

Rand, William; Stummer, Christian

Article — Published Version

Agent-based modeling of new product market diffusion: an overview of strengths and criticisms

Annals of Operations Research

Provided in Cooperation with:

Springer Nature

Suggested Citation: Rand, William; Stummer, Christian (2021) : Agent-based modeling of new product market diffusion: an overview of strengths and criticisms, Annals of Operations Research, ISSN 1572-9338, Springer US, New York, NY, Vol. 305, Iss. 1-2, pp. 425-447, <https://doi.org/10.1007/s10479-021-03944-1>

This Version is available at:

<https://hdl.handle.net/10419/287220>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>



Agent-based modeling of new product market diffusion: an overview of strengths and criticisms

William Rand¹ · Christian Stummer²

Received: 6 October 2019 / Revised: 19 December 2020 / Accepted: 8 January 2021 /
Published online: 10 February 2021
© The Author(s) 2021

Abstract

Market diffusion of new products is driven by the actions and reactions of consumers, distributors, competitors, and other stakeholders, all of whom can be heterogeneous in their individual characteristics, attitudes, needs, and objectives. These actors may also interact with others in various ways (e.g., through word of mouth or social influence). Thus, a typical consumer market constitutes a complex system whose behavior is difficult to foresee because stochastic impulses may give rise to complex emergent patterns of system reactions over time. Agent-based modeling, a relatively novel approach to understanding complex systems, is well equipped to deal with this complexity and, therefore, may serve as a valuable tool for both researchers studying particular market effects and practitioners seeking decision support for determining features of products under development or the appropriate combination of measures to accelerate product diffusion in a market. This paper provides an overview of the strengths and criticisms of such tools. It aims to encourage researchers in the field of innovation management, as well as practitioners, to consider agent-based modeling and simulation as a method for gaining deeper insights into market behavior and making better-informed decisions.

Keywords Complex systems · Agent-based modeling · New product diffusion · Market simulation · Overview

1 Introduction

Bringing new products to market on a regular basis is a necessity for the long-term survival of a company. In doing so, managers face several challenges. First, market introduction of innovations is usually costly and failure can result in forfeiture of extensive investments

✉ Christian Stummer
christian.stummer@uni-bielefeld.de

William Rand
wmrand@ncsu.edu

¹ Department of Business Management, North Carolina State University, 2801 Founders Drive, Raleigh, NC 27695, USA

² Department of Business Administration and Economics, Bielefeld University, Universitaetsstr. 25, 33615 Bielefeld, Germany

in the development of the new product. Second, there is only a single opportunity to “get it right” in the important initial phase of market penetration, in which a successful take-off can set up a wave of contagious consumption; in consumer markets, this takeoff often determines whether the innovation survives in the market (Delre et al. 2007b; Golder and Tellis 2004). Third, it is difficult to predict the course of launching a new product into a consumer market because market stakeholders—such as consumers, distributors, and competitors—are not homogenous but rather diverse, and their behavior is influenced by the actions and reactions of others. Therefore, a better understanding of market behavior is a major concern for innovation management.

While the first two abovementioned issues (i.e., cost and single opportunity) “merely” increase the pressure on decision-makers, the main difficulty lies in appropriately predicting market behavior arising from the heterogeneity of stakeholders in the market (with respect to their individual characteristics, attitudes toward a product’s attributes, needs, objectives, etc.) and their interactions with each other. Thus, a consumer market is a prime example of a complex system for which both micro-level analysis (i.e., a consumer’s adoption of an innovation) and macro-level analysis (i.e., the overall pattern of innovation diffusion) are of interest.

Complex systems are inherently intricate, typically involve stochastic elements, may show chaotic behavior, and are predisposed to unexpected and emergent outcomes (Foote 2007; for a discussion on the characterization of complex systems, see Ladyman et al. 2013; a great source of material on complexity science is the Santa Fe Institute 2020). The outcome of these systems emerges through the large number of interactions among a system’s entities and of these entities with their environment, forming loops of recirculating signals and feedback (Holland 1998, 2014; Miller and Page 2009). The effects of interactions occasionally make the observed emergent phenomena in complex systems difficult to understand and might lead to counterintuitive findings. For example, Helbing et al. (2000) concluded that putting a column (a pillar) just before an emergency exit, slightly asymmetrically, about one meter away from the exit, helps to reduce the harmful consequences of irrational herding behavior in collective panic (e.g., when a fire breaks out in a crowded building). Another example is the emergence of dominant designs for which it can be shown that even substantial technological advantage might not be sufficient to guarantee a leading market position (Haurand and Stummer 2018a). In certain cases, the results of a complex system analysis could be considered to be intuitive and still contribute to answering important questions. For example, Watts and Dodds (2007) show that seeding appropriate individuals in a word-of-mouth campaign can result in accelerated diffusion of a new product, but complexity can arise from identifying exactly which members of the network to seed. In their analysis, Watts and Dodds argue that, occasionally, the people with the most connections are not the ones who should be seeded.

Agent-based modeling (ABM) has turned out to be particularly useful for studying the behavior of complex systems. Its appeal stems from the fact that ABM only requires the encoding of micro-rules governing the behavior of involved stakeholders in order to observe emergent macro-level behavior (while knowledge of the specific macro-dynamics is not necessary). An overview of the background and recent state of the field of ABM as well as examples of applications from various disciplines is provided by Macal (2016). He indicates that ABM is being applied to a wide variety of fields, from energy management to airport safety to innovation diffusion; further recent applications can be found, for example, in Marketing (Sonderegger-Wakolbinger and Stummer 2015), fashion supply chains in the apparel industry (Backs et al. 2021), or management education (Stummer and Kiesling 2021). An early review with respect to innovation management and new product

development research was provided by Garcia (2005). On a more aggregate level of market modeling, in computational economics, Dawid (2006) explored how to use ABM for investigating innovation and technological change in industries.

Since this time, the field has continued to evolve and there is a substantial amount of new research and knowledge generation that has occurred. The current paper aims to encourage both researchers and practitioners to leverage the benefits of ABM—while being aware of the limitations—for studying consumer market behavior when planning the launch of new products. To this end, it not only provides an overview of the strengths and criticisms of ABM but also offers a starting point for employing ABM in the field of innovation management.

The remainder of the paper is organized in the following manner: Sect. 2 introduces the general idea underlying ABM and describes its basic features. Section 3 elaborates the strengths of ABM in the context of market introduction of an innovation. Section 4 considers the criticisms of applying an ABM approach for this purpose. Section 5 addresses the setting up of agent-based models and lists software that might be useful when implementing ABM-based simulation tools. Section 6 outlines two examples of ABM of new product market diffusion. Section 7 provides an outlook to promising avenues for future research on using ABM in this field.

2 Background

When past data is not available to inform future projections (e.g., for new products or new markets) and conducting a real-world experiment is impossible or too expensive (e.g., as the product does not yet actually exist), potential management measures under consideration can be tested by means of a market model. In certain instances, analytical approaches (e.g., based on mathematical programming) can identify an optimal strategy. However, for complex problems in which (time) dynamics are important, such an analytical solution may be difficult to find or may not exist at all. In these instances, simulation approaches such as system dynamics (SD), discrete event simulation (DES), and agent-based simulation come into play (for a comparison, see Borshchev and Filippov 2004).

Among these approaches, ABM is the most recent, as the necessary computational capacity was not previously available: its expansion in the social sciences began only in the early 1990s (e.g., Holland and Miller 1991) while SD and DES date back to the 1950s and 1960s; Klein et al. (2018) provide an overview of the development of ABM in the social sciences. In ABM, an *agent* is “an autonomous computational individual or object with particular properties and actions” and an *agent-based model* is a computational model in which “a phenomenon is modeled in terms of agents and their interactions” (Wilensky and Rand 2015, p. 1). Macal (2016) distinguishes four different levels of ABM, among which adaptive ABM is the most far-reaching (the other three levels are labeled individual, autonomous, and interactive ABM). In an adaptive ABM approach, interacting autonomous agents represent stakeholders who may change their behavior as a result of receiving new information or, more generally, learning. Thus, agents can remember previous encounters with various situations as well as the outcomes of their prior behaviors in such situations (i.e., they store experiences into their internal state). This type of ABM can often represent the reality in markets into which new products are introduced.

ABM can be considered a particular mindset in that it describes a system from the perspective of its constituent units (Bonabeau 2002). These units—the agents—are (1)

self-contained and uniquely identifiable, (2) autonomous and self-directed, that is, an agent relates individual information to its own decisions and actions, (3) have an individual state (e.g., having adopted a particular innovation) that varies over time (i.e., the agent's behavior may be conditioned on its state), and (4) exhibit dynamic interactions with other agents that influence their behavior (Macal and North 2010). Thus, the behavior of agents affects their own actions, the actions of other agents, and the environment. Technically, ABM can be characterized as a decentralized bottom-up approach. As such, it can account for (1) population heterogeneity in terms of attributes and decision-making processes, (2) the impact of social influences on the dynamics of markets, and (3) the emergent phenomena arising from agents' interactions (Negahban and Yilmaz 2014). Thus, ABM often provides a natural complement to other approaches to understanding complex systems, such as system dynamics, social network analysis, and machine learning (Rand et al. 2018).

In a market model, consumer agents are usually heterogeneous with regard to how they make their individual decisions (i.e., which factors they are driven by and what weights they have assigned to these factors). For example, certain consumer agents can be more price sensitive, while others are more quality sensitive. Moreover, consumer agents can communicate with each other through word of mouth and might be exposed to marketing messages from advertising campaigns. Periodically, consumer agents have to decide whether to adopt an innovation, reject it, or postpone the decision. Other agents who represent distributors, points of sale, competitors, etc. can be modeled in a similar manner and each may have different aims and actions at their disposal.

An expedient starting point for further reading about the purpose and advantages of ABM is the now classic exposition by Bonabeau (2002) on when to employ ABM. Wilensky and Rand (2015) provide a general overview of the use of ABM in a wide variety of fields and a fundamental how-to guide for the construction and use of ABM in scientific research. Railsback and Grimm (2019) adopt an approach that is more oriented toward the natural sciences but is still useful in the social sciences. An extensive tutorial on ABM in the social sciences (including readings and demonstration software) is available from a website maintained by Axelrod and Tesfatsion (2020). Tesfatsion (2020a) also provides a comprehensive website dedicated to tracking all the work around ABM and economics. For general-purpose ABM, the email discussion list maintained by SIMSOC (2020) as well as the network for computational modeling in social and ecological sciences (CoMSES 2020) and its accompanying OpenABM website are useful sites.

3 Strengths

Human behaviors, reactions, and interactions are the missing elements in numerous traditional approaches for predicting system behavior and testing interventions (Macal 2016). ABM can overcome this shortcoming. To this end, a typical ABM approach has three elements—namely, a set of agents, a set of agent relationships and methods of interaction, and an environment in which the agents interact with each other and which might serve as the testbed for possible interventions. In the following, we elaborate on the strengths of ABM in relation to these elements.

3.1 Heterogeneity and individuality of stakeholders

ABM can account for the heterogeneity of diverse stakeholders across a population. Consumer innovativeness—that is, the predisposition of a consumer to buy new products more often and more quickly than other people (Midgley and Dowling 1978)—provides a prime example in this regard, as it drives the consumers' decision to adopt on their own, independent of being exposed to advertising or discussing the product with a peer (as will be addressed in Sect. 3.3). Often, the consumer population is divided into different classes based on the amount of innovativeness present in the group: those who are the most innovative are referred to as innovators and those who are the least innovative as laggards (Rogers 2003). This classification is merely based on when the consumer adopts; however, that conflates natural innovativeness with the effect of word of mouth, advertising, and network effects. ABM—at least in theory—provides a means to separate these forces (although this has not been well explored in the literature yet).

Furthermore, ABM not only accounts for heterogeneous characteristics of agents (e.g., their innovativeness, preferences, or communication behavior) but also keeps track of individual agents and their experiences during the course of a simulation run. This individual information is made up of the history of an agent's decisions, an agent's internal notion of the external world, an agent's observation of the reactions of other agents in response to their actions, and the retained memory of past events (Macal and North 2010). All of these individual aspects of the agent can affect an agent's decisions going forward. In other words, even if two agents are exactly the same at the beginning of the simulation run (i.e., heterogeneity does not play a role), due to dynamic, and often random, effects during the run they may make different individual decisions in the future.

In their comparison of ABM and SD, Borshchev and Filippov (2004) provide an illustrative example of the advantages of modeling individual agents in contrast to not distinguishing between the members of a certain group, as in SD approaches. In their example, they examine how the word-of-mouth activity of a consumer may depend on how long ago the purchase of an innovation took place. It is assumed that immediately after an adoption event, a consumer engages actively in word-of-mouth communication regarding the product, which is followed by a decrease in the intensity of promoting the product, before it stabilizes at a moderate level (i.e., after some time consumers will talk about their experience only when asked directly by a peer). Such behavior can be easily implemented in ABM because each consumer agent can individually store—and thus remember—the time of product adoption. However, in SD, this is not possible because SD does not distinguish between the entities included in the adopters' group type or compartment¹. Therefore, aggregating the adopters in SD into one (or any reasonable finite number) of compartments will distort the results. While it is possible to create an increasing number of containers to store different consumers on the basis of time since purchase, ABM provides for this in a much more convenient manner.

¹ It should be noted that SD can model a limited amount of heterogeneity by having different stocks representing different levels of innovativeness for instance, but modeling individuality is not possible in SD, and modeling extreme heterogeneity, where each agent is unique from all other agents, would be impractical and defeat the purpose of using SD where the goal is to accumulate common types in a common stock.

3.2 Decision-making behavior

ABM provides researchers with the ability to apply various behavioral rules that take into account different elements of agents' decision-making (e.g., when adopting an innovation). Nagahban and Yilmaz (2014) distinguish the following six main variants of modeling the decision-making process: *Preference matching* (e.g., Schramm et al. 2010) is a straightforward approach that evaluates the degree of similarity between a consumer agent's preferences and product attributes (including the traditional five factors: relative advantage, compatibility, trialability, observability, and perceived risk). Alternatively, the modeled innovation adoption process may follow a *stage-based* approach in which consumer agents undergo several stages before making the final decision to adopt or reject the product (e.g., as described by Rogers 2003). *Utility* functions are also commonly used for evaluating product choice. In calculating the individual utility value, personal preferences (i.e., weights for some decision criteria), word-of-mouth influence, or impact of advertising, budget constraints, etc. may play a role (e.g., Delre et al. 2007b), which distinguishes utility functions from simpler preference-matching functions. In application cases where social influence triggers innovation adoption, decisions can be modeled based on an *exposure threshold*, that is, a consumer agent adopts the product only if the proportion of their neighbors who have already adopted it is greater than a critical threshold. Preferences might dynamically evolve over time, depending on the consumer agent's *past experience* with a product, which of course requires some sort of learning process. Finally, choices might be made *randomly*. It must be noted that several of these aspects can be combined, thereby enhancing the flexibility of ABM.

3.3 Interaction among stakeholders

One of the powerful aspects of ABM is that (like the real world) it is naturally decentralized; thus, only local information is available to each agent. Consequently, modeling the interactions among agents (i.e., who is, or could be, connected to whom, and the mechanisms of these interactions) is rather important. Interactions can occur in diverse forms, and the literature can be confusing, because before the advent of ABM, it was often necessary to conflate different notions of interaction to make them easier to understand (e.g., the Bass model conflates direct network effects and word of mouth).

In an attempt to simplify this concept, we divide interactions into two broad categories: (1) direct interactions, where consumers directly interact with some other agent (e.g., in word-of-mouth communication), and (2) indirect interactions, where consumers do not directly interact with an agent but are affected by knowledge of the total sum of other agents' decisions (e.g., in the form of social influence). In the following, we also discuss the various ways for modeling social networks in which these interactions might occur.

3.3.1 Word of mouth and advertising

Dating back to the original studies on innovation diffusion (Ryan and Gross 1943), researchers have realized that there are at least two methods of direct interaction: (1) word-of-mouth, direct conversations, or interactions among consumers and (2) advertising interactions between consumers and the brand.

Consumers create and share word-of-mouth information regarding products (for an overview, see Berger 2014) and, thus, may influence their peers' attitudes in a positive or negative manner (for empirical results regarding the mechanisms of word of mouth, see, e.g., Dellarocas 2003; Leskovec et al. 2007; Richins 1983). This influencing usually occurs within a user's social network (Young 2009). In his original model, Bass (1969) did not distinguish between this force and the overall force of social network effects, which we will describe in the next section. However, in ABM versions of the Bass model (Rand and Rust 2011), researchers have the opportunity to model this process more directly.

Advertising is the second form of direct interaction. ABM can account for various forms of advertising (e.g., mass media advertising campaigns, point-of-sale advertising, etc.; for studies on the potential influence on consumer behavior, see, e.g., Abernethy and Franke 1996; Horsky and Simon 1983), in which the direct interaction occurs between a consumer agent and an abstract advertising agent. Since this advertising agent is external to the social network, this is often characterized as an external force (Young 2009). In the Bass model mentioned above, this force includes both the decision to adopt an innovation because the consumer is influenced by advertising and the decision to adopt an innovation independently from any advertising event, but again ABM could enable researchers to separate these different effects. Moreover, ABM considers the relationship between advertising and word-of-mouth, exploring when one force might have more or less effect than the other (Rahmandad and Sterman 2008).

3.3.2 Social influence

Indirect interaction happens when one agent's decision is influenced by the decisions of many others, even though that decision is not directly communicated to the focal agent (Clements 2004). The most common type of indirect interaction is social influence. Fashion markets provide an illustrative example in this regard, as consumers in these markets exchange not only product information but also norms related to consumptive behavior (Cialdini and Goldstein 2004). Procedurally, social influence can be modeled through a threshold mechanism of collective action, that is, as long as the proportion of adopters in an agent's personal network remains below the threshold (i.e., only a few of the agent's peers behave in a particular manner), the agent is not affected by social influence; however, once the number of these peers exceeds the threshold, the consumer agent suddenly decides to change its mind and behaves differently (Granovetter and Soong 1986). ABM provides researchers with the ability to model consumers who have varying degrees of trust in the different members of their social network and, thus, the social influence exerted on them may vary.

3.3.3 Social network

As in real markets, in which not all consumers interact directly with all others, agents in a market model typically interact only with a subset of other agents. How the agents are interconnected is termed an agent-based model's topology or connectedness (for a detailed discussion, see Macal and North 2010). Social networks are the most prominent means to represent this connectedness. They may consider different types of social ties, that is, strong ties with people within their social circles and weak ties with other people (Watts and Strogatz 1998). It is noteworthy that weak ties may also play a crucial role in

innovation diffusion because they often function as bridges among different social groups (Brown and Reingen 1987; Goldenberg et al. 2007; Hu et al. 2019).

Several mechanisms have been proposed for determining the linkages among agents (for an overview, see Kiesling et al. 2012; Negahban and Yilmaz 2014). While random networks (Erdős and Rényi 1959; Watts and Dodds 2007) or regular networks (Goldenberg et al. 2010) do not approximate actual social networks very well, small-world networks (Watts and Strogatz 1998) and scale-free (preferential) networks (Barabási and Albert 1999; Delre et al. 2010) exhibit characteristics that are typical of social networks (e.g., some of the agents function as hubs with numerous connections, while most of the agents only have a few connections). Empirical networks (e.g., Leskovec et al. 2007), of course, would be best as they are based on data extracted from social networking sites, but creating such a network for a consumer market is difficult, if not impossible, due to lack of data or restrictions on the access to that data. One solution that researchers have employed over the years is to generate synthetic networks that either simulate the properties of a known network—where not all the data can be accessed—or, in certain cases, merely simulate the properties of an expert’s belief regarding the underlying properties of this network (Chica and Rand 2017; Trusov et al. 2013). In ABM, the social network can be refined as new data regarding the underlying network is collected.

Spatial representation in network generation might take into account that two consumer agents located close to each other have a higher probability of being connected in the social network than consumer agents living farther apart (e.g., Günther et al. 2011). Further, networks can be static (i.e., all links are fixed) or dynamic (i.e., a few links might be added or removed in the course of a simulation run). As different markets might exhibit different network structures of consumers and several studies (e.g., Bearden and Rose 1990; Delre et al. 2007a) have demonstrated that the selected network type might make a difference for innovation diffusion, it is advisable to give due consideration to this issue.

3.4 Testbed for strategies and scenarios

A particular strength of ABM lies in its ability to be used as a testbed for strategies before they are employed in actual markets (remember that usually there is only a single opportunity to succeed with the market introduction of an innovation). Moreover, corresponding simulation experiments can be run in an early phase of product development to aid in determining the features of the prospective new product and to learn about its possible diffusion in a market that might not even exist when the simulation is executed. To this end, multiple “futures” might be considered, each of which can be represented through a scenario for which a simulation might be run; each simulation can be easily adapted to a particular future through parameterization of the respective market [an example is provided by Günther et al. (2017)]. Combining ABM with traditional methods of scenario analysis that explore different alternative futures can deliver the benefits of both, thereby resulting in robust quantitative projections (Roper et al. 2011). Simulation results from such application cases must of course be interpreted at the qualitative level rather than adhering too closely to quantitative outcomes.

From a research viewpoint, ABM provides an opportunity to test the conditions under which the diffusion of innovations succeeds or fails. For example, Delre et al. (2007b) study the effects of targeting and timing of advertising campaigns on consumer adoption and innovation diffusion. ABM might also be used for investigating competition among several brands (Schramm et al. 2010) or the effect of repeat purchases (Stummer et al.

2015), which would be impossible through the traditional diffusion model, and its extensions, proposed by Bass (1969).

4 Criticisms

Although ABM has a number of benefits, it is subject to criticism. In this section, we discuss criticism that was raised with respect to (1) parameterization, (2) verification and validation, (3) arbitrariness, (4) lack of causality, and (5) computational cost. However, most of these critiques hold true for numerous modeling techniques and, in certain cases, are less of a concern for ABM than for other approaches.

4.1 Parameterization

An ABM that is complex enough to model realistic innovation diffusion scenarios will often have a larger number of parameters than traditional modeling approaches, and it is not always possible to infer the correct value for all of these parameters. As a result, how to identify suitable parameter values for an agent-based model is a frequent concern of researchers and practitioners using ABM. The best way to do so depends on the market that is being modeled and the particular goal of the simulation study. If the goal is simply to explore a proof of existence, then as long as the parameters are internally consistent, there is no need for additional validation (Holland 2012). If the focus is on investigating abstract market behavior (e.g., the impact of sparse vs. dense social networks on innovation diffusion), parameters could be based on reasonable values taken from literature. However, if the goal of the simulation study is to make real-world empirical predictions, then the parameters must be derived from relevant empirical studies. Typically, choice-based conjoint data are used to elicit consumer preferences (e.g., Zhang et al. 2011). For an illustrative example of how to collect data required for parameterization of ABM for new product market diffusion, see Sect. 6.2.

4.2 Verification and validation

Verification is the process of ensuring that the model corresponds with the conceptual model, while validation provides the modeler with confidence in terms of how accurately the model represents the actual system (Balci 1994). Although it is impossible to completely verify or validate a model (Grimm and Railsback 2005), substantial effort needs to be made to make sure the model is scientifically correct. In fact, validation and verification are among the greatest challenges in ABM (Midgley et al. 2007).

In their respective guidelines, Rand and Rust (2011) suggest verifying a model using (1) documentation, relating the implemented model to the conceptual model; (2) programmatic testing, ensuring that the code works at the micro-level; and (3) test cases, ensuring that the output of the model makes sense for conditions where the output is known. When validating a model, researchers must perform (1) micro-face validation, which ensures that the agents correspond to their real-world counterparts “on face”—that is, that the consumer agents’ behavior correspond in a meaningful way to the behavior of actual consumers or that the agents possess a realistic amount of information; (2) macro-face validation, which checks that the output makes sense “on face”; (3) empirical input validation, which assesses the validity of the model’s parameters by comparing them to real-world data; and

(4) empirical output validation, which compares the output of the model to real-world output (Rand and Rust 2011). Further, a sensitivity analysis can be conducted, which involves varying parameter values and observing the effects of any such values on system behavior (Ten Broeke et al. 2016). The findings from this analysis can then be used to highlight parameters that have the greatest effect on the system's behavior.

North et al. (2010) provide a real-life example in which an agent-based model is developed, calibrated, verified, and validated for Procter & Gamble. To this end, North et al. used household panel data (including detailed time-series purchase histories from hundreds of shoppers covering multiyear periods), scanner data from store checkout counters at a variety of retail stores, aggregate and time-series industry statistics (including market shares, sales volumes, and advertising trends), and detailed industry data (including information on retail store shelf stocks, product pricing numbers, and product promotion counts), all of which received from Nielsen and Information Resources Inc. (IRI). Extensive material on empirical validation and verification of agent-based models is available on the website maintained by Tesfatsion (2020b).

4.3 Arbitrariness

Another concern related to validation is what critics express as “Well, a model can show anything”. What they mean by this statement is that since the agent-based model is constructed by the researcher, it can generate whatever results the researcher wishes to achieve and, thus, results are arbitrary. The best response to this criticism is that if the model is well validated, then it must correspond to a real-world phenomenon or at least mirror it so well that it is impossible for validation tests to tell the difference.

This criticism is not unique to ABM. Game theoretic models and regression models also require researchers to examine numerous different models before selecting the one they decide to present. Regardless of the modeling framework, researchers must convince their audience—that is, other researchers as well as practitioners—that the model was set up in a reasonable manner and that the model represents a fair description of reality. Only then can the model be helpful in explaining the phenomenon that the modeler originally intended to examine. If the model is able to make out-of-sample predictions, then the model has gained an additional level of validation.

In many ways, this issue is related to Lucas' (1976) critique of macroeconomics, according to which no macro model is useful for predicting beyond the data that is already observed, because predictions require the use of data that was not previously used to validate the model. The goal is for ABM to help combat the Lucas critique by identifying not only the data process that generates the patterns of interest but also by identifying the generative mechanisms that give rise to these patterns. In this case, the Lucas critique no longer holds since the behavioral model can assist in moving beyond historical data (Rand 2019).

4.4 Lack of causality

Causality plays a significant role in management publications with techniques such as natural experiments or randomized controlled trials becoming increasingly important in the traditional management science toolkit. ABM, and simulation methods in general, is often criticized as lacking a means to assess causality. This criticism is fair. Even if the inputs to an agent-based model and the outputs against out-of-sample empirical data are validated,

all they show is that the model is one possible explanation of the relationship between the input and output. Occasionally, that is the only goal of the model—that is, to show that the model is one possible explanation of the relationship between input and output—which is also referred to as an “existence proof” (Holland 2012).

However, if an agent-based model is constructed well, then it will be constructed from previously established causal mechanisms. Thus, it is still assembled from causal theory even if the final aggregation of mechanisms is not proven to be causal. Often, ABM is employed when one of the traditional methods of establishing causality cannot be used. For example, the necessary natural experiment that would help establish that causality does not exist or conducting a randomized control trial to establish that causality is too costly. In these cases, if the researcher builds the ABM from individual mechanisms that are well-grounded and which may have been independently validated, then even though it would be difficult to argue that the model is causal, it would still further validate the theory.

Further, it may also be the case that in order to develop these causal relationships, the researcher must almost always restrict the data to a much smaller dataset than all of the possible data related to the phenomenon at hand. However, ABM has no such restriction; thus, it is possible to create a model using ABM that can take advantage of all the accessible data.

4.5 Computational cost

Finally, ABM is often criticized as being computationally expensive, which is true as simulating up to millions of agents requires substantial computational resources. However, one of the reasons why ABM continues to be increasingly useful is that the cost of computation is always decreasing. Moreover, the benefit of the computational cost is in the rich detail that the model generates. Thus, the cost is not without benefit. For example, a game theory model can be computationally cheap but a Nash equilibrium reveals nothing about how the model achieved that equilibrium; it only says that it will. In contrast, ABM not only identifies an existing final equilibrium state, but also provides all data related to the system’s path to get to that equilibrium as well as the properties and behaviors of each agent (Rand and Rust 2011).

If the goal is to decrease computational cost, then the researcher can make decisions to do so. The researcher can reduce the resolution of the agents, having one agent represent the actions of a thousand agents, or they can choose to not record every action taken by each agent. A trade-off between computational time and the level of detail being recorded is inevitable, and the researcher should make this decision appropriately (Wilensky and Rand 2015).

5 Implementation

5.1 Setting up the model

Before actually setting up the model, it is necessary to determine whether ABM is appropriate for the specific project or decision under investigation. For this purpose, Rand and Rust (2011) provide four indicative indicators (i.e., medium numbers, local and potentially complex interactions, heterogeneity, and rich environments), one necessary indicator (i.e., temporal aspects), and one sufficient indicator (i.e., adaptive agents).

They also examine the match between these indicators and the market diffusion of an innovation, thereby concluding that this application case is well-suited for an ABM approach.

After opting to develop an agent-based model, the following questions need to be answered when designing the model (these questions are drawn and merged from lists by Macal and North (2010) and Rand and Rust (2011)): *What specific problem should be solved by the model?* This question relates to the scope of the model, that is, to the aspects that must be examined with the market model. *What should be the agents in the model, and what properties does each agent have?* This relates to the stakeholders and which of their attributes must be considered in the model. *What is the agents' environment and how do they interact with the environment?* *What agent behaviors are of interest?* This includes a particular consideration of adoption decisions. *How do the agents interact with each other?* *Where might the data come from, particularly data on agent behaviors, for such a model?* This question relates to inputs and outputs of the ABM approach. *What is the order of events in the model? How can the model be validated?*

“It can scarcely be denied that the supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of existence” (Einstein 1934, p. 165), or as it is often summarized, “Make everything as simple as possible, but not simpler.” This quote certainly applies to setting up agent-based models. Therefore, it is advisable to begin with straightforward decision rules for the agents. Once a basic understanding of the system is obtained, more complex agent behaviors can be integrated (Bona-beau 2002; Garcia 2005; North and Macal 2007). Lower levels of complexity in models might also help in convincing decision-makers to accept ABM because higher complexity in models reduces transparency and makes it more difficult to explain the model's outputs (Macal 2016).

5.2 Software

The ABM community has developed several software toolkits that enable individuals to set up agent-based applications. The most popular ones are open source-based products such as NetLogo (2020), Repast (2020), and MASON (2020), as well as commercial products like AnyLogic (2020). NetLogo is an open-source tool that has a graphical integrated development environment (IDE) and uses a language similar to natural language, which makes it easy for new users to work with NetLogo. It has also been used to develop very large-scale applications. Further, the Recursive Porous Agent Simulation Toolkit (Repast) is a software framework originally built in Java but is now available in a number of other languages. It has often been cited for its ability to work on high performance computing architectures. The Multi-Agent Simulator of Networks (MASON) is a rather fast toolkit written in Java. AnyLogic is a comprehensive proprietary simulation package that enables not only ABM but also dynamic modeling systems and other types of simulations. In addition to these already popular packages, Mesa (2020) is a Python-based agent-based software toolkit that has recently become increasingly popular, partially due to the popularity of the Python language. Lately, several researchers also use the Julia framework for ABM (e.g., Basurto et al. 2020; for a corresponding software package, see Vahdati 2019). The previously mentioned network CoMSES (2020) includes a computational model library, access to an active community, and various educational resources.

6 Sample applications

In the following section, two illustrative applications of applying ABM to new product market diffusion are presented with references to some of the issues that have been covered in Sect. 3 and 4. With regards to the criticisms of ABM, we will specifically describe how parameterization, verification, and validation were addressed within these two applications. However, we do not go into detail about arbitrariness, causality, and computational cost since those are more general criticisms, and our discussion of them in the context of these applications would largely be repetitive. The first application focuses on investigating theoretical considerations related to market behavior when the initial market diffusion has to be supplemented with a post-launch promotional campaign. In the second application, the agent-based model deals with repeat purchase decisions and it accounts for several competing products; this case also shows how decision-makers might take advantage from such a simulation approach.

6.1 Targeting and timing promotional activities for new products

The agent-based model proposed by Delre et al. (2007b) aims to study the effects of targeting and timing of promotional activities on furthering the takeoff and subsequent diffusion of new products. With regard to targeting, they investigate whether it is more favorable to target numerous small groups of consumers in distant places (“throwing gravel”) or to target a proportion of consumers from rather large groups (“throwing rocks”). With regard to timing, they investigate when is the best time to initiate a mass media promotional campaign and, in doing so, take advantage of the difference between white goods (i.e., longer-term consumer durables; e.g., refrigerators) and brown goods (i.e., shorter-term consumer durables; e.g., consumer electronics).

The only *stakeholders* considered in this model are consumers. The respective consumer agents have individual expectations concerning the quality of the new product and they are heterogeneous in their sensibility to their neighbors’ behavior—that is, a minimum share of adopters among the direct neighbors in their social network is required before social influence is exerted in their direction. Both consumer characteristics are represented by just a single parameter for each agent.

The *decision-making behavior* of consumer agents is modeled in a straightforward manner. First, a consumer agent must be aware of the existence of the product, which is the case once at least one of its direct neighbors has already adopted the product. Second, the utility value of the consumer agent needs to exceed an individualized minimum level of utility. An agent’s utility is calculated as the weighted sum of product value for this agent and social influence exerted on it. The product value is set to 1 if the agent’s expectation of product quality is lower than the actual product quality, and it is 0 otherwise. During initialization of a run, the parameters for the agents’ expectations are drawn from a uniform distribution ranging from 0 to 1; the actual quality value of the new product is set to 0.5. The social influence is 1 if the share of direct neighbors who have already adopted the new product is higher than the agent’s threshold value in this respect, and it is 0 otherwise; this parameter is drawn from a normal distribution that can be modified.²

² For additional details, see Delre et al. (2007b, p. 830).

Word of mouth in this model is merely a means to make other consumer agents aware of the new product: once a consumer agent adopts the product, this event automatically makes all the agent's direct neighbors aware of the new product. *Advertising* is done in the form of external promotion, that is, a mass media campaign. When a consumer agent is affected by such a campaign, it becomes aware of the new product.

The effect of *social influence* depends on the consumer agent's individual sensibility (as described above). The underlying *social network* is a small-world network to which random links are added.

In their paper, Delre et al. (2007b) test *alternative launching strategies*, which differ in the targeting of the post-launch mass media promotion campaign and its timing. This is modeled by varying the advertising received by the agents. It must be noted that during the initial market introduction, a number of consumer agents are made aware of the new product in order to begin its diffusion in the market. Once this initial diffusion process levels off, the post-launch campaign is necessary to prolong market penetration.

Parameterization is partially based on insights from prior studies (e.g., the social influence is stronger for brown than for white goods) but mostly Delre et al. (2007b) simply chose reasonable parameters. *Verification* and *validation* of this agent-based model is only briefly mentioned. The authors run sensitivity analyses; an empirical validation is not performed.

The findings show that strategic planning of seeding is a key determinant for innovation diffusion. They suggest, for example, that management must avoid both huge premature campaigns and weak late campaigns. Moreover, the results constitute a theoretical contribution to the distinction among product categories—that is, they offer suggestions on how to position promotional campaigns in different markets.

6.2 Innovation diffusion of repeat purchase consumer products

In their work, Stummer et al. (2015) demonstrate how ABM can be used to evaluate product launch strategies for a repeat purchase consumer product in a competitive setting. The product under investigation is a novel high-performance second-generation biofuel (produced from biomass through the Fischer–Tropsch process), which, at that time, was under development at Vienna University of Technology and that upon market introduction had to compete against both regular and premium fuel (both produced from crude oil). As the authors learned later, the biofuel being investigated ultimately did not make it to the market but the model is nonetheless useful for understanding how the product might have diffused in the market.

The main group of *stakeholders* considered in the agent-based market model are consumers who are heterogeneous in various respects: they have individual preferences for a fuel's attributes (i.e., quality, price, environment friendliness, brand, consumption, and raw material); show individual mobility behavior and, thus, fuel consumption patterns; and apply individual strategies for choosing a gas station, which partially depends on the geographical location of both the user's home and the gas station. Gas stations form a secondary group of stakeholders. They are more or less attractive for consumers and carry all or just a subset of fuel types. In principle, they could proactively decide on their product range, prices, and additional advertising campaigns. However, in the numerical analysis in this paper, the parameters for each gas station are exogenous and fixed over the simulation horizon.

The *decision-making* process of consumer agents follows Rogers' (2003) stage-based model of how innovations are adopted—that is, consumers must become aware of the new fuel, form an attitude (e.g., through word of mouth or being exposed to advertising) about its attributes, make a purchasing decision, gain first-hand experience when driving the refueled car, and exchange information about the fuel, thereby seeking reinforcement of their prior decision. The consumers' purchasing decision (i.e., which type of fuel to choose for refilling the gas tank at a given point in time during a simulation run) is based on the consumers' individual utility function, in which individual preferences as well as their attitudes toward the fuels' attributes are taken into account.

Word-of-mouth communication between consumer agents plays a prominent role in this agent-based model. Consumers who are directly interconnected in the social network meet periodically and mutually exchange some of their opinions on (selected) fuels and fuel attributes, thereby updating their respective information bases and affecting each other's attitudes. The selection of the topics discussed by the agents (e.g., the quality of the novel biofuel) follows three key assumptions, namely, (1) consumers tend to talk when they have obtained new information, (2) consumers will pass on information regarding a product attribute if it is unexpected and important (to them), and (3) bad news travels fast. It must be noted that the extent of information received thus far by a consumer agent is recorded in the agent's local database. Accordingly, it becomes increasingly difficult to change a consumer agent's mind as they require more and more information and have already formed a sound attitude. *Advertising* is modeled in a similar manner as word-of-mouth communication but the information exchange takes place unidirectionally with an artificial advertising agent that approaches a subset of consumer agents selected with respect to the type of advertising event (e.g., mass media advertising, focused advertising with respect to some target groups, or on-site advertising at selected gas stations). The impact of information received from an advertising agent is considerably smaller than the impact of information received from a peer or through first-hand experience.

Social influence is not a decisive factor in this diffusion model because the type of fuel used is not observable by other consumers, and there is no easy way for consumers to determine the market share of a particular fuel type. Thus, there is no group pressure to behave differently just because of the observable behavior of others.

Consumers are connected through a scale-free *social network* that also has a spatial component. Parameters for this network are set in a manner that makes it highly clustered, and communication about fuels is highly localized, which mirrors results from a sociological study conducted with respect to communication patterns regarding fuels.

The simulation tool, implemented in MASON, was used as a *testbed for several pricing strategies* when introducing the novel biofuel in the market. These strategies include three price levels as well as penetration pricing and price skimming. Moreover, the effects of a delisting policy is tested in further simulation experiments.

Parameterization was a prime concern for Stummer et al. (2015). They first conducted several expert interviews to learn about relevant decision attributes. Then, they convened a focus group discussion to more closely capture the consumer perspective (e.g., importance of fuel characteristics, communication behavior, and credibility of producers). Next, a pre-study and conjoint experiment with a representative sample of 1,000 consumers were conducted to elicit consumer preferences for a fuel's attributes and learn about the consumers' driving habits; tank refilling strategies, such as when and where they refuel; and product recommendation behavior. Data from this survey was directly used to parameterize the 10,000 consumer agents for market simulation—that is, preferences, driving habits, refilling strategy, and recommendation behavior from each respondent were used for

parameterization of 10 agents each. Further, the abovementioned sociological study with hundreds of interviews was conducted in order to learn how often, when, with whom, and on which topics consumers discuss fuels. Finally, the authors accounted for geographical population distribution taken from census data and the positions and types of gas stations taken from OpenStreetMap.

Verification and validation of the simulation results followed the procedure suggested by Knepell and Arangno (1993). All the required checks succeeded: (1) conceptual validity is shown as the model is grounded in well-established theory, in particular, the framework by Rogers (2003); (2) internal validity is shown by means of unit and integration tests as well as by conducting simulation experiments with extreme parameters; (3) micro-level external validity is shown by analyzing and verifying individual agent's decisions; (4) macro-level external validity is shown by running the simulation just for the premium fuels (i.e., without the biofuels present on the simulated market) and comparing results to actual market shares of premium fuels; and (5) cross-model validity is shown by reproducing similar results with the Bass model after appropriately calibrating its input parameters.

Simulation results also smoothly passed a face validation when being presented to practitioners from the fuel market. While it was not surprising for them that lower prices yield quicker market penetration and larger market shares, they emphasized that the value added from such an ABM approach lies in the opportunity to compare the outcomes from several alternative scenarios and to learn which combination of measures (including advertising campaigns) yields which market share at which point in time.

7 Outlook to further research

From the two examples discussed above and from the overview of ABM provided, it is evident that the main benefits of ABM lie in its ability to capture emergent phenomena and its flexibility to represent various market settings. Thus, in numerous instances, ABM is “the only game in town to [appropriately] deal with such situations” (Bonabeau 2002, p. 7287). This paper has highlighted the strengths and criticisms of applying ABM in innovation management; moreover, it provides starting points for researchers, as well as practitioners, who are willing to try out the method for their own purposes.

Despite the major progress that the ABM community has made since Holland and Miller (1991), Epstein and Axtell (1996), and Bonabeau (2002) published their seminal works and the numerous ABM applications in innovation management that are based on sound empirical data and provide useful results (e.g., Kangur et al. 2017; Stummer et al. 2015; Sun et al. 2019; Wolf et al. 2015), there remains substantial research to be done in the application of ABM to new product diffusion. For example, as most ABM approaches in the field of innovation management involve agents that represent humans, a particular challenge lies in quantifying, calibrating, and justifying soft factors driving the behavior of their real-world counterparts, such as occasionally irrational behavior and subjective choices (Bonabeau 2002). Therefore, it would be useful to develop standardized methods for relating human behavior to the rules embedded in agents in an agent-based model. Smith and Rand (2018) provide an example of how rules of agent behavior can be derived from laboratory experiments and argue for a deepening of the relationship between behavioral scientists and agent-based modelers. Not only would this have the benefit of providing researchers interested in ABM with valid rules of human behavior, it would also provide behavioral scientists with a testbed where they could see how their research would unfold

on a large scale via the ABM approach. Further research is necessary to create a standardized methodology out of this process and to specifically apply it to innovation diffusion research.

Several drivers of consumer adoption are often conflated in the literature, which include: (1) the effect of advertising, (2) the effect of word of mouth, (3) indirect social influence, and (4) the individual's own innovativeness and risk-taking behavior. Therefore, a particularly promising area for the use of ABM in research on new product adoption lies in disentangling these different effects. After all, if we can pull apart, for example, consumer innovativeness from word of mouth, then we can provide marketing managers with new insights into how to strategically invest in cultivating influencer relationships. Although there has been some empirical work that attempts to untangle these effects (e.g., Aral et al. 2009), theoretically, all these different forces can be modeled separately within ABM. However, with a few exceptions (e.g., Watts and Dodds 2007), not much research has clearly divided them and understood the different roles each of these effects plays.

This issue will become even more important, since it is safe to predict that interactions on diverse social media platforms (e.g., Facebook, Twitter, LinkedIn, etc.) will continue to grow in frequency and variety and, thus, the impact of referrals and normative social influence will increase. Although there has been substantial research on the spread of information on social media (e.g., Lerman and Ghosh 2010; Yoo et al. 2016) and on new product adoption decisions (as illustrated throughout this paper), there is little work relating the spread of information on social media to actual purchase decisions (e.g., regarding the question of how a firm's social media presence influences the diffusion of its new products). Research relating these two areas of modeling would be important in order to better understand the relationship between social media and product adoption. An ABM approach might be capable of doing this.

The social media platforms mentioned above (and new and unrealized platforms), as well as the large number of apps that incorporate social network features, might be also used to gain more insight regarding the structure of individuals' social networks. This new source of big data has provided researchers with the ability to build models that contain more realistic models of users' social networks (Chica and Rand 2017; Rand et al. 2015). ABM could benefit from better incorporation of data on social ties for transition from traditional and theoretical to empirical and more realistic social network structures (Negahban and Yilmaz 2014), thereby creating an opportunity for further research.

Further, the emergence of smart products increases uncertainty regarding future markets and simultaneously provides new management opportunities (e.g., Dawid et al. 2017; Decker and Stummer 2017; Raff et al. 2020). Given the highly unknown nature of these markets, it is evident that a method like ABM, which can make forecasts about new and different markets, would be useful as a tool for learning about potential market behavior well before deciding to enter markets in which factors such as trust or perceived disempowerment play a more crucial role for adoption processes than in traditional markets (Michler et al. 2020; Schweitzer and van den Hende 2016; Souka et al. 2020).

The same holds true for various business model innovations. Two-sided digital platforms provide a prominent example (for overviews, see Parker et al. 2016; Stummer et al. 2018); initial ABM applications have already been introduced by Haurand and Stummer (2018b, 2019) and Heinrich and Gräbner (2019), but more work needs to be done in this regard. However, in addressing these challenges and forecasting the behavior of future markets, it may be necessary to combine ABM approaches with other approaches, such as scenario analysis, thereby enabling the simulation of several possible alternative futures in order to test various innovation or technology strategies (e.g., Günther et al. 2017). Similar

to the combination of lab experiments and ABM described above, developing and applying such multi-method approaches—particularly in the area of decision-making under uncertainty—is another promising avenue for further research.

Finally, this paper is mainly concerned with applying ABM to analyzing alternative strategies for market introduction of new products and furthering their diffusion into their respective markets. What has been neglected thus far in most ABM works is supply-related restrictions—that is, the majority of ABM studies essentially assume infinite supply or production capacity and zero manufacturing lead times (Negahban and Yilmaz 2014). Consequently, it would be worthwhile to pursue research activities to extend the focus of ABM from market introduction to aspects related to both supply and production as was done, for example, by Backs et al. (2021). The same applies for other aspects of intrafirm organizational design. For example, for increasing the “smartness” of products, software developers necessarily play a more prominent role in developing such products; however, employing and integrating these experts may change the hitherto existing “rules of the game” in numerous extant teams that are predominantly constituted of traditional engineers (Porter and Heppelmann 2015). ABM could aid the study of organizational measures that must be applied to overcome resistance from potential team members. Additional issues that can be addressed by ABM in an innovation management setting are, for example, co-location of departments, product development–marketing integration, information dissemination between different departments, and structures of innovation networks (Garcia 2005). For overviews on using ABM for organization structures, see Dawid et al. (2001), Fioretti (2012), and Gómez-Cruz et al. (2017); corresponding examples of applications in the context of innovation management are described by Backs et al. (2019) and Günther (2007).

It is evident from this overview that there are several areas of new product market diffusion, in particular, and innovation management, within a broader scope, that are ripe for analysis using ABM tools. Not only do already developed ABM tools provide substantial insight into complex markets but, as discussed above when laying out future research opportunities, the promise of ABM to help understand new and uncertain areas of market progress is substantial. Moreover, ABM tools are likely to benefit from increasing availability of computing power, thereby strengthening the role of these tools in supporting innovation management.

Funding Open Access funding enabled and organized by Projekt DEAL.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Abernethy, A. M., & Franke, G. R. (1996). The information content of advertising: A meta-analysis. *Journal of Advertising*, 25(2), 1–17.
- AnyLogic. (2020). *AnyLogic simulation software*. <http://www.anylogic.com/>. Accessed 30 October 2020.

- Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51), 21544–21549.
- Axelrod, R., & Tesfatsion, L. (2020). *On-line guide for newcomers to agent-based modeling in the social sciences*. <http://www2.econ.iastate.edu/tesfatsi/abmread.htm>. Accessed 31 October 2020.
- Backs, S., Günther, M., & Stummer, C. (2019). Stimulating academic patenting in a university ecosystem: An agent-based simulation approach. *Journal of Technology Transfer*, 44(2), 434–461.
- Backs, S., Jahnke, H., Lüpke, L., Stücken, M., & Stummer, C. (2021). Traditional versus fast fashion supply chains in the apparel industry: An agent-based simulation approach. *Annals of Operations Research (forthcoming)*. <https://doi.org/10.1007/s10479-020-03703-8>.
- Balci, O. (1994). Validation, verification, and testing techniques throughout the life cycle of a simulation study. *Annals of Operations Research*, 53(1), 121–173.
- Basurto, A., Dawid, H., Harting, P., Hepp, J., & Kohlweyer, D. (2020). Economic and epidemic implications of virus containment policies: Insights from agent-based simulations. In *Universität Bielefeld Working Paper in Economics and Management, 05-2020*, Bielefeld: Bielefeld University.
- Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439), 509–512.
- Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, 15(5), 215–227.
- Bearden, W. O., & Rose, R. L. (1990). Attention to social comparison information: An individual difference factor affecting consumer conformity. *Journal of Consumer Research*, 16(4), 461–471.
- Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, 24(4), 586–607.
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, 99(suppl. 3), 7280–7287.
- Borshchev, A., & Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools. In *Proceedings of the 22nd international conference of the system dynamics society*. <https://www.anylogic.de/resources/articles/from-system-dynamics-and-discrete-event-to-practical-agent-based-modeling-reasons-techniques-tools/>. Accessed 30 October 2020.
- Brown, J. J., & Reingen, P. H. (1987). Social ties and word-of-mouth referral behavior. *Journal of Consumer Research*, 14(3), 350–362.
- Chica, M., & Rand, W. (2017). Building agent-based decision support systems for word-of-mouth programs: A freemium application. *Journal of Marketing Research*, 54(5), 752–767.
- Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, 55(1), 591–621.
- Clements, M. T. (2004). Direct and indirect network effects: Are they equivalent? *International Journal of Industrial Organization*, 22(5), 633–645.
- CoMSES (2020) *A growing collection of resources for computational model-based science*. <http://www.comses.net>. Accessed 30 October 2020.
- Dawid, H. (2006). Agent-based models of innovation and technological change. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 1235–1272). Amsterdam: North-Holland.
- Dawid, H., Decker, R., Hermann, T., Jahnke, H., Klat, W., König, R., & Stummer, C. (2017). Management science in the era of smart consumer products: Challenges and research perspectives. *Central European Journal of Operations Research*, 25(1), 203–230.
- Dawid, H., Reimann, M., & Bullnheimer, B. (2001). To innovate or not to innovate? *IEEE Transactions on Evolutionary Computation*, 5(5), 471–481.
- Decker, R., & Stummer, C. (2017). Marketing management for consumer products in the era of the internet of things. *Advances in Internet of Things*, 7(3), 47–70.
- Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, 49(10), 1407–1424.
- Delre, S. A., Jager, W., & Janssen, M. A. (2007a). Diffusion dynamics in small-world networks with heterogeneous consumers. *Computational & Mathematical Organization Theory*, 13(2), 185–202.
- Delre, S. A., Jager, W., Bijmolt, T. H. A., & Janssen, M. A. (2007b). Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of Business Research*, 60(8), 826–835.

- Delre, S. A., Jager, W., Bijmolt, T. H. A., & Janssen, M. A. (2010). Will it spread or not? The effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, 27(2), 267–282.
- Einstein, A. (1934). On the method of theoretical physics. *Philosophy of Science*, 1(2), 163–169.
- Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up*. Washington: Brookings Institution Press.
- Erdős, P., & Rényi, A. (1959). On random graphs I. *Publicationes Mathematicae (Debrecen)*, 6, 290–297.
- Fioretti, G. (2012). Agent-based simulation models in organization science. *Organizational Research Methods*, 16(2), 227–242.
- Foote, R. (2007). Mathematics and complex systems. *Science*, 318(5849), 410–412.
- Garcia, R. (2005). Use of agent-based modeling in innovation/new product development research. *Journal of Product Innovation Management*, 22(5), 380–398.
- Goldenberg, J., Libai, B., Moldovan, S., & Muller, E. (2007). The NPV of bad news. *International Journal of Research in Marketing*, 24(3), 186–200.
- Goldenberg, J., Libai, B., & Muller, E. (2010). The chilling effects of network externalities. *International Journal of Research in Marketing*, 27(1), 4–15.
- Golder, P. N., & Tellis, G. J. (2004). Growing, growing, gone: Cascades, diffusion, and turning points in the product life cycle. *Marketing Science*, 23(2), 207–218.
- Gómez-Cruz, N. A., Loaiza-Saa, I., & Ortega-Hurtado, F.-F. (2017). Agent-based simulation in management and organizational studies: A survey. *European Journal of Management and Business Economics*, 26(3), 313–328.
- Granovetter, M., & Soong, R. (1986). Threshold models of interpersonal effects in consumer demand. *Journal of Economic Behavior & Organization*, 7(1), 83–99.
- Grimm, V., & Railsback, S. F. (2005). *Individual-based modeling and ecology*. Princeton: Princeton University Press.
- Günther, M. (2007). *Agent-based simulation of intra-organizational knowledge diffusion and the impact on the emergence of innovations* [in German]. PhD thesis, School of Business, Economics, and Statistics, University of Vienna.
- Günther, M., Lüpke, L., & Stummer, C. (2017). Cross-over between scenario analysis and agent-based market simulation for technology planning. In *Proceedings of PICMET '17: Technology Management for Interconnected World* (pp. 1–9). Portland International Conference on Management of Engineering and Technology (PICMET).
- Günther, M., Stummer, C., Wakolbinger, L. M., & Wildpaner, M. (2011). An agent-based simulation approach for the new product diffusion of a novel biomass fuel. *Journal of the Operational Research Society*, 62(1), 12–20.
- Haurand, M. D., & Stummer, C. (2018a). Stakes or garlic? Studying the emergence of dominant designs through an agent-based model of a vampire economy. *Central European Journal of Operations Research*, 26(2), 373–394.
- Haurand, M. D., & Stummer, C. (2018b). The early-stage development of two-sided digital platforms: A simulation approach. In *Proceedings of the European conference on information systems (ECIS)*. AIS Electronic Library, Research Paper 49.
- Haurand, M. D., & Stummer, C. (2019). Evaluating market entry strategies for two-sided digital platforms under competition: A simulation approach. In *Proceedings of the fortieth international conference on information systems (ICIS)*. AIS Electronic Library, Paper 2188.
- Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, 407(6803), 487–490.
- Heinrich, T., & Gräbner, C. (2019). Beyond equilibrium: Revisiting two-sided markets from an agent-based modelling perspective. *International Journal of Computational Economics and Econometrics*, 19(3), 153–180.
- Holland, J. H. (1998). *Emergence: From chaos to order*. Redwood City: Addison-Wesley.
- Holland, J. H. (2012). *Signals and boundaries: Building blocks for complex adaptive systems*. Cambridge: MIT Press.
- Holland, J. H. (2014). *Complexity: A very short introduction*. Oxford: Oxford University Press.
- Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents in economic theory. *American Economic Review*, 81(2), 365–370.
- Horsky, D., & Simon, L. S. (1983). Advertising and the diffusion of new products. *Marketing Science*, 2(1), 1–17.
- Hu, H., Wang, L., Jiang, L., & Yang, W. (2019). Strong ties versus weak ties in word-of-mouth marketing. *Business Research Quarterly*, 22(4), 245–256.

- Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, 52, 166–182.
- Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, 20(2), 183–230.
- Klein, D., Marx, J., & Fischbach, K. (2018). Agent-based modeling in social science, history, and philosophy: An introduction. *Historical Social Research*, 43(1), 7–27.
- Knepell, P. L., & Arangno, D. C. (1993). *Simulation validation: A confidence assessment methodology*. Los Alamitos: IEEE Computer Society Press.
- Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a complex system? *European Journal for Philosophy of Science*, 3(1), 33–67.
- Lerman, K., & Ghosh, R. (2010). Information contagion: An empirical study of the spread of news on digg and twitter social networks. In: *Proceedings of the Fourth International Conference on Weblogs and Social Media* (pp. 1–9). <https://arxiv.org/pdf/1003.2664.pdf>. Accessed 30 October 2020.
- Leskovec, J., Adamic, L. A., & Huberman, B. A. (2007). The dynamics of viral marketing. *ACM Transactions on the Web*, 1(1), 228–237.
- Lucas, R. E. (1976). Econometric policy evaluation: A critique. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 1, pp. 19–46).
- Macal, M. C. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, 10(2), 144–156.
- Macal, M. C., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3), 151–162.
- Mahajan, V., Muller, E., & Bass, F. M. (1990). New product diffusion models in marketing: A review and directions for research. *Journal of Marketing*, 54(1), 1–26.
- MASON. (2020). *MASON multiagent simulation library core in Java*. <http://cs.gmu.edu/~eclab/projects/mason/>. Accessed 30 October 2020.
- Mesa. (2020). *Mesa: Agent-based modeling in Python 3+*. <https://mesa.readthedocs.io/en/master/>. Accessed 30 October 2020.
- Michler, O., Decker, R., & Stummer, C. (2020). To trust or not to trust smart consumer products: A literature review of trust-building factors. *Management Review Quarterly*, 70(3), 391–420.
- Midgley, D., & Dowling, G. R. (1978). Innovativeness: The concept and its measurement. *Journal of Consumer Research*, 4(4), 229–242.
- Midgley, D., Marks, R., & Kunchamwar, D. (2007). Building and assurance of agent-based models: An example and challenge to the field. *Journal of Business Research*, 60(8), 884–893.
- Miller, J. H., & Page, S. E. (2009). *Complex adaptive systems: An introduction to computational models of social life*. Princeton: Princeton University Press.
- Negahban, A., & Yilmaz, L. (2014). Agent-based simulation applications in marketing research: An integrated review. *Journal of Simulation*, 8(2), 129–142.
- NetLogo (2020). *NetLogo multi-agent programmable modeling environment*. <http://ccl.northwestern.edu/netlogo/>. Accessed on 30 October 2020.
- North, M. J., & Macal, C. M. (2007). *Managing business complexity*. New York: Oxford University Press.
- North, M. J., Macal, C. M., Aubin, J. S., Thimmapuram, P., Bragen, M., Hahn, J., Karr, J., Brigham, N., Lacy, M. E., & Hampton, D. (2010). Multiscale agent-based consumer market modeling. *Complexity*, 15(5), 37–47.
- Parker, G. G., Van Alstyne, M. W., & Choudhary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. New York: Norton & Company.
- Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are transforming companies. *Harvard Business Review*, 93(10), 97–114.
- Rahmandad, H., & Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science*, 54(5), 998–1014.
- Railsback, S. F., & Grimm, V. (2019). *Agent-based and individual-based modeling: A practical introduction* (2nd ed.). Princeton: Princeton University Press.
- Raff, S., Wentzel, D., & Obwegeser, N. (2020). Smart products: Conceptual review, synthesis, and research directions. *Journal of Product Innovation Management*, 37(5), 379–404.
- Rand, W. (2019). Theory-interpretable, data-driven agent-based modeling. In P. K. Davis, A. O'Mahony & J. Pfautz (Eds.), *Social-behavioral modeling for complex systems* (pp. 337–357). Hoboken: Wiley.
- Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, 28(3), 181–193.
- Rand, W., Rust, R. T., & Kim, M. (2018). Complex systems: Marketing's new frontier. *AMS Review*, 8(3), 111–127.

- Rand, W., Herrmann, J., Schein, B., & Vodopivec, N. (2015). An agent-based model of urgent diffusion in social media. *Journal of Artificial Societies and Social Simulation*, 18(2), 1.
- Repast. (2020). *Repast Symphony cross platform Java-based modeling system*. https://repast.github.io/repast_simphony.html. Accessed 30 October 2020.
- Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of Marketing*, 47(1), 68–78.
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York: Free Press.
- Roper, A. L., Cunningham, S. W., Porter, A. L., Mason, T. W., Rossini, F. A., & Banks, J. (2011). *Forecasting and management of technology*. New York: Wiley.
- Ryan, B., & Gross, N. C. (1943). The diffusion of hybrid seed corn in two Iowa communities. *Rural Sociology*, 8(1), 15.
- Santa Fe Institute (2020). Complexity explorer: *Online courses and educational materials about complexity science*. <https://www.complexityexplorer.org/>. Accessed 30 October 2020.
- Schramm, M. E., Trainor, K. J., Shanker, M., & Hu, M. Y. (2010). An agent-based diffusion model with consumer and brand agents. *Decision Support Systems*, 50(1), 234–242.
- Schweitzer, F., & van den Hende, E. A. (2016). To be or not to be in thrall to the march of smart products. *Psychology & Marketing*, 33(10), 830–842.
- SIMSOC (2020). *News and discussion about computer simulation in the social sciences*. <https://www.jiscmail.ac.uk/cgi-bin/webadmin?A0=simsoc>. Accessed 30 October 2020.
- Smith, E. B., & Rand, W. (2018). Simulating macro-level effects from micro-level observations. *Management Science*, 64(11), 5405–5421.
- Sonderegger-Wakolbinger, L. M., & Stummer, C. (2015). An agent-based simulation of customer multi-channel choice behavior. *Central European Journal of Operations Research*, 23(2), 459–477.
- Souka, M., Böger, D., Decker, R., Stummer, C., & Wiemann, A. (2020). Is more automation always better? An empirical study of customers' willingness to use autonomous vehicle functions. *International Journal of Automotive Technology and Management*, 20(1), 1–24.
- Stummer, C., & Kiesling, E. (2021). An agent-based market simulation for enriching innovation management education. *Central European Journal of Operations Research* (forthcoming). <https://doi.org/10.1007/s10100-020-00716-3>.
- Stummer, C., Kiesling, E., Günther, M., & Vetschera, R. (2015). Innovation diffusion of repeat purchase products in a competitive market: An agent-based simulation approach. *European Journal of Operational Research*, 245(1), 157–167.
- Stummer, C., Kundisch, D., & Decker, R. (2018). Platform launch strategies. *Business & Information Systems Engineering*, 60(2), 167–173.
- Sun, X., Liu, X., Wang, Y., & Yuan, F. (2019). The effects of public subsidies on emerging industry: An agent-based model of the electric vehicle industry. *Technological Forecasting & Social Change*, 140, 281–295.
- Ten Broeke, G., Van Voorn, G., & Ligtenberg, A. (2016). Which sensitivity analysis method should I use for my agent-based model? *Journal of Artificial Societies and Social Simulation*, 19(1), 5.
- Tesfatsion, L. (2020a). *Agent-based computational economics*. <http://www2.econ.iastate.edu/tesfatsi/ace.htm>. Accessed 30 October 2020.
- Tesfatsion, L. (2020b). *Empirical validation and verification of agent-based models*. <http://www2.econ.iastate.edu/tesfatsi/EmpValid.htm>. Accessed 30 October 2020.
- Trusov, M., Rand, W., & Joshi, Y. V. (2013). Improving prelaunch diffusion forecasts: Using synthetic networks as simulated priors. *Journal of Marketing Research*, 50(6), 675–690.
- Vahdati, A. R. (2019). Agents.jl: Agent-based modeling framework in Julia. *Journal of Open Source Software*, 4(42), 1611.
- Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. *Journal of Consumer Research*, 34(4), 441–458.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393(6684), 440–442.
- Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: Modeling natural, social, and engineered complex systems with NetLogo*. Cambridge: MIT Press.
- Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirical grounded agent-based modelling approach. *Technological Forecasting & Social Change*, 94, 269–285.
- Yoo, E., Rand, W., Eftekhari, M., & Rabinovich, E. (2016). Evaluating information diffusion speed and its determinants in social media networks during humanitarian crises. *Journal of Operations Management*, 45, 123–133.

- Young, H. P. (2009). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *American Economic Review*, *99*(5), 1899–1924.
- Zhang, T., Gensler, S., & Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach. *Journal of Product Innovation Management*, *28*(2), 152–168.
- Zhong, X., & Ozdemir, S. Z. (2010). Structure, learning, and the speed of innovating: A two-phase model of collective innovation using agent based modelling. *Industrial and Corporate Change*, *19*(5), 1459–1492.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.