PRE-PRINT VERSION

Wakolbinger L.M., Stummer C., Günther M. (2013) Market introduction and diffusion of new products: Recent developments in agent-based modeling. International Journal of Innovation and Technology Management, 10 (5), 1340015.
DOI: 10.1142/S0219877013400154

The final publication is available at World Scientific via https://doi.org/10.1142/S0219877013400154.

International Journal of Innovation and Technology Management

Market introduction and diffusion of new products: Recent developments in agent-based modeling

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Received 6 July 2011
Accepted 29 September 2011

Market introduction and diffusion of new products is complex and multifaceted since it involves spatially dispersed customers with individual preferences who may be exposed to a wide range of influences including word-of-mouth communication within a social network. During the past decade agent-based modeling approaches for simulating this process have become increasingly popular, because they not only capture the customers' behavior more realistically, but also allow for new insights for innovation management. The aim of this work is to provide an overview of recent developments, to discuss challenges, and to highlight promising directions for future research.

Keywords: New product market introduction; innovation diffusion; agent-based simulation.

1. Introduction

The ability of firms to generate a continuous stream of new products may be more important than ever in allowing a firm to maintain competitive advantage and thus to secure long-term success [Artz *et al.* (2010)]. To this end, firms need a high-quality process, a clear and visible strategy, enough people, and a respectable research and development (R&D) budget [Cooper and Kleinschmidt (2007)]. Correspondingly, large amounts of resources are at stake. The corporate R&D investments in the countries of the EU-27, for instance, summed up to €139.7 bn in 2009 [OECD (2011)]. On the firm level, several large EU companies have spent more than four billion euros on R&D in the same year (e.g., Volkswagen, Nokia, Sanofi–Aventis, Siemens) and many of the top-1000 EU industrial enterprises have invested even more than 50% of their net sales which is not only the case for the "usually suspected" biotechnology companies, but also for companies from various other sectors ranging from

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pharmaceuticals, chemicals, software, electrical components & equipment, telecommunication equipment, and semiconductors to alternative energy, health care equipment & services and leisure goods [Hernández Guevara *et al.* (2010)]. However, just spending resources on R&D is not sufficient since inadequate marketing and timing of introducing new products to market can hamper a firm's commercial success (for illustrative cases cf. Christensen [1997]). This is in line with empirical findings by Cooper [2001] pointing out that insufficient marketing effort is among the major drivers of innovation failure (i.e., in 14% of the investigated cases) and in this respect clearly "outperforms" factors such as "technical problems in development and production" that turned out to be responsible for failure in "just" 6% of cases.

Diffusion research seeks to understand the spread of innovations. It can deliver insight into market behavior when introducing new products and thus contributes to reducing innovation failure. The probably best known diffusion model has been introduced by Bass [1969]. It characterizes the diffusion of an innovation as a contagious process that is initiated by mass communication and propelled by word-of-mouth. Rather than explicitly explaining the effects that shape the diffusion curve, the Bass model aims at providing an empirical generalization of the spread of an innovation. As diffusion processes go beyond the classic scenario of a single market monopoly of durable goods in a homogenous, fully connected social system, numerous researchers have attempted to extend the Bass framework to reflect the complexity of new product growth (for a discussion cf. Peres *et al.* [2010]). Nevertheless, aggregate-level models of innovation diffusion, such as the Bass model and its successors, do not explicitly account for distinct consumer preferences, but model consumer behavior from an aggregate macro-level perspective. They neglect, for example, the population's heterogeneity [van den Bulte and Lilien (2001)], as well as network externalities [van den Bulte and Stremersch (2004)] or spatial effects [Berger (2001)].

While the classical models have to make strong assumptions to achieve analytical aggregation, agent-based models replace this construct with simulation and, thus, can overcome the above limitations. Agent-based simulations are particularly well suited to properly capture emergent phenomena, i.e., system behavior that has not explicitly been implemented by the modeler but instead results from the (simple) rules that dictate the interactions of agents [Garcia (2005)]. In general, agent-based simulation approaches have received considerable attention in the research of social behavior within the past decade. This development is particularly driven by (i) the increasing availability of advanced computing capacities, (ii) the willingness of many decision-makers to trust findings based on simulation models rather than those based on more abstract theoretical-analytical models [Dawid and Fagiolo (2008)], and (iii) the opportunity to analyze at little cost various scenarios with respect to the impact of marketing activities, governmental policies and so forth [Fagiolo *et al.* (2007)].

Notably, innovation diffusion research constitutes a particularly popular field of application for agent-based modeling approaches. Contributions may be roughly distinguished in three groups concerning the type of product and/or market investigated. Most authors deal with a generic product in a non-specified market (e.g., [Alkemade and Castaldi (2005); Deffuant *et al.* (2005); Delre *et al.* (2010); Moldovan and Goldenberg (2004); Valente and Davis (1999)]). Others stick with generic products but explicitly refer to markets with distinct characteristics which allows them to analyze the diffusion processes in these various markets. Examples include the comparison of a market in which social influence plays a major role (e.g., fashion) with a market of low social influence (e.g., groceries) [Delre *et al.* (2007b)] or the investigation of differences between brown (i.e., electronics) and white (e.g., household products) goods [Delre *et al.* (2007a)]. The third group of agent-based models, finally, also takes into consideration specific products such as fax machines [Guseo and Guidolin (2010)], pharmaceuticals [Guseo and Guidolin (2009)], movies [Broekhuizen *et al.* (2011)], free online games for children [van Eck *et al.* (2011)], or agricultural technologies [Berger (2001)] as well as several green products such as water-saving innovations [Schwarz and Ernst (2009)], fuel cell vehicles [Cantono and Silverberg (2009); Schwoon (2006)], fuels from biomass [Günther *et al.* (2011b); van Vliet *et al.* (2010)], or energy-saving technologies [Faber *et al.* (2010)]. Concerning market dynamics, most of the work published so far focuses on a single generic innovation [Alkemade and Castaldi (2005); Cantono and Silverberg (2009); Moldovan and Goldenberg (2004); Schwoon (2006); Valente and Davis (1999)] and does not take into account a competitive environment. However, some (more recent) agent-based models deal with several products. They, for example, analyze multiple competing energy technologies in the Netherlands [Faber *et al.* (2010)] or investigate the impact of the market introduction of an innovative fuel from biomass on the sales of conventional fuels [Günther *et al.* (2011b); van Vliet *et al.* (2010)].

Our work aims at providing an overview of recent developments in agent-based modeling of new product diffusion processes. To this end, we will resort to papers that have recently been published in peer-reviewed journals and particularly discuss salient (distinctive) model features, namely the consideration of marketing activities (Sec. 2.1), governmental policies (Sec. 2.2), and various social influences such as word-of-mouth, specific social rules, and network externalities (Sec. 2.3), with respect to the (subset of) papers that have dealt with these issues. Section 3 then outlines remaining research challenges in this young field and Sec. 4 concludes with an outlook to promising directions for further research.

2. Salient model features

Agent-based models of new product market introduction and diffusion can be classified according to the following questions:

- What is the *main research focus*?
- Is the model *applied* to markets with specific characteristics or particular industries?
- What *type(s) of products* are investigated? Does the model take into consideration competing products?
- Which *marketing activities* are applied?
- Which *governmental policies* are investigated?

- What types of *social influences* have been considered?

Since the first three characteristics are primarily constitutive (for an overview cf. Tab. 1), in the following we will focus on the latter three.

Authors	**Research question**	**Area of application**	**Type of product**
Alkemade and Castaldi [2005]	Influence of advertising strategies, individual preferences vs. social value and positive and negative externalities for different network structures	–	Single generic innovation
Berger [2001]	Assessment of policy options in the context of resource use changes	Agricultural technologies	Agricultural water-saving innovations
Bohlmann *et al.* [2010]	Effect of network structure and heterogeneity on innovation diffusion	–	Single generic innovation
Broekhuizen *et al.* [2011]	Impact of social influences on marketing inequalities; how ABM and empirival surveys can complement each other	Motion picture industry	Movies
Cantono and Silverberg [2009]	Influence of subsidies on diffusion of fuel cell vehicles	Cars	Fuel cell vehicle
Deffuant *et al.* [2005]	Impact of social value dynamics; role of extremists	–	Single generic innovation
Delre *et al.* [2007a]	Influence of marketing activities on innovation diffusion	Brown good (electronics); white goods (household products)	Single generic innovation in investigated markets
Delre *et al.* [2007b]	Influence of network structure on innovation diffusion	Markets that differently react to social influence (e.g. fashion vs. groceries)	Single generic innovation in investigated markets
Delre *et al.* [2010]	Impact of social influence vs. individual utility; role of VIPs	–	Single generic innovation
Faber *et al.* [2010]	Effectiveness of subsidy schemes for combined heat and power (CHP) micro-plants	Micro-cogeneration of electricity with domestic heating	Multiple competing energy technologies (micro-CHP and incumbent condensing boilers)
Günther *et al.* [2011b]	Influence of marketing activities on adoption of biofuel	Fuels	Fuel from biomass vs. conventional fuel
Guseo and Guidolin [2009]	Impact of communication in a network that evolves dynamically	Pharmaceutical products	Pharmaceutical drug
Guseo and Guidolin [2010]	Impact of network externalities on the diffusion of network goods	Information technology	Fax machines in the U.S. (1964-94)
Janssen and Jager [2002]	Influence of governmental policies on the adoption of green products	Green products	Single generic innovation
Ma and Nakamori [2005]	Influence of product evolution on innovation adoption	–	Generic innovations (different product characteristics)
Moldovan and Goldenberg [2004]	Impact of negative word-of-mouth; effectiveness of advertising; role of opinion leaders	–	Single generic innovation

Schwarz and Ernst [2009]	Impact of governmental policies on the diffusion of water-saving innovations	Water-saving innovations	Showerhead; toilet flush; rainwater harvesting system
Schwoon [2006]	Impact of governmental policies and infrastructure build-up on the diffusion of fuel cell vehicles	Cars	Fuel cell vehicles
Valente and Davis [1999]	Accelerating the diffusion of innovations through opinion leaders	–	Single generic innovation
van Eck *et al.* [2011]	Influence of knowledge and personal characteristics of influential consumers on the adoption process	Free online games for children	Online applications to create own television or radio program
van Vliet *et al.* [2010]	Impact of marketing activities and governmental policies on the diffusion of fuels	Fuels	Different types of fuel (petrol, diesel, FT petrol, FT diesel, ethanol, biodiesel)
Zhang *et al.* [2011]	Impact of technology change (technology push), consumer interactions (market pull), and regulatory policies (regulatory push)	Cars	Alternative fuel vehicles
Zhang and Nuttall [2011]	Impact of government policies on the dynamics of innovation diffusion	Energy market	Smart meters

Table 1: Overview of agent-based models of innovation diffusion

2.1. *Marketing activities*

A considerable number of agent-based modeling approaches deal with direct marketing activities such as TV or radio commercials as well as with product information events. Since these marketing measures are typically associated with high expenditures, companies need to carefully design their marketing strategies with respect to targeting, timing, and pricing. In this context, agent-based simulations can be valuable for managerial diagnostics when analyzing the impact of various marketing activities on the new product diffusion process.

In terms of *targeting*, companies have to decide which (types of) customers to address when communicating their innovation. Delre *et al.* [2007a], for example, investigate whether it is more effective to further the diffusion process by targeting numerous small scattered groups or by focusing on few large groups. In their model, companies can either introduce their product to some customers who spread out information about the product through word-of-mouth or launch promotional campaigns in order to create product awareness. It turns out that none of these (pure) targeting strategies provides the best results; instead, the optimal strategy (measured in terms of market penetration) lies in between the two extremes. Simulation results by Günther *et al.* [2011b] suggest that directly addressing opinion leaders can considerably accelerate the diffusion of innovations (for a discussion of the specific social roles of opinion and resistance leaders cf. Sec. 2.3). Furthermore, they found that for direct marketing, the speed and success of innovation diffusion varies with respect to characteristics of the targeted geographical area (e.g., large vs. small cities).

Timing of marketing activities can affect the new product's takeoff, influence customer acceptance, and generate competitive advantage [Delre *et al.* (2007a); Golder and Tellis (1997)]. In order to achieve a critical mass of adopters, communication activities should be set at the beginning of a new product's market introduction [Guseo and Guidolin (2009)]. Simulation experiments with various timing strategies for a fuel from biomass indicate that intermittent mass communication activities (i.e., advertising campaigns that address customers in intervals) evoke a faster takeoff of the innovation than activities with a continuous timing pattern [Günther *et al.* (2011b)]. Addressing opinion leaders at early stages of the diffusion process and convincing them to use the innovation can also help to countervail a potential failure caused by resistance leaders [Moldovan and Goldenberg (2004)].

When investigating *pricing* strategies (e.g., skimming vs. penetration), recommendations for a particular strategy depend on the company's objectives, since, for example, increased sales are not necessarily linked to higher profits. Furthermore, pricing typically needs to be an integral part of the marketing strategy in order to fully deploy its intended effect. In the case of Fischer–Tropsch (FT) fuels, for instance, agent-based simulations show that it is of particular importance that pricing is coupled with proper activities for increasing the fuels' popularity [Günther *et al.* (2011b); van Vliet *et al.* (2010)].

As a further means to reduce market risk of a new product, companies can alter *product characteristics* aiming at an improved product functionality and/or apply more direct marketing activities in order to increase customer product awareness and product popularity [van Vliet *et al.* (2010)]. Ma and Nakamori [2005], for example, have introduced a model that is concerned with the impact of product characteristics on customer acceptance. To this end, they model the diffusion of innovations as an evolutionary process in which products are regarded as the result of selection processes based upon constructional ('product') and environmental ('market') criteria and in which new products accordingly stem from mutation and crossover.

An overview of investigated issues concerning marketing activities is provided in Table 2.

2.2. *Governmental policies*

Governmental policies such as regulations, subsidies and/or taxes can have an impact on the diffusion of innovative products for obvious reasons. In their analysis of water-saving innovations, for instance, Schwarz and Ernst [2009] demonstrate that the diffusion of shower heads and toilet flushes is strongly influenced by governmental regulations (e.g., agents have to install water-saving innovations like dual-flush toilets) while providing subsidies in these cases have only minor impact. Subsidies, however, evoke a positive effect on the diffusion of innovations that are coupled with high investment costs such as rain-harvesting systems. This finding is in line with results by Faber *et al.* [2010] who identify a positive influence of subsidies on the market penetration of micro-cogeneration technologies.

Introduction of taxes constitutes another governmental measure that has been

Authors	Marketing activities
Alkemade and Castaldi [2005]	Learned strategy vs. random advertising
Broekhuizen *et al.* [2011]	Buzz (determined by pre-release advertising budget)
Delre *et al.* [2007a]	Targeting (small groups vs. large groups); timing
Delre *et al.* [2007b]	Unspecified external marketing effort
Günther *et al.* [2011b]	Timing; targeting; pricing
Guseo and Guidolin [2009]	Timing
Ma and Nakamori [2005]	Changes in product characteristics
Moldovan and Goldenberg [2004]	Advertising
Schwarz and Ernst [2009]	Informational campaign
Valente and Davis [1999]	Opinion leader recruitment
van Eck *et al.* [2011]	Mass media
van Vliet *et al.* [2010]	Popularity buzz
Zhang *et al.* [2011]	Products; pricing

Table 2. Marketing activities in agent-based models of innovation diffusion

investigated by means of agent-based models. For the case of fuel cell vehicles, for example, combining a rather high tax ("shock tax policy") with a build-up of infrastructure (i.e., filling stations) turned out to have a positive impact on the diffusion with respect to takeoff and market penetration [Schwoon (2006)]. While this correlation is not surprising per se, agent-based models can, at least to some degree, predict the extent of these effects for various governmental measures as well which should be of interest for policy-makers. Taxing of non-green products with the purpose to accelerate the replacement of incumbent products with new, more environmentally friendly ones is also addressed by Janssen and Jager [2002] in their co-evolution (between consumers and producers) model. A further, rather counterintuitive, finding was reported by Zhang *et al.* [2011] who investigated fuel economy mandates (e.g., penalities for vehicles with a driving range lower as 27.5 miles per gallon) with respect to their impact on the diffusion of hybrid and electric vehicles on the US market. This measure turned out to actually lead to an increase in the market share of fuel-inefficient vehicles and therefore to an increased air pollution. The authors explain this finding with the consumers' willingness to pay the higher prices (increased by penalties passed on by the manufacturers) instead of quitting to buy SUVs, and conclude that both society and individual consumers are negatively impacted by policies that impose fees that can be re-directed toward the retail price of a product.

In another paper, Zhang and Nuttall [2011] evaluate four different scenarios of the so-called free real-time visual display device policy for smart electricity meters (a technology that offers consumers detailed information about energy consumption) that has been enacted in the UK from 2008 to 2010. They simulated several scenarios in which they varied (i) who has to finance the program (i.e., government, electricity suppliers, or distribution network operators) and (ii) the strategy of deploying the devices (i.e., competitively or by a single organization). It turned out that the U.K. government, in mandating an electricity supplier-financed competitive roll-out, actually has pursued a rather ineffective strategy, because electricity suppliers tend to avoid mass communication necessary to widely disseminate the policy since they ultimately have to bear the costs for the meters.

Generally, the extent to which governmental policies influence the diffusion of innovations apparently depends on the specific type of product and the characteristics of the market (i.e., the underlying social network) under investigation (for an overview of corresponding agent-based models cf. Tab. 3).

Authors	**Governmental policies**
Berger [2001]	Pricing policies; credit market policies; governmental interventions (e.g., taxes)
Cantono and Silverberg [2009]	Subsidy policies
Faber *et al.* [2010]	Efficiency of fixed purchase subsidy and decreasing price difference schemes
Janssen and Jager [2002]	Taxes
Schwarz and Ernst [2009]	Subsidies; regulations
Schwoon [2006]	Taxes; infrastructure build-up
van Vliet *et al.* [2010]	Policy measures (e.g., reducing taxes)
Zhang and Nuttall [2011]	Responsibility for financing (government, electricity suppliers, distribution network operators) and deploying (competition vs. monopoly) of smart meters
Zhang *et al.* [2011]	Influence on manufacturers (vehicles' design and production behavior) and consumers' purchasing equilibrium

Table 3. Governmental policies in agent-based models of innovation diffusion

2.3. *Social influence*

Aggregate models of new product diffusion often subsume social influence in a single parameter. Social influence, however, is a complex phenomenon that has multiple dimensions. In the following, we will review how agent-based models have considered the influence of (1) word-of-mouth for different network structures, (2) agents with specific social roles (e.g., opinion leaders) and (3) network externalities. An overview is provided in Table 4.

Word-of-mouth

Word-of-mouth impacts a consumer's purchase decision to a much higher degree than external information sources like advertising campaigns [Brown and Reingen (1987)]. For this reason, agent-based models of innovation diffusion put an emphasis on modeling word-of-mouth processes. While they most often refer to positive word-of-mouth only, some models also consider negative word-of-mouth, which can have an even stronger effect [Moldovan and Goldenberg (2004)].

Authors	**Social influence**
Alkemade and Castaldi [2005]	k-regular network; random network; small-world network Positive and negative network externalities
Berger [2001]	Cellular network
Bohlmann *et al.* [2010]	Cellular network; random network; small-world network; scale-free network
Cantono and Silverberg [2009]	Cellular network
Deffuant *et al.* [2005]	Small-world network based on geographical proximity; Extremists
Delre *et al.* [2007a]	Small-world network
Delre *et al.* [2007b]	Regular to random network (different degrees of randomness)
Delre *et al.* [2010]	Regular network; scale-free network (undirected/directed and unweighted/weighted); VIPs
Günther *et al.* [2011b]	Network based on geographical and preferential proximity; opinion leaders
Guseo and Guidolin [2009]	Cellular (dynamic) network
Guseo and Guidolin [2010]	Cellular network; network externalities
Janssen and Jager [2002]	Small-world network
Moldovan and Goldenberg [2004]	Cellular network; opinion leaders; resistance leaders
Schwarz and Ernst [2009]	Small-world network based on geographical and preferential proximity
Schwoon [2006]	Regular network
Valente and Davis [1999]	Random network; opinion leaders
van Eck *et al.* [2011]	Scale-free network
Zhang *et al.* [2011]	Number of connections based on empirically study; randomly assigned
Zhang and Nuttall [2011]	Square lattice with periodic boundary conditions; regular (local) and random interactions

Table 4. Social influence in agent-based models of innovation diffusion

The impact of word-of-mouth on the diffusion of a new product is most likely influenced by the topology of the communication network that typically represent a social network of customers in a market [Günther *et al.* (2011b); Schwarz and Ernst (2009); van den Bulte and Yogesh (2007); van Vliet *et al.* (2010)]. The network's structure therefore sets the basis for modeling the interaction between agents. Within the network, agents are represented as vertices while edges between them describe their mutual relationships. The heterogeneity of an agent-based system therefore originates from two sources, namely, the characteristics of the individual agents in the network (i.e., structural heterogeneity) and the strength of connections between agents (i.e., relational heterogeneity) [Bohlmann *et al.* (2010)]. Several types of network structures have been proposed in the literature, the most common ones being (i) cellular automata networks, (ii) regular networks, (iii) random networks, (iv) small-world networks, and (v) scale-free networks. In the cellular automata network, (groups of) individuals are represented by cells that have a particular state (e.g., adopters vs. non-adopters) which makes it straightforward to model the influence of neighbors in the direct social environment on an individual's product adoption ("neighboring pressure") [Berger (2001); Cantono and Silverberg (2009); Guseo and Guidolin (2009); Guseo and Guidolin (2010); Moldovan and Goldenberg (2004)]. The random network algorithm, introduced by Erdös and Rényi [1960] has considerably shaped research on complex networks over many years [Wang and Chen (2003)]. More recently, however, random networks have been widely replaced by small-world networks [Watts and Strogatz (1998)] that represent reality more accurately than random networks [Barabási and Bonabeau (1999)]. Scale-free networks that are characterized by their hubs (i.e., nodes with a vast number of connections to other nodes in the social network) constitute another appealing alternative for modeling word-of-mouth processes, because they reflect structural heterogeneity that is determined by the different roles held by various societal actors [Barabási and Bonabeau (2003)].

Specific social roles

The most prominent role in these scale-free networks is played by the so-called opinion leaders who can heavily affect the process of innovation diffusion [Alkemade and Castaldi (2005); Günther *et al.* (2011b); Moldovan and Goldenberg (2004); Valente and Davis (1999); van Eck *et al.* (2011)]. Their influence does not necessarily stem from persuasion, but can be attributed to their numerous social connections which allow them to effectively distribute information to a large group of potential customers [Delre *et al.* (2010)].

Since (most) opinion leaders increase the speed of the spread of information as well as the adoption process itself and, thus, the adoption percentage, targeting those opinion leaders may be a particularly effective marketing strategy. For an illustrative example confer to the work of van Eck *et al.* [2011] who extended the model by Delre *et al.* [2007a] and use data from free online games for children. In contrast, a special type of opinion leader, so-called "resistance leaders", can also severely hamper an innovation's diffusion even in the presence of (other) opinion leaders distributing positive word-of-mouth [Moldovan and Goldenberg (2004)].

Network externalities

Several agent-based models of new product diffusion have taken into consideration network externalities, i.e., they assume that the utility of the investigated new products increases with the number of adopters [Rohlfs (2001)]; fax machines may serve as an example. In these cases, the successful diffusion of a new product depends on achieving a critical mass of customers using the product [Guseo and Guidolin (2010)]. As for global network externalities, for which the whole market is observed, the local social environment can play a major role for certain types of products that constitute (positive or negative) local network externalities. In the fashion industry, for example, customers follow general fashion trends, but still want to be special in their close environment [Alkemade and Castaldi (2005)].

3. Challenges

In spite of the considerable progress in the development of agent-based models of new product diffusion that have been achieved during the past decade, several challenges have remained, which is not surprising given that agent-based models have a rather young research history as compared to well-established mathematical and statistical tools [Cioffi-Revilla (2002)]. In the following, particularly prominent challenges will be highlighted with respect to (1) modeling, (2) calibrating, (3) validating, and (4) analyzing. Further progress is needed in all of these fields.

Modeling

With the incorporation of social networks, individual consumer preferences, and more sophisticated decision rules, agent-based models also become considerably more complex. In some cases, this development has been (partly) compensated by intentionally describing agents and decision rules in a more stylized way [Fagiolo *et al.* (2007)] following the postulation that the complexity should be in the results and not in the assumptions of the model [Axelrod (2007)]. This, however, comes with the risk of missing important aspects of the real-world behavior and, thus, ending up with an inadequate model. The modeler's challenge therefore lies in finding the right balance between a rather simple model that may be enriched later-on and a descriptive and quite complex model that can be simplified wherever justified [Edmonds and Moss (2006)]. When dealing with customers who have widely homogeneous lifestyles, for example, it will be justified to model agent characteristics in less detail [Schwarz and Ernst (2009)].

A related issue concerns the implementing of an agent-based model. In recent years, numerous software platforms for agent-based modeling and simulation have been introduced; modelers therefore are confronted with an abundant range of programming languages, libraries, frameworks, and modeling environments to choose from; for an overview confer Kiesling [2011]. In a practical setting, however, these tools are of only limited help for managers who do not have sufficient programming skills and/or time at their hands. The challenge therefore lies in designing an agent-based tool kit for the purpose of providing managers with a means to (at least to some extent) implement their ideas for an agent-based model of new product market introduction and diffusion themselves.

Calibrating

A decade ago Chattoe [2002] stated that the most interesting agent-based simulations do make extensive use of data, but nonetheless are rather "inspired by" than actually based on data. Although the field has evolved in the meantime, there is still a need to further combining agent-based models of market introduction and diffusion of new products with empirical methods for the sake of calibrating (and also validating). Promising methods are (i) sample surveys (typically based on pre-studies with focus groups), (ii) stylized facts grounded on existing findings, (iii) participant observations, (iv) field and laboratory experiments, (v) role-playing games, (vi) case studies, and (vii) integration of spatial data (for an in-depth discussion of the strengths and weaknesses of these methods cf. Janssen and Ostrom [2006] or Robinson *et al.* [2009]).

In modeling innovation diffusion, sample surveys (e.g., conjoint analysis for retrieving proper preference data as done by Garcia *et al.* [2007] and Kiesling *et al.* [2009]) have become more common recently. This is facilitated by an increasing number of existing (household) surveys that are publicly available and may be used for the purpose of calibrating agent-based simulations. Note that data collected from panels could be particularly valuable because they are more or less the only way of collecting reliable data about change at the individual level [Hassan *et al.* (2010)]. References to stylized facts can be found quite often as well (e.g., regarding varying innovativeness among customers following Rogers [2003]; for an example cf. Günther *et al.* [2011b]). Participant observation, field or laboratory experiments, and role-playing games, on the other hand, are far less common although they could provide guidance in designing crucial processes such as how agents search for information, exchange information, remember the past, are influenced by their peers, or decide to purchase the new product. They also could be valuable in setting up the social network given that up to now mostly artificial networks have been used with a few exceptions such as an attempt to gather information through retrospective data or network analysis of small communities [Bohlmann *et al.* (2010)]. Experiments and role-playing games as well as case studies furthermore seem particularly promising approaches for validating simulation outcomes. Integration of spatial data, finally, is another prime challenge. Actually, in most of the papers listed in this survey network structures (such as those referred to in Sec. 2.3) do not take into account the spatial distances between agents although evidently it is more likely that two persons know each other if they live close-by. The corresponding agents therefore should be connected in the social network with a higher probability as has been demonstrated by Günther *et al.* [2011b] or Schwarz and Ernst [2009]. Spatial calibration also plays a role whenever the geographical distance between agents and the point of sale where the product is available has an influence on product choice. This influence may be indirect as in an example by Kiesling *et al.* [2009] in which agents are willing to cover only a limited area when deciding for a gas station (that potentially carries a novel fuel). The influence might also be more direct as described in a work by Berger [2001] in which the costs for agricultural products heavily depend on transportation costs.

Multiple methods exist to gather data for calibrating (and validating) agent-based models and they all have comparative advantages and complementarities for injecting data into the simulation. Some are useful for modeling reasoning and decision making of agents (e.g., derived from laboratory experiments or participant observation) and others provide information on individual motivations in general (e.g., surveys or stylized facts from previous studies). Since each approach is different in its focus and has its own pros and cons, modelers need to learn systematically from the findings of each approach and to use them for maybe even more carefully calibrating their simulations.

Validating

The validation of simulations, i.e., ensuring that the simulation results reflect and explain processes that are observed in real markets as well, has been an area of concern for quite some time [Conway (1963); Garcia *et al.* (2007)]. The challenge originates from a rather large parameter space that leads to high degrees of freedom and a large range of simulation results [Kennedy *et al.* (2006)]. In this context, sensitivity analysis can help to explore how the results depend on (i) micro-macro parameters, (ii) initial conditions and (iii) across-run variability induced by stochastic elements [Fagiolo *et al.* (2007)]. For instance, it can be tested whether variations in the number of agents result in differing simulation outcomes [Cioffi-Revilla (2002)].

First and foremost, the difficulty to carry out proper validation lies in the prevalent lack of reliable data (for references to measures that may be applied in this respect cf. the preceding paragraph). Not only is it difficult to collect data over the whole time period of the diffusion process [Bohlmann *et al.* (2010); Valente and Davis (1999)], agent-based models also typically contain stochastic elements which complicates the accurate comparison of simulation outcomes with real-world data [Rogers and von Tessin (2004)]. Thus, subjective methods such as face validation (i.e., evaluation of simulation outcomes through experts) have been used in order to detect errors and inconsistencies at the early stages of the simulation study (for examples cf. works by Garcia *et al.* [2007] or Günther *et al.* [2011b]). Note that there is no consensus yet about how (and if) agent-based models should be empirically validated [Fagiolo *et al.* (2007)].

Analyzing

The most common approach for analyzing results of simulation scenarios is graphical comparison (e.g., scatter plots, histograms, and box plots). A quantitative and more objective interpretation of simulation results can be achieved by using confidence intervals or hypothesis testing, for which, however, essential statistical requirements are often not fulfilled [Yilmaz (2006)].

Although widely accepted output measures of innovation diffusion exist (e.g., total number of adopters), agent-based simulation offers new opportunities for interpretation of results like the geographical spread of an innovation. This can be particularly helpful in analyzing regional effects of different market introduction strategies. The challenge in these cases is to find proper indices.

4. Conclusions

Agent-based approaches for simulating new product market introduction and diffusion have become increasingly popular during the past decade, because they not only allow to merely capture the behavior of diverse customers more closely, but in doing so also bring new insights to the field of innovation management. As Garcia and Jager [2011] has phrased it, *"one of the important contributions of agent-based simulation is that it may reveal [..] system complexities by demonstrating that small changes in parameters sometimes result in very different outcomes"*, which is not a failure of the approach but has to be attributed to the complexity of real-world innovation diffusion. They conclude that the more complexly a system behaves and the more different the outcomes obtained, the more can be gained by understanding the underlying processes. Accordingly, this field offers plenty of opportunities for further research not only in overcoming the "toy model" concern, but also to eventually provide valuable managerial support for practical purposes.

From a methodological point of view, working on proper representations of social networks (that, for instance, also consider spatial and/or preferential proximity of agents) seems to be particularly worthwhile. The reason why is that a considerable part of complexity stems from designing the (social) network, since networks are inherently difficult to capture due to structural complexity, network evolution, connection diversity, dynamical complexity, node diversity, and/or meta-complication [Strogatz (2001)]. Furthermore, customer interaction could be modeled in more detail, e.g., regarding types of (informational and/or normative) influences that are exerted on each other, time patterns of when which information is exchanged and/or differences with respect to varying communication channel (e.g., face to face vs. blogs; for the latter cf. Droge *et al.* [2010]). Further promising issues concern the consideration of supply-side limitations and the competition between several providers targeting the same group of consumers. The prime challenge for the time being, however, remains the calibration and validation of agent-based simulations of innovation diffusion.

From an application-oriented point of view, we feel that agent-based modeling of innovation diffusion is on the rise and we expect to see an increase in the number of real-world applications in the next years which should also help to overcome the lack of data and to even better demonstrate the (practical) value of such an approach. A further field of application may be education where agent-based models of innovation diffusion can be used in game-based business simulations for management training (for a recent example cf. Günther *et al.* [2011a]).

On a more general note, working on agent-based simulations of new product market introduction and diffusion requires competencies in business administration (particularly with respect to innovation management and marketing), quantitative modeling, sociology, informatics, and expertise in the corresponding (specific) field of application as well as potentially in other disciplines that typically are not available in one single researcher but in an interdisciplinary team of researchers. Thus, such a research endeavor not only can be of theoretical and practical relevance but also may provoke enriching interdisciplinary cooperations with colleagues from other communities.

Acknowledgements

We thank the Austrian Science Fund (FWF) for financial support of our work by grant No. P20136-G14. Furthermore, we are indebted to Elmar Kiesling for supporting this work with his expertise.

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