2013

The Contribution of Social Simulation in the Advancement of Marketing Issues and Challenges

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Issues and Challenges

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Introduction

The marketplace is a complex social system due to the interaction of multiple individual agents (i.e., consumers, firms or distributors) pursuing very different objectives. In addition, agents in a marketplace respond distinctly to a particular incentive or situation. For example, a particular marketing message could raise brand awareness among some people while remain innocuous among others. In turn, this gives rise to the emergence of collective behaviors, such as the development of fads, the viral adoption of products and services, or even crowdsourcing behaviors. However, the emergence of these aggregate behaviors is often overlooked by traditional empirical techniques.

Traditional modeling approaches, such as regression-based or structural-equation modeling, present important limitations when it comes to study complex business phenomena. As North et al. (2010) point out, one important limitation relates to the constrained number of factors these approaches can incorporate as well as the level of detail they can accommodate. Kiesling et al. (2012) highlight that some of these traditional methodologies are not properly designed to account for the pervasive effect of interaction and community-building on an agent's behavior. They argue this limitation significantly constraints the utility of traditional approaches to address policy implementation (what-if) questions, which are quite frequent in managerial decisions. Finally, these traditional techniques fail to explicitly incorporate consumers' heterogeneity and the complexity behind social phenomena (North et al., 2010; Kiesling et al., 2012); two features that are bound to be present in every marketing interaction between two or more agents.

It is until recently that marketing scholars started to explore the complexities of marketplaces by applying social simulation approaches. This rising interest is motivated by the possibility, opened by these simulation models, to more effectively monitor and evaluate the outcomes of marketing actions and policies. In particular, agent-based modeling (ABM) is one of the most popular simulation approaches applied by marketing scholars thanks to its ground-up or bottom-up nature. This is because, in ABM, the group-level structures emerge as a result of the simulation, based on a population of heterogeneous agents and the operational rules of their interactions. In other words, the model is defined at the individual or micro-level, and the representation of these features in a simulation result in the emergence of collective or macro-level phenomena. In more traditional linear approaches, the emergence of such aggregate behaviors must be explicitly accounted for in the model and hence, not a result of the model itself. This significantly limits the traditional scope's ability to address the non-linearity of effects that certain factors have, in the presence of different contexts, on an agent's behavior. By favoring complexity over simplicity, ABM is able to capture and simulate this hierarchical system of interactions between the individual elements and its aggregate structures.

In marketing, examples where the presence of this non-linearity of effects exists can be found abundantly. For example, when a marketer is considering launching a new product or brand, one of the key criteria used by decision-makers is the speed of adoption this product will have in the market. This determines, in turn, a myriad of other marketing variables such as the stock level needed to meet the demand or the time it will take to recover the funds invested in the launch. The rate of penetration of a new market offering is highly influenced by the intrinsic features of the population it will be introduced to. This encompasses not only the distinct behaviors of each individual member of this population but also the collective or aggregate behaviors emerging from the interaction among them. Examples of collective behaviors range from word-of-mouth phenomena in the diffusion of messages or fashions to group-identification effects, such as brand communities, in consumer's behaviors.

Much effort is being put by companies and marketing practitioners to integrate all business areas and departments in the achievement of marketing objectives. This concept has been named *holistic marketing*. It means that a company must leverage all its resources to ensure the customer experiences a 360-degree interaction through all possible points-of-contact. This entails the consistency of policies and actions across all of a firm's functional areas, which implies the coordination among employees not only at the individual but also at the group-level. Effective application of a holistic marketing strategy heavily relies in the understanding of how incentives have distinct outcomes at inter and intra departmental levels. The interdependence of multiple layers of aggregate structures with the heterogeneous nature of individual agents requires the explicit consideration of non-linear effects brought by social interactions. Moreover, these interactions of agents at multiple levels determine and sustain, both at the same time, the whole system, its organization and performance. In this way, the aggregate cannot be understood as the sum of its parts but as more than that, with some sort of indirect communication between agents of different levels building synergies. This degree of complexity and the circularity of effects make the use of ABM approaches, compared to traditional ones, of great utility to evaluate holistic marketing strategies.

Despite the evident power of ABM to understand the complexities of marketplaces, the adoption of such methodology in top-level marketing journals has been rather slow. A few notable pieces have been published providing guidelines and frameworks for the development of rigorous research based on social simulation approaches in the study of marketing issues (Garcia et al., 2007; Jager, 2007; Rand and Rust, 2011). However, there still exists a lack of thorough and comprehensive reviews about the contribution of social simulation to the field of marketing, as it exists for other fields such as organizational management (Harrison et al., 2007). To foster widespread acceptance of social simulation methodologies in academic publications, the need for a comprehensive and critical review of marketing applications becomes crucial.

Thus, the purpose of this paper is twofold. On the one hand, the proposed review will provide the researcher with a state-of-the-art repository for this strand of research. This facilitates the identification of relevant gaps in the literature and future research avenues. On the other hand, it contributes to assess the way social simulation has actually improved our understanding of the dynamics of markets and its participants when marketing strategies are implemented. Both goals aim at qualitatively assessing the extent of social simulation's contribution to the advancement of marketing as an academic field. What this research ultimately attempts is to bridge the gap between simulation experts and marketing scholars and practitioners working on common issues but with different perspectives.

Balancing the pros and cons

For marketers, the more realistic representation of consumer decision-making, offered by ABM, is very appealing (Jager, 2007) since it allows a better understanding of market dynamics. In particular, ABM's ability to incorporate the complexities of human behavior into a framework that warrants the development of aggregate features in a market is of great value for marketers. This feature can substantially improve the efficacy of marketing strategies by allowing marketers to more accurately monitor the results of a marketing policy’s implementation. Because of this, ABM has recently gained popularity as a modeling tool in marketing.

This technique has several strengths. This method is highly attractive as an empirical approach for its ground-up nature. In other words, the macro-scale dynamics of the whole system are not described directly. These larger scale phenomena arise from micro-level interactions between agents when the model is implemented. The researcher only needs to define the parameters at the individual level and the aggregate or macro-level behaviors will show as an emergent property of the system (Garcia and Jager, 2011). In this way, ABM does not only facilitate the examination of theories of consumer behavior at the micro-level, but the results can also be used to explore emergent collective phenomena in marketplaces (Rand and Rust, 2011).

Thanks to this bottom-up, disaggregated approach, ABM is able to incorporate characteristics that are difficult to include in traditional models; accounting, in a much less restrictive way, for heterogeneity and social structure (Kiesling et al., 2012; Rand and Rust, 2011). In particular, consumers modeled with ABM can be boundedly rational, which means that they make decisions based on the information they collect from their local context rather than from a global perspective. From a marketing perspective, this feature is particularly attractive because it resembles more appropriately the way certain consumer’s information-acquisition processes work. For example, research in the field of marketing communications suggests the influence of mass communications on people’s attitudes works through a two-step process. First, ideas flow from mass media to opinion leaders and, second, they flow from opinion leaders to the less media-involved population groups (Katz and Lazarsfeld, 1955). This implies that people interact primarily with their own social groups and acquire ideas from opinion leaders in their group, thus acquiring information from local sources rather than globally.

Another interesting property of ABM for marketers is the autonomy of agents. Each agent is capable of autonomous behavior but with an adaptive nature (Rand and Rust, 2011). They adapt their strategies by using heuristics, reinforcement learning and other knowledge transmission processes that make their decisions sensitive to the history of the system (Rand, 2006). Several consumption patterns are transmitted from generation to generation through a complex system of beliefs and values. The prevalence of homeownership in some cultures, for example, is a result of a cultural predisposition towards this form of housing tenure. This preference for homeownership is passed on from parents to kids in the form of shared knowledge and as a rite of passage from one life-cycle stage to another. ABM can capture how this behavior feeds its way back into the system to reflect the interdependence of individual and collective behaviors in the sustainability of this consumption pattern.

According to Zenobia et al. (2009), ABM is particularly suitable when cognitive biases are important. Cognitive biases are deviations in judgment, under particular circumstances, from what is broadly called rationality (Kahneman and Tversky, 1972). The sources of these biases can be numerous including the use of mental shortcuts, such as heuristics, the distortion of beliefs (i.e., wishful thinking), or even social influence. A popular cognitive bias in marketing is what has been named the decoy effect. This bias consists of the way preferences for two rival offerings may change after a third offering is introduced. For example, when given two product alternatives, where one is cheaper than the other, most consumers tend to select the cheaper option. However, when a third more expensive option is introduced, consumers tend to select the middle offering, which happens to be the most expensive option from the original pair. ABM offers the researcher the versatility to define these behaviors as operating rules of the simulation and to track the unfolding behaviors this cognitive bias produces.

A property of ABM that is not frequently exploited by marketing scholars is the possibility to account for stigmergic interactions. Stigmergy is a form of indirect communication established between agents through modifications performed on their environment with the objective of influencing other agents' decisions (Goldstone and Janssen, 2005). A classical illustration of stigmergy is the trail of pheromones that ants leave to direct other ants to food sources. One of the most visible stigmergic effects in marketing is the system of reviews and recommendations displayed in the majority of online retailers. These "trails" left by past customers are used to attract other visitors to buy a product or service. In a way, brand community building and crowdsourcing strategies also exploit stigmergic interactions. In these cases, the actions of participants help to create, define and shape a platform (or a product in the case of crowdsourcing). In turn, this collectively created platform attracts other people to become members and keep contributing to its development.

ABM represents complexities in a way that facilitates model comprehension by managers and stakeholders (Rand and Rust, 2011). In this way, ABM is especially appealing for marketing researchers and practitioners that are trying to account simultaneously for multiple dimensions in the same model. For example, the assessment of a marketing policy may require the simultaneous consideration of consumer psychological processes, competitors' strategies, and distribution channel dynamics. Each of these forces has its own domain of action and a distinct degree of influence over each other. Through ABM one can model the interactions between agents belonging to different structures and examine how the unfolding behaviors of these structures shape the organization of the system.

Despite its advantages and strengths, ABM faces very important challenges and difficulties. Agent-based models have been criticized for being ‘‘toy models’’ and unrepresentative of real-world phenomena (Garcia and Jager, 2011) because they don’t deal with real data. However, ABM also provides a way to integrate real-world data and complexities into a model (Rand and Rust, 2011). And even when a limited amount of data is available, simulation models can still be useful and leveraged to explore possible relations and their results until more data is available (Louie and Carley, 2008). In addition, agent-based simulation models have been positioned in a suitable spot between theory-creating and theory-testing approaches (Davis et al., 2007), benefiting the development of rigorous theories.

Criticisms about ABM also point out that most of these models are merely “computer games” because they have so many parameters that they can fit any data set (Rand and Rust, 2011). These assessments highlight that is very important to ensure that an agent-based model is valid, that inputs and outputs correspond to the real world. Yet, as Miller and Page (2007) observe, it should be noted that *“models need to be judged by what they eliminate as much as by what they include”*.

Thus, the need for validation is the most recurring critique (Kiesling et al., 2012) made to ABM in the marketing literature. While the discussion of these issues extends beyond the scope of this work, given its importance, it will be discussed briefly in a separate section. However, it suffices to say that validation falls within a much broader category of criticism: the absence of a generalized methodology on how to build, describe, analyze, evaluate and replicate ABM (Rand and Rust, 2011; Squazzoni, 2010). This is a critical point for the widespread acceptance and recognition of ABM as a modeling technique among scholars. However, advancements on other aspects are still needed in order to allow marketers to "*benefit from having a simulation tool that not only describes the dynamics of certain markets, but is also suitable for testing strategies to influence these markets"* (Jager, 2007).

A review of marketing applications

Marketing applications of ABM approaches have centered on studying the dynamics of marketplaces. Marketplaces are composed of agents with different motivations and goals, showing a multiplicity of sizes and with an ample array of degrees of influence over other agents. Consumers depend on manufacturers to get the products they demand, and vice versa. Manufacturers, in turn, depend on distributors to get the goods to the point-of-sale. Consumers are influenced by the messages sent by companies to attract them to buy from them but, at the same time, rely on the recommendations from other customers like themselves. A company invests significant amounts of money to distinguish itself from competitors, creating a diversity of different options for consumers to choose from. These consumers are so heterogeneous in their demands that oftentimes they test several competing brands before they become loyal to one. And so the story goes on.

However, regardless of this heterogeneity in the nature of agents, the use of social simulation in marketing seems to confirm a well-known adage among marketers: *Everything starts and ends with the consumer*. No matter what the ultimate objective of the research is, the majority of marketing applications using ABM techniques attempt to model consumers' behaviors in different contexts. Some exceptions are Hill and Watkins (2007) and Watkins and Hill (2009) where a firm's perspective is used to model sales agents' individual philosophies to explain the long-term financial success of companies. In addition Wilkinson and Young (2002) examine the role of heterogeneous strategies and competition within complex networks of firms.

One of the most popular and pioneer applications of social simulation models to marketing phenomena is the study of diffusion of innovations or new products (Garcia, 2005; Rand and Rust, 2011). This has become particularly important since the advent of Internet and other Information Technologies (IT). The popularity of IT has given rise to a business culture based on heavy expenditures on research and development for companies to remain competitive. These investments tend to materialize in new products or improved versions of previous ones. Under this context, managers face the challenging task of predicting the success of a given innovation in a highly volatile and complex market before it is actually launched or even produced (Gilbert et al., 2007). The complexity in the introduction of innovations becomes apparent when consumers interact among each other to inform about their experiences with the new product. Word-of-mouth, blogs and review sites on the Internet, as well as the use of viral marketing tactics, are just some of the many ways these interactions take place in the modern marketplace.

ABM approaches have advanced our understanding of how these interactions influence the acceptance and diffusion of new products or innovations.

Janssen and Jager (2001), for instance, examine the role of social networks, preferences and the consumer's need for identity in the continuity and survival of products in a marketplace. Their result shows the importance of psychological factors to explain a variety of market dynamics, such as fashions and lock-in products. Goldenberg et al. (2001) addressed the role of word-of-mouth (WOM) in the process of personal communications identifying the distinct effects of marketing strategies on WOM spread in the presence of weak and strong ties among a network's members. Exploring the effects of viral marketing strategies, Sharara et al. (2001) propose an adaptive diffusion model that underlines the important role and effect that peers' confidence has on people's recommendations for the adoption of different products over time. Other relevant studies that use ABM to model the role of influentials or opinion leaders in the diffusion of innovations or new products are Goldenberg et al. (2009), Goldenberg et al. (2010) and Watts and Dodds (2007).

Using the spatial divergence approach, Garber et al. (2004) demonstrate that the less uniform a product's distribution, the higher the likelihood of generating a "contagion process". Complementarily, but from an epidemic framework, Delre et al. (2007) propose a model including heterogeneity in decision-making and social influence in personal networks, showing that in high clustered networks innovations diffuse faster than in random networks. Their argument is that when people cluster in groups, they are more exposed to social influence and peer pressure, thus, making the decision to adopt sooner. Toubia et al. (2008) and Delre et al.

(2010) have explored network effects on diffusion while Goldenberg et al. (2009, 2010) have done so in product adoption.

What these studies show is the importance of social groups and networks in the speed of diffusion of products and the functional form this diffusion will take: fashion, contagion, etc. However, there are still a lot of questions and issues within this area that ABM could help explore and delve into. For instance, almost all of these works highlight the significance of belonging to solid and cohesive groups that consumers trust and feel identified with. The ability of ABM to identify emergent aggregate structures leads us to ask whether this need for identity within groups may reflect a behavior produced by the super structure. In other words, the collective agent (i.e., brand community, consumer association) that emerged from the interactions of individual consumers seems to have gain control over them. Thus, it may appear as if the subagents of this super-agent have given up, to a certain degree, some of their agency or capacity of action in exchange for some sense of belonging.

Within the modeling of consumer interactions and networks, other studies such as Heppenstall et al. (2006) and Rauh et al. (2012) have associated local interactions among consumers and its shopping activities to preferred retail locations. These studies reproduce the spatial patterns of consumers to determine the dynamics of buying power flows as well as the emergence of conditions explaining particular competitive strategies among firms. Given the advances in geographic information systems (GIS) as well as the ability of ABM to incorporate this layer of information, the study of path dependence holds a promising future. In particular, the concept of stigmergic interactions could be further explored using ABM. For instance, little attention has been paid to understand the spatial dimension of these interactions among firms from the same industry. In a world where telecommunications have advanced substantially, where distance is no longer an obstacle for communication, how can we explain the existence of industrial hubs, such as Silicon Valley? Could it be some type of indirect communication between firms?

Recently, multi-agent approaches have been used in marketing to analyze the effectiveness of marketing strategies under different contexts and marketplaces. These applications allow for the examination of individual-level behavior reactions to the various elements of the marketing mix: product, price, promotions (or communications) and place (distribution). Practitioners, such as consumer packaged goods manufacturer (CPG) Procter & Gamble (P&G), are actively using ABM to improve its supply chains and to improve its cost saving strategy. Some applications that have created simulated consumer environments to test the effect of a change in marketing strategy include Twomey and Cadman (2002) for the telecommunications and media markets, Ulbinaite et al. (2011) for insurance services, and Takechi et al. (2009) for the movie rental business.

In terms of the elements of the marketing mix that have been explored, there is a wide variety of orientations. Cao (1999) uses ABM to evaluate the effectiveness of advertising, more particularly banner advertising on the Internet. The attitudes of consumers to several elements of a banner (i.e., type, size, color, contrast, position and content) are incorporated in the negotiation decision to determine their effects on the click-through rate. Schwaiger and Stahmer (2003) address the decision-making process of Category Managers in retail stores and supermarkets concerning prices, promotions, assortment and placement using a multi-agent system. The core of their simulation system is the definition of multiple agents from real sales records of supermarket customers.

Schuster and Gilbert (2005) design a multi-agent simulation to explore two scenarios within the distribution of online music: the disintermediation of the value chain and the lock-in of consumers to a popular music download platform (iTunes). These two scenarios serve the authors to show how the success of firms following different strategies may depend on the interplay of these strategies over time.

Finally, two of the most relevant studies among those that explore the effectiveness of marketing strategies are Delre et al. (2007) and Libai et al. (2005). The first uses ABM to explore the efficacy of various promotional strategies when launching a new product. In particular, these authors focus on decisions related to the targeting and the timing of promotions. They found that the optimal strategy for marketers crafting promotion strategies to launch a new product is to target small cohesive groups of consumers in distant areas. As for the timing issue, their results indicate two tactics to avoid with mass media: huge premature and weak late campaigns. Along the same line, Libai et al. (2005) study the allocation of marketing resources during the penetration stage of new products into multiple markets using stochastic cellular automata. They find that strategies that disperse marketing efforts are superior to strategies concentrating marketing efforts in supporting the stronger market regions.

As it was noted earlier, most of these studies aim at evaluating the implementation of strategies from a consumer’s standpoint. They miss to incorporate the impact of these strategies over other agents in the market, such as distributors and competitors. A worth noting exception is North et al. (2010). They develop a holistic multi-scale consumer market model where they include extraordinary detail and coverage in terms of the different nature of agents it considers. Further research could also explore the important role of repeat purchase by the same consumers.

In addition, a multi-scale approach could potentially benefit from the use of ABM by delving into the notion that agents and structures can be conceptually inseparable (Giddens, 1979). Particularly, for complex market systems, ABM approaches could help marketers to explore the concept of morphogenesis (Archer, 1995); the idea that change occurs for agents and structures in temporally and intertwined complex ways. To summarize this ontology and apply it to marketplaces we could think that the origin of consumers and companies materializes within the context of the existing market structures. However, on a larger time scale, these market structures change as a consequence of the unfolding actions and decisions of the individuals that constitute them. Due to the relevant role of structures, more research is needed to identify the most appropriate algorithms and parameters for modeling different types of actual markets and market conditions (Kiesling et al., 2012).

As this review of marketing applications illustrates, agent-based modeling displays countless benefits to model complex marketing behaviors. This feature helps the researcher and practitioner to depict richer pictures of real-market situations. As it has been pointed out previously, this modeling approach has been accused of being “toy models” or “computer games”. It is beyond the scope and objectives of this research to discuss validation issues in ABM. However, for the purpose of thoroughness, the next section briefly addresses the issue of validation of ABM and lists the research efforts carried out by some marketing studies in this respect.

Validation issues

As with other modeling techniques, we are bound to ask ourselves to what extent multi-agent simulation models could provide the researcher with an accurate way to depict reality. The starting point to provide an answer to this question is to address the issue of validation of simulation models. In essence, a validated simulation model is one that matches as accurately as possible the real-world (Garcia et al., 2007; Yilmaz, 2006). In particular, for marketing, validation implies testing whether our model captures actual market issues and phenomena.

From an operational standpoint, a multi-agent model is composed of two models, the conceptual (or theoretical) and the computational (or implemented) model (Louie and Carley, 2008). The first step is to establish a conceptual framework where all agents involved and their relationships defined, and the underlying assumptions of this system are laid out appropriately. The next step is to design the computational model, that is, to formalize the conceptual representation developed in the previous step into mathematical relationships or algorithms. Thus, validation of a simulation model starts by endorsing both conceptual and computational models together, in other words, showing that the computational model corresponds to the conceptual one. This process is known in the literature as verification (North and Macal, 2010; Rand and Rust, 2011; Louie and Carley, 2008).

As the previous discussion noted, agent-based models in marketing encompass individual agents, such as consumers or firms, whose behaviors are observed at an aggregate level, as in a market or an industry. For this, two different perspectives need to be taken into account: a micro and a macro perspective (Garcia and Jager, 2011). The first one deals with the parameters used when we define the model at the micro level, that is, the individual-agent level. The second perspective involves the validation of the model's outputs at the aggregated or collective level. Thus, validation of simulation models in marketing must take place at the definition of model's inputs as well as for the resulting outputs.

From a managerial perspective, the definition of models at the input-level is particularly relevant because the more complex a system is, the wider the assortment of different empirical realities. In this sense, any small change in the input parameters may result in significantly different outcomes. Thus, validation of inputs means making sure that the mechanisms laid out in the simulation model for the individual agents and their interactions correspond to real-world scenarios. According to Miller and Page (2007) this process entails designating an equivalence class that maps a subset from a real-world state to a model state. In other words, validating our model at the micro-level involves finding an equivalent way to explain the complexity of a real market by a simplified set of rules or metrics. Input-level validation consists of determining to what extent the underlying assumptions and the mechanisms described are appropriate to represent the real world. For managers this implies that, when complex markets or industries are being investigated, meaningful insights could be extracted from the understanding of the underlying processes governing agents and its interactions.

However, prediction is also an important aspect of simulation models, and one that managers rely on to make decisions. In this sense, output or macro-level validation makes sure that the simulation model produces an outcome that resembles as close as possible the happenings of the real world. In other words, this implies showing that the resulting aggregate behaviors reflect processes observed in real markets (North and Macal, 2010) or, alternatively, that the real market is a possible output for the model.

In modeling complex systems, the idea that *"the whole becomes not only more than but very different from the sum of its parts"* (Anderson, 1972) implies a transformation function from individual to aggregate levels. Furthermore, these aggregated agents or super-structures could potentially create, in turn, other higher-level structures. Thus, the task of validation for ABM approaches is still a work in progress (Miller and Page, 2007). In particular understanding this transformation function implies developing a theory that explains how new collective entities emerge from lower-level ones. In this respect, it is worth highlighting the work conducted by Yilmaz (2006) in the validation and verification of agent-based computational organization models. The author uses the notion of social contracts to evaluate a model's consistency. Social contracts enable local consistency analysis to be performed on the verification of interaction dynamics among agents. The notion of local consistency is, in turn, extended to the validation of emergent macro-level phenomena through the development of process validation metrics.

The majority of the work concerning validation issues within the marketing literature is related to empirical validation of model's inputs and outputs. At the input-level, Van Eck et al. (2011) demonstrate how to empirically validate consumer interaction issues and processes by using empirical data on opinion leaders found in online gaming communities. Schwaiger and Stahmer (2003) use real world data, extracted from a supermarket's customer cards, sales data and interviews, to define and model individual agents' preferences. Validation of model outputs has been carried out using conjoint analysis, providing another method in grounding heterogeneity in consumer preferences in agent-based models (Garcia et al., 2007; Zhang et al., 2011).

Concluding remarks and opportunities for future research

For some years now, marketers have been praising for a more holistic approach of a company's marketing efforts across all areas. Within this framework, traditional models show serious limitations to address the complexities of managing all of a company's touch points with a customer. ABM opens the door for marketing scholars and practitioners to explore the unfolding behaviors and outputs of an increasingly connected and interactive marketplace. But now that the door is open, and we are able to see the realm of possibilities behind it, we need to provide a solid ground for future research. This implies balancing this paradigm's achievements with its limitations.

Agent-based modeling offers a promising methodology for marketing-related research. So far, ABM approaches have particularly contributed to innovation diffusion research. It has advanced our understanding of innovation spread and provided greater insight on topics such as the role of social network topologies, social ties, network externalities and word of mouth. Furthermore, agent-based modeling has also been shown to have tremendous potential for practical applications when answering policy implementation questions. These questions include the evaluation of marketing strategies or changes in marketing mix's elements, among others.

However, marketing scholars and computer scientists could benefit even more from ABM approaches if greater efforts are undertaken to overcome some of its limitations. In addition, overcoming these limitations imply finding ways to connect more disciplines and sciences across a common understanding of social processes.

One important limitation that needs special attention is the definition of processes that connect the micro and macro-level mechanisms in a complex system. There is still a lack of theoretical clarity about the role of "social influence" in the individual agent behaviors and preferences (Kiesling et al, 2012). In particular, more research is needed to incorporate meso-level mechanisms within the modeling of marketplaces. For instance, for some luxury products, buying decisions often reflect a consumer's self-concept and the effect that reference groups and social institutions have on it. The notion of coupling heuristics, or "handshakes" as Andreas Tolk referred to them in his keynote speech in EPOS 2012, are a useful way to refer to this idea. As we move towards the study of multi-level complex markets, we need to develop "handshakes" to be applied between theories of individual psychological processes with those of higher-level patterns of behavior.

The widespread acceptance of this paradigm will necessarily involve the convergence towards a commonly accepted methodology to develop and validate ABM models. Thus, major efforts should be devoted to overcome this challenge, building up a common modeling framework, based on a clear-cut definition of key concepts and a thorough understanding of their role in the system (Kiesling et al., 2012). Marketing is a business discipline grounded in many other disciplines, such as sociology, psychology and economics. Therefore, the future of ABM approaches in the study of marketing-related issues will rely on the efforts carried out to reduce the ABM divide of social scientists (Squazzoni, 2010). It would be beneficial to integrate these techniques into a common modeling framework. Such a framework should rely on common definitions of key concepts and interaction mechanisms across disciplines.

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