and shows how the integration is related to the environmental and product-specific factors.

	Dependent variable:					
	Integration			Efficiency		
Collaboration	9.065*** (0.191)	109.944*** (2.159)	109.944*** (0.971)	0.167*** (0.010)	2.023*** (0.066)	2.023*** (0.066)
Collaboration²		−32.868*** (2.159)	−32.868*** (0.971)		−1.001*** (0.066)	−1.001*** (0.066)
Technical	17.270*** (0.191)	209.446*** (2.159)	209.446*** (0.971)	0.672*** (0.010)	8.150*** (0.066)	8.150*** (0.066)
Technical²		10.798*** (2.159)	10.798*** (0.971)		−3.979*** (0.066)	−3.979*** (0.066)
Interaction			3,236.958*** (39.821)			10.147*** (2.706)
Constant	−5.605*** (0.146)	7.562*** (0.053)	7.562*** (0.024)	−0.421*** (0.008)	−0.002 (0.002)	−0.002 (0.002)
N	1,681	1,681	1,681	1,681	1,681	1,681
R^2	0.861	0.880	0.976	0.745	0.922	0.923
Adj. R^2	0.861	0.879	0.976	0.744	0.922	0.923
Note:						*p<0.1; **p<0.05; ***p<0.01

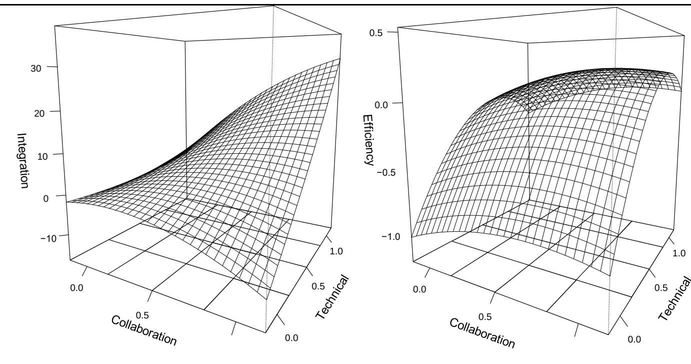


Figure 11. Relation of exogenous dimension to integration and efficiency.

This relation can be described by an upward-sloping plane, which is nearly stationary for different values of the environmental factor. The plane rises as the product-specific factor increases. The linear coefficient is computed as 86.389. The relation to IOIS efficiency can also be described by a plane, which is now nearly linear in its relation to the product-specific factor (-2.365). The relation of efficiency to the environmental factor is relatively weak, which results in an overall flat plane. The main difference to the IOIS integration is that the IOIS efficiency decreases with higher values of the product-specific factor. *H7, therefore, cannot be confirmed.*. On the one hand, the level of IOIS integration increases with higher values of the environmental and product-specific factors. On the other hand, contradictory to the hypothesis, the IOIS efficiency goes down with higher values of the environmental and product-specific factors.

The different regression models given in Figure 12 show how the **IC climate dimension** relates to IOIS integration and efficiency. The climate dimension comprises the IC prerequisites and behavior. The last regression model, which uses the linear and cubic polynomial of both factors as well as the interaction, fits best for both DVs. All factors of the two models are highly significant with $p<0.01$, except for the linear behavioral relation to IOIS efficiency. Figure 12 shows that IOIS integration exhibits a parabolic shape on the behavioral factor.

	Dependent variable:					
	Integration			Efficiency		
Prerequisites	14.265*** (0.335)	173.002*** (2.216)	173.002*** (2.072)	0.200*** (0.007)	2.430*** (0.046)	2.430*** (0.046)
Prerequisites²		−14.387*** (2.216)	−14.387*** (2.072)		−0.776*** (0.046)	−0.776*** (0.046)
Behavior	−5.481*** (0.335)	−66.479*** (2.216)	−66.479*** (2.072)	−0.002 (0.007)	−0.029 (0.046)	−0.029 (0.046)
Behavior²		−138.855*** (2.216)	−138.855*** (2.072)		−2.644*** (0.046)	−2.644*** (0.046)
Interaction			−1,321.680*** (84.961)			−11.212*** (1.871)
Constant	4.394*** (0.257)	8.785*** (0.054)	8.785*** (0.051)	0.023*** (0.005)	0.122*** (0.001)	0.122*** (0.001)
N	1,681	1,681	1,681	1,681	1,681	1,681
R^2	0.553	0.867	0.884	0.346	0.791	0.795
Adj. R^2	0.553	0.867	0.884	0.345	0.791	0.795
Note:						*p<0.1; **p<0.05; ***p<0.01

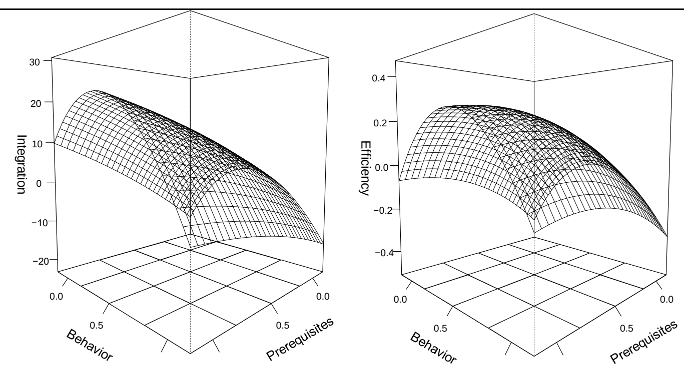
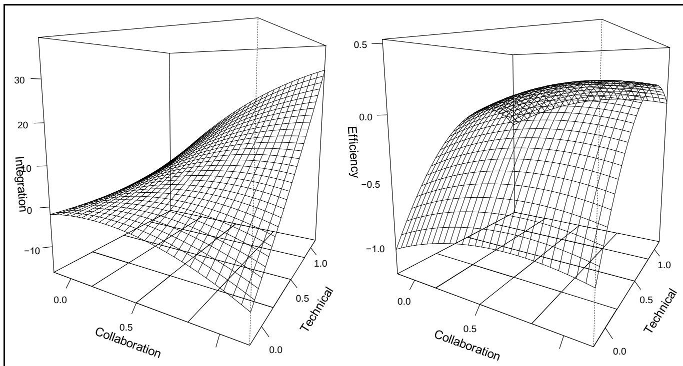


Figure 12. Relation of IC climate dimension to integration and efficiency.

This leads to a maximum which is shifted towards low levels of integration. This shift can also be seen in the negative linear relation of the behavioral factor to the IOIS integration of -5.481. The IC prerequisites exhibit a positive relation to IOIS integration. This can be seen in Figure 12 and derived from the positive linear factor of the regression (14.265). The relation of both factors, behavior and prerequisites, to IOIS efficiency is similar. The behavioral factor exhibits a reverse U-shape. This time, the maximum is more towards the middle, which can also be concluded from the linear coefficient of IC behavior with the IOIS efficiency. This coefficient is minimal (-0.002) with a small significance of $p>0.1$. The IC prerequisites do also have a positive influence on IOIS efficiency, with a linear relation of 0.2. *H8 cannot be unambiguously confirmed*. While the IC prerequisites show a positive effect on both IOIS integration and efficiency, the effect of the IC behavior is not as clear. For the integration, the behavioral factor even tends to have a negative effect. A positive effect between the climate dimension and IOIS integration and efficiency can therefore not be established.

The **operational dimension** comprises the joint influence of the collaboration and technical compatibility factors. Figure 13 indicates a very good fitting of all regression models with the only exception of the intercept parameters.

A positive relation of both factors to IOIS integration can be derived from the positive linear coefficient for collaboration (9.065) and technical compatibility (17.270). The relation to IOIS efficiency is also positive for collaboration with a coefficient of 0.167 and technical compatibility with 0.672. The plot of both regressions in Figure 13 shows that the effect of the joint factors on IOIS integration has a more complex shape than most previous observations. In general, the levels of integration are rising with both factors and reach their maximum for maximum values of collaboration and technical compatibility. Overall, *H9 can be accepted*.



	Dependent variable:					
	Integration			Efficiency		
Collaboration	9.065*** (0.191)	109.944*** (2.159)	109.944*** (0.971)	0.167*** (0.010)	2.023*** (0.066)	2.023*** (0.066)
Collaboration²		−32.868*** (2.159)	−32.868*** (0.971)		−1.001*** (0.066)	−1.001*** (0.066)
Technical	17.270*** (0.191)	209.446*** (2.159)	209.446*** (0.971)	0.672*** (0.010)	8.150*** (0.066)	8.150*** (0.066)
Technical²		10.798*** (2.159)	10.798*** (0.971)		−3.979*** (0.066)	−3.979*** (0.066)
Interaction			3,236.958*** (39.821)			10.147*** (2.706)
Constant	−5.605*** (0.146)	7.562*** (0.053)	7.562*** (0.024)	−0.421*** (0.008)	−0.002 (0.002)	−0.002 (0.002)
N	1,681	1,681	1,681	1,681	1,681	1,681
R^2	0.861	0.880	0.976	0.745	0.922	0.923
Adj. R^2	0.861	0.879	0.976	0.744	0.922	0.923

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 13. Relation of operational dimension to integration and efficiency.

Discussion and Conclusion

This study contributes to the existing literature by introducing a simulation model which enables the investigation of IOIS integration and efficiency in triadic supply chains. Different influencing factors are used in the simulation, which allow the exploration of exogenous, climate, and operational dimensions. The factors themselves are founded in the RBV, RV, and DCT. The implementation of these factors is realized by varying a range of simulation parameters, including the dimensions of environmental dynamism as proposed by Davis et al. (2009) under ceteris paribus conditions. Answering the research question the direct and joint effects show that IOIS in supply chain triads are influenced by (1) complex exogenous environments which foster the integration of IOIS while diminishing the efficiency. (2) high levels of IC prerequisites as well as strong collaboration and high technical compatibility, which lead to an increase in IOIS integration and efficiency, (3) IC behavior which exhibits a spike of IOIS integration and efficiency for mid-range values.

Implications for Research and Management

We contribute to the link between supply chain management and IS research by diving deep into the integration and efficiency of IOIS (Mikalef et al., 2020; Du et al. 2019). Inspired by Q. Zhang & Cao (2018) the model bears the development and usage of IOIS in supply chain triads at its core. We outline that some factors have a purely positive or negative effect on IOIS integration and efficiency. However, other factors cause a trade-off between IOIS integration and efficiency or do not have a clear trend associated. While both the environmental and product-specific factors cause higher levels of integration, the efficiency can be observed to go down for more complex environments. A purely positive relation of both integration and efficiency can be proved by investigating IC prerequisites, collaboration as well as technical compatibility which have varying degrees of positive influence on IOIS integration and efficiency. Additionally, motivated by Rajaguru and Matanda (2013), we show that IC behavior is degrading IOIS integration and efficiency after reaching a certain level. A reason for this can be found by the simulation experiments, which lead to frequent communications between the actors for high levels of IC behavior. This focus on one activity causes a neglect of the other ones, which leads to a decline of value creation. Another contribution to the literature is considering IC climate as an intermediate construct (Klein & Rai 2009; Kembro et al. 2017). This construct is influenced negatively by IC prerequisites and positively by IC behavior. Notably, the IC climate is negatively related to both IOIS integration and efficiency. Both values exhibit a substantial increase as a certain level of IC climate is necessary for the deployment and use of IOIS. However, once that level is reached, a steady decrease in integration and efficiency can be observed for increasing values of IC climate. Focusing on the operational dimension high levels of both technical compatibility and collaboration foster a maximum of IOIS integration. However, in regard to efficiency, a different pattern emerges. As high levels of technical compatibility, which consists of IOIS complexity, compatibility, and the relative advantage, are reached, the efficiency drops slightly. This drop suggests that dynamic capabilities might need to be applied cautiously in supply chain triads regarding the ease of system integration between the partners. This result indicates that total technical openness in regard to the deployed IOIS might lead to a loss in efficiency for the individual actors. Proprietary systems, on the other hand, can lead to more efficient IOIS deployments in supply chains.

In the following we highlight insights that can support management in deciding on the use of IOIS in triadic supply chains. The exogenous factors are characterized by a trade-off between IOIS integration and efficiency. The environmental factor shows that higher market volatility, uncertainty, and fragmentation, as well as high competitive pressure, decrease the profitability of an IOIS. These factors increase the integration of IOIS. The product-specific factors show a similar pattern, which is even stronger. As technological uncertainty and product complexity go up, the efficiency drastically decreases, while IOIS integration strongly increases. When it comes to the practical deployment of IOIS, one must therefore pay attention to the exogenous environment in which the system is to be used (Li & Lin 2006). To prevent a low efficiency or integration of the IOIS, the system should therefore not be used in supply chains with very high or very low market or product-specific factors. When examining the IC climate dimension, an even clearer picture of its influences on the IOIS integration and efficiency can be observed. IC prerequisites, which according to Kembro et al. (2017) and Rajaguru and Matanda (2013) represent the power structure, trust, dependency, and cultural fit in a relation, exhibit a positive influence on both integration and efficiency. In contrast, the IC behavior, comprising goal compatibility, decision synchronization, and information sharing, displays a maximum IOIS integration and efficiency at intermediate levels. The experiments show that extensive information exchange hinders actual value creation as it binds capacity. The overall effect of the IC climate dimension follows a similar pattern whereby IC prerequisites have generally a negative effect on the IC climate. In communities where many entities have high levels of IC prerequisites, the fluctuation of partners might be rather high, leading to lower levels of IC climate (Kembro et al. 2017). IC behavior, on the other hand, is found to have a positive relation to IC climate. The last dimension examined in this study is the operational dimension, which consists of collaboration and product-specific factors. Collaboration encapsulates shared investment, knowledge, and vertical interaction of the supply chain partners. Stronger collaboration results in higher levels of IOIS integration and efficiency. Following Wang et al. (2006) technical compatibility subsumes the compatibility and complexity of the developed IOIS as well as the relative advantage offered by the new system. For higher technical compatibility, a positive influence on the integration and efficiency of IOIS can be observed in the individual experiments. A more differentiated conclusion must be drawn when considering the combined effects of collaboration and product-specific factors. Maximum technical compatibility might not be necessary for high efficiency of the IOIS.

Having Figure 1 in mind and linking it to the simulation results the implications for management can be summarized as follows: (1) *Market:* The best supply chain segments to deploy IOIS are characterized by a medium level of fragmentation, volatility, uncertainty, and competitive pressure. (2) *Product:* Products to be managed with IOIS should not have unusually high or low technological uncertainty and component complexity. (3) *Partner selection*: It is advantageous to select dependent partners with high levels of mutual trust, cultural fit, and a favorable power structure to join with an IOIS. (4) *Relationship shaping*: Goal compatibility, decision synchronization, and information sharing need to be considered carefully to gain maximum value from the IOIS. (5) *Collaboration*: To optimize the advantages of an IOIS, shared investment, knowledge, and vertical integration need to be increased. (6) *Technical compatibility*: When it comes to technical implementation, IOIS complexity should be minimized and compatibility to existing systems maximized. However, the IOIS does also need to offer a relative advantage over existing systems to ensure regular usage.

Limitations and Future Research Avenues

The computational complexity of the simulation, also due to the intricate nature of interactions and dependencies in triadic supply chains and IOIS, is one of the most significant limitations of this study. Even though a considerable effort is made to reduce the runtime of the individual experiments, time and CPU capacity are limiting factors. More performant programming languages than Python and more CPU power would allow conducting more extensive multi-way joint experiments. Unfortunately, the resources of this study are limited to the hardware of mid-range personal computers. An opportunity for further research would be to optimize the software or provide more computing power. Moreover, examining larger supply chain networks to study IOIS adoption (e. g., due to network effects), adding factors that influence the rate and extent of technology adoption such as resource availability or compatibility or joining more than two factors in the experiments would allow a more holistic examination of the model. Especially the influence of the IC climate on the IOIS integration as well as efficiency yield unexpected results, which could be investigated further using additional data. There is also a limitation regarding the fitting of the regression models themselves. As seen in the different plots, a cubic function might not always gain the best fit possible. More advanced probability distribution fittings could generate a better match of the data. The best fit could most likely be achieved by using splines as described by Silverman (1985). More advanced fitting methods do have the downside that their results are significantly harder to interpret. This challenge is especially apparent for spline fittings. However, the approach of probability distribution fitting could potentially lead to higher degrees of fitting while maintaining interpretability. It is a conscious decision not to include any shocks but to build a model representing a steady market environment. This decision is made to create a baseline model first before exogenous events are introduced. However, the global Covid-19 crisis shows how severe the impact of external shocks on global supply chains can be, making research in this area even more relevant. Correspondingly, research on the impacts of exogenous events and on how IS can cope with exogenous shocks in supply chains is highly relevant. The simulation model developed in this study could be used as a baseline and complemented with exogenous influencing factors, e. g., coming from green IOIS (Leidner et al., 2022) or IOIS Governance research (Wilkin & Chenhall 2020).

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