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Agent-based simulation of innovation diffusion: a review

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Abstract Mathematical modeling of innovation diffusion has attracted strong academic interest since the early 1960s. Traditional diffusion models have aimed at empirical generalizations and hence describe the spread of new products parsimoniously at the market level. More recently, agent-based modeling and simulation has increasingly been adopted since it operates on the individual level and, thus, can capture complex emergent phenomena highly relevant in diffusion research. Agent-based methods have been applied in this context both as intuition aids that facilitate theory-building and as tools to analyze real-world scenarios, support management decisions and obtain policy recommendations. This review addresses both streams of research. We critically examine the strengths and limitations of agent-based modeling in the context of innovation diffusion, discuss new insights agent-based models have provided, and outline promising opportunities for future research. The target audience of the paper includes both researchers in marketing interested in new findings from the agent-based modeling literature and researchers who intend to implement agent-based models for their own research endeavors. Accordingly, we also cover pivotal modeling aspects in

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depth (concerning, e.g., consumer adoption behavior and social influence) and outline existing models in sufficient detail to provide a proper entry point for researchers new to the field.

Keywords Agent-based modeling · Simulation · Innovation diffusion · Review

1 Introduction

Mathematical modeling of innovation diffusion has attracted strong academic interest since a number of pioneering works by Fourt and Woodlock (1960); Mansfield (1961) and Bass (1969) appeared in the 1960s. In particular, the model developed by Bass (1969), which characterizes the diffusion of an innovation as a contagious process that is initiated by mass communication and propelled by word-of-mouth, is widely cited and was selected as one of ten most influential papers in the first 50 years of Management Science (Hopp 2004).

Management practitioners also show considerable interest in diffusion models because firms' ability to successfully market innovations determines whether they can create competitive advantage and secure long-term success. Managers can therefore benefit considerably from tools that help them to pre-estimate the market response to new products, provide model-based decision-support, and allow them to assess new product introduction strategies.

Aggregate models such as the Bass model, which provides an empirical generalization based on a differential equation formulation, provide such support only to a limited degree, as they are not designed for what-if type questions. Furthermore, these models do not explicitly consider consumers' heterogeneity and the complex dynamics of social processes that shape the diffusion and can therefore tackle only a limited set of theoretical issues. Aggregate models have also been criticized for a lack of predictive and explanatory power.

To overcome these limitations and open up new research opportunities, agent-based modeling and simulation has increasingly been adopted in diffusion research in recent years. This trend is in line with a broader development in the social sciences (cf. the overview provided by Squazzoni 2010). One reason why the use of this bottom-up methodology has gained momentum in recent years lies in its ability to model complex emergent phenomena—such as the diffusion of an innovation in a socio-economic system—that more traditional modeling approaches cannot capture easily. In agent-based diffusion models, the atomic model element is not the social system as a whole, but the individual consumer, or agent. Consumers' heterogeneity, their social interactions, and their decision making processes can be modeled explicitly. The macro-level dynamics of the social system emerge dynamically from the aggregated individual behavior and the interactions between agents.

The literature on agent-based models (hereafter ABMs) of innovation diffusion can be divided into two major streams. The first stream is aimed at theoretical insights and is therefore concerned with highly abstract and generic representations of diffusion processes. The second stream, which has experienced significant growth in recent years, is concerned with the practical application of ABMs to provide forecasts, decision support, and policy analyses for specific applications based on empirical data.

The current paper addresses both streams of research. While innovation diffusion models and their applications have been reviewed extensively over the past 30 years (Mahajan and Muller 1979; Mahajan et al. 1990; Sultan et al. 1990; Parker 1994; Mahajan et al. 1995, 2000; Meade and Islam 2006), far less attention has been paid to the fast growing literature on agent-based diffusion models. A number of reviews have addressed related aspects: Garcia (2005) outlines (potential) uses of ABMs in innovation/new product development research, Dawid (2006) reviews agent-based computational economics models of innovation and technological change, Peres et al. (2010) broadly review diffusion modeling efforts, and Hauser et al. (2006) summarize research on innovation from a marketing perspective. The literature on ABMs of innovation diffusion, however, has not been reviewed so far and the purpose of the current paper is to fill this gap.

Our review intends to provide an overview on ABMs' impact in innovation diffusion research by (i) contrasting it with traditional diffusion modeling approaches and highlighting advantages in Sect. 2; (ii) discussing key modeling aspects in Sect. 3; (iii) evaluating theoretical advances that ABMs have contributed to diffusion research in Sect. 4; (iv) reviewing ABMs' practical impact in terms of applications to real-world problems in Sect. 5; (v) and concluding by emphasizing challenges that should be addressed in the future in Sect. 6.

2 Background

Innovation diffusion research seeks to understand how new ideas, products and practices spread throughout a society over time (Rogers 1962). The term "diffusion" embraces concepts such as contagion, mimicry, social learning, organized dissemination and others (Strang and Soule 1998). Diffusion research is an interdisciplinary field with roots in anthropology (Wissler 1915), sociology (Tarde 1903), geography (Hägerstrand 1967), political science (Walker 1969), economics (Griliches 1957), and marketing (Arndt 1967). From an economic perspective, the theory of innovation diffusion is based on the recognition that *"innovation…does not lend itself to description in terms of a theory of equilibrium"* (Schumpeter 1928, p. 64) but must be understood as a dynamic process dominated by social influences. Empirical groundwork for the diffusion paradigm was laid by Ryan and Gross (1943), who found that social contacts, social interaction, and interpersonal communication were important influences on the adoption of new behaviors (Valente and Rogers 1995).

Driven by managers' interest in planning and improving the launch of new products and obtaining forecasts of sales, the marketing tradition of diffusion research has come on strong since the early 1960s. Early efforts to mathematically model a new product's spread in a marketplace were rooted in analogies in the models of epidemics, or biology and ecology (Mahajan and Muller 1979). These efforts produced a number of seminal contributions. Fourt and Woodlock (1960) developed a simple penetration model to forecast sales of new grocery products. Mansfield (1961) formulated a model to investigate which factors determine how rapidly the use of a new technique spreads from one firm to another. The most influential contribution to date was made by Bass (1969), who introduced a differential equation growth model for consumer durables and provided a closed-form solution. Because these "traditional" models of innovation diffusion look at the market as a whole, they are commonly referred to as aggregate or macro-level models.

The following section provides a brief introduction to aggregate models of innovation diffusion using the Bass model, which is still widely used in industry today (Thiriot and Kant 2008), as a salient example.

2.1 Aggregate models of innovation diffusion

Aggregate models are typically based on a formulation of differential equations that specify the flow(s) between mutually exclusive and collectively exhaustive subgroups such as adopters and nonadopters (Chatterjee and Eliashberg 1990). This modeling paradigm has produced a rich stream of literature which has been reviewed by numerous authors. Mahajan and Muller (1979) review early contributions, Mahajan et al. (1990, 1995, 2000) provide an overview of the Bass model, its extensions and applications, Sultan et al. (1990) meta-analyze 213 estimates of innovation and imitation parameters of the Bass model, and Parker (1994) reviews theoretical origins, specifications, data requirements, estimation procedures and pre-launch calibration possibilities for aggregate models. More recently, Meade and Islam (2006) review the wealth of literature from a forecasting perspective and conclude that few research questions have been finally resolved.

Although diffusion modeling has become a vibrant research tradition, most reported work has consisted of refinements and extensions of the Bass diffusion model without alteration of its basic premise (Mahajan et al. 1990; Bemmaor 1994). Most models therefore still show the structure of the basic epidemic model introduced by Bass, which we outline in the following.

Following Rogers (1962) diffusion of innovations theory, Bass characterizes the diffusion of an innovation as a contagious process driven by external influence (e.g. advertising, mass media) and internal influence (e.g. word-of-mouth). More precisely, Bass specifies that an individual's probability of adopting a new product at time t, given she/he has not adopted yet, depends linearly on two influences: one that is not related to previous adopters and is represented by the parameter of external influence denoted as p, and an influence that is related to the number of previous adopters, represented by the parameter of internal influence denoted as q (Goldenberg et al. 2000). Based on these parameters, the limiting probability that an actor who has not adopted yet at time t does so at time $t + \Delta t (\Delta t \rightarrow 0)$ is described by the hazard model

$$\frac{f(t)}{1 - F(t)} = p + qF(t), \tag{1}$$

where $f(t)$ is the probability of adoption at time t, $F(t)$ is the cumulative distribution function of adoptions at time t, and p as well as q are parameters. Aggregate models are primarily concerned with modeling $n(t)$, the flow of consumers from the potential market M to the current market (Mahajan and Muller 1979). Equation 1 is therefore typically used in the following reexpressed form:

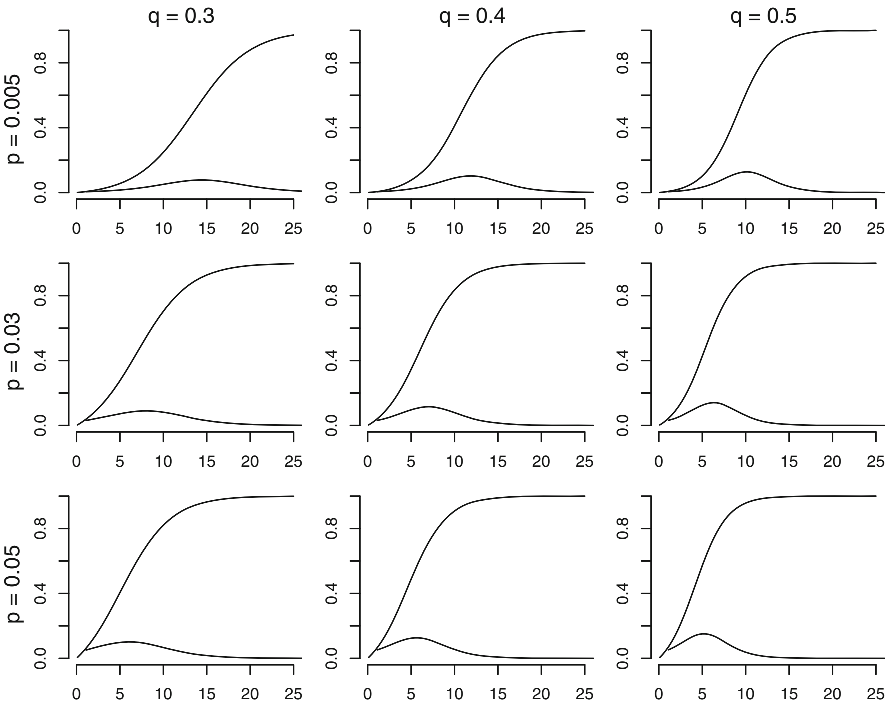

Fig. 1 Bass model adoption curves $N(t)$ and $n(t)$ for various values of p and $q (M = 1)$

$$n(t) = \left(p + q\frac{N(t)}{M}\right)(M - N(t)), \tag{2}$$

where $N(t)$ is the number of consumers having adopted by time t. Plotting $n(t)$ over time yields a (skewed) bell-curve of new adoptions, whereas plotting $N(t)$ yields the typical S-shaped cumulative adoption curve. Figure 1 illustrates various diffusion curves for typical values of p and q (Sultan et al. 1990 report that the average value of $p = 0.03$ and the average value of $q = 0.38$).

Based on this original formulation, a number of efforts have been made to extend and refine the Bass framework to reflect the complexity of new product growth. One of the advantages of this modeling paradigm is that it provides a parsimonious and analytically tractable way to look at the whole market and interpret its behavior. A related advantage is that these models make use of market level data to forecast sales, which is typically more readily available than individual-level data. Assuming that sufficient data points are available, the model can be fitted to early sales data to obtain parameter estimates for new products. For the Bass model, the well-researched estimation literature covers a number of estimation methods, including ordinary least squares (Bass 1969), maximum likelihood (Schmittlein and Mahajan 1982), nonlinear least squares (Srinivasan and Mason 1986) and genetic algorithms (Venkatesan et al. 2004). The Bass model fits many historic data on completed diffusion processes well (cf. Sultan et al. 1990) and is excellent at backcasting. However, several limitations of aggregate-level models in general, and the Bass model in particular, have been identified in the literature.

Predictive power A number of authors have raised concerns over the reliability of parameter estimates (cf., e.g., Van den Bulte and Lilien 1997) and over the use of the Bass model for forecasting purposes (e.g. Bernhardt and Mackenzie 1972; Heeler and Hustad 1980; Kohli et al. 1999). Mahajan et al. (1990, p. 9) note that *"parameter estimation for diffusion models is primarily of historic interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes"*. Because the models need data at both turning points (takeoff prior to growth and slowdown prior to maturity) to provide stable estimates (Srinivasan and Mason 1986; Tellis 2007), there is little use for them before or around takeoff (Goldenberg et al. 2000), which is the time these forecasts are most valuable. In other words, traditional diffusion models require as input information about the events (takeoff and slowdown) that managers would like to predict (Tellis 2007).

Explanatory power Traditional aggregate models are not behaviorally based (Goldenberg et al. 2000). It is therefore not surprising that these models do not reproduce the complexity of real-world diffusion patterns. Innovation failures, oscillations, and collapses of initially successful diffusions are phenomena observed in reality, but not explained by aggregate diffusion models (Strang and Macy 2001; Maienhofer and Finholt 2002). Also, while the two coefficients of Bass-type models have appealing interpretations (internal and external influence, respectively), it is not clear whether they truly reflect the underlying diffusion mechanisms. Hohnisch et al. (2008) therefore refer to these models as "phenomenological" and thus underline that they provide empirical generalizations and do not aim to explain the mechanisms that cause diffusion processes. This can be linked to a more general widespread neglect of process in the social sciences, as criticized by Chattoe, who notes that *"collection of aggregate time series data does little to explain social change even when statistical regularities can be established"* (Chattoe 2002, p. 114).

Population heterogeneity The mathematical form of the Bass model requires the assumption that the potential adopter population is homogeneous (Tanny and Derzko 1988; Chatterjee and Eliashberg 1990; Bemmaor 1994; Van den Bulte and Stremersch 2004), which may be considered a gross simplification since potential adopters are typically heterogeneous in economic factors such as income, in their individual preferences, the information they have etc., and consequently in their propensity to adopt. The heterogeneous population argument was already used by Rogers (1962), who defined five adopter categories based on propensity to adopt. For a discussion of the debate between two alternative explanations for diffusion processes, viz. individual heterogeneity on the one hand, and awareness and information spreading mechanisms on the other hand, we refer to Bemmaor (1994).

To consider heterogeneity in traditional diffusion models, compartmental approaches were developed that aggregate the population into a relatively small number of states such as unaware, aware, in the market, adopters etc. (e.g., Urban et al. 1990). However, compartment models still assume homogeneity and perfect mixing within compartments and do not consider heterogeneity in individual attributes and in the network structure of interactions (Rahmandad and Sterman 2008). For the Bass model, efforts to explain changes in parameter estimates due to underlying heterogeneity of the population were also made (e.g. Bemmaor and Lee 2002). Nevertheless, the fundamental issue that Bass-type models are not sufficient for hypothesis testing about the process that drives adoption behavior remains, since aggregate fit of models based on different theoretical assumptions (e.g., heterogeneity vs. information spreading mechanisms) are often indistinguishable (Emmanouilides and Davies 2007).

Social processes Due to the parsimonious structure of aggregate models, it is also not possible to distinguish effects of different social processes on diffusion. In the Bass model, for example, the internal influence parameter p is often interpreted as word-of-mouth (hereafter WoM). However, it can also capture imitation effects such as social learning, social pressures, or network effects (Van den Bulte and Stremersch 2004). Furthermore, Bass-type models make very specific assumptions about the structure of social interactions. The formulation implies a fully-connected social network in which everyone in the target population is directly connected to everyone else, and can potentially influence all others (Shaikh et al. 2006). It also presumes that the influence of adopters on non-adopters is a linear function of the number of adopters throughout the diffusion periods (ibid.). Because of these simplifying assumptions, the coefficient of imitation cannot be expected to directly reflect the underlying social mechanisms that shape diffusion processes.

Prescriptive guidance In their general typology of explicative models, Evered (1976) draw attention to *"the almost paradoxical contrast between the future-oriented nature of what practicing managers actually do, and the past-oriented nature of most of our scientific theories."* Traditional diffusion models illustrate this contrast. Managers planning the introduction of a new product are interested in predicting the effects of the decision variables at their disposal, most notably the marketing mix factors product, price, promotion, and distribution, none of which were initially considered explicitly in early diffusion models.

This issue has been recognized and various authors have included marketing mix variables into aggregate diffusion models in order to better describe reality and potentially provide directions for how to alter the diffusion process by manipulating those variables (Ruiz-Conde et al. 2006). In particular, marketing mix variables considered include price (Robinson and Lakhani 1975; Bass 1980; Feichtinger 1982; Jain and Rao 1990; Bass et al. 1994, 2000), distribution and supply restrictions (Jones and Ritz 1991; Jain et al. 1991), and promotion and advertising (Dodson and Muller 1978; Horsky and Simon 1983; Simon and Sebastian 1987; Dockner and Jorgensen 1988; Bass et al. 1994).

Two basic approaches for incorporating these variables are (i) via a separable, or (ii) via a non-separable function (Ruiz-Conde et al. 2006). The former specification assumes that marketing variables have a direct effect on sales, separate from the part that describes the diffusion process. The non-separable specification, by contrast, assumes that the marketing variables moderate the diffusion process, so that both parts cannot be separately included in the model.

In the Bass model, marketing mix is typically incorporated by means of a non-separable function that makes p and/or q dependent on explanatory marketing variables, i.e., $p(t) = f(\text{marketing variables}(t))$ and/or $q(t) = f(\text{marketing variables}(t))$. In the former case, marketing variables affect the adoption decision via external influence, whereas in the latter case, they stimulate interpersonal communication. Some models also consider the effect of marketing on the size of the potential market (m). For a comprehensive review of marketing variables in macro-level diffusion models, we refer to Ruiz-Conde et al. (2006).

While traditional aggregate models that include marketing mix variables have become highly sophisticated, there appears to be no consensus on what marketing variables to include and in which part of the models to include them (Ruiz-Conde et al. 2006). Furthermore, the incorporation of prices into models of innovation diffusion failed to significantly enhance the explanatory power of those models (Bottomley and Fildes 1998). As Meade and Islam (2006) note in their 25 years review, it is also fair to say that in most of these contributions, the emphasis has still been on the explanation of past behavior rather than on forecasting future behavior. The general approach has thus remained more descriptive than normative (Delre et al. 2007a) and aggregate models still provide limited potential for policy (what-if) analyses.

Many of the issues and limitations outlined here can be overcome through an individual-based modeling approach, which we will discuss in the following section.

2.2 Individual level models of innovation diffusion

Long before the widespread incursion of agent-based models in the social sciences, which gained momentum only in the last 10 years (cf. Chen and Yang 2010); Eliashberg et al. (1986, p. 176) suggested that *"diffusion models that start at the microlevel have a rich potential in terms of a better understanding of the diffusion process and as a tool for managerial action."* Mahajan et al. also advocate an individual-level modeling approach to *"study the actual pattern of social communication, and its impact on product perceptions, preferences and ultimate adoption"* (Mahajan et al. 1990, p. 20). One of the first micro models of innovation diffusion was introduced by Chatterjee and Eliashberg (1990), who propose an analytic method to aggregate individual-level behavior based on specific heterogeneity assumptions. They consider perception of the innovation, personal preference, and the perceived reliability of information as individual-level determinants of adoption. They also provide a closed formulation of the interface between individual and aggregate level to link individual decision-making and aggregate dynamics. However, the analytical tractability of the model hinges on limited analysis of aggregated variables and consumer characteristics (Delre 2007). The framework also cannot incorporate heterogeneity related to linkages in the social network (Bohlmann et al. 2010).

Chatterjee and Eliashberg's model generated much interest on the impact of heterogeneity in diffusion models. This question has been a matter of discussion in innovation diffusion research for a long time (cf. Rogers 1976), but due to the limitations of aggregate models, it remained largely untackled until the advent of ABMS.

ABMS differs fundamentally from both aggregate differential equation and aggregate simulation approaches such as system dynamics (cf. Milling 1996; Maier 1998; Milling 2002). Unlike both, it is a bottom-up, disaggregate approach and thus not limited in its capacity to account for heterogeneity and social structure. The elementary modeling unit is not the (complex) system, but rather the individual. It has its roots in cellular automata modeling, which has a long tradition in the social sciences that goes back to at least Schelling's (1971) seminal model of segregation dynamics. However, ABMs also differ from cellular automata in some important respects. First, cells in a cellular automaton are typically characterized by a single finite state variable; agents' state, interaction, internal processing, and behavior, by contrast, tends to be more complex. Second, the structure of local interactions in a cellular automaton model is typically based on a regular lattice; ABMs can be based on arbitrary local interaction structures. These and other differences notwithstanding, terminology in the literature is inconsistent and cellular models are frequently referred to as "agent-based". Since they also follow an individual-based approach, they fit within the scope of this review.

There is also no universally agreed upon definition of what constitutes an agent. It can be characterized as an autonomous decision-making entity that interacts with other agents and/or with its environment based upon a set of behavioral rules. Key characteristics of agents include autonomous behavior, interdependency, simple rules, and adaptive behavior (cf. Macy and Willer 2002).

Finally, ABMs differ from differential equation models not only in terms of modeling granularity, but also fundamentally in how the results are obtained. Rather than describing the whole system directly and "phenomenologically", macro-scale dynamics in ABMs are emergent phenomena that arise from micro-level interactions between agents when the model is executed.

To illustrate the contrast between these two approaches, we demonstrate that the Bass model is equivalent to a very specific agent-based model in which each of M homogeneous agents indexed by $i = 1, \ldots, M$ is in one of two states: potential adopter or adopter. We use a set of variables $X = (x_i, \ldots, x_M) \in \{0, 1\}$ to describe agents' adoption state (i.e., $x_i = 1$ iff agent i has adopted).

In the Bass model, each actor's probability to adopt at time $t + \Delta t$, given that it has not adopted by time t, is described by the hazard model in Equation 1. In the analogous agent-based formulation in discrete time, we can use agents' explicit state variable x_i rather than the cumulative distribution function of adoptions $F(t)$. The probability of agent i to transition from non-adopter to adopter state is then given as a function of the state of the system (X) as follows:

$$f(X) = \left(p + \frac{\sum_{i=1,\ldots,M} x_i}{M} q\right)(1 - x_i) \tag{3}$$

Like in the original Bass model, the probability of agent i to adopt, given that it has not adopted so far, depends linearly on an independent external influence p and an internal influence q that depends on the fraction of prior adopters. The formulation implies homogeneity and global interconnectedness, i.e., each agent's individual probability

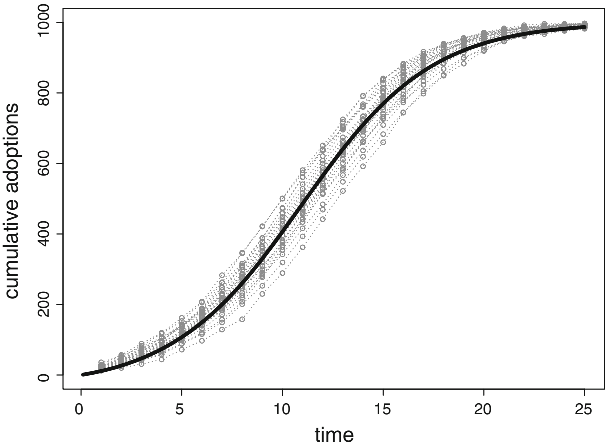

Fig. 2 Bass diffusion curve (*solid*) and 25 replications of the equivalent agent-based formulation (*dotted*) for $p = 0.01$, $q = 0.3$, $M = 1{,}000$

of adoption is influenced uniformly by the adoption state of all other agents. Obviously, $f(X) = 0 \; \forall \, i$ for which $x_i = 1$ and $f(X) \in [0, 1] \; \forall \, i$ for which $x_i = 0$, i.e., all agent that already have adopted remain in the adopter state and all agents that have not adopted so far do so with the same probability in the current period.

To derive findings, stochastic agent-based models are typically implemented as a simulation program and executed multiple times with varying random seeds to obtain a distribution of outcomes. Figure 2 illustrates a Bass diffusion curve as well as 25 replications of the equivalent agent-based simulation with the same parameter setting.[1] For this very special and simple stochastic model, the differential equation formulation of the Bass model provides an analytical solution. If agent-based models become only slightly more complicated, however, the equivalent system of differential equations can usually not be solved in closed form.

Agent-based simulations allow modelers to overcome these limits of mathematical tractability. The bottom-up modeling approach can easily incorporate micro-level drivers of adoption, bounded rationality, imperfect information, and individuals' heterogeneity in terms of attributes, behavior, and linkages in the social network. ABMs of innovation diffusion are therefore more behaviorally based than aggregate models. In the spirit of modern complexity science, these models have the potential to explain complex non-linear diffusion patterns observed in the real world as the result of relatively simple local micro-level interactions.

3 Agent-based modeling of innovation diffusion

In this section, our aim will be to discuss different strategies for modeling consumer behavior and social influence, two key aspects in agent-based models of innovation

[1] We use a synchronous updating regime in our implementation, i.e., state changes of agents are a function of the state of the system in the previous period. For an overview of the critical importance of updating, cf. Radax and Rengs (2010).

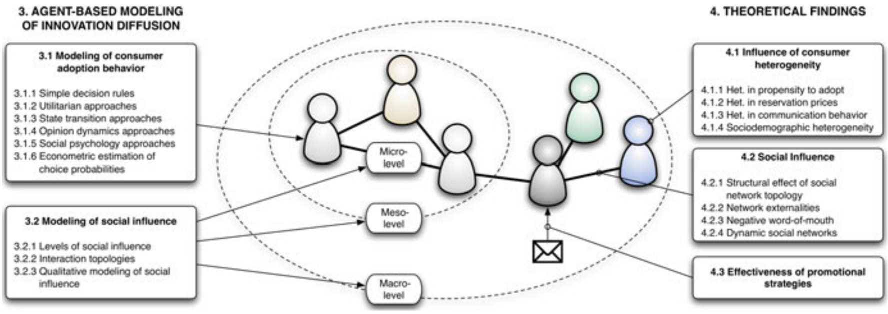

Fig. 3 Key elements of an agent-based diffusion model and structuring of Sects. 3 and 4 of this review

diffusion. To this end, we will systematically identify different approaches and point to specific models in the literature as illustrations. Figure 3 illustrates key elements of an agent-based diffusion model (consumer agents and their interactions) and provides guidance to the structuring of Sects. 3 and 4.

3.1 Modeling of consumer adoption behavior

A pivotal element of agent-based diffusion models is the explicit representation of consumers' decision making processes, most importantly those related to the decision to adopt an innovation (or to reject it, which, however, is not considered explicitly in most models). A number of both deterministic and stochastic approaches have been developed to model these decisions, ranging from simple decision rules to sophisticated psychological models. In the following, we examine the most common approaches.

3.1.1 Simple decision rules

Perhaps the simplest conceivable decision rule is to adopt as soon as the first of an agent's acquaintances has adopted. This rule can be interpreted as a contagious spread of information about the innovation. Threshold models use similar mechanisms, but typically stipulate that a consumer adopts only once a certain proportion of its acquaintances has adopted. The threshold is typically varied across the population and either deterministic, i.e., agents decide deterministically once the threshold is reached (e.g., Valente and Davis 1999; Goldenberg et al. 2000; DeCanio et al. 2000; Alkemade and Castaldi 2005), or probabilistic, i.e., agents adopt with a certain probability once the threshold is reached (e.g., Bohlmann et al. 2010).

Diffusion models in the economics literature (e.g., Kocsis and Kun 2008; Hohnisch et al. 2008; Cantono and Silverberg 2009; Faber et al. 2010) typically use simple decision rules based on cost minimization or heterogeneous reservation prices. These models frequently assume falling prices due to learning effects and tend to interpret social influence as benefits due to network externalities. These network externalities occur when the utility of a network good increases with the number of peers or the share of the market that has adopted (cf. David 1985; Katz and Shapiro 1986, 1992).

3.1.2 Utilitarian approaches

From a classical rational choice perspective, innovation diffusion phenomena pose an explanatory challenge. They do not fit directly into classical economic thinking because homogeneous, perfectly rational individuals acting in a perfect market with complete information would always adopt at the same time. When we acknowledge that individuals are neither homogeneous, nor perfectly informed, (expected) utility is an obvious candidate concept for modeling adoption decisions, given that it constitutes a key building block of standard microeconomic theory of individual choice behavior. One could therefore expect utility theoretic approaches to feature prevalently in the literature. Surprisingly, however, the number of contributions that analyze innovation diffusion in a utilitarian framework is limited. Many of them use "utility" as an interpretive tag rather than explicitly modeling the choice between a single or multiple innovations and non-adoption (i.e., utility of highest alternative opportunity) by means of utility functions that represent individual preferences. Delre et al. (2007a,b, 2010), for example, formulate threshold functions for individual utility based on heterogeneous "quality expectations" and social utility components to obtain a utility aspiration level for each consumer agent. Conceptually, their approach does not differ fundamentally from other threshold models, apart from the interpretation of thresholds as "utility aspiration levels". In a similar vein, Choi et al. (2010) introduce a fixed individual utility component which is interpreted as a "quality perception" and formulate social utility, which they interpret as benefits due to network externalities, as a linear function of the proportion of adopters in the neighborhood.

Few attempts have been made to integrate multi-attribute preference modeling approaches (for an introduction to multi-criteria decision making, cf. Keeney and Raiffa 1993) into ABMs of innovation diffusion so far.

3.1.3 State transition approaches

A number of models represent adoption behavior by means of a single dichotomous variable that represents agents' external state, i.e., agents are either in a "potential adopter" or an "adopter" state. In this respect, state-transition-based innovation diffusion models differ from many infectious disease models, which are frequently refered to as an inspiration and analogy for innovation diffusion models, since these models typically use more than two states (e.g., SEIR—susceptible, exposed, infected, removed/recovered). Goldenberg and Efroni (2001), for example, model adoption as a probabilistic transition between two states that results either from spontaneous transformation or from WoM induced awareness.

Other models, by contrast, represent the decision making process as a sequence of transitions between more than two states. Goldenberg et al. (2007), for example, consider rejection explicitly and specify separate transition probabilities for adoption/rejection based on positive WoM, advertising, and negative WoM. Deffuant et al. (2005), use a fixed state transition scheme based on interest (no, maybe, yes) and information states (not-concerned, information request, no adoption, pre-adoption, adoption). Thiriot and Kant (2008) also model adoption decisions as a sequence of transitions between multiple states, viz. awareness, information seeking, adopter, WoM spreading.

3.1.4 Opinion dynamics approaches

Opinion dynamics in social systems have been studied intensively in recent years (Kocsis and Kun 2008). For an introductory article, we refer to Hegselmann and Krause (2002). A number of innovation diffusion models have adopted ideas from the rich stream of opinion dynamics literature, stipulating that consumers develop preferences in a collective process of opinion formation. In a so-called CODA (continuous opinions, discrete actions) model put forward by Martins et al. (2009), for example, each agent has a probabilistic opinion assigned to the proposition "A is the best choice that can be made". This opinion is updated by means of Bayesian interference based on observed adoption behavior of neighboring agents. Refusal in adopting is increasingly weighted by neighbor agents as evidence against the innovation. Deroïan (2002) simulates the emergence of a collective evaluation of an innovation based on individual propensities to adopt that are interpreted as opinions. The author incorporates the idea of "bounded confidence" (cf. Hegselmann and Krause 2002) by assuming that consumers with similar opinions tend to form stronger bonds while those with very different opinions tend to diminish the level of received influence.

3.1.5 Social psychology approaches

Social psychology approaches, arguably the most sophisticated and least parsimonious, are based on psychological theories of behavior. Rather than representing consumers as instances of homo economicus, these models incorporate the behavioral richness exhibited by "homo psychologicus" in real life (Jager et al. 2000). Adoption decisions are therefore based on psychological rules rather than perfect rationality. For a comparison of the suitability of various social psychological theories for consumer agent design, we refer to Zhang and Nuttall (2011).

Ajzen's theory of planned behavior (TPB, cf. Ajzen 1991) is a commonly used theoretical foundation for modeling consumer agents' behavior in application- and policy-oriented diffusion models. It postulates that attitude, perceived behavioral control, and intention are predictors of behavior. Kaufmann et al. (2009) use TPB to model the diffusion of organic farming practices. Agents (i.e., farmers) adopt if their intention exceeds an empirically derived threshold. Schwarz and Ernst (2009) use TPB as a framework to model consumers' decisions to adopt or reject water-saving innovations using two different kinds of decision rules: a cognitively demanding deliberate decision rule and a very simple decision heuristic. Zhang and Nuttall (2011) model smart metering adoption behavior based on TPB.

Another commonly used social psychological framework is the "consumat" approach developed by Jager et al. (2000). In this framework, consumer agents (so-called "consumats") switch between various cognitive strategies (viz. comparison, repetition, imitation, and deliberation) depending on their level of need satisfaction and their experienced degree of uncertainty. This approach has been used in various theory-oriented and applied models (Jager et al. 2000; Janssen and Jager 2001; Schwoon 2006).

3.1.6 Econometric estimation of choice probabilities

While theoretical models need to be less concerned with methods for initializing the simulation with empirical data, practical applications and policy analyses do require such methods. Statistical methods can be used to model adoption behavior and facilitate parameterization. Dugundji and Gulyás (2008), for example, make use of pseudo-panel microdata to estimate individual adoption probabilities based on demographic characteristics, availability of alternatives, and percentage of agents' neighbors and socioeconomic peers that make each choice. Although correlational rather than theory-driven and behavioral, such econometric estimation approaches can be useful for applied models, even though they do not offer deeper insights into causal mechanisms.

3.2 Modeling of social influence

The critical relevance of social influence in the diffusion of innovations has been recognized for a long time and was considered early on in traditional differential equation models of innovation diffusion (e.g., through the internal influence parameter in the Bass model). ABMs offer researchers the opportunity to explicitly model the interactions that exert social influence, and thereby allow them to take the structure of social interactions into account. This is important, because, as remarked by Katz (1961), *"it is as unthinkable to study diffusion without some knowledge of the social structures in which potential adopters are located as it is to study blood circulation without adequate knowledge of the veins and arteries."* In this section, we systematically review approaches for modeling social influence by distinguishing three levels of influence and briefly reviewing the social network models typically used to structure interactions in agent-based diffusion models. Finally, we also cover qualitative approaches to model social influence.

3.2.1 Levels of social influence

Social influence is a generic concept that can operate on multiple levels. For the purpose of this review, we differentiate between micro-, meso-, and macro-level social influence.

Micro-level social influence is transmitted locally through pairwise communication links. WoM is arguably the most relevant form of micro-level social influence. Evidence of its powerful role in the diffusion of innovations is well documented in both industry market research and scholarly research (e.g., Arndt 1967; Reingen and Kernan 1986; Brown and Reingen 1987; Mahajan et al. 1990; Herr et al. 1991; Buttle 1998). Many of the reviewed models incorporate positive WoM mechanisms, and a

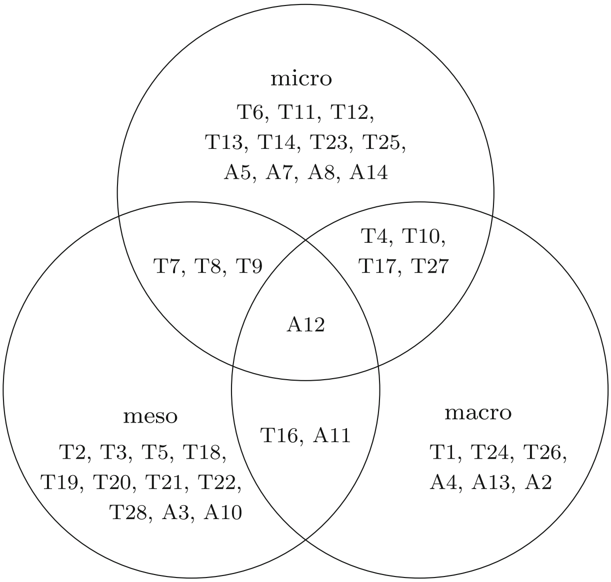

Fig. 4 Levels of social influence modeled in the papers reviewed

few of them (Moldovan and Goldenberg 2004; Goldenberg et al. 2001; Deffuant et al. 2005) also consider negative WoM, which evidence suggests has a much stronger effect than positive WoM (Richins 1983).

We define *meso-level social influence* as any influence that stems collectively from an agent's immediate social environment (i.e., neighborhood in the social network). Concepts associated with meso-level social influence include group conformism, social comparison, herding behavior, local network externalities, and conspicuous consumption, which holds that the intrinsic value of a products may be less important than the social meaning (Veblen 1899). In many of the reviewed papers, the term "social influence" is used in the sense of meso-level social influence.

We consider *macro-level social influence* as global interactions at the level of society as a whole. Examples for this type of influence include influence of the aggregate network-level opinion (e.g., Deroïan 2002) or macroeconomic feedbacks (externalities) such as learning effects, which are based on cumulative sales (e.g., Hohnisch et al. 2008).

Figure 4 illustrates the levels of social influence modeled in each of the papers reviewed. The codes in the Venn diagram correspond to the codes listed in Table 1 (theoretical papers, listed as T1–T29 and covered in Sect. 4) and Table 2 (applied papers, listed as A1–A15 and covered in Sect. 5), respectively. Most, but not all of the reviewed models incorporate social influence, and the levels of modeling vary widely among them. The majority of papers considers a single level, most commonly either the micro-level or the meso level. Eight theoretical papers model social influence on two levels. Applied models, with the exception of A11 (i.e., Schwoon 2006) which considers meso- and macro-level influence, and A12 (i.e., Vag 2007) which considers all three levels, model only a single level of social influence.

3.2.2 Interaction topologies

In order to model micro- and meso-level social influence, it is necessary to define the topology of interactions between agents. Consumer agents and the links they have with each other form a graph that represents the social network in which interactions take place. Whereas the Bass model formulation implies a fully-connected social network, ABMs may use more realistic interaction topologies that resemble real-world social networks. Although some models assume a complete graph or a regular structure (e.g., von Neumann or Moore neighborhoods in cellular automata models), the majority of the reviewed models relies on generative algorithms to systematically create graphs that reproduce characteristic features of real-world social networks.

One of the first and most generic generative graph algorithms is the random graph model introduced by Gilbert (1959) and, more commonly acknowledged, by Erdős and Rényi (1960). This graph model is used prevalently in diffusion models and often serves as a baseline for comparisons with other network structures. The diameter of the resulting random graphs tends to be small, i.e., the largest number of links on the shortest path between any two nodes is small, which is a characteristic the generated graphs share with most real-world social networks (Travers and Milgram 1969). In reality, however, social networks tend to be highly clustered, which means that the probabilities of nodes being connected are not independent, but triadic closures are likely. More precisely, there are higher conditional probabilities that an arbitrary pair of nodes are linked, provided both are linked to a third node. In a social context, this means that networks tend to be "cliquish", i.e., A being linked to B as well as to C implies a strong likelihood that C is also linked to B.

Networks that have a small diameter and are also highly clustered are called small-world networks and can be generated by means of a generative algorithm developed by Watts and Strogatz (1998), which interpolates between random and regular networks. Small-world graph models are frequently used in the models reviewed in this paper due to their topological similarities with real-world social networks.

Finally, a notable characteristic of many social networks is the relatively high number of nodes with a degree that greatly exceeds the average (where "degree" refers to a node's number of links). This corresponds to the notion that some people have a much larger number of acquaintances than others and serve as "hubs" in the network. More specifically, many (but not all) social networks exhibit the scale-freeness property, i.e., the probability $P(k)$ that a node in the network is connected to k other nodes decays as a power law (Barabási and Bonabeau 2003). A network model that captures this characteristic was proposed by Barabási and Albert (1999). It starts with a few nodes linked to each other; nodes are added one by one and attached to existing nodes with probabilities according to the degree of the target node. Therefore, the more connected a node is, the more likely it is to receive new links. The resulting networks are scale-free, but typically not highly clustered. This algorithm is also used in several of the reviewed papers.

3.2.3 Qualitative modeling of social influence

Most of the papers reviewed incorporate social influence either as the spread of awareness of an innovation, positive or negative WoM, or by considering the share of adopters in the agent's network neighborhood when making adoption decisions. Thiriot and Kant (2008) propose an entirely different approach which allows them to study social representations of innovations. They formalize beliefs and messages as associative networks that consist of directed associations between concepts. Consumer agents embody a belief base, a list of currently salient social objects, and are linked to an agent profile which contains the default exposure to mass channels, background knowledge, and subjective production of knowledge. Agents communicate and exchange messages, which contain transmissible associative networks that may cause them to revise their beliefs.

Kim et al. (2011) suggest a different approach to qualitatively model characteristics of an innovation and their communication. They argue that available product information is frequently subjective and imprecise and apply fuzzy set theory to transform linguistic product evaluations on multiple cost and benefit attributes into crisp numbers. When evaluating the overall performance of each available product, agents incorporate information obtained from neighbors that have adopted a product into their evaluation through graded mean integration.

4 Theoretical findings

We identified four major areas of research along which we will structure our review of theoretical findings: (i) impact of consumer heterogeneity on innovation diffusion, (ii) role of social influence in diffusion processes, (iii) effectiveness of promotional strategies, and (iv) endogenous innovation and competitive diffusion. Each of these four areas leverages a specific methodological strength of agent-based modeling, viz. (i) the ability to explicitly model decision making entities individually, (ii) the ability to account for the interactions between them, (iii) the ability to address what-if-type questions, and (iv) the ability to capture emergent market dynamics.

In cases where a paper's contributions fall into more than one of these four subject areas, findings are discussed separately in the respective subsections. Table 1 provides an overview of the theoretical papers reviewed and specifies for each paper the modeling of agents' adoption decision making and the interaction topologies used.

4.1 Consumer heterogeneity

A key strength of ABMs is that they overcome the homogeneity assumption of traditional aggregate diffusion models. This section reviews the progress in understanding the impact of consumers' heterogeneity made possible through ABMs.

Table 1 Modeling of agent-decision making and interaction topologies in the theoretical papers reviewed

Code	Reference	Agent decision-making	Interaction topology
T1	Abrahamson and Rosenkopf (1997)	Threshold based on individual assessment and "bandwagon pressure"	Densely-linked "core stratum" + weakly-linked "peripheral stratum"
T2	Alkemade and Castaldi (2005)	Exposure and over-exposure threshold (neighborhood)	k-regular; random; small-world
T3	Bohlmann et al. (2010)	Probabilistic threshold (neighborhood)	Lattice; random; small-world; scale-free
T4	Cantono and Silverberg (2009)	Price below individual reservation price	Lattice with periodic boundary conditions
T5	Choi et al. (2010)	Utility (individual + network effects)	Small-world
T6	Deffuant et al. (2005)	Fixed state transition scheme based on interest and information states	Small-world
T7	Delre et al. (2007a)	Threshold function (individual preference and social influence part)	Small-world
T8	Delre et al. (2007b)	Threshold function (individual preference and social influence part)	Small-world
T9	Delre et al. (2010)	Individual and social utility thresholds; total utility adoption threshold	Regular lattice; scale-free with a faster decay of the number of links; undirected/directed and unweighted/weighted
T10	Deroïan (2002)	Evolving (based on homophily) directed graph (influence links, also negative influence—inhibitive)	Propensity to adopt based on expected utility (interpreted as an individual opinion)
T11	Goldenberg and Efroni (2001)	Random spontaneous; word-of-mouth induced based on the number of neighboring adopters	Lattice
T12	Goldenberg et al. (2001)	Probabilities for becoming informed through weak-tie w-o-m, strong-tie w-o-m and exposure to marketing efforts	Lattice
T13	Goldenberg et al. (2000)	Heterogeneous individual utility threshold	multidimensional (2–5) lattic
T14	Goldenberg et al. (2007)	Probabilities of being influenced by positive word-of-mouth, advertising, and/or negative word-of-mouth	"dynamic small-world" with changing weak ties

Table 1 Continued

Code	Reference	Agent decision-making	Interaction topology
T15	Goldenberg et al. (2009)	Probabilistic adoption (either because of wom or advertising)	None, no explicit social network, but probabilities for adoption as a consequence of w-o-m
T16	Goldenberg et al. (2010a)	Adopt if the global network externality threshold level is exceeded and w-o-m is received	Square lattice (Moore neighborhood)
T17	Hohnisch et al. (2008)	Price below heterogeneous reservation price (time-dependent in the extended model)	Lattice
T18	Janssen and Jager (2001)	"consumat" approach (cf. Jager et al. 2000)	Small-world
T19	Janssen and Jager (2002)	"consumat" approach (cf. Jager et al. 2000), social and personal needs	Small-world
T20	Janssen and Jager (2003)	"consumat" approach (cf. Jager et al. 2000)	Small-world; scale-free
T21	Kocsis and Kun (2008)	Local cost minimization in the presence of network effects	Square lattice with random rewiring (small-world)
T22	Kuandykov and Sokolov (2010)	Fraction of adopters in the neighborhood; 2 fitting parameters	Random; 3 clusters with random internal and external links; scale free
T23	Martins et al. (2009)	Continuous opinions, discrete actions (CODA); Bayesian interference	Square lattice with random rewiring (small-world)
T24	Moldovan and Goldenberg (2004)	Adoption and rejection are result of positive w-o-m/advertising or negative w-o-m (with a specified probability)	None
T25	Rahmandad and Sterman (2008)	Passive agents; state changes at stochastic rates	Fully connected; random; small-world; scale-free; lattice
T26	Schramm et al. (2010)	Individual adoption threshold as a function of feature, price, promotion and social influence	None
T27	Thiriot and Kant (2008)	Awareness—information search—adoption (not formally specified)	Small-world
T28	Valente and Davis (1999)	Threshold of neighbors	Random allocation of ties
T29	van Eck et al. (2011)	Threshold function (individual preference and social influence part)	Scale-free

4.1.1 Heterogeneity in propensity to adopt

The most common approach to incorporate consumers' heterogeneity is to specify it in terms of an intrinsic "propensity to adopt", typically through heterogeneous adoption thresholds drawn from a distribution. One of the first micro-simulation studies to investigate heterogeneity in this manner was conducted by Goldenberg et al. (2000). They propose a cellular automata model in which cells are characterized by an adoption threshold that is randomly drawn between zero and one and interpreted as a "quality expectation". The spread of an innovation with a certain fixed "product quality" is modeled spatially on a lattice in which cells decide whether or not to adopt once a sufficient number of neighboring cells have adopted. Simulation results exhibit strong fluctuations in sales and suggest that heterogeneity may have a strong influence on innovation diffusion.

Delre et al. (2007a,b, 2010) also use heterogeneous adoption thresholds in their models. They interpret these thresholds as "utility aspiration levels" and specify them as weighted sums (with heterogeneous weighting factors) of two separate threshold functions: (1) a social utility threshold, i.e., a minimum fraction of adopters in the social neighborhood, and (2) a utility threshold function based on agents' heterogeneous "quality expectation". They find that increasing heterogeneity accelerates diffusion because the critical mass is reached sooner than in homogeneous populations (Delre et al. 2007b).

In addition to an adoption ("exposure") threshold, Alkemade and Castaldi (2005) introduce an "over-exposure" threshold to incorporate the idea that innovations tend to be considered no longer "fashionable" once their user base becomes too large. Each agent adopts when the proportion of adopters in their neighborhood exceeds its exposure threshold, but remains below its over-exposure threshold. Heterogeneity in both thresholds is introduced by drawing the exposure threshold from a uniform distribution and adding a fixed value to obtain the over-exposure threshold. While heterogeneity is incorporated in the model, the effect of varying degrees of heterogeneity are not analyzed in the paper.

4.1.2 Heterogeneity in reservation prices

A conceptually different, but structurally very similar approach is to model heterogeneity in terms of varying individual reservation prices. Cantono and Silverberg (2009) follow this approach and investigate the path of diffusion of a new energy technology when some consumers are willing to pay more for goods that are perceived as "green". Agents adopt once any of their neighbors has adopted *and* the price falls below their individual reservation price drawn from a lognormal distribution. Learning economies reduce the price as a function of the extent of previous adoption, which may lead to delayed adoption for a certain range of initial conditions. Results indicate that a limited subsidy policy can trigger diffusion that would otherwise not happen when reservation prices are heterogeneous, learning economies are in a certain range, and initial price levels are high.

Hohnisch et al. (2008) also model heterogeneous reservation prices, but draw them uniformly and independently. Agents adopt once the price falls below their reservation price, which is interpreted as a subjective "individual valuation". The authors also formulate an extended model in which these "individual valuations" are time-dependent. They explain the empirical finding of a delayed "take-off" of a new product by a drift of the percolation dynamics from a non-percolating regime to a percolating regime which occurs because the probability of buying increases over time with the cumulative number of buyers. Heterogeneity in reservation prices plays a critical role in this process and determines whether diffusion takes place or fails.

4.1.3 Heterogeneity in communication behavior

In a comparison of agent-based and differential equation-based diffusion models, Rahmandad and Sterman (2008) investigate the impact of heterogeneity in terms of contact frequency. They model the spread of a contagious disease and therefore do not incorporate deliberate adoption decisions, but rather model adoption as state changes triggered by a stochastic processes. Nevertheless, they stress that results extend beyond epidemiology to innovation adoption. With respect to heterogeneity in individual contact rates, they find that it causes slightly earlier mean peak times as high-contact individuals rapidly seed the epidemic, followed by lower diffusion levels as the high-contact individuals are removed, leaving those with lower average transmission probability and a smaller reproduction rate. Note, however, that although the authors emphasize the transferability of results, caution is required when translating these findings to an innovation diffusion context.

4.1.4 Sociodemographic heterogeneity

A more empirically-oriented approach to represent heterogeneity in propensity to adopt is to link it directly to individuals' sociodemographic characteristics. While such an approach compromises explanatory power, it has the advantage that empirical data (if available) can be used more easily. Dugundji and Gulyás (2008) follow this approach in investigating the impact of heterogeneity on the adoption of transportation mode alternatives and use empirical pseudo-panel micro data to parameterize their model. They consider both observed heterogeneity (in terms of sociodemographic characteristics, individual-specific attributes of the choice alternatives, and the availability of alternatives) and unobserved heterogeneity (in terms of common unobserved attributes of the choice alternatives in the error structure of their econometric estimation model). They find that heterogeneity has a dramatic impact on the magnitude of the transportation mode shares, on the speed of the transition to a steady state, and very fundamentally on the number of possible observable steady-state solutions and conclude that *"heterogeneity cannot be ignored in any true empirical application"* (Dugundji and Gulyás 2008, p. 1051). Policy implications of the study are examined in Sect. 5.2.

In all of the papers referred to above, heterogeneity is found to affect the diffusion of innovations considerably. It may cause fluctuations in sales, delay take-off, result in irregular diffusion patterns that deviate significantly from the typical s-shaped curve, and explain diffusion failure, all of which are phenomena that are frequently observed in the diffusion of real products.

4.2 Social influence

Innovation diffusion cannot be explained as a result of individual heterogeneity alone, but it is also fundamentally a social process (Rogers 2003). ABMs allow researchers to consider interactions between individuals on the micro-level and have therefore produced novel insights into the role of social influence, which we review in this section.

4.2.1 Structural effect of social network topology

The effect of the structure of links in consumers' social network, through which awareness, information, and opinions about an innovation are spread, is one of the most intensively researched topics in the agent-based innovation diffusion literature. Advances in network modeling and the development of generative algorithms for small-world (Watts and Strogatz 1998) and scale-free (Barabási and Albert 1999) networks have strongly stimulated research in this area. In the following, we group papers by the topologies being compared.

Small-world versus regular versus random networks A number of authors (Alkemade and Castaldi 2005; Delre et al. 2007b; Kocsis and Kun 2008; Martins et al. 2009; Choi et al. 2010) have analyzed diffusion in small-world networks with varying degrees of randomness (i.e., interpolations between regular and random networks, cf. Watts and Strogatz 1998). Alkemade and Castaldi (2005) compare diffusion in regular, random, and small-world networks and vary network density as well as "exposure" thresholds (i.e., minimum proportion of adopters in the neighborhood) and "over-exposure" thresholds (i.e., maximum proportion of adopters in the neighborhood). The latter thresholds inhibit adoption if the proportion of adopters in the social neighborhood is already too large for it to still be "fashionable". Results indicate that in a sparse network cascades occur even when consumers' exposure threshold is high. As the network density increases, cascades become more unlikely and the critical exposure threshold becomes smaller. The authors find that the critical exposure thresholds are similar for small-world and regular networks. On the random network, no cascades occur if the density is sufficiently low, because the network becomes disconnected.

Delre et al. (2007b) also compare various interpolations between regular and random networks, but base their model on different assumptions. They do not consider "overexposure" and model agents' decision making by means of a threshold function that consists of an individual utility part (obtained if the quality of the innovation exceeds a threshold) and a social utility part (obtained if the fraction of adopters in the agent's social neighborhood exceeds a threshold). Results indicate that innovations diffuse faster in more regular (i.e., clustered) networks than in random networks because individuals are exposed to more social influence and may therefore decide to adopt sooner. As a unique contribution among all reviewed papers, the authors also investigate how the dimension of personal networks (i.e., 1 = only direct first acquaintances, 2 = direct first acquaintances and their acquaintances etc.) affects the diffusion and conclude that bigger personal networks are associated with slower diffusion, particularly in random networks.

A different modeling approach is taken by Kocsis and Kun (2008), who focus on the diffusion of telecommunications technology, an industry characterized by strong positive network externalities. They develop an opinion dynamics model in which adoption decisions depend on a cost minimization procedure that is based on the number of agents in the personal network that decide to adopt or reject a technology. The proposed model constructs a small-world type network starting from a square lattice topology with periodic boundary conditions and randomly rewiring edges. The authors vary the share of rewired edges and find that in the presence of network externalities, rewired edges (i.e., increasing randomness) can facilitate but can also hinder diffusion, depending on how advantageous the advanced technologies are in comparison with the lower level ones.

In many of the reviewed models, agents' decision to adopt is considered a signal in favor of an innovation by neighboring agents. An interesting approach is to also interpret neighbors' refusal to adopt as evidence against the product. Martins et al. (2009) formulate a model that incorporates this idea by means of a Bayesian system. To examine the impact of small-world effects, they conduct experiments with a regular square lattice topology and varying degrees of random rewiring. Results show that more rewiring (i.e., a higher degree of randomness) is associated with faster diffusion and an increased final proportion of adopters, which contradicts results by Kocsis and Kun (2008). This can be explained by the differing modeling assumptions. Whereas Kocsis and Kun (2008) model only positive feedback effects due to externalities, Martins et al. (2009) also implicitly model a "diffusion of rejection", which may spread faster in more clustered networks. The authors also study the influence of the location of early adopters, comparing instances of clustered versus randomly scattered "seed" adopters (1% of the population) and find that the process of innovation diffusion from an initial cluster is much slower than in the case of randomly spread adopters.

Motivated by the question why diffusion sometimes propagates throughout the whole population and why at other times it halts in its interim process, Choi et al. (2010) study the diffusion of network products in random and small-world networks. They specify the consumers' willingness to adopt as a function of the product's intrinsic value perceived by each consumer (normally distributed constant) and the benefit due to local network effects based on the proportion of adopters in the agent's neighborhood. In line with results of Kocsis and Kun (2008), they find that network structure plays a moderator role for the link between network effects (i.e., positive externalities of adoption) and innovation diffusion. Results also suggest that a new product is less likely to reach full diffusion in random networks than in cliquish networks because randomness in the topology makes it harder for an innovation to build up network benefits at the initial stage. However, once the diffusion process reaches a critical mass, diffusion is faster in a random network.

Scale-free versus random Scale-free network topologies (Barabási and Albert 1999) have also attracted considerable interest, although somewhat less than small-world networks, which appear to be more appropriate interaction models for many (but not all) markets. A paper that focuses exclusively on comparing the diffusion in scale-free and random networks was put forth by Kuandykov and Sokolov (2010). In their model, consumers adopt with a probability that is determined by the fraction of adopters in the neighborhood and two fitting parameters that control time to adoption start and S-curve steepness, respectively. System behavior and the resulting shape of the diffusion curve are a direct consequence of the choice of these two aggregate-level parameters. Based on (only) a single replication per condition analyzed in the paper, the authors observe faster adoption for a random network compared to a scale-free network with the same number of nodes. However, time to full adoption in the random network tends to grow with the number of links. Results also indicate that innovation spreads remarkably faster through what the authors refer to as a "clustered random network" (a network in which agents are distributed among three clusters that are then connected sequentially) than through one uniform cluster with the same total population and the same number of initial adopters.

Small-world versus scale-free versus random Few authors have compared all three of the most common network topologies so far. The first paper to compare the effect of small-world and scale-free networks on market dynamics was put forth by Janssen and Jager (2003). They model agents' behavior from a social psychology perspective and adopt the "consumat" approach (Jager et al. 2000), which incorporates alternative assumptions on behavioral rules. The proposed model simulates market dynamics that emerge from agents' choice between multiple products which are replaced as soon as they become unprofitable. It is not a dedicated diffusion model, but results relate to innovation diffusion nonetheless. Findings indicate that a scale-free network leads to a market dominated by far fewer products as opposed to a small-world network. Results also show that in scale-free networks, a small proportion of consumers (hubs, or early adopters) may have an exceptional influence on the consumptive behavior of others. Rahmandad and Sterman (2008), while primarily concerned with comparing stochastic agent-based and deterministic differential equation models, also study the impact of different network structures. In particular, they compare fully connected, random, small-world, scale-free and lattice networks. In line with previous research, they find that higher clustering slows diffusion to other regions, because it increases the overlap in contacts among neighbors. In the small-world and regular lattice networks, this leads, on average, to lower peak prevalence and higher peak times. Because the model is concerned with the spread of contagious diseases, one should be cautious when interpreting results from an innovation diffusion perspective.

One of the most comprehensive studies on the impact of social network topology to date was conducted by Bohlmann et al. (2010), who compare diffusion in cellular (Moore neighborhood), random, small-world, and scale-free networks. Furthermore, they also study how the strength of communication links between two market segments—an innovator segment and a follower segment—affects diffusion. They formulate a model with probabilistic adoption ($p = 0.5$) when a threshold (proportion of adopting neighbors) is reached. By varying this adoption threshold, the authors find that it affects the likelihood of diffusion cascades differently among the various network structures: diffusion appears more likely in clustered networks under high adoption thresholds. The random network exhibits more consistent peak adoption across threshold levels. Moreover, the effect of network structure becomes more significant when agents' adoption threshold increases. For the two-segment model with varying link strength between innovator and follower market segments, results unsurprisingly indicate that an early emphasis on innovator adoptions rather than innovator-to-follower communications can speed market adoption when follower communications are weak. The authors conclude that network topologies are a key factor in determining an innovation diffusion process and its pattern and that in particular highly clustered networks can have substantially different diffusion patterns than more randomly connected networks.

Other network topologies In an early contribution, Abrahamson and Rosenkopf (1997) first suggest that a focus on social networks could enrich theories that explain the timing and extent of innovations' diffusions. Their social network model is based on a densely-linked core stratum and a weakly-linked peripheral stratum. Depending on initial adopters' location, they distinguish between "trickle-down" diffusion processes, which emanate from core strata, and "trickle-up" processes that originate from the peripheral strata. The former tend to diffuse innovations congruent with network norms while the latter tend to diffuse contra-normative or competence-destroying innovations. Agents adopt if their individual assessment and a "bandwagon pressure" exceeds an agent-specific threshold. The authors use small-sized networks with only 21 nodes and vary density and structure of links in and between core and peripheral strata. Simulating both trickle-down and trickle-up diffusion processes, they find that small, seemingly insignificant idiosyncracies of network structures can have large effects on the extent of an innovation's diffusion. These results have important implications that are not fully elaborated upon in the paper. In particular, the findings suggest that it may be more appropriate to tackle questions in diffusion research with modern complexity theory rather than with deterministic differential equations.

In order to model the effect of social hubs in the diffusion process, Delre et al. (2010) test the impact of the number of contacts as well as degree and direction to which social influences determine individual's choice to adopt. Like in previous work (Delre et al. 2007a,b), agents' decision making is based on heterogeneous utility thresholds defined as the sum of social and individual utility parts. However, unlike in prior contributions, the authors use "broad-scale" networks (Amaral et al. 2000), i.e., scale-free networks with a cut-off parameter (faster decay of the number of links) to structure interactions and motivate this with constraints people often have in building links with other people. Furthermore, their approach differs from prior work in that connections can be directed and weighted. In particular, they assume that the influence of a neighbor is proportional to the number of links it has and that the probability of directing the link from i to j depends on the number of links that i and j have. Results demonstrate that social influences can have a positive effect on the diffusion of the innovation if a given critical mass is reached, but also can have a negative effect otherwise. Social influence may decrease the chances for the diffusion to spread significantly if the innovation is of lower quality (i.e., induces less individual utility) and thus hardly reaches the critical mass. Uncertainty about the innovation success therefore increases in more socially susceptible markets. These results dissent with the common intuition that fashionable markets are easy to penetrate because consumers tend to copy each other. When the weights are stronger for those neighbors that have more relationships, the innovation reaches higher degrees of penetration. However, this effect is relatively small compared to other network factors. The direction of the relationships among consumers does not substantially affect the final market penetration. Finally, results indicate that innovations have, on average, fewer chances to spread in markets with high social influence.

Strong versus weak ties Granovetter's "strength of weak ties" theory (Granovetter 1973) has also attracted interest in the innovation diffusion literature. It postulates that individuals are often influenced by others with whom they have only tenuous or even random relationships. Although these ties are weaker in absolute impact than more stable, frequent, and intimate "strong ties", they may unlock and expose interpersonal networks of external influences in distant networks, thus paving the path for the spread of information throughout society (Goldenberg et al. 2001).

Adopting this theory, Goldenberg et al. (2001) break down the personal communication between closer and stronger communications that are within an individual's own personal group (strong ties) and weaker and less personal communications that an individual has with a wide set of other acquaintances and colleagues (weak ties). They formulate a cellular automata model that does not explicitly represent agents' adoption decision processes, but rather models the spread of information about an innovation by means of probabilistic state changes of passive cells. The probability of an individual cell becoming informed is based on probabilities of becoming informed via weak-tie WoM, strong-tie WoM and exposure to marketing efforts. In their full factorial experimental design the authors systematically vary these three probabilities as well as the size of each individual's personal network and the number of weak tie contacts. Results indicate that the influence of weak ties on information dissemination is at least as strong as the influence of strong ties and that the process is dominated by WoM rather than by advertising.

Summarizing results of the reviewed studies, it can be concluded that the topology of the social network involved in consumers' decision making is consistently found to have a large impact on innovation diffusion. Random networks, as opposed to more regular or more clustered ones, tend to favor the spread of information and they are therefore frequently associated with faster diffusion and an increased share of adopters at the end of the diffusion process. However, in markets in which positive externalities of adoption or strong meso-level social influence (e.g., group conformism, herding behavior etc.) exist, diffusion appears to be both more likely and faster in more clustered networks. Social influences can have a positive or negative effect in these markets, depending on whether a given critical mass is reached. These markets are therefore more uncertain concerning the final success of the innovation.

Overall, managers planning the introduction of an innovation are well-advised to bear in mind that people participate in different networks for different markets and to take into account the characteristics of particular networks relevant for the product, since this may be a critical factor at the early market stage and determine whether a new product diffuses or fails. From a theory-building standpoint, the strong impact of network topologies implies that researchers must be careful when selecting a network structure for diffusion research.

4.2.2 Network externalities

Netwerk externalities (cf. Katz and Shapiro 1986, 1992) have garned attention in the marketing literature (for an overview, cf. Stremersch et al. 2007) because they affect the diffusion of innovations in numerous industries including information technology, entertainment, and communications. The source of these externalities may be global or local, i.e., the utility of the innovation may depend on the proportion of adopters in the entire social system or in the local social neighborhood (Goldenberg et al. 2010a).

As noted in Sect. 4.2.1, Kocsis and Kun (2008) model local network effects in their opinion dynamics model of telecommunications technology. However, they do not use network externalities as an explanatory variable. Choi et al. (2010) also model the diffusion of network products, but they focus on the role of network structure and do not study the impact of network externalities in detail.

Goldenberg et al. (2010a), by contrast, focus specifically on the effect of network externalities and seek to analyze their absolute impact. To this end, they formulate both an agent-based and an aggregate model. In the ABM, consumers consider adoption only if the proportion of adopters in the population exceeds an agent-specific threshold drawn from a truncated normal distribution (this part of the formulation incorporates global network externalities). Once this threshold is exceeded, an agent adopts with a probability determined by two parameters, one of which controls the influence of the fraction of adopters in the agent's (Moore) neighborhood on a two-dimensional lattice (incorporates local network externalities), and the other controls the influence of "external factors" such as advertising. The authors perform simulations with varying adoption threshold distributions and influence parameters and demonstrate that network externalities consistently have a "chilling" effect on the profitability of new products. They substantiate this claim by formulating an aggregate model to which they fit empirical diffusion data on six network products and, thus, are able to confirm the "chilling" effect of externalities.

The paper by Goldenberg et al. sparked a vivid debate on agent-based approaches in marketing, which commentors consider promising (Stremersch et al. 2010; Gatignon 2010; Rust 2010), and on the substance and theoretical foundations of the contribution. On a substantive level, Stremersch et al. (2010) and Gatignon (2010) criticize that imposing the existence of a threshold on the network externalities process—which the authors aim to validate through theoretical reasoning—"loads the dice" in favor of finding chilling effects. They also question more generally whether the chosen individual level process is reasonable and argue that the simplifications made to model it may lead to erroneous outcomes. Rust (2010) further challenges the conclusions and argues that the construction of the model makes the substantive implications a foregone conclusion. In a rejoinder, Goldenberg et al. (2010b) respond to the criticism by defending the global threshold assumption. While no final conclusions can be drawn, it appears that a consensus has emerged from the discussion that future research on network externalities can benefit significantly from the flexibility provided by ABMs.

4.2.3 Negative word-of-mouth

The destructive potential of negative WoM has long been acknowledged (Richins 1983), but its important role in innovation diffusion processes has been neglected in traditional models. To investigate the interplay between positive and negative WoM induced by opinion and resistance leaders, respectively, Moldovan and Goldenberg (2004) extend a previous model (Goldenberg et al. 2001) that focused exclusively on the role of strong and weak ties. In the extended model, consumers are in one of three states: uninformed (not spreading WoM), adopter (spreading positive WoM), or resistor (spreading negative WoM). The population is exogeneously divided into three groups: (1) opinion leaders, who may only adopt the innovation, (2) resistance leaders, who may only reject the innovation, and (3) regular consumers subject to both positive and negative WoM. Adoption occurs, at a certain probability, as a result of positive WoM or advertising, while rejection occurs as a result of negative WoM. The social network is not modeled explicitly. Instead, global interconnectedness is assumed. The authors vary the proportion of opinion and resistance leaders in the market as well as the probabilities of being influenced by advertising and positive/negative WoM imparted by ordinary consumers, opinion leaders, and resistance leaders, respectively. As can be expected, results indicate that resistance leaders will reduce sales significantly, as a function of both their relative number and the strength of their social influence.

In a related contribution that also extends the model introduced in Goldenberg et al. (2001, 2007) investigate the interplay of weak and strong ties with positive and negative WoM. Moreover, they link diffusion directly to the net present value of the firm. Again, adoption is not modeled as a deliberate decision process, but rather as a probabilistic transition between three states (adopt/reject/none), based on probabilities of being influenced by positive WoM, advertising, and/or negative WoM. The network used in the simulations is a dynamic small-world-type network that consists of both permanent strong ties and randomly changing weak ties. To create the experimental conditions, the authors vary size of strong ties and weak ties, percentage of disappointed consumers, and probability of being influenced by advertising and positive/negative WoM via strong/weak ties, respectively. Results indicate that the presence of weak ties, which is beneficial to the firm under normal circumstances, might adversely affect it in the presence of dissatisfied consumers. Even a small percentage of dissatisfied consumers can cause considerable damage to long-term profits, since they create an invisible diffusion of product rejection which may not be noticed immediately.

Deffuant et al. (2005) develop a model that simulates the formation of positive and negative opinions about an innovation and their spread via positive and negative WoM. In particular, they investigate the role of a minority of "extremists" with very definite opinions. The proposed model evolved from previous work in an agricultural context (Deffuant et al. 2002) and differs significantly from the cellular automata based threshold-models outlined above. Rather than modeling passive automatons with a binary adoption state and stochastic state transitions, Deffuant et al. model agents' adoption behavior with a state transition scheme based on interest (no, maybe, yes) and information states (not-concerned, information request, no adoption, pre-adoption, adoption). Interest is based on social opinion, individual benefit and uncertainty intervals around these continuous values. Individual benefit estimates are probabilistically influenced by social opinion. Social opinion is spread via discussions, which are modeled as message exchanges about the social value and the information state. Discussions are triggered by messages from the media that reach individuals at random, with a given frequency. Both initial social value and initial individual benefit are drawn from a normal distribution. Using a small-world type network, the authors experiment with varying initial distributions of social opinion and individual benefit as well as varying average size of the individual's social network and the frequency of mass media messages. Results suggest that innovations with high social value and low individual benefit have a greater chance of succeeding than innovations with low social value and high individual benefit. Extremists with very definite opinions can polarize the social value and strongly affect adoption when the density of the social network and the frequency of discussion are high.

The results of the reviewed studies unequivocally suggest that managers planning the market introduction of an innovation should heed the common wisdom that warns of the destructive power of negative WoM.

4.2.4 Dynamic social networks

Real-world social networks, unlike their idealized representations in most diffusion models, are not static, but evolve over time. This may not be relevant if the speed of diffusion is faster than changes in the social network structure and the structure of the social network is not influenced by the innovation itself, but it may be highly relevant for certain types of innovations. In a policy-oriented study, Deroïan (2002) therefore model the social network as a set of relationships generated by the agents themselves. The authors thereby endogenize the evolution of the social network as a step-by-step process based on the assumption that two individuals are more confident in each other if they share a common opinion (i.e., homophily). The simulation captures the emergence of a collective evaluation of an innovation and explains diffusion failure as the formation of a negative collective evaluation. Unlike most other models reviewed, Deroïan uses a directed influence graph that incorporates both positive and negative (inhibitive) influence. Drawing on ideas from the opinion dynamics literature, the authors model adoption decisions based on individual opinions (i.e., continuous propensities to adopt). The formation of these opinions, as a cumulative process, gradually increases the pressure of the whole community on individual opinions. The authors examine the impact of receptivity and network size on opinion and diffusion dynamics. Results confirm that the diffusion of an innovation can be affected by the state of the influence network in the demand side and that irreversible dynamics occur in the system.

4.3 Effectiveness of promotional strategies

ABMs of innovation diffusion offer the potential to explicitly incorporate marketing variables, thus allowing decision-makers to compare different scenarios and test various strategies in what-if experiments. Remarkably, theoretical models have so far largely neglected marketing variables such as product (e.g., product attributes), pricing, and distribution (exceptions that include pricing and changing product designs are outlined in Sect. 4.4). Promotion is by far the most widely studied marketing variable in the agent-based innovation diffusion literature.

Using a cellular automata model (cf. Sect. 4.2.1 for a brief model description), Goldenberg et al. (2001) compare the effect of marketing efforts, weak-tie and strong-tie WoM. Results clearly indicate that beyond a relatively early stage of the diffusion process, the effect of external marketing efforts (e.g., advertising) quickly diminishes and strong and weak ties become the main forces propelling adoption. These results support Rogers (2003) argument that advertising may be effective in the initial stages of information dissemination, but its importance diminishes after product takeoff and WoM becomes the main mechanism that drives adoption.

Considering both positive WoM from opinion leaders and negative WoM from resistance leaders, Moldovan and Goldenberg (2004) also investigate the effectiveness of advertising (cf. Sect. 4.2.3 for a brief model description). They find that in markets in which both opinion and resistance leaders play a role, advertising has a small and nonlinear effect on market size. According to their results, advertising may decrease market size at high levels, since it activates the market's resistance leaders, who (like opinion leaders) are assumed to be highly attentive to advertising and well connected. Based on this finding, the authors also show that activation of opinion leaders in advance of unfocused advertising messages may mitigate the destructive effect of resistance leaders and increase market size significantly.

Alkemade and Castaldi (2005) investigate whether firms can learn about the network structure and consumer characteristics when only limited information is available, and use this information to evolve a successful directed-advertising strategy. The authors focus on fashionable products and model both "exposure" and "over-exposure" thresholds (cf. Sect. 4.1.1). Firms are boundedly rational and not fully aware of the structure of the communication channels among consumers. A genetic algorithm is used to identify efficient strategies to target individual consumers and model the strategy search and learning behavior of the firm. Scenarios with varying assumptions about whether consumers may decide to use the product again after discontinuing its use are tested. As expected, results exhibit either oscillating behavior or a permanent negative effect that causes the diffusion to "die off". The authors compare diffusion results obtained with a dynamic advertising strategy (adapted after each period) to random advertising results and demonstrate that the evolved directed-advertising strategies outperform random advertising.

Studying advertising strategies in the context of positive and negative WoM in small-world-type networks, Goldenberg et al. (2007) compare linear and concave advertising strategies (cf. Sect. 4.2.3 for a brief model description). Findings indicate that the optimal level of advertising is affected strongly by the WoM process. In line with Moldovan and Goldenberg (2004), the authors find that too much advertising might indeed negatively affect profitability because although it increases the number of adopters, it indirectly also increases the number of disappointed customers and thus triggers an earlier start of the negative WoM process.

Delre et al. (2007a) investigate how promotional strategies affect the diffusion of new products in terms of final market penetration and time to takeoff. They specify "external marketing effort" as a probability for any non-adopter agent to be convinced to adopt each period and compare multiple timing strategies and two targeting strategies: targeting many small groups in distant places ("throwing gravel") and targeting a small number of large groups ("throwing rocks"). These strategies are tested in brown goods (i.e., electronics) and white goods markets (i.e., household products). Findings indicate that (i) the absence of promotional support and/or a wrong timing of the promotions may lead to a failure of product diffusion; (ii) the optimal targeting strategy is to address distant, small and cohesive groups of consumers; and (ii) the optimal timing of a promotion differs between durable categories (white goods, such as kitchens and laundry machines, versus brown goods, such as TVs and CD players).

An interesting promotional strategy is to leverage the important role of highly connected individuals (i.e., "hubs" or "opinion leaders") and use it as a marketing instrument. In a pioneering, predominantly conceptual contribution, Valente and Davis (1999) investigate how the diffusion of innovations can be accelerated through opinion leader recruitment. They use homogeneous agents that adopt once 15% of their neighbors have adopted. The formal description of the underlying model is sketchy and the network model used, which randomly allocates seven ties per agent, does not appear to resemble most real-world social network structures very closely. Nevertheless, simulation results demonstrate that diffusion occurs faster when initiated by opinion leaders rather than by random or marginal agents and that targeting opinion leaders may therefore accelerate diffusion.

Similar to Valente and Davis (1999), Delre et al. (2010) also investigate the effectiveness of opinion leader recruitment (cf. Sect. 4.2.1 for an outline of their model). Results suggest that the most important function of highly interconnected hubs is to inform others about the new products, but that their effect on the decision making of consumers can be often overestimated. They also find that in markets in which such hubs do not exist, diffusion is less likely to occur. For such markets, direct-to-consumer advertising could be an alternative strategy to stimulate the spreading of the new product in different areas of the network.

Finally, van Eck et al. (2011) also study the role of opinion leaders, but take into account not only their central network position, but also the influence of personality traits and knowledge among influential consumers. To this end, they extend the model developed by Delre et al. (2007a). Like in the original model, agents' adoption decisions are based on a utility threshold function that includes individual preference and social influence parts. Social pressure, however, is not modeled as a threshold, but rather as a continuum (i.e., if more neighbors adopt the product, normative influence in favor of the product increases). Furthermore, the small-world network used in the original model is replaced with a scale-free network to better account for the central position of opinion leaders. The authors test critical assumptions by means of an online survey on the WoM behavior of children in the context of the diffusion of free Internet games. The empirical data supports the hypotheses that opinion leaders (i) are better at judging product quality, although they do not know more about the product, (ii) are more innovative than followers, (iii) take more central positions in the network, and (iv) are less susceptible to normative influence than followers. The authors parameterize the model accordingly and find significant differences between networks that contain opinion leaders and those that do not. In particular, opinion leaders increase the speed of the spread of information, the adoption process itself, and the maximum adoption percentage. The results indicate that targeting opinion leaders is a valuable marketing strategy not only because of their central position, but also because of their influential power.

Overall, we can conclude that advertising can be an important driver for diffusion success, particularly in the initial stages of information dissemination. Advertising strategies directed at highly connected individuals can be effective in accelerating diffusion. In the presence of negative WoM, however, too much advertising might even have an adverse impact on innovation success. To mitigate the destructive effect of negative WoM, firms should aim to activate opinion leaders in advance. While absence of promotional support may lead to failure of product diffusion, optimal timing and targeting of distant, small, and cohesive groups of consumers may accelerate diffusion. Nevertheless, the most important role of advertising is to spread initial awareness. Adoption itself is mostly driven by WoM, in particular after takeoff, rather than directly being influenced by advertising.

4.4 Endogenous innovation, co-evolution and competitive diffusion

Theoretical models have so far focused on the diffusion of singular innovations and largely neglected competition with existing products or competitive diffusion of multiple innovations. However, there are some notable exceptions that consider multiple exogenously defined or endogeneously emerging products.

Goldenberg and Efroni (2001) conceptualize innovation not as an antecedent that precedes diffusion, but rather as a consequence of emerging needs that propagate in the market. The proposed stochastic cellular automata model incorporates inter-firm competition for the exclusive discovery of emergent "marketing awareness" and estimates a firm's probability of being "first and alone" in the market. The spread of awareness of a need is modeled via two mechanisms: spontaneous, discovery-driven transformation with a fixed probability and WoM induced awareness with a probability which is based on the number of (Moore-) neighbors in the "aware" state. Firms can sample the market to identify new needs. To create the experimental conditions, the authors vary the probabilities for spontaneous and WoM driven adoption as well as the number of firms. Results show that if traditional exploration is applied, there is a high probability that at least one other competitor will discover the same need before, or concurrently with, the firm in question. Hence, pioneer status cannot be achieved by exclusive dependence on market-based information. These findings suggest that alternative methods to identify emergent needs based on information that is invariant to market awareness are necessary.

Janssen and Jager (2001, 2003) also endogenize innovation, but model market dynamics from a social psychology perspective. In the proposed models, products remain in the market as long as they maintain a minimum level of market share, else they will be replaced by a new product. Agents' decision making is modeled following the "consumat" approach developed by Jager et al. (2000) and agents switch between various cognitive strategies (social comparison, repetition, imitation, deliberation) depending on their level of need satisfaction and their experienced degree of uncertainty. A small-world-type network topology is used in Janssen and Jager (2001), and complemented with experiments with scale-free networks in Janssen and Jager (2003). Results indicate that market dynamics is a self-organized property that emerges from the interaction between agents' decision making process, the product characteristics, and the structure of interactions between agents. The behavioral rules that dominate the artificial consumer's decision making determine the resulting market dynamics, such as fashions, lock-in and unstable renewal.

To analyze the diffusion of green products, Janssen and Jager (2002) formulate a co-evolutionary model in which both consumers and firms are heterogeneous in their behavioral characteristics. Each firm produces one core product which it changes in an evolutionary process if it does not meet its business target, defined as a minimum average profit rate. Firms are assumed to be either innovators or imitators who copy successful competitors. Consumer agents have two needs: a social need and a personal need. Personal need satisfaction depends on the difference between the characteristics of the consumed product and the preferred "ideal" characteristics. It is assumed that social need satisfaction rises linearly with the number of neighbors who consume the same product. The total level of need satisfaction is defined as a weighted sum of personal and social need satisfaction and rescaled by the relative price level. Consumer agents are heterogeneous in their personal preferences regarding product characteristics and weights of personal and social needs. Simulation results suggest that more deliberation, as is usually the case with important consumptive decisions, yields a faster diffusion in a market in which firms do not adapt their products, but a slower and incomplete diffusion in a market in which firms continuously adapt their product designs.

Schramm et al. (2010) model brand level interactions in the diffusion of durable products and define multiple types of agents (innovators, early adopters, late adopters) that differ in their sensitivity to features, price, promotion, and social influence. Individual adoption thresholds are specified as a function of feature, price, promotion and social influence and compared to fixed exogenous adoption thresholds to determinate adoption behavior. The proposed model does not incorporate social networks and only considers global feedback (total proportion of consumer agents that have adopted). Parameters used in the simulation runs are not fully specified in the paper. The authors present simulation results for sample scenarios modeling the digital camera market and conclude that ABM can be applied to improve understanding of the brand and market-level reactions to changes in marketing mix strategy.

5 Applications and policy analyses

The papers reviewed in the previous section apply ABMs as tools to explore theoretical research questions by means of thought experiments. Rather than predicting the spread of particular innovations at actual markets, these models aim at general insights about diffusion processes on a highly abstract level. Given that ABMs are "much more concerned with theoretical development and explanation than with prediction" (Gilbert 1997), it is not surprising that the majority of papers reviewed falls into this category.

Table 2 Applications and policy analyses reviewed

Code	Reference	Application domain
A1	Berger (2001)	Agricultural innovations
A2	Broekhuizen et al. (2011)	Cinema market
A3	Dugundji and Gulyás (2008)	Transportation mode alternatives
A4	Faber et al. (2010)	Micro-cogeneration of electricity
A5	Gallego and Dunn (2010)	Healthcare provisioning
A6	Günther et al. (2011)	Alternative fuels
A7	Kaufmann et al. (2009)	Organic framing practices
A8	Kim et al. (2011)	Automobile market
A10	Schwarz and Ernst (2009)	Water saving innovations
A11	Schwoon (2006)	Fuel cell vehicles
A12	Vag (2007)	Mobile phones
A13	van Vliet et al. (2010)	Alternative fuels
A14	Zhang and Nuttall (2011)	Smart metering
A15	Zhang et al. (2011)	Alternative fuel vehicles

This notwithstanding, attempts have also been made to demonstrate the methodology's potential as a practical tool for tackling real-world problems. As ABMs mature, the number of contributions that adopt an applied perspective and aim at providing decision-makers with forecasts, management diagnostics, policy analyses and decision support is increasing rapidly. In this section, we review the still limited, but growing body of applied literature. Table 2 provides an overview of the reviewed papers and their application domain. We structure our review around the major substantive domains in which studies have been conducted so far, each of which is typically based on empirical microdata from a particular geographic region.

5.1 Agriculture

Rural sociology is the research tradition credited with forming the basic paradigm for diffusion research. According to Rogers (2003), it has produced the largest number of diffusion studies so far. By that standard, the number of ABMs concerned specifically with agricultural innovations is still small; only two of the reviewed papers fall into this category.

The first, Berger (2001), simulates the diffusion of agricultural innovations and water resource use in Chile and assesses policy options in the context of resource use changes and the Mercosur agreement. In light of scarce aggregate agronomic data in transition and developing countries, the authors motivate the agent-based approach with its ability to make use of rich available microdata (e.g., from experimental stations, farm records, sample surveys, experts' opinions, and direct observations on field trips), to account for technical, financial, and behavioral constraints at the farm level, to capture a rich set of interactions, and to explicitly model space. The model consists of an economic and a hydrologic component bound into a spatial framework; agents represent farms that interact in various ways, including contagion of information, exchange of land and water resources, and return-flows of irrigation water. The authors identify likely diffusion patterns for specific agricultural innovations and also investigate expected consequences in terms of changes in the use of water, farm incomes, and structural effects of the innovation processes.

Kaufmann et al. (2009) study the diffusion of organic practices through farming populations in Latvia and Estonia and evaluate the effectiveness of policies to promote them. In particular, they model the effect of social influence, introduction of a higher subsidy, and increased support by organic farm advisors. Based on theory of planned behavior, farm agents exchange opinions, update subjective norm estimates, and adopt organic farming practices if intention exceeds an empirically derived threshold. The authors use a survey dataset collected from regions in Latvia and Estonia and model the complete population of organic and conventional farmers in both countries. Results suggest that social influence alone makes little difference and that economic factors (e.g., introduction of a subsidy) are more influential. However, the combined adoption rate from social and economic influences is higher than the sum of the proportion of adopters resulting from just social influence and from just subsidies. The authors derive specific policy recommendations for both countries and conclude that policies are more effective if they are sensitive to the specific contexts.

5.2 Energy, transportation and environmental innovations

Judging by the number of agent-based studies in this area, environmental innovations appear to be of particular concern to innovation diffusion researchers. This may on the one hand be attributed to their societal relevance, and on the other hand to a number of aspects that call for an individual-based approach, such as the high relevance of social influence as well as varying consumer preferences and attitudes toward "green innovations". Zhang et al. (2011) also argue that environmental innovations do not follow the prototypical Bass diffusion curve because of long take-off times and diffusion discontinuities.

Several authors have looked into alternative transportation modes and alternative energy sources for transportation. Simulating the diffusion of fuel cell vehicles, Schwoon (2006) study the impact of governmental policies and public infrastructure build-up programs. Consumers' behavior is modeled by means of the "consumat" approach (cf. Jager et al. 2000). Findings indicate that a reasonable tax on conventional cars would be sufficient to overcome the "chicken and egg problem" of car producers not offering fuel cell vehicles as long as there are no hydrogen filling stations, and infrastructure not being set up unless there is a significant number of fuel-cell vehicles on the road.

Zhang et al. (2011) investigate factors that can speed the diffusion of hybrid and electric vehicles on the US market. They model the relationship between multiple agents with unique objectives: (i) consumers, who maximize utility and minimize cost, (ii) manufacturers, who maximize profits, and (iii) governmental agencies, that maximize social benefits. Manufacturer agents optimize their products by means of simulated annealing. Consumer agents choose any or none of the available vehicles to buy. All consumer agents are assumed to be affected by WoM and domain-specific knowledge in the same way and they are not embedded in an explicit social network. Consumers' decision making is grounded in empirical choice-based conjoint data, i.e., each consumer agent is initialized with individual preferences (with respect to vehicle design, fuel type, miles per gallon, miles between charge, and price) corresponding to an individual respondent in a panel survey of automobile experts (the authors acknowledge that the sample population is favorably biased toward alternative fuel vehicles). The authors compare the impact of three mechanisms: an alternative fuel vehicle mandate (i.e., technology push), WoM (i.e., market pull), and fuel economy mandates (i.e., regulatory push). Unsurprisingly, mandating manufacturers to produce only hybrid and electric vehicles is found to speed diffusion of these types of vehicles, in particular that of hybrid options. WoM also positively affects diffusion by decreasing the preference for fuel-inefficient vehicles and inducing a higher willingness to pay for alternative fuel vehicles. Perhaps most interestingly, the authors find that fuel economy mandates (i.e., any vehicle that does not achieve at least 27.5 miles per gallon must pay a penalty) lead to an increase in the market share of fuel-inefficient vehicles and therefore increase air pollution. This counterintuitive finding results from consumers willingness to pay the higher prices (due to penalties passed on by the manufacturers) in order to buy SUVs (including hybrid). The authors 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 vehicle. Results also indicate that there is little interest in electric vehicles and that price will have to decrease and miles between charges have to increase significantly for this type of vehicle in order to reach the mainstream market. Methodologically, the study demonstrates how a thorough verification and validation of agent-based diffusion models can be achieved by grounding, calibrating, verifying, and harmonizing the model.

Günther et al. (2011) simulate the diffusion of a second-generation biomass fuel on the Austrian market. In the proposed model, fuels are characterized by the attributes price, quality, and "expected environmental friendlyness". Consumers' adoption decisions are modeled by means of heterogeneous information and utility thresholds; agents adopt once they have obtained sufficient information (from other consumer agents or through promotional activities) and the utility of the biomass fuel exceeds their adoption threshold. Consumers spread information in a "preference-based" network in which links are created based on geographic distance and agents' consumer type. Homophily is assumed, i.e., agents of the same type are more likely to be connected. In their simulation experiments, the authors divide the market into four segments (price-sensitive, quality-seeking, "eco-consumers" and "snob buyers") and set agents' preference weights accordingly. They conduct experiments to compare the effectiveness of promotional timing (continuous vs. intermittent) and targeting (experts, consumers in different regions) strategies and combine them with one of two dynamic pricing strategies (skimming vs. penetration). Results indicate that directing promotional activities at opinion leaders can accelerate diffusion considerably. Furthermore, results clearly indicate that speed and success of diffusion is dependent on the geographic area targeted (e.g., large vs. small cities).

A different model that is also concerned with the adoption of transportation fuels is put forth by van Vliet et al. (2010). They examine the impact of marketing activities and governmental policies on the diffusion of various conventional fuels and fuel blends (produced by means of 13 different production chains). In their model, fuels are characterized by four attributes: driving costs, environment, performance, and reputation. The authors assume lexicographic preferences; in particular, they assume that price is most important and that other attributes only play a role if prices are similar. The authors define eleven consumer types on the basis of sociodemographic data. Experiments with policies such as price reductions (e.g., through tax and import tariff reductions), perceived emission reductions (through a successful large scale sustainable biomass certification scheme), and addition of a "buzz-factor" that increases perceived market share reveal that sustained combinations of interventions are required to bring about a transition away from petrol or diesel. Results suggest that adoption of alternative fuels is likely confined to niche markets with a share of 5% or lower.

Motivated by traffic congestion problems in the Netherlands, Dugundji and Gulyás (2008) study the effects of household heterogeneity and their interactions in the adoption of various transportation mode alternatives. Their approach starts out with classic econometric methods (multilevel nested logit model), but combines the static estimation model with agent-based methods to simulate the evolution of choice behavior over time. Assuming that each agent's choice (which represents that of multiple households) is directly influenced by the choices of its neighbors and socioeconomic peers, interactions are modeled in both social and spatial network structures. Simulation results of a multinomial logit formulation of the model indicate that there is a unique emergent equilibrium solution with a mode share of 60% for automobile commuters, approximately 25% for public transit, and approximately 15% for bicycle commuters. Simulation results of a nested logit version, however, are dramatically different with a mode share of approximately 93% for public transit commuters. The paper presents a promising methodological approach for combining agent-based modeling with econometric estimation, which allows researchers to make use of empirical microdata. However, counterintuitive and inconsistent results do not allow to draw any practical conclusions for the application case at hand. Furthermore, because the model does not focus on innovations, the approach cannot be applied directly to cases where consumers are not aware of the full set of available alternatives.

The models discussed so far in this section aim for predictive accuracy. However, due to the inherent problem that innovation diffusion predictions can only be validated ex-post, all of them are, at least to some extent, speculative thought experiments until data for validation becomes available. One of only a few ABMs that demonstrably replicate observed market behavior is put forth by Kim et al. (2011), who model diffusion in a competitive automobile market. In the proposed model, consumers evaluate available cars characterized by multiple cost and benefit attributes based on available product information, their individual preferences, and social influence. An innovative aspect of their approach is the use of multi-attribute fuzzy decision making. The authors simulate the diffusion of six full-sized cars available in the Korean market. To obtain data for model parameterization, they conduct a survey with 400 potential consumers to estimate their individual weights for nine attributes as well as sensitivity to social influence. Calibrating the small world social network parameters with observed diffusion data, the authors find that the simulated results fit actual sales data well. The approach for model calibration and ex-post validation is interesting and initial results appear promising. It would be even more intriguing to examine whether the calibrated model is also capable of producing ex-ante estimates of the diffusion of newly introduced cars, rather than replicating past observed diffusion when calibrated appropriately.

Apart from alternative transportation modes and energy sources, innovations that may reduce domestic water and energy consumption have also garned recent interest. In the remainder of this section, we review three models that evaluate government policies to promote such innovations.

The first, Schwarz and Ernst (2009), is concerned with the diffusion of water-saving innovations in Southern Germany. In the proposed model, each agent represents the households of one of five "lifestyle groups" on one square kilometer. The definition of these lifestyle groups ("Sinus-Milieus") is not specified in the paper. Agents decide upon adoption or rejection of shower-heads, toilet flushes, and a rain-harvesting system. Depending on the innovation category and lifestyle group, one of two decision rules is used to make adoption decisions: (1) a cognitively demanding deliberate decision rule, which is based on multi-attribute utility functions, or (2) a simple rule based on a lexicographic heuristic and imitation. The authors use empirical data from a questionnaire survey and validate the model with historic marketing data on toilet flush adoption. Simulation results suggest that water-saving innovations are likely to diffuse further in Southern Germany and that therefore water demand per capita is bound to further decrease if water-related habitual behavior remains more or less constant.

Faber et al. (2010) model the adoption of domestic micro co-heating and power (micro-CHP) in the Netherlands, which produces electricity in cogeneration with domestic heating. Assuming falling prices due to learning effects, they examine whether subsidy schemes can effectively accelerate the diffusion of micro-CHP. In the proposed model, agents are perfectly rational and make decisions to buy conventional condensing boilers or adopt micro-CHP based on total upfront and usage cost. The authors account for heterogeneity by modeling five house types with corresponding levels of natural gas needed for domestic heating, but do not model any interactions between agents. The proposed model is therefore a micro-model, but lacks important characteristics of ABMs, which is why no emergent phenomena can be expected in the results. Publicly available empirical data from various sources as well as estimates for gas and electricity use for the five housing types modeled are used in the simulations. Not surprisingly, the authors find that the market diffusion of micro-CHP is affected significantly by fuel prices. In particular, results show that the effect of electricity price considerably offsets the effect of gas price. Based on simulations of various subsidy schemes that affect either cost of purchase or costs for usage, they also conclude that subsidies could considerably accelerate the diffusion of micro-CHP.

Finally, Zhang and Nuttall (2011) introduce a model that simulates the diffusion of smart electricity meters (a technology that offers consumers detailed information about energy consumption) in Great Britain as a function of different policy options. Consumers' decision making is formalized using theory of planned behavior. More precisely, consumer agents' attitude is expressed as a function of electricity prices and individual price sensitivity. Their subjective norm toward choosing an option is influenced by WoM and the agent's individual motivation to comply. Perceived behavioral control is influenced by a range of environmental factors such as smart metering infrastructure or service availability. Combining these factors, a consumer agent's intention to choose an option is formalized as a function of it's attitude, subjective norm, and perceived behavioral control toward choosing an option. Electricity supplier agents adjust electricity prices once every three months and disseminate price information to consumer agents. The environment is modeled as a square lattice with periodic boundary conditions. Consumer agents are linked to neighboring agents as well as to random remote agents. The authors note that the resulting interaction structure exhibits both small-world and scale-free characteristics. Four scenarios are evaluated, varying who pays for the smart meters (government, electricity suppliers, or distribution network operators) and how they are rolled out (competitively or monopoly). Adoption is fastest in the government-financed competitive roll-out scenario, followed by government-financed monopoly roll-out and electricity supplier-financed competitive roll-out. After the introduction of smart meters, the simulation shows a dynamically unstable state of consumer switching. As a policy implication, the authors suggest that the U.K. government, in mandating electricity supplier-financed competitive roll-out, is currently persuing the least effective strategy because electricity suppliers tend to avoid using any mass media to disseminate the policy since they have to bear the cost of the meters.

5.3 Miscellaneous

In recent years, the spectrum of substantive domains in which pioneering applications of agent-based diffusion models have been developed has grown rapidly. To forecast future preferences, Vag (2007) develops a dynamic conjoint model that simulates changes in consumers' individual product priorities and presents an application to the mobile phones market. Unfortunately, the author does not provide a formal specification of the model. The results presented are highly sensitive to chosen parameters and appear highly path dependent and unstable. The author does not discuss managerial implications.

Studying the diffusion of medical practices in healthcare systems, Gallego and Dunn (2010) identify how innovation diffusion processes may lead to inequality of overall levels of recommended care. Using empirical network data from Australia, they simulate the diffusion of medical practices through a population of clinicians and find that stronger clustering within hospitals or geo-political regions is associated with slower adoption amongst smaller and rural facilities.

An application to the motion picture market is put forth by Broekhuizen et al. (2011). Using an ABM, they show that cross-cultural differences in social influence cause market inequalities and validate these results with survey data from China, the Netherlands, Italy, and Spain. The ABM they develop mimics the behavior of movie visitors and incorporates the social influences they exert on each other before and after visiting movies. This explicit distinction between the effects of coordinated consumption (i.e., social influence derived from intended behavior of others) and imitation (i.e., social influence derived from the past behavior of others) is a unique contribution of their paper. The model can be summarized as follows: Each simulation period, consumer agents become aware of movies with a probability determined by the buzz these movies create, which before release depends on pre-release advertising budget and after release depends on success at the box office. Then, agents are selected according to their heterogeneous probabilities of attending a movie. For each agent, expected utility, which is specified as the sum of individual and social utility parts, is calculated for each movie it is aware of. Individual utility is based on the fit between individual preferences and the movie characteristics; social utility is based on the fraction of agents that have seen the movie (imitation), and the proportion of agents that are informed about the movie but have not seen it yet (coordinated consumption). Hence, social influence is modeled on the macro-level and no social network is used to structure interactions. The main simulation results provide an explanation why a few movies dominate the market and show that social influence is the main driver of market inequalities. Furthermore, results indicate that coordinated consumption has a much stronger effect (almost four times) than imitation. The authors confirm this result empirically by means of a cross-national field study in countries selected based on their level of individualism (vs. collectivism). Results suggests a U-shaped relationship between a country's level of collectivism-individualism and members' susceptibility to social influence. Apart from the explicit distinction between pre- and post-purchase WoM as an important theoretical contribution, and the generated insights about cultural differences in the motion picture industry, the paper also contributes methodologically by demonstrating how agent-based modeling and empirical surveys can complement each other to create new insights that could not be gained using either method alone.

Although the wide array of applications is already impressive, agent-based modeling can not be considered a proven predictive tool for innovation diffusion yet. However, calibration and validation techniques have matured considerably in recent years, which is evident in a number of recent contributions. As the methodology continues to mature, it can be expected to become increasingly accepted not only as a research tool to guide intuition and facilitate theory building, but also as a decision support tool that provides managerial insights and policy recommendations not easily available with more traditional modeling techniques.

6 Conclusions

Even though agent-based diffusion models are still in their infancy, they have already created intriguing new research opportunities by facilitating a transition from an aggregate-level to an individual-level perspective. In this concluding section, we strive to highlight major remaining challenges and propose potential directions for future research.

In a recent review of developments in the diffusion and new product growth modeling literature, Peres et al. (2010) identified a number of shifts in research interest over the past two decades. Agent-based modeling offers researchers excellent opportunities to pursue these new interests, which include aspects such as consumer interdependencies as adoption drivers, spatial diffusion, brand-level analysis, and a shift from forecasting to managerial diagnostics.

So far, ABMs have advanced the understanding of innovation diffusion and yielded theoretical insights on aspects such as the role of social network topologies, strong and weak social ties, network externalities, positive and negative WoM, and advertising. However, there is still a lack of theoretical clarity about "social influence", a term that is used prevalently but inconsistently in the literature to denote a number of distinct concepts modeled with a wide range of different mechanisms. Further empirical research is also needed to clarify what micro-, meso-, and macro-level mechanisms of social influence act in different types of markets, market conditions, and stages of the diffusion process. It would be beneficial to integrate these mechanisms into a common modeling framework, which should be based on a clear-cut definition of key concepts and a thorough understanding of their relevance in various markets and under various conditions.

More research is also needed on the structure of social systems, which plays a key role in diffusion processes. Progress in network modeling has allowed diffusion studies with various stylized network structures and produced interesting results, but it is still unclear which generative algorithms and parameters are appropriate for modeling different types of actual markets. Because of the large impact on diffusion patterns, this is an important area for empirical research in the future. It may benefit from individuals' growing tendency to declare their social relationships and communicate online, as well as from new methods that facilitate large-scale sampling of the generated data.

Future research may also aim at bridging the gap between highly abstract theoretic models on the one hand, and very specific models for particular applications on the other hand. As this review has shown, models for theory-building are typically based on simple, if not simplistic, conceptions of human decision making. These models do not aim to provide forecasts or facilitate managerial diagnostics and the quantitative results they produce should therefore only be interpreted qualitatively with respect to the modeled effects. More recently, however, this role of ABMs in diffusion research as tools for theoretical inquiry has been complemented by ABMs tailored to particular application domains. The latter models provide managerial guidance and policy analyses, but they are not generic enough to be used in any other than the narrow substantive domains modeled. The gap between these two extremes may be the area in which progress would be most beneficial in terms of providing managers with simple, robust, adaptive and easy to control models that are as complete as possible (cf. Little 1970) and still applicable to a range of applications as wide as possible. So far, none of the reviewed models are designed to be used by and provide decision support to end-users directly, which may be attributed to their still relatively early stage of development. To make progress toward providing such support, both more solid empirical foundations and better, more adaptable and versatile models need to be developed.

To this end, additional aspects and more sophisticated decision rules need to be incorporated into models which, however, also makes them more complex. Theoretic models have so far largely avoided this complexity by intentionally describing agents and decision rules in a highly stylized manner, following the postulation that the complexity should be in the results and not in the assumptions of the model (Axelrod 2007). This approach comes with the risk of missing important aspects of the modeled real-world behavior and, thus, ending up with an inadequate model. The critical challenge for future research therefore lies in striking an appropriate balance between simple models (Keep It Simple Stupid—KISS) that may be enriched later on, and descriptive models (Keep It Descriptive Stupid—KIDS) that can be simplified wherever justified (Edmonds and Moss 2006).

A recurring issue (cf., e.g., Garcia et al. 2007; Midgley et al. 2007; Windrum et al. 2007; Ormerod and Rosewell 2009), which we continue to emphasize here, is the difficulty of validating ABMs in general, and agent-based diffusion models in particular. Like conventional differential equation models, agent-based diffusion models can only be validated ex-post. A viable approach is to use historic diffusion data for validation, which, however, is not very helpful for highly specialized forecasting models for a particular innovation as results are largely irrelevant in retrospective. Striking the proper balance between application-specific model detail and generic applicability is therefore important as it may allow modelers to reuse validated models or model components. While ABMs share many of the problems of aggregate models with respect to validation, these problems are exacerbated by the difficulty of simultaneously mapping networks, collecting individual-level data, and tracking diffusion (Peres et al. 2010). Furthermore, their typically much larger parameter space and degrees of freedom also makes validation a daunting task. Future research may therefore strive to establish a collection of validated model components, mechanisms, and parameters for specific types of markets and market conditions, which can be assembled as needed to model the diffusion of particular innovations.

Our review has also shown that a number of key aspects have been largely neglected so far, despite their relevance in diffusion processes and ABMs excellent ability to tackle them. First, scant attention has been paid to the spatial dimension of diffusion processes, despite ABMs' rich potential to account for spatial heterogeneity. This is surprising, since innovation diffusion has long been recognized and modeled as a spatial process (cf., e.g., the pioneering empirical work and models developed by Hägerstrand 1967). Few attempts have thus far been made to account for space explicitly, some notable exceptions in the applied literature (Gallego and Dunn 2010; Günther et al. 2011; Schwarz and Ernst 2009) notwithstanding. Garber et al. (2004) suggest using the spatial dimension of sales data for early prediction of new product success and apply agent-based modeling as a testbed for cross-entropy measurement against observed sales data. Cellular automata models are also based on a pseudo-spatial regular structure, but it is unclear how this discrete spatial structure relates to actual space, in which consumers are distributed continuously, irregularly, and heterogeneously. In order to recognize the theoretical and practical importance of spatial diffusion and obtain insights into its effect, modelers will have to broaden the scope of ABMs.

Second, it is remarkable that repeat purchase has not been considered in most ABMs so far. While diffusion models are per definition primarily concerned with initial adoption, repeat purchase plays an important role in diffusion processes, e.g. as a social signal. Furthermore, it is a major source of revenue in many goods and services industries (Peres et al. 2010). ABMs that account for repeat purchase could improve our understanding of how initial adoption and repeat purchases interact and jointly shape diffusion processes. Repeat purchases should also not be neglected for practical reasons, since they determine firms' long-term growth and profitability. Developing ABMs for sales rather than for adoption is therefore a promising area for future research (cf. Peres et al. 2010; Delre et al. 2010).

Finally, our review has shown that modelers have so far paid little attention to competition. Most of the reviewed ABMs are based on the assumption that the innovation has its own exclusive market potential, which is not affected by competitors' products and actions. While this may be a reasonable approach in some cases, more often than not, firms face intense competition from incumbent products and/or other innovators when introducing new products. Janssen and Jager (2001, 2002, 2003) have therefore developed market dynamics models that capture competition on an abstract level based on detailed psychological models of consumer behavior. Buchta et al. (2003) model competition between an incumbent and an entrant to study the emergence of disruption. However, their model does not take diffusion processes into account. Future research may build upon these approaches and model consumer behavior in a competitive multi-brand context to realistically capture market dynamics and obtain insights into their effects as well as to provide managers with decision support in a competitive setting. To make progress toward models that account for competition, it is also necessary to identify appropriate mechanisms to explicitly model product characteristics and consumer preferences. Early attempts in this direction have already been made in some of the applied models reviewed. We expect this development to continue as the number of real-world applications increases.

Despite various remaining challenges and limitations, ABMs have already proven to be useful tools for theoretical diffusion research and also demonstrated their potential for practical applications. The field offers excellent opportunities for interdisciplinary research and we hope that this review has provided an overview of the broad range of efforts made by a vibrant and growing research community as well as a glimpse of what may lie ahead.

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