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ORIGINAL PAPER

Business model analysis using computational modeling: a strategy tool for exploration and decision-making

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Abstract A business model is an essential part of a company—regardless of whether the company is a small entity or a global enterprise. Interest in business models in research and in practice has grown significantly in the last decade. Strategic initiatives and changes in business models are particularly cost intensive and uncertain. Thus, the analysis and understanding of a business model's structure and its changes induced by strategic initiatives is crucial. Approaches to business model analysis needs to support strategists and decision-makers, enabling them to evaluate strategic initiatives and alternatives in fluent environments where there is little or no prior experience. However, regrettably, the qualitative approaches currently available fall short of providing sound guidelines especially in uncertain, highly volatile situations that involve rapid technological developments and agile competitors, which middle managers and top-level executives are often faced with. The quantitative approach used in the article concerning business model analysis is founded on a systemic simulation methodology which enables decision makers to obtain insightful experimental designs with a company's business model. Computational modeling helps to understand business models as complex systems with dynamic interdependencies and thereby it can complement existing tools. This article uses the approach for a case study in the e-commerce

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business. It discusses advantages and disadvantages of computational modeling as a strategy and management tool.

Keywords Business model analysis · Simulation-based experiments · Strategy tool · Management tool · Business model innovation · System dynamics

JEL Classification C63 (Computational techniques simulation modeling) · M10 (General business administration)

1 Introduction

An essential part of the DNA of every company is its business model. In short, "a business model depicts the content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities" (Amit and Zott 2001: 511). Or, "a business model describes the rationale of how an organization creates, delivers, and captures value" (Osterwalder and Pigneur 2010: 55). The continuously increasing complexity of business, as well as the recurrent need to adapt to local conditions and technological developments, urges companies to unceasingly innovate their products, services, processes, and business models (Schwaninger 2010; Smith et al. 2010; Markides 2013). Such innovations are achieved through strategic initiatives which enable companies to open up new fields of action, explore, and exploit potential competitive advantages (March 1991). Since strategic initiatives are executed in the frame of existing business models of companies (Osterwalder and Pigneur 2010; Bieger and Reinhold 2011; DaSilva and Trkman 2013), they can significantly influence the dynamics in a business model. However, decision makers' misconceptions, especially when intervening and changing a complex object, such as a company's business model, represent an existential risk since essential interactions in dynamically-complex systems are currently not well understood (Paich and Sterman 1993; Sterman 2001; Gonzalez et al. 2005; Bucherer 2010). For instance, the impact of strategic initiatives on a business model might be temporally delayed, spatially diverse, may have knock-on effects on other elements of a business, and might provoke reactions from competitors or other agents in the business system (Porter 1996; Markides 1999; Sterman 2001; Chesbrough 2010; Markides 2013). Simultaneously, critical evaluations of business model changes induced by strategic initiatives are difficult since conventional management tools (e.g., SWOT analysis, industry analysis, portfolio analysis)[1] cannot sufficiently capture and depict the respective dynamic complexity (e.g., Osterwalder and Pigneur 2010; Groesser 2015a). This is because the scope of the analysis of these management tools is typically not broad enough to sufficiently address the magnitude of the potentially involved impacts (e.g., Sterman 2000a; Katz and Grösser 2013; Schwenke and Grösser 2014). Even more, existing methods with their limitations in addressing resulting dynamics may even produce a false perception of certainty in high-risk situations (Demil and Lecocq 2010). Thus, decisions

[1] The term *tool* is a generic name for frameworks, concepts, approach, or methods (Jarzabkowski and Kaplan 2015).

about executing strategic initiatives that influence a business model which are based on erroneous or inadequate information can severely threaten a company's existence.

Managers are therefore in growing need for additional strategy or management tools to address such complex challenges (Sargut and McGrath 2011). The aim of the paper is to introduce computation modeling and an experimental simulation approach as a complementary method to address dynamic complexity and interactions of strategic initiatives, business models, and business model elements. We answer the question: How can the effects of strategic initiatives on business models be analyzed while accounting for relevant dynamic complexity? Our findings show that computational modeling and simulation experiments facilitate estimating the consequences of executing strategic initiatives given the tight interdependencies between business model elements.

In this paper, we use the system dynamics (SD) methodology and apply it to a case study to demonstrate how computational modeling can help management cope with the challenges at hand. SD captures essential characteristics of management reality, for instance, nonlinear behaviors, accumulations, delays, and information feedback, which are not systematically taken into account by existing methods (Morecroft 1984; Sterman 2001; Schöneborn 2003; Morecroft 2007; Warren 2008). The computational modeling approach is most helpful in providing insights about the type and magnitude of interaction in business models and allows for an integrated evaluation and thereby complements the existing methods for the analysis of business models.

The remainder of the paper is structured as follows: In the following section, the paper addresses computational modeling and how it can help analyze business models and how the application can also benefit management control systems (MCS). The paper then provides details about the research design we use. The fourth section embarks on the case study about an e-commerce company. It demonstrates how computational modeling is used to analyze and improve a company's business model. For the case study, we introduce the essential parts of the quantitative model. Next, we analyze the implications of different scenarios and strategic initiatives on company success. From this, we derive recommendations for action that have the potential to achieve sustainable success. The fifth section discusses our approach to business model analysis with respect to theoretical and practical relevance. The last section concludes the paper and provides a path for further research.

2 Computer-based simulation of business models

Business models as a management tool

The term "business model" was first mentioned by Bellman et al. (1957). While they were investigating business games for management training, the term is mentioned just once: "And many more problems arise to plague us in the construction of these business models than ever confronted an engineer" (Bellman et al. 1957: 474). The definition of business model seems to be intrinsically connected to a representation of reality, a simulation of the real world through a model. The interest in business models in research and in practice has grown significantly in the last decade (Mahadevan 2000; Willemstein et al. 2007; Johnson et al. 2008; Osterwalder and Pigneur 2010;

Wirtz 2011). Many definitions and interpretations of the business model concept exist, leading to an inconsistent and even ambiguous state of the research (Bucherer 2010; Zott et al. 2011; Abdelkafi 2012).

In principle, literature in the field of organizational research and strategic management define business models as a system of interdependent activities, which promise a value proposition through the deployment of resources aiming at the creation of value (Levinthal 1997; Porter and Siggelkow 2008). A clearly defined business model explicates assumptions about "customers, the behavior of revenues and costs, the changing nature of user needs, and likely competitor responses" (Teece 2010: 174). Baden-Fuller and Morgan provide a seriously considered approach of a business model using the analogy of a recipe. If business models assume the same role as a recipe, they constrain to probable combinations and represent the "ingredients that must be arranged and combined according to the recipe (i.e., to some generic business model), but yet have many possibilities for innovation. Just as the creative chef will innovate to produce a new recipe for a successful dish, the creative entrepreneur or manager may innovate to build a new business model" (Baden-Fuller et al. 2010: 144; Baden-Fuller and Morgan 2010: 166). The analogy of business models as recipes helps to understand the role of variation and innovation within the constraints of (available) ingredients and intended purposes. Moreover, the recipe analogy motivates decision makers to use the business model concept to experiment with their organizations and to motivate strategic initiatives (Baden-Fuller and Morgan 2010: 168). In principle, improving existing business models is a trial-and-error learning process (Sosna et al. 2010).

Existing approaches used to analyze and improve business models and company success need to support strategists and decision makers to enable them to evaluate alternative strategic initiatives in contexts where there has been little or no prior experience. One such tool is the business model canvas (Osterwalder and Pigneur 2010). This tool provides a business model framework by addressing nine building blocks: key partners, key resources, key activities, value proposition, customer relationships, channels, customer segments, cost structure, and revenues stream. A second method, which is often used in the German-speaking world, is the magical triangle of a business model (Gassmann et al. 2013). The triangle differentiates the revenue stream from the value proposition, and the value creation chain. It thereby poses the following questions: Who is the customer, how is value generated, and what do we offer on the market? By addressing these three questions and by defining the customer segments, the value proposition of the value chain, the revenue mechanism, and the specificity of the business model provide a base for business model development. For an existing business or for a start-up, the tools identify and describe the content of these building blocks or questions in qualitative terms and help define a conceptually consistent business model. In other words, the current management tools on business models help to facilitate creative potential by simplifying the situation at hand and help to provide an overview on the complex subject of the "business model".

On a more general level, frequently used management tools (e.g., Rigby and Gillies 2000; Rigby 2001; Jarzabkowski et al. 2013) are often unable to analyze interrelated dynamics in business in a consistent and systematic manner. Presently, also the tools used for business model analysis have the same shortcomings. They are mostly limited to qualitative indicators, concepts, or factors, and do not provide much detail of operational specifics of the situation analyzed and they are limited when attempting to understand interactions of implemented changes in a coherent manner. Moreover, the actions and reactions of other agents in the market are rarely taken into account, and if so, then only on a qualitative basis. The derived recommendations partially reflect a realistic assessment (Groesser 2015b).

The shortcomings of standard tools to deal with the dynamics in business have motivated researchers to improve several of the standard management tools for general strategy and management tools, A well-known example is the improvement of the Balanced Scorecard (BSC) by amalgamating it with the SD simulation methodology to determine medium- and long-term effects of interventions and the impact on a company's success (Schöneborn 2003; Bianchi and Montemaggiore 2008; Bianchi 2010; Katz and Grösser 2013). The amalgamation with SD allows a BSC to conceptualize and use feedback loops by means of which individual indicators from different business areas are interrelated. Modifying the BSC and using simulation methodology reduces the inadequacies or shortcomings of the BSC (Rieg and Esslinger 2012). This is just one example of a strategy or management tool which had a fundamental weakness in accounting for a business's dynamics. And it is just one example where standard management and strategy tools have been complemented by using a simulation methodology; further examples exist (Schwenke and Grösser 2014).

Since decision makers are faced with rapidly increasing levels of complexity and are in need of more powerful approaches to cope with the pressing complexities (Sargut and McGrath 2011), it seems feasible to also apply simulation modeling to the area of business models to support management in decision-making (Ashby 1956; Morecroft 1984; Warren 2005; Schwaninger 2009).

Simulation in management accounting

Simulation modeling methods are also used in MCS. Labro (2015) has pointed to several advantages these methods have in addressing management accounting research questions. As suggested by Leitner and Wall (2015) in their overview of simulation-based research in management accounting and control, simulation models allow for the investigation of the aggregate and the macro-level performance of rather complex organizational settings as a result of intertwined decisions at the micro-level under the regime of different MCSs. In principle, MCS are formal, routine-based systems that help to maintain or alter organizational activities and guide the behavior of a firm's employees (Guenther 2013: 269). In addition, MCS are regarded as a means to provide information for decision-making purposes (Simons 2000; Merchant and Van der Stede 2003; Anthony and Govindarajan 2007). The field of MCS research has not yet found a consistent use of definitions, conceptualizations, and theoretical perspectives (Berry et al. 2009) frequently ranging from systematic use of management accounting (Chenhall 2003) to broader conceptualizations including the implementation of strategic initiatives (Simons 1995; Merchant and Otley 2006). Moreover, a number of MCS frameworks exist that differ in their essential elements such as planning, performance measurement, rewards, feedback and feed-forward information loops (Otley 1999).

"MCS emerged in a time when most of the organizations were offering products and not services, the variety of organizational forms were more limited then today, and the boundaries of the organization were clearer. Today, more and different organizational forms with unique products emerge, which have due to their network-like character no clear boundaries. These developments require different forms of management control and MCS" (Strauß and Zecher 2013: 264–265). In addition, Labro and Vanhoucke (2007) constitute further support for simulation in accounting research. Their study, using an extensive simulation analysis, focuses on the accuracy of cost systems and the nature, level, and bias of cost accounting errors. Given the existing studies and approaches as detailed here, we believe that applying simulation methods to analyze and improve a company's business model can substantially contribute to the field of strategic planning and control in management accounting. As stated above, management accounting has primarily focused on cost modeling schemes. To date, SD is not frequently applied in management control research (e.g., Schöneborn 2003), even though SD offers the opportunity to investigate complex and interrelated processes and hence, simulation modeling could contribute to investigate the dynamics of MCSs (Leitner and Wall 2015). In our paper, we use the computational simulation methodology of SD and thus, contribute with a systemic approach which captures a more strategic planning perspective and includes additional elements besides cost elements and their relevant feedback mechanisms in a dynamic business system. The focus of our strategic planning approach is on modelling short- and long-term effects and resulting patterns.

Computational simulation methodology

Given the complex interdependencies of individual factors and their ripple effects in a business model (Sillanpää and Laamanen 2009), computer-based simulation of scenarios provides a more appropriate management tool in this context. Furthermore, it supports analysis of future environmental developments and evaluation of the potential success of different strategic initiatives in business models.

In the realms of simulation modeling, several approaches exist (Davis et al. 2007; Harrison et al. 2007); the commonly employed methodologies are discrete-event simulations, agent-based simulations, and SD simulations. Although several other approaches exist, we have opted for SD since it has been used extensively in management research and practice (e.g., Morecroft 1984; Lane 1992; Morecroft and Sterman 1994; Sterman 2000b; Repenning 2002; Black et al. 2004; Harrison et al. 2007; Sterman et al. 2007; Rudolph et al. 2009; Rahmandad and Repenning 2015). As simulations are versatile, they can be relatively easily combined with other management tools and augment them accordingly. In this paper, we intend to model and experiment with computational models of business models. To follow, we briefly introduce the SD simulation methodology which we employ.

System dynamics modeling and simulation accounts for accumulations, nonlinearities, delayed cause-and-effect, and feedback relationships between variables which are the building blocks of dynamic complexity (Groesser 2012; Groesser 2015a). Dynamic complexity is the reason why intuitive decisions often lead to unexpected results or to

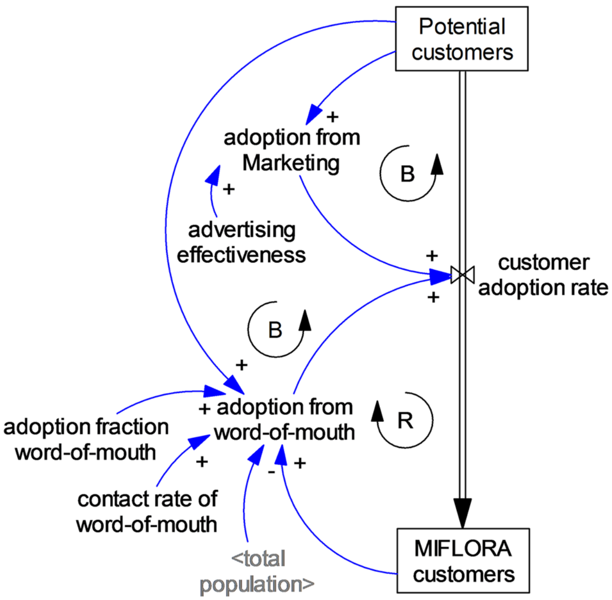

Fig. 1 Bass diffusion model as one part of the MIFLORA model (Bass 1969; Sterman 2000b)

short-term success and long-term failure (Senge 1990; Sterman 2000a). SD enables decision makers to identify and assess the consequences of their actions in dynamic and complex situations from an integrated perspective. On this basis, the approach allows one to develop formal and quantitative models of business models. Modeling with SD is about constructing models as continuous feedback systems. SD models are formal differential equation models. They incorporate hypotheses about the causal connections of parameters and variables as functional units, and the outcomes of their interactions. Each structural interrelationship can be tested both logically and empirically (Barlas 1996; Schwaninger and Groesser 2008, 2009; Groesser and Schwaninger 2012).

The stock and flow diagram in Fig. 1 shows our adjustment of the commonly known Bass diffusion model (Bass 1969: 216) and serves as a point of departure for the development of the simulation for MIFLORA GmbH.[2] It depicts the causal interdependencies between variables by means of causal arrows. These causal connections have either a positive (+) or negative (−) polarity. A (+) means that a change in the variable causes a change in the dependent variable in the same direction. For instance, a larger number of existing *MIFLORA customers* leads to more *adoption through word-of-mouth* and consequently to a higher *customer adoption rate*.[3] A (−) indicates that a change in one variable causes a change in the dependent variable in the opposite direction. For instance, the higher the *total population* is, the lower the adoption will be through word-of-mouth. In addition to the interdependencies, accumulations are accounted for, e.g., *MIFLORA customers* or *potential customers*, as well as inflow and

[2] In the following, we refer to the company as MIFLORA.

[3] In the following, model variables are written in *italics*.

outflow, e.g., *customer adoption rate*, by the stock and flow diagrams. A stock is a reservoir or accumulation, like water in a bathtub, and is represented by a rectangle; flows, like the spigot and drain in a bathtub, fill or drain the stock and are depicted as pipes with valves. The last conceptual elements of SD models are reinforcing feedback loops, denoted by the letter R, and balancing feedback loops, denoted by the letter B. Loops are the foundations for endogenous dynamics in a model (Richardson 2009). An example for the first concept is the loop R in Fig. 1; the more adopters who use the product and talk about it in a positive way, the faster the number of adopters increases—a virtuous cycle. To illustrate the latter concept, the reservoir of potential adopters is limited which reduces the number of new adoptions once the number of potential adopters becomes smaller and smaller—a balancing feedback loop. SD is a quantitative computational approach with considerable experience in modeling business situations. We use this experience and apply it to simulate business models and to analyze relevant scenarios.

3 Research design

The data needed to specify a computation model of a business model principally comes from the mental models of the decision makers, so the procedures used to elicit knowledge from mental models become critically important (Hall et al. 1994; Markóczy and Goldberg 1995). We chose a single case study approach (Eisenhardt 1989; Yin 2013) to analyze a company's business model, its possible strategic initiatives, and the resulting consequences on the company's business model in-depth. For our analysis, we chose the startup company MIFLORA for three reasons: First, we had unlimited access to the top-management of the company, as well as to available numerical data; second, the case is revelatory in providing insights about an e-commerce start-up firm with a non-durable product with an extremely short life-cycle—flowers (Stake 1996). As such, the company can be seen as representative for other industries with extremely short product life cycles such as the current increase of online food retailers. And third, the case is in an industry with a high degree of innovation where competitive advantages can be rendered obsolete quickly (Teece 2007). As many start-up business models, MIFLORA operates according to an absolute-growth-prior-to-profit principle. Furthermore, the short shelf life of flowers and the low revenue per order makes logistical aspects, for instance, planning and purchasing, of the business model highly complex. Thus, MIFLORA provides an appropriate and insightful case to illustrate the capabilities of computational modeling for business model analysis. Moreover, Cusumano (2013), a professor at MIT, examined 26,000 active firms that were created by living MIT alumni. Remarkably, 5–7 years after their founding only 30 % of MIT start-ups were successful. Stricter definitions of return on capital suggest only 5 % of startups succeed and merely 1 % go public (Gage 2012). (Cusumano 2013: 26) posits that "it should be possible for potential investors as well as would-be entrepreneurs to evaluate startup ventures more systematically". Consequently, the need for analysis and evaluation of e-commerce business models is strongly emphasized (e.g., Groesser and Buergi 2014).

Our research and consulting project ran for 6 months. The modelers worked for 40 days, attending internal meetings, gathering data, mapping, developing equations, executing simulations, and preparing for meetings to perform the case study analysis. For a successful application at a company-wide level, it was necessary to have a strong link to top-level management and ensure absolute commitment of our research partners in the company. Both dimensions of the weak market test, i.e., extent of usage as well as intensity of usage of the new method had to be met to a high degree (Labro and Tuomela 2003: 431). It is not sufficient for implementation and real impact when there is no direct involvement of final decision makers. Therefore, we conducted 11 in-depth expert interviews with the company's management team. The objective of the interviews was to reconstruct the historical development of the company and to understand the business mechanisms of MIFLORA as well as to determine reflections about strategic initiatives. Second, we used a comprehensive database with 500,000 data points created by Zendesk.[4] By means of this database, we were able to obtain and analyze information about customer behavior, buying processes, and related partners relevant to our case company. Third, we used the results of a customer survey about the perception of MIFLORA price-quality ratio and its market position compared to its competitors. The information was used to identify the relevance of customer ratings, on various websites, for the purchasing decision. Fourth, we facilitated four workshops with the management team and approached outside experts on production and information technology to deepen our understanding of the company, the related business, and the influence of technology. This rich textual and numerical data was used to successively develop our simulation model (Luna-Reyes and Andersen 2003; Luna-Reyes et al. 2003; Andersen et al. 2012). We fed back our insights from the computational modeling into workshops designed for the participating decision makers to encourage reflection and improvement. Hence, the workshops were used for critical evaluation and validation of our findings (Vennix 1995; Luna-Reyes et al. 2003; Black and Andersen 2012). Our simulation model was developed in an iterative way, continuously improving it and validating it against available empirical data (Homer 1996) to ensure a high level of validity of the model and the derived insights (Forrester and Senge 1980; Groesser and Schwaninger 2012). The latter was performed inter alia by simulating the past as well as present developments and then, comparing the simulated data, e.g., on sales and costs per order, with historic data. We used the simulation software Vensim DSS, V6.3[5]. The simulation model is detailed in the online appendix. Our research followed the protocol of the constructive research approach (Kasanen et al. 1993) in decisive, but not all, aspects and can be considered as contributing to this body of knowledge (Labro and Tuomela 2003). Similarly to what Lindholm (2008) did in the context of corporate real estate management, we implemented computational modeling at a start-up company and consequently tested whether the approach yielded benefits for practice. In the paper, we do not report about an application, but introduce a novel approach to the field of management accounting. We also aim to generalize the newly discovered knowledge in the discussion. We provide a rich description of the

[4] Zendesk (http://www.zendesk.de) is a customer service provider. It is designed for companies that want to establish and improve their customer relationships.

[5] ©Vensim (www.vensim.com) is developed by Ventana Systems.

modeling process and the case context, and consequently, intend to enable the reader to replicate the approach in other situations (Labro and Tuomela 2003).

4 Case study: modelling and analysis of MIFLORA's business model

Business model of MIFLORA

The incubator "Venture Stars" founded, financed, and otherwise supported several successful startups such as "vaola", "vitafy", and "ePetWorld". MIFLORA, a supplier of fresh, high quality cut-flower arrangements, also belongs to this portfolio. When comparing to local florists, MIFLORA demonstrates three major advantages that add to its customer value. First, MIFLORA benefits from a short supply chain. Flowers are not stored at wholesalers, intermediaries, or flower shops; this allows MIFLORA to send flowers directly to customers allowing them to be four days faster and to guarantee the delivery of fresher flowers. Second, since no intermediaries are necessary, MIFLORA obtains the intermediaries' margins, which MIFLORA passes on to its customers in the form of lower prices. Third, European florist champion Nadine Weckardt designs the arrangements. To summarize, MIFLORA offers customers the possibility to purchase fresh floral arrangements designed by a master florist at lower prices throughout Germany. MIFLORA's direct competitors are other leaders in the market, namely "Fleurop", "Blume2000.de", and "FloraPrima".

Furthermore, the products are primarily aimed at B2C-market, i.e., customers wishing to send flowers on occasions such as birthdays and wedding anniversaries. Through differentiation in quality, MIFLORA aspires to establish a high-end market position. In terms of customer services, MIFLORA utilizes the semi-automated customer care software Zendesk. The web-based ticket system organizes requests from various contact options such as email, social media, and customer hotline. From a distribution perspective, the first contact between customer and MIFLORA occurs through one of its online partners, for instance, Google's Search Engine Marketing and Deal platforms such as Groupon. The channels forward customers to the MIFLORA website for further product selection and ordering, including payment.

The revenue stream of a typical shopping basket is divided into three components: flower arrangement, additional gifts, and shipping costs. The cost structure reflects the relevant resources and partners: cost of goods sold, logistic costs, and marketing cost per order. Apart from online partners, a strategic network of suppliers reduces risks and ensures scalability: from printing companies for transport protection issues over large-scale gardening firms to Venture Stars providing investor contacts and HR recruiting possibilities. Moreover, major activities involve the improvement of the IT-infrastructure enabling MIFLORA to create an efficient mix of online marketing tools and an appealing website in cooperation with the product design by star florist Nadine Weckardt. Figure 2 summarizes MIFLORA's business model.

Structure of the simulation model

To enable us to analyze MIFLORA's business model, we created a SD model (Fig. 3) from detailed qualitative and quantitative data sources. As previously defined, we

<table>
<tr><td rowspan="3">Key Partners

• Commercial, large-scale nurseries
• Logistic companies (transportation Netherlands to Munich)
• Intra-Germany logistic partners
• Incubator for finance issues & HR recruiting</td><td>Key Activities

• Product design in cooperation with top florists
• Provision of IT-Infrastructure
• Best-in-class online marketing
• Customer Care as innovation</td><td rowspan="3">Value Proposition

• Delivery of high-quality cut flowers arrangements
• 7 days freshness guarantee
• Top-design by European floristic champion
• Higher quality at lower prices than local retailers</td><td>Customer Relationships

• Customer Care Service available by hotline and email
• Tracking tool Zendesk to secure customer loyalty</td><td rowspan="3">Customer Segments

• B2C market
• Customers with strong internet affinity
• Urban, middle- to high-income segment of population with affinity for high quality</td></tr>
<tr><td rowspan="2">Key Resources

• Ecommerce Know-how
• Investor contacts</td><td rowspan="2">Channels

• Search Engine Marketing (SEM)
• Deal platforms
• Affiliates</td></tr>
<tr></tr>
<tr><td colspan="3">Cost Structure

• Cost of goods sold (flower and plants auction at FloraHolland in Aalsmeer, Netherlands)
• Logistic costs (intra-Germany partner DHL)
• Marketing costs per order (proportional cost for customer acquisition)
• Others (payment charge, packaging, HR)</td><td colspan="2">Revenue Streams

• Sales per customer to be divided into flower arrangement, add-on present and shipping charge
• Various Cross-Selling (event voucher, accessories, sweets…) and Upselling methods (WOW-Effects, individual number...)</td></tr>
</table>

Fig. 2 Business model canvas for MIFLORA (as of September 2014)

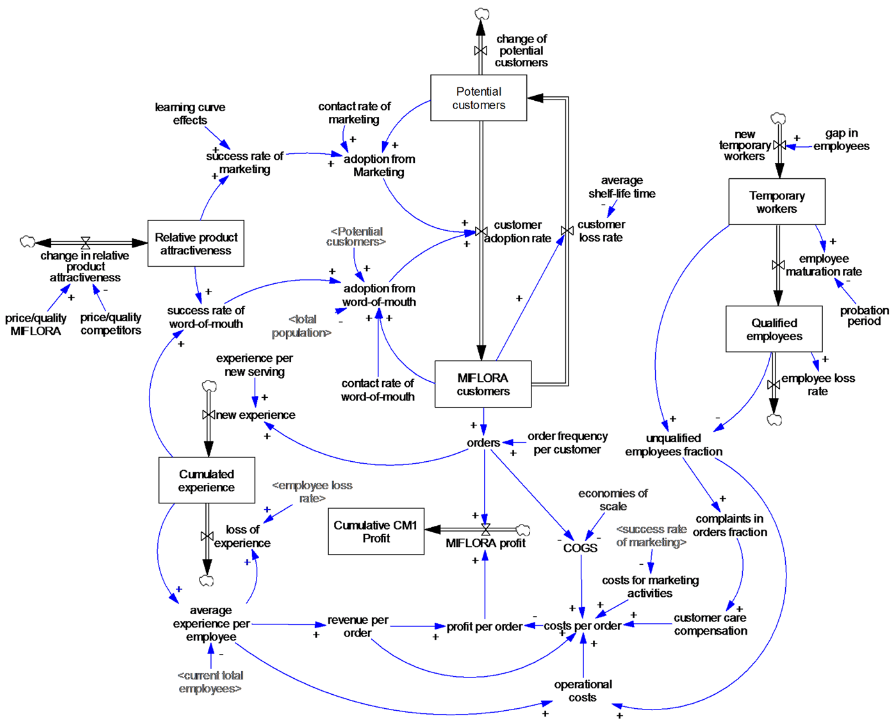

Fig. 3 An extract of MIFLORA's business model in the system dynamics notation

understand a business model as system of interdependent activities, which generate a value proposition through the deployment of resources. The business model canvas (Osterwalder and Pigneur 2010; Wirtz 2011) applies this understanding and structures the elements of a business model (Fig. 2). The simulation uses the classic Bass diffusion theory (Bass 1969: 216) as a basis for the purchasing decision (cf. Fig. 1). The Bass model describes the process of how products diffuse in a population by means of interacting adopters and potential adopters. Adopters are classified as innovators or as imitators and the speed and timing of adoption depends on their degree of innovativeness and the degree of imitation among adopters (Bass 2004). The fundamental dynamics present are *adoption from advertising* and *adoption from word-of-mouth* (Morecroft 2007). Based on this widely accepted model, we further detailed and adjust the purchasing adoption decision with aspects relevant to our case study. Even though the Bass model describes the diffusion of new *durable* goods, we use it as basis to model MIFLORA's service which is distributing non-durable products—flowers. The reasons are, first, that the mechanisms in the Bass model are also highly relevant for products with short lifecycles (e.g., Norton and Bass 1987; Kurawarwala and Matsuo 1996), second, we adjust the model to represent the short-term nature of the non-durable products. And third, since MIFLORA distributes exclusively via web sales and marketing and without intermediaries, we use the study by Shah (2014) to inform our model and specify the purchasing decision. In this context they have identified four recurring customer behaviors: making a purchase trip, responding to a promotion, buying marked-down items, and returning previously purchased products (Shah 2014). We used these behavior traits as a point of departure and adjusted them to the case of an e-commerce purchase situation. We have considered comparison websites that not only evaluate the price-performance ratio of our offerings, but also record recommendations and previously made experiences by other customers. In addition, the potential of promotions including discounts via communications channels such as newsletters prior to Valentine's or Mother's Day is dynamically linked to the growing customer database. Furthermore, we also account for the management's strategic decision to focus on a long-term development of brand recognition.

The revenue generated during the time around Valentine's and Mother's Day is a special feature of the flower market and has been accounted for in the simulation. The company's profit or loss is the product of the number of orders and the respective profit per order, i.e., revenues less variable costs as previously described. Except for marketing cost per order, which increases straight proportional as Search Engine Marketing platforms grant rather marginal volume discount for small and medium-sized enterprises, the other major cost elements, i.e., material, production and logistic costs, behave nonlinear due to economies of scale and learning curve effects. However, in this model the term *profit* solely refers to *Contribution Margin I* which excludes the administrative overhead. In the following, we detail several causal mechanisms of the simulation model as examples.

First, the *Potential customers* and *MIFLORA customers* are decisive values to identify the *customer adoption rate* and *customer loss rate*. The *customer adoption rate* is determined by *adoption from marketing* and *adoption from word-of-mouth* (Eq. 4). The *contact rate* is the relative frequency by which customers come into contact with

MIFLORA marketing or learn about the product through other *MIFLORA customers* respectively. The rate is multiplied by the ratio of *Potential customers* and *total population* to determine the effective number of contacts. The respective *success rate* describes the actual fraction people adopting the product (Eqs. 5, 6). The *customer loss* (i.e., flowing back to *Potential customers*) accounts for the *average shelf-life time* of the product (Eq. 3).

$$MIFLORA\ customers = Customer\ adoption\ rate - Customer\ loss\ rate \tag{1}$$

$$\begin{aligned} Potential\ customers = {} & Customer\ loss\ rate - Customer\ adoption\ rate \\ & - Change\ potential\ customers\ due\ to\ population\ changes \end{aligned} \tag{2}$$

$$Customer\ loss\ rate = \frac{MIFLORA\ customers}{Average\ shelf\ life\ time} \tag{3}$$

$$\begin{aligned} & Customer\ adoption\ rate \\ & \quad = Adoption\ from\ marketing + Adoption\ from\ word\ of\ mouth \end{aligned} \tag{4}$$

$$\begin{aligned} & Adoption\ from\ marketing \\ & \quad = MIFLORA\ advertising \times Success\ rate\ of\ marketing \\ & \qquad \times Potential\ customers \end{aligned} \tag{5}$$

$$\begin{aligned} & Adoption\ from\ word\ of\ mouth \\ & \quad = MIFLORA\ customers \times Success\ rate\ of\ word\ of\ mouth \\ & \qquad \times \frac{Potential\ customers}{Total\ population} \end{aligned} \tag{6}$$

Second, the model sector regarding staff structure and key resources examines growth limitations and disadvantages of particularly intense periods of growth (see right, central elements in Fig. 3). The *unqualified employees fraction* is a key indicator for quality and relating compensation costs as well as the satisfaction of customers (Eq. 7). The number of *Temporary workers* is defined by the inflow of *new hires* and outflow of *employee maturation rate* (Eq. 8). *New temporary workers* are calculated by multiplying the *gap in employees* with the *time to hire temporary workers* (Eq. 9). The *gap in employees* (Eq. 10) highlights the difference between *current employees* and *needed employees* which is the product of *orders* and *order capacity per employee* (Eq. 12). The *employee maturation rate* describes the process of recruiting *temporary workers* after a certain *probation period* (Eq. 13). The then *Qualified employees* are decimated by *employee loss rate* (Eq. 14), which is defined by multiplying them with the average *normal loss rate of employees* (Eq. 15).

$$\begin{aligned} &\textit{Unqualified employees fraction} \\ &\quad = \frac{\textit{Qualified employees}}{(\textit{Qualified employees} + \textit{Temporary workers})} \end{aligned} \tag{7}$$

$$\textit{Temporary workers} = \textit{New temporary workers} - \textit{Employee maturation rate} \tag{8}$$

$$\begin{aligned} &\textit{New temporary workers} \\ &\quad = \textit{Time to hire temporary workers} \times \textit{Gap in employees} \end{aligned} \tag{9}$$

$$\textit{Gap in employees} = \textit{Employees required} - \textit{Current total employees} \tag{10}$$

$$\textit{Current total employees} = \textit{Temporary workers} + \textit{Qualified employees} \tag{11}$$

$$\textit{Employees required} = \textit{Orders} \times \textit{Order capacity per employee} \tag{12}$$

$$\textit{Employee maturation rate} = \textit{Temporary workers} \times \textit{Probation period} \tag{13}$$

$$\textit{Qualified employees} = \textit{Employee maturation rate} - \textit{Employee loss rate} \tag{14}$$

$$\textit{Employee loss rate} = \textit{Qualified employees} \times \textit{Normal loss rate} \tag{15}$$

In addition, the model depicts loss of employees through fluctuation (bottom central elements in Fig. 3). In this context, the *Cumulated experience* is considered as an indicator for the company's know-how (Eq. 16). It is calculated by the difference between *new experience*, which is defined as product of *orders* and *experience per new serving* (Eq. 17), and *loss of experience*, which is calculated by the amount of *average experience per employee* multiplied by the average time of *employee loss rate and loss of temporary workers* (Eq. 18).

$$\textit{Cumulated experience} = \textit{New experience} - \textit{Loss of experience} \tag{16}$$

$$\textit{New experience} = \textit{Orders} * \textit{Experience per new serving} \tag{17}$$

$$\begin{aligned} &\textit{Loss of experience} \\ &\quad = \textit{Average experience per employee} * (\textit{Employees loss rate} \\ &\qquad + \textit{Loss of temporary workers}) \end{aligned} \tag{18}$$

Simulation base run

We simulate the base run with parameter settings we identified from the available data. The model and parameter values used are documented in the online appendix. The simulation runs from 2010 until 2020. MIFLORA started to operate in 2013. Years are the unit of measure. The base run simulation shows that the adoption rate depends on success rates and contact rates since both are determined as influencing parameters for the respective adoptions. Therefore, the increasing adoption is to be justified by increasing success rates, which itself depends on improved *Relative product attractiveness*. From 2015, the increase in *MIFLORA customers* has intensified, whereby the existing employees' capacity needs to experience growth. However, a normal delay in the recruitment process creates additional demand for *Temporary workers*. In the short-term, temporary workers are mostly unskilled and consequently, deterioration in quality can be observed, which explains the increase in *customer care compensation* (Graph 3 in Fig. 4) in the context of otherwise lower costs (Graph 1, 2 and 4 in Fig. 4). The declining *costs of goods sold* (*COGS*), *costs for marketing activities*, and *operational costs* are mainly caused by economies of scale, and the learning curve effect is due to improving *average experience per employee* and *unqualified employees fraction*. One insight is that the company will become profitable early 2017. In addition, the simulation suggests that the *profit per order* is quite limited because, on the one hand, the customers' willingness to pay becomes exhausted due to an increasing price difference to the competitors or decoration alternatives and the lack of improvement in product experiences. On the other hand, the flattening effect curve indicates the fact that it is quite difficult to reduce further cost elements beyond a certain threshold. The number of orders or, in other words, the rate of customers adopting MIFLORA products then will primarily affect the company's profit.

When there are external changes, we intend to identify conflict situations within MIFLORA's existing business model with computational experiments. The SD simulation methodology does not fulfill predictions of the future rather it provides estimates and analyses about possible outcomes of certain events and actions (Ford and Flynn 2005). After we show the impact of different scenarios, we will also implement strategic initiatives. A strategic initiative is the decision taken on an internal change of one or more elements of the business model by the management. Osterwalder and Pigneur (2010) address business model changes by uncovering all possible options to design and adjust business models. The adjustments of business models are strategic initiatives in the understanding we use in the remainder of the paper. The initiatives are

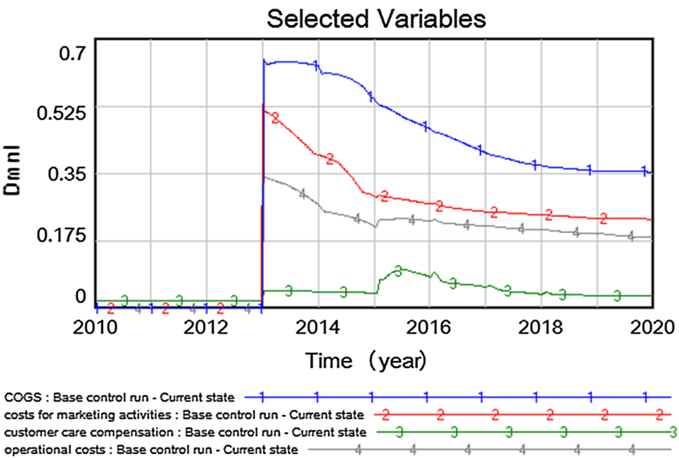

Fig. 4 Development of different cost positions

Table 1 Summary of scenarios and implemented strategic initiatives

Scenario	Scenario variable	Value	Strategic inititative	Influenced elements in the structure of the business model
S1: Superior competing product	Price/quality competitors	73 % (base run) 100 % (S1)	(1) Media-for-equity deal	Marketing partner, investment process
S2: Increased contact rate	Contact rate of word-of-mouth	7,5 (base run) 37,5 (S2)	(2) Expansion to Austria	Austrian population, growth circle
S3: Tighten in g supply of flowers	COGS (cost of goods sold)	Dynamic (base run) dynamic multiplied by factor 2 (S3)	(3) Continuous costs reduction effort supported by external experts	Adjusted lookup tables of costs for marketing activities and operational cost (50 % reduction of initial assumptions)

analyzed with regard to their impacts on the success and sustainability of MIFLORA's business. Table 1 shows the three scenarios and strategic initiatives. Based on the results of the simulation experiments findings, we derive recommendations for action.

Scenario S1: a superior competing product is introduced

Scenario S1 assumes that Blume2000 has developed a similarly high quality product in terms of quality measures for an extremely low price simultaneously to the market entry of MIFLORA. Under these circumstances, it is not possible for MIFLORA to establish itself in the market, which is indicated by the stagnating number of *MIFLORA customers* (Graph 1 in Fig. 5 on the left compared to the base run in Graph 2). Hence, several recommendations arise for real business activities. Given extensive analysis of the simulation model, price competition with discount stores is not effective and thus, the strategic initiative to stand out with superior product properties is the only way to succeed. The cooperation with the European master florist should only be the first step and more unique selling propositions must follow.

The strategic initiative most appropriate here would be to close a media-for-equity deal. A media-for-equity deal is an innovative funding concept for high-growth entrepreneurial companies. It is based on a barter scheme (O'Sullivan and Sheffrin 2003: 243) in which advertising inventory provided by media companies is traded against equity. Once MIFLORA fulfills predefined criteria, the media-for-equity mechanism is activated in the simulation model and the additional marketing activity (Graph 2 in Fig. 5 on the right). The increased contacts lead directly to a higher *adoption from marketing*.

Scenario S2: increased contact rate

Scenario S2 considers a five fold increase in the external factor *contact rate of word-of-mouth* triggered by a series of social events. We assume that the social interaction

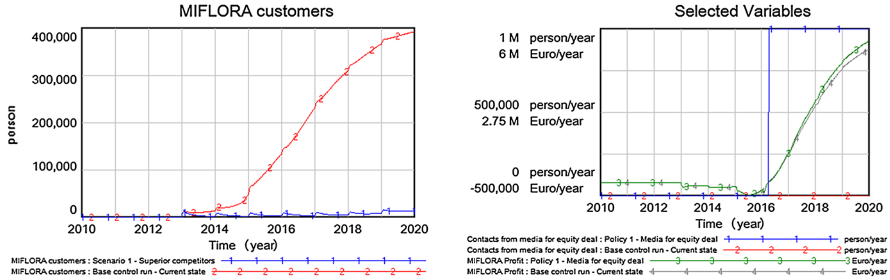

Fig. 5 Superior competing product enters the market (*left*, #1) and MIFLORA's response by a media-for-equity-deal (*right*, #1 and #3)

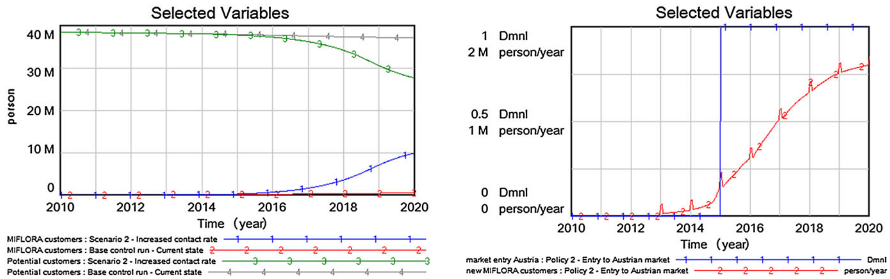

Fig. 6 Increased contact rate of word-of-mouth (*left*, #1 and #3) and management decision on expansion to Austria (*right*)

and the respective contract rate increases accordingly in this period of time. The *adoption from word-of-mouth* would be far more dynamic than changes in the *adoption from marketing* loop. The number of *MIFLORA customers* increased exponentially in the first years (Graph 1 in Fig. 6, left, compared to Graph 2) and significantly influenced the market share. Furthermore, adoption from word-of-mouth is ideal for companies since it attracts new customers without an additional marketing budget. To summarize, the simulation model analysis clearly identifies the substantial benefit of the *contact rate of word-of-mouth*. Consequently, the strategic initiative of influencing this variable is most crucial to further drive this positive development of MIFLORA. Respective examples of struggling companies such as Eastman Kodak, which failed to introduce the right actions at their peak of success, underline this importance. The second strategic initiative is an internal management decision with respect to an expansion of the MIFLORA business. The nearest suitable market is Austria, due to its economic attachment in terms of logistical infrastructure and linguistic similarity, which reduces costs related to translation tasks and the complexity of customer service. The entry into the Austrian market depends on available financial funding. The model depicts this mechanism with the stock *Net working capital*, which represents the *cash inflow* and delayed *cash outflow*. As soon as sufficient funds are available, the variable *market entry Austria* switches from the value 0 to 1 and thus enables the expansion to Austria. The simulation shows that the expansion occurs after a consolidation phase and triggers the beginning of a strong increase in *MIFLORA customers* (Graph 2 in

Fig. 6, right). The stock *Potential customer* is not only affected quantitatively, but also in its behavior pattern.

Scenario S3: tightening supply of flowers

The third scenario considers a reduced supply of flowers caused by environmental conditions. The competitive equilibrium significantly increases the price of the cost of goods sold. The simulation shows that under otherwise unchanged parameters, MIFLORA is not profitable at any time (Graph 2 in Fig. 7, left, compared to base run in Graph 1). Previous recommendations primarily attempted to increase the number of *orders*. These measures are certainly important since a critical size has to be reached to be an established market participant and to benefit from economies of scale. However, the simulation also reveals that at the same time, cost factors have to be considered. If process optimization is implemented at an early stage, even the first strong growth period can be profitable and generate resources for further management plans. If the company does not break even by increasing adoption of customer, MIFLORA loses its attractiveness for investors since the chance of profitability decreases disproportionally. Considering the extensive analysis of the simulation model, the strategic initiative has to control cost factors to prevent insolvency despite growth.

The third strategic initiative assesses the hire of external consultants in order to review the internal cost structure, and in particular, to optimize production processes. In the foundation phase, MIFLORA has limited resources and needs to focus its organization on its core competences. Furthermore, its incubator Venture Stars shows a positive record in acquiring externals due to their competence in quickly, objectively and accurately identifying costs reduction potentials. A finding through simulation reveals that an early focus on cost reduction does not merely have a positive effect on the profit in the short-term, it is also crucial for the company's success in the long-term (Graph 2 in Fig. 7, right, compared to Graph 1). Financial resources, that become available through process optimizations, can be used for necessary product quality improvements or to create a loyal customer base.

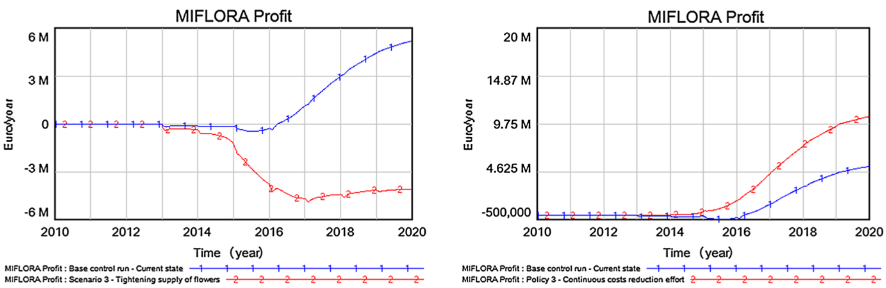

Fig. 7 Tightening supply of flowers (*left*, #2) and strategic initiative on continuous cost reduction effort (*right*, #2)

Management recommendations

The first scenario has analyzed the market effects of a competing product, which is superior in terms of quality and price. MIFLORA was not able to establish itself in the market. The key-learning outcome of the devastating result is the knowledge that the success of MIFLORA strongly depends on whether it can position itself as a synonym in the cut-flower market for quality and modern design. MIFLORA has to offer customers a real added value compared to cheaper mass-products. Moreover, the simulation strongly emphasized continuous product optimization. Once a superior product enters the market, the chance of successfully obtaining a customer adoption significantly decreases. Consequently, a team employed to improve business processes should be established. This acquired competence could be offered to other non-competing floristic partners, making MIFLORA a provider for consulting services. Hence, the business model in terms of a broader product portfolio is diversified, which is a necessary step to ensure sustainable development.

The second scenario has clarified the role of word-of-mouth within an ideal marketing concept. The result of exponentially increasing MIFLORA number of customers illustrates how beneficial a customer-advert-customers approach works. This allows us to draw the conclusion that management should focus on such network effects. The simulation has identified that exponential growth is achievable with a respective contact rate. Therefore, it is strongly recommended that management significantly expand this product range as well as to initiate similar marketing activities, which are crucial steps for MIFLORA's positive long-term performance.

The third scenario has highlighted the relevance of cost management and long-term planning. The management is recommended to initiate process improvements and continuously pursue cost reductions as soon as possible. Aiming at gaining a high number of customers should not be the only priority. External consultants should continuously review business processes and structures to impartially provide new input for business improvement. In addition, MIFLORA must diversify their suppliers and their product portfolio to become less dependent on the development of a singular cost element. By changing the supply chain, the profit margin increases, costs are reduced, and the financial resources may be designated to more important business activities. In addition, the dependencies on few partners with strong bargaining power are reduced.

5 Discussion

In the following, we outline the advantages and disadvantages of computational modeling with SD for business model analysis. Thereafter, we discuss the limitations of our study as well as the practical implications for businesses.

Advantages

First, by amalgamating computational methods with existing business modeling approaches provides an insightful, valid, relatively rapid, and inexpensive approach to business model analysis and design (Eden et al. 2000). Moreover, from a perspective of consistency, it is known that humans cannot deduce the behavioral consequences from a system with many interdependent elements (Miller 1956; Forrester 1961; Sterman et al. 2015). Computational modeling is one of the means, among others, to reduce the issue that qualitative models seem to be not sufficient when systems are highly complex (Sterman 2000a). Hence, it enables a deep and integrated understanding of a system through the quantitative exploration of systemic interdependencies.

Second, the approach can improve a company's capabilities when analyzing the interdependencies in their business models when confronted with external changes in the environment. Since simulation approaches are capable of representing highly complex situations and handling them in a reasonably simple way, it becomes possible to address a higher degree of the dynamic complexity of business reality (Groesser and Schwaninger 2012). As a direct consequence of structuring and linking the knowledge about a business system, SD allows decision makers to take decisions which are based on an integrative qualitative and quantitative analysis.

Third, any tool for decision-making has to satisfy several criteria to effectively deliver decision support. According to (Little 1970: B470) these criteria are: simplicity; robustness; ease of control; adaptiveness; completeness on important issues; and easiness of communication. In close connection with the decision maker, a computational modeling process begins with a simple model structure and continuously improves in an evolutionary way using rapid prototyping. As a result, this process of elaboration and calibration creates a robust and purpose-oriented, sufficient model. Furthermore, the involved decision makers learn how to control the model during its execution. The unfolding model is permanently represented as a visual object to ensure transparent communication with the target audience (Black and Andersen 2012; van Nistelrooij et al. 2015).

Fourth, and this is closely related to the previous point, SD can be used to elicit concepts and ideas communicated during management meetings and organize them in a clear and coherent manner (Vennix 1996). Our research using SD simulation modeling followed best practice in group model building and client engagement (Andersen and Richardson 1997; Richardson 2013). Thereby, we operationalize what Labro and Tuomela (2003) and Kasanen et al. (1993) refer to as the intervening role of researchers. In essence, we support the development of theoretically grounded solutions of practical problems. The process of computational experiments is a creative and iterative process that provides additional insights and possibilities for reflection for both the modelers, and in particular, for engaged managers. This quantitative experimentation, i.e., simulation-based prototyping of strategic initiatives, is a strength of the simulation approach. This creative and discursive process is generic and can also be applied in other contexts (Van den Belt 2004). As implied in a study by Degraeve et al. (2000), main characteristics of a novel construct proven in a singular case are likely to be useful to other organizations. In particular, the process of experimenting, analyzing and elaborating computational business models is novel and transferable to other situations.

Fifth, risks can be identified through sensitivity analysis of the feedback dynamics in a simulation model. Risks are often identified in the following three areas: firstly, balancing feedback loops that limit a desired growth or decay; secondly, reinforcing feedback loops that lead to undesired growth or decay; and thirdly, external factors that exacerbate any of above two types of feedback loops. Analysis of feedback dynamics can make some systemic risks apparent, which otherwise might be too vague to attract notice. System dynamics can be used to quantify risks which are attributed to be most relevant (Rodrigues and Bowers 1996).

Sixth, SD emphasizes a continuous perspective (Sterman 2000b). This perspective strives to look beyond single events to see the dynamic patterns underlying them in the short-, as well as, the long-term. Then, by identifying those patterns, simulations help to understand the causes for current issues and can support decision makers to tackle them.

And finally, applying computational modeling supports the validation of strategic initiatives to be implemented and their effect on existing business models—such as engineers who test new technologies or products extensively in a laboratory before they enter the market. In particular, the possibility to experiment with different scenarios and strategic initiatives in a computational environment has the potential to reduce erroneous management decisions and reveal disregarded factors and patterns that could become relevant in the future (Groesser 2015b).

Disadvantages

Computational modeling of complex systems is a relatively innovative approach for top management decision makers. Some disadvantages of this method relate to the relative easiness of linking variables together to quickly create large, highly complex models. Some users may be overwhelmed by this complexity if they do not exercise cautious modeling behavior (Groesser and Schwaninger 2012). The existence of user-friendly visual representations has, in some cases, been a disservice by offering the false impression that modeling is always simple and quickly done. In addition, inclusion of uncertain or only hypothesized feedback loops may create complex model behavior that may be difficult to track, to falsify, or to validate. Moreover, the empirical evidence about the learning outcomes of computational modeling and its effectiveness is still inconclusive (Karakul and Quadrat-Ullah 2008; Sterman 2010; Qudrat-Ullah 2014). Consequently, it is not yet possible to state that the businesses applying computational modeling systematically produce better results than those that are not using it and thus, the requirements of the strong market test are yet not met (Lukka 2000; Labro and Tuomela 2003: 429). At the same time, this is a call for action to conduct more empirical research with computational simulation methods to master the strong market test.

Limitations

Our study is limited in several respects. We use a single case study of an e-commerce startup company and the generalizability of the case might be limited. However, we could demonstrate both the effective use of simulation methodology to analyze the interdependencies of elements in business models and the effective and beneficial support of strategic decisions in a real business setting. A further limitation is the selection of the model boundary. Although, the computational modeling of MIFLORA's business model within the market context is depicted in the best possible way, we had to define model boundaries, i.e., we had to decide on variables that are not included. For instance, the decision whether to found a company in the first place was not modelled. Moreover, the model focuses on activities in the German market and pays little attention to current global trends. In addition, social aspects such as employee management, certain aspects of customer satisfaction, as well as investors' behavior during the loss-generating period regarding exit strategies, have not been included in the model. Many more variables could have been included from a theoretical-conceptual perspective. However, we discussed the model boundary selection several times with the management team and achieved, after several iterations, agreement to represent the relevant aspects of the business in a sufficient way.

Practical implications

Throughout the project, the management team provided us with feedback about the value and effects of the project. The managers acknowledged that the project raised awareness about several strategic issues. First, based on the simulation findings, they realigned their focus on the formation of a strong brand. The management's main target is now clearly defined as becoming the synonym for quality and modern design in the cut-flower market. Second, the marketing team currently fosters activities that trigger word-of-mouth advertising. In this regard, the simulation has helped to understand and develop an intuitive feeling of the importance of the effect of a network, for instance, the reinforcing dynamics of word-of-mouth adoption. Third, the result of the scenario and strategic initiative concerning cost elements was exceptionally informative for the management team, triggering an immediate diversification of suppliers. In summary, the project has been of significant value for both the creation and evaluation of strategic decisions concerning the analysis and elaboration of business models. Within weeks, the management adopted this new way of thinking and recognized the relative ease as well as the rich variety of applications possible with the SD methodology despite the initial complicated appearance. In this context, the MIFLORA CEO stated: "I have experienced the simulation approach as a powerful small model which provided real value added. It led to direct changes in the business." Furthermore, the management team expressed a genuine interest in computational modeling as strategy tool. MIFLORA's head of finance and business development at Venture Stars mentions: "We are currently looking how to transfer the gained knowledge to other start-ups in our portfolio." Our case provides counter-evidence to Huelsbeck et al. (2011) who show that the decision makers' confidence in their business model remained high despite poor results in the testing of their company's business model. The case of MIFLORA is a further successful example where this approach has been implemented in managerial controlling of a company. The weak market test is passed when a manager is willing to apply the construct to his or her actual decision-making problem (Labro and Tuomela 2003: 429). Lukka (2000), in the other side, has specified that the weak market test should refer to the actual implementation of the construct and not only the willingness of the managers to implement it. Given the positive response of MIFLORA's management as stated above the requirements of both definitions regarding the weak market test have been fulfilled.

On a more general level, computational modeling influences the decision making process, especially for long-term planning. Decision makers can use the decision support offered by computational models which simulate different strategic initiatives within a complex business model or changed environmental conditions. Thus, they can draw further conclusions based on a different type of analysis. Despite the positive influence of our case, the drawbacks of complex computational models can be that decision makers tend to engage (external) experts rather than use the models themselves. The skills and experience of these experts are then crucial and form the basis of trust for strategic decisions. The advantage of this investment is that a computational approach enables decision makers to evaluate strategic initiatives in complex business environments.

And finally, both the computational models used and the modeling process employed to develop and analyze the business model function as boundary objects (Carlile 2002; Spee and Jarzabkowski 2009). A boundary object is a means to facilitate and improve the quality of discussions in a team of decision makers, employees, and analysts. A boundary object has the capacity to overcome organizational, cultural, or other types of boundaries between organizational entities (Black and Andersen 2012). The capabilities of computational modeling to visualize complex interrelationships provide a value highly appreciated by practitioners.

6 Conclusion and future research opportunities

A computational modeling approach enables a company to analyze and optimize its business model by means of simulation experiments. The majority of strategic planning in management control focuses on cost simulation modeling. However, the SD methodology, as a supplement to existing techniques, facilitates a more integrated and systemic assessment of business models, in particular when evaluating external changes and possible strategic initiatives to respond to these changes. In addition, the active involvement of the final decision makers in the development process further supports a greater acceptance and in-depth understanding, as well as, model validation (Barlas 1996; Groesser and Schwaninger 2012). Hence, the risk of neglecting or underestimating dynamic interaction, delays, nonlinearities, accumulation effects, and feedback is reduced (Sterman 2000a). As a result, the acquired understanding about the system helps to generate sustainable success for a company. This approach is unique in providing insights about the extent of interactions of business model elements while integrating the expertise of the organizational professionals.

The reality of business shows that mid-sized companies and large enterprises use multiple business models simultaneously (Markides 2013). A step forward could be to analyze and characterize single business models and then integrate them to represent a corporate model (Aspara et al. 2013). By this, the unique advantage of a computational modeling approach can achieve benefits: it can uncover latent reinforcing potential impacts as a result of the interactions of individual business models, as well as, provide the opportunity to improve understanding of the requirements to achieve growth in the dynamics of individual business models. In other words, by using the SD approach, synergies can be exploited and conflicts can be identified that emerge from the interaction between business models, such as the competition of scarce resources within the company. However, it is also quite clear that the system dynamics approach in management control is at its beginning. Future research has to connect computational modeling to management accounting topics and demonstrate its potential benefit as an additional strategic planning tool.

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