Multiscale Agent-Based Consumer Market Modeling

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Consumer markets have been studied in great depth, and many techniques have been used to represent them. These have included regression-based models, logit models, and theoretical market-level models, such as the NBD-Dirichlet approach. Although many important contributions and insights have resulted from studies that relied on these models, there is still a need for a model that could more holistically represent the interdependencies of the decisions made by consumers, retailers, and manufacturers. When the need is for a model that could be used repeatedly over time to support decisions in an industrial setting, it is particularly critical. Although some existing methods can, in principle, represent such complex interdependencies, their capabilities might be outstripped if they had to be used for industrial applications, because of the details this type of modeling requires. However, a complementary method—agent-based modeling—shows promise for addressing these issues. Agent-based models use business-driven rules for individuals (e.g., individual consumer rules for buying items, individual retailer rules for stocking items, or individual firm rules for advertizing items) to determine holistic, system-level outcomes (e.g., to determine if brand X's market share is increasing). We applied agent-based modeling to develop a multi-scale consumer market model. We then conducted calibration, verification, and validation tests of this model. The model was successfully applied by Procter & Gamble to several challenging business problems. In these situations, it directly influenced managerial decision making and produced substantial cost savings. *© 2010 Wiley Periodicals, Inc.* *Complexity 000: 000–000, 2010*

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1. INTRODUCTION

Every day, companies that manufacture consumer packaged goods (CPG) make decisions that affect the characteristics of their products as well as their strategies for effectively marketing these products to consumers. Finding answers to common questions, such as how

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to increase sales levels or how to adapt to marketplace changes, requires the companies to consider multiple issues across time. For example, when a competitor introduces a new marketing campaign, the CPG company, to craft an appropriate response, must project the campaign's effect over time—both on sales and on the consumers' view of the marketplace. Modeling these and other time-based impacts is often difficult because of the complex sequence of interlocking, nonlinear behaviors that is often an intrinsic part of large-scale markets. For example, imagine a simple scenario in which one CPG manufacturer lowers the price of a product to increase sales. Other manufacturers may react with even lower prices to remain competitive, so that after this price change, the result is actually a decrease in the original manufacturer's sales.

At the same time, manufacturers increasingly find their decisions interlinked with those of others in the marketplace (e.g., customers, consumers, suppliers). This interdependency reflects the new realities in today's markets, where goals associated with competing for market share and position now require an equal emphasis on partnering effectively with suppliers and retailers and on anticipating and planning for changes in consumer demographics and desires. Decisions that must be made include how to gain a short-term tactical advantage as well as how to craft mid-term and long-term strategies for growth.

Most consumer market models tend to have a "piecemeal" focus; many focus on a single aspect or subpart of the market, such as supply chains for manufacturers, point-of-sale data for individual retailers, or panel data for consumers. A holistic approach is needed to complement these existing piecemeal approaches (e.g., modelers should not have to build separate models for every brand in a category). The "virtual market learning lab" meets this need.

The virtual market learning lab is the result of a 6-year partnership between Argonne National Laboratory and Procter & Gamble (P&G). The goal of this P&G-sponsored project has been to develop an innovative, computational agent-based model of consumer markets. The resultant virtual market learning lab technology represents a new milestone at the forefront of agent-based modeling of the consumer market in terms of its extraordinary detail, broad coverage, and the large number of agents it considers. Some of the advances achieved in this project have resulted in a joint Argonne/P&G patent application [1]. The virtual market learning lab has been successfully applied by P&G to several challenging business problems, in which its use directly influenced managerial decisions.

This article first briefly surveys the range of techniques commonly used for modeling consumer markets, then introduces agent-based modeling and compares and contrasts it with traditional approaches. Next the article describes the virtual market learning lab and discusses its verification and validation. It concludes with a discussion of the next steps for agent-based consumer market modeling.

2. RELATED WORK

Although there is an escalating need for models that can operate at multiple levels of detail to address strategic as well as tactical issues, the limitations of both current techniques and current data sources in providing robust decision support systems pose challenges. Leeflang and Wittunk [2] have an excellent review of the history of model building in support of marketing decisions. This article considers both traditional and agent-based approaches to modeling consumer markets.

2.1. Traditional Approaches

Traditional modeling techniques, while powerful, tend to be limited in the (1) number of factors that they can incorporate, (2) level of detail on each factor that they can accommodate, and (3) behavioral complexity that they can account for. Consequently, they may not be sufficient for holistically representing interdependent systems, such as those that commonly underlie the decisions of consumers, retailers, and manufacturers.

This is not to say there has not been steady progress in developing data sources and quantitative models—indeed, there has been. Despite this progress, however, manufacturers still find many of the issues raised several decades earlier by Little [3] to be relevant today, although in a slightly different form. First, models that can be used over time to answer short-, mid-, and long-term questions are hard to find ("good models are hard to find" [3]). Second, finding models that can adapt to the type of data available and the granularity decisions require is even harder ("good parameterization is even harder" [3]). Third, most models do not incorporate all the players in a system or all the interactions among those players ("most models are incomplete" [3]). Finally, managers have not been gaining insight into the dynamics of their marketplace by using the models ("managers do not understand models" [3]).

Today's managers have a wealth of models available, ranging from stochastic consumer behavior models, which excel in providing explanatory power, to empirical models, which are excellent with regard to providing tactical support. The plethora of models reflects the speed with which model developers have capitalized on improvements in data sources, improvements in computer speed and memory, and analytic advances.

Managers have come to rely on stochastic behavior models. These include brand choice models such as the NBD-Dirichlet approach, purchase incidence models, and purchase timing models. These models are discussed in Refs. [4–7]. Although these models are typically embraced

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for their descriptive strengths, they have become important because they allow managers to understand the "whys" behind behavior and provide explanatory components that can be used to make predictions. Another strength of these models is their scope: they are often marketplace representations that encompass the behavior in an entire category. However, they can be limited in granularity and thus in the types of decisions they can readily address. They also have limited capability for handling true market discontinuities.

Econometric models (e.g., regression-based, Monte Carlo integration [MCI], and multinomial logit [MNL] models) have made great strides as decision support tools, in part because of their strong performance in tactical applications. The statistical analysis of historical data that these models employ has been shown to adequately provide support for routine decisions [8]. Typically, separate models are built to address specific marketing problems (e.g., there are different models for product, pricing, and advertizing decisions). This strength, however, can also become a weakness. If many models and submodels are created for a single category, users may have to rely on their own imperfect judgment to bridge the gaps among disparate model results. Model complexity, real or perceived, becomes a user issue. Another well-known limitation is that the models must rely on only a limited range of responses: those that are reported on in the historical data. Finally, there are limits in the ways the models can handle multiple and possibly simultaneous moves by multiple competitors across time.

In spite of the impressive growth in both the number of data sources and the degree of detail, which has yielded more and better data for econometric modeling and tracking, data challenges remain. For example, although extensive records on purchases for panels of consumers exist, details on the specific contexts behind the purchase data are often lacking. Researchers might want to know what the consumer actually saw and considered when choosing what to purchase.

Spurred by limitations in syndicated data, another area of growth and development has been the design and modeling of experiments that incorporate more contextual marketplace components. Experiments with consumers offer a means of control over various elements, such as the shelf set and marketing conditions (for multiple brands and items). This control enables researchers to more fully explore and model the impact of context; for example, see Ref. [9]. Furthermore, conditions that are outside the range of historical data can be set; this ability is a key issue for managers in many practical situations. An experimental approach also gives researchers an option to conduct a deeper analysis at the individual level, which can be an asset in targeting decisions. However, practical limitations on the size of the sample and the amount of contextual detail that can be presented in an experimental setting restrict the scope of these models.

Some of these challenges have been difficult for traditional methods to overcome, in part because the decisions to be made and modeled exist within a contextualized system rather than as isolated events. Systems can be both difficult to model and difficult for managers to internalize. Even seasoned managers may be more skilled at seeing immediate causes and effects rather than the whole picture. The question is, "When should you deal with simple subsystems, and when should you consider the entire system?" Errors caused by treating systems as a sequence of problems to be solved one at a time, without recognizing or taking into account interactions, side effects, or repercussions of decisions, can lead to suboptimal or even catastrophic consequences [10].

2.2. Agent-Based Approaches

Agent-based modeling is a relatively new approach for modeling consumer markets. It is emerging as an exciting complement to traditional statistical approaches, since it offers the possibility of using business-driven rules for individuals (e.g., "I buy brand X because . . .") to determine holistic, system-level outcomes (e.g., "Brand X's market share is rising"). As agent-based modeling is a relatively new technique, and since this article presents an agent-based model of a consumer market, this section defines agent-based modeling and compares it with the traditional techniques discussed in the previous section.

2.2.1. Agent-Based Modeling and Simulation

This section presents a brief overview of agent-based modeling and simulation. More details can be found in Ref. [11]; here is a short summary:

1. Agents are autonomous decision-making entities or self-directed objects.
2. Agent-based models are made up of agents and a framework for agent interactions.

Agent-based modeling allows the behavior of system components (i.e., the agents) to be used to forecast the behavior of the overall system. Agent-based modeling is being used to simulate a wide range of systems. These include industrial supply chains [11], nascent economies [12, 13], international political systems [14, 15], possible future energy infrastructures [16], and complex commodity markets [17].

Although the commonly used traditional techniques for modeling consumer markets (discussed in the previous section) are powerful with regard to their purposes, they are generally not able to provide sufficient levels of detail with regard to the interdependent behaviors of consumers, retailers, and manufacturers. Some common interdepen-

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dencies include the reactions of consumers to combinations of retailers' and manufacturers' behaviors; the reactions of one retailer to other retailers' behaviors; the reaction of one manufacturer to other manufacturers' behaviors; the reaction of one retailer to the manufacturer's behavior; etc.

As previously mentioned, CPG manufacturing companies regularly make choices on what characteristics their products should have and what marketing strategies they should use. In making these decisions, they typically have to address many issues to ensure they will increase sales while adapting to marketplace changes. The example given—of how to react to a competitor's marketing campaign—generally requires the company to project the campaign's effects over time both on sales and on the consumers' view of the marketplace. The analysis of these situations is often difficult because of the complex sequences of interlocking, nonlinear[1] behaviors commonly found in large-scale, competitive CPG markets. (As mentioned, if one CPG manufacturer lowers its prices to increase sales, but competitors lower their prices too, the original manufacturer's sales may actually decrease.)

Some of the traditional methods discussed in the previous section can represent such interdependencies by using simplifying assumptions. However, they are still limited to predicting either (1) only a small number of steps into the future (because of the high rates of change that could be caused by the feedback that would take place between decisions) or (2) long-run averages that ignore the transient conditions that occur on the way to equilibrium. Furthermore, the level of detail required in order to practically apply these predictions can sometimes overwhelm the current capabilities of these traditional methods. The amount of data needed for an analysis is generally a function of the number of variables and their combinations that need to be estimated. In other words, these methods often require an enormous amount of data in order to be used. For example, if a company was considering lowering the price of a product and wanted to gauge the effect this reduction would have on consumers by using a traditional method, it would have to obtain data from a long period of time in the past when prices had previously been lowered in order to statistically predict the outcome of the new scenario.

[1] *The term "nonlinear" here means that changes in system outputs are not directly proportional to changes in system inputs. For example, consider two simple functions F(x) and G(x). If F(1) = 2, F(2) = 4, F(3) = 6, and so on, then F(x) is linear (actually F(x) = 2x). If G(1) = 2, G(2) = 4, and G(3) = 1,000,000, then G(x) is nonlinear. Marketplace relationships that abstractly resemble G(x) are very common.*

As stated earlier, traditional techniques tend to be limited in the (1) number of factors that can be included, (2) level of detail on each factor that can be accommodated, and (3) behavioral complexity that can be accounted for in each analysis. Consequently, they usually neither holistically represent the detailed interdependencies involved in the decisions of consumers, retailers, and manufacturers nor can they address the simultaneous need to computationally represent the inherently nonlinear behavior (e.g., learning and lock-in) found in marketplaces like the CPG marketplace. Traditional methods are typically not able to fully account for the fact that each market participant's subsequent decisions are intimately and sensitively dependent on all previous decisions by every market participant, including itself.

2.2.2. Agent-Based Modeling of CPG Markets

There is currently a small amount of work that applies agent-based modeling to CPG markets. The work can be broken up into two overall categories. The first one models the activity within individual retail stores. The second one models market-level purchasing trends. Both of these types of models are considered here.

The first major approach to the agent-based modeling of consumer markets focuses on consumer activity within individual retail stores. The main goal is to study store layouts or physical plans to improve store sales through better shelf placement of goods. Casti's "SimStore" retail store simulation is a good example of this type of model [18]:

> The starting point for SimStore is a real supermarket in the Sainsbury chain, one located in the London region of South Ruislip. The agents are individual shoppers who frequent this store. These electronic shoppers are dropped into the store, and then make their way to the various locations in the store by rules such as "wherever you are now, go to the location of the nearest item on your shopping list," so as to gather all the items they want to purchase.

The second major approach focuses on market-level purchasing trends by simulating the purchasing and usage choices of many individual consumers. The main goal is to improve the profitability of certain organizations by determining how and why consumers select certain products. Models of this type include those developed by Adjali, Dias, and Hurling [19]; Brannon et al. [20]; and Schenk, Löffler, and Rauh [21]. Related papers and articles covering other or more general types of consumer market modeling include those by Janssen and Jager [22]; Jager [23]; Jager, Janssen, and Vlek [24]; Said, Bouron, and Drogoul [25, 26]; and Collings et al. [27]. As described later, the virtual market learning lab is different from these efforts because of the comprehensiveness of its modeling

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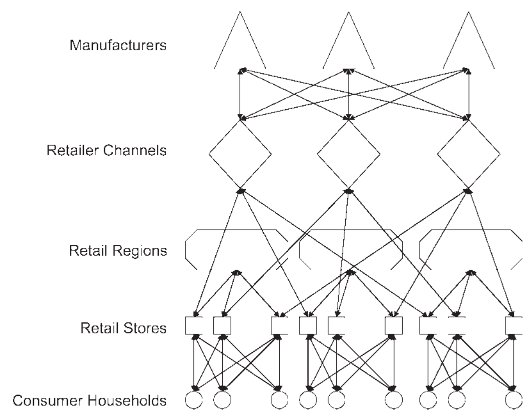
and the depth of the verification and validation it has undergone. The models by Adjali, Dias, and Hurling [19]; Brannon et al. [20]; and Jager, Janssen, and Vlek [24] are considered in more detail here since they represent a good spectrum of current work.

Adjali, Dias, and Hurling [19] describe "the architecture for an agent-based consumer behavior model drawing from the marketing and the behavioral sciences literature." It then shows "some simulation results exploring and comparing different consumer behavior models using real, individual-based market data." The Adjali, Dias, and Hurling model is based on a real map of a city and thus is more spatially detailed than the virtual market learning lab model. However, it is also more limited than the virtual market learning lab in terms of population size, and it does not model the complex interactions among retail stores, retail chains, and manufacturers. Thus, it is more detailed in one respect but less complete overall and less well validated than the virtual market learning lab.

Brannon et al. [20] discuss a model of the "consumer apparel purchase decision" process. The model uses a substantial set of psychological factors that involves motivations, preferences, and constraints to represent the methods used by consumers to choose items of clothing. The result is a detailed model of consumer choice that is interesting because it attempts to explicitly (rather than implicitly, like the virtual market learning lab) account for consumer identity and self image. However, the virtual market learning lab is a more complete model since it represents retail store, retail chain, and manufacturer interactions. The virtual market learning lab has also undergone more detailed verification and validation.

Jager, Janssen, and Vlek [24] discuss a model of consumer agents that uses a "consumat" approach. This approach is described as one that represents consumers who use a multitheoretical framework, which combines concepts from several different theoretical viewpoints. In particular, Jager, Janssen, and Vlek [24] cites "theories about human needs ..., motivational processes ..., social comparison theory ..., classical and operant conditioning theory ..., social learning theory, decision and choice theory ..., theory of reasoned action ..., theories on relative deprivation ..., and the theory of normative conduct." The Jager, Janssen, and Vlek framework combines these ideas by using (1) a two level "pressure system" that models group and individual forces, (2) a two-part "state system" that represents individual reasoned behavior and social orientation, (3) an "impact system" that defines the consequences of consumer choices, and (4) a policy "response system." The result is a rich description of consumer behavior. However, the virtual market learning lab models—and also the Adjali, Dias, and Hurling model and Brannon et al. model—are more complete since they represent retail store, retail chain, and manufacturer interactions. In addition, the virtual market learning lab has undergone more detailed verification and validation.

FIGURE 1



Overview of the virtual market learning lab agents and agent relationships.

3. VIRTUAL MARKET LEARNING LABORATORY

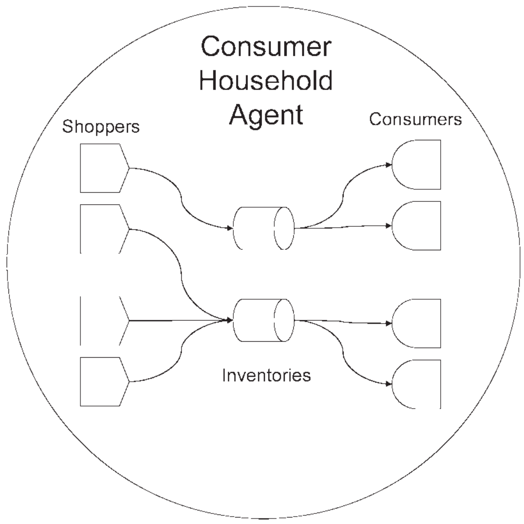
The virtual market learning lab is a large-scale, agent-based model of consumer markets codeveloped by Argonne and P&G. It represents the shopping behavior of consumer households and the business behavior of retailers and manufacturers in a simulated national consumer market. All of the major participants associated with one category of products (e.g., laundry detergent) are simulated during each model run. Figure 1 provides a high-level overview of the agents and agent relationships used in the model. Figure 1 itself may seem fairly simple. However, there is a high level of complexity and feedback inherent in the agent interactions. This complexity coupled with the need for detailed results precludes high-level parametric summarization.

The Figure 1 agents represent the major participants in CPG markets, such as consumer households, retail stores, retail regions, retail channels, and manufacturers. The agent relationships represent interactions, such as supplier options, competitive responses, and management directives. This section discusses the virtual market learning lab's design and implementation relative to the major actors and actions. It then outlines the model's usage.

3.1. Virtual Market Learning Lab Structure

The virtual market learning lab is an agent-based consumer market model that has been implemented by using the Recursive Porous Agent Simulation Toolkit (Repast)

FIGURE 2



Virtual market learning lab consumer household.

toolkit [28]. Repast is a widely used, free and open source, agent-based modeling and simulation (ABMS) toolkit that is available directly from the Web at http://repast.sourceforge.net [29]. The virtual market learning lab was originally developed by using Repast for Java [28] and was more recently upgraded to use Repast Simphony [30].

The virtual market learning lab uses consumer households to represent CPG purchasers and users. A household is a group of people who live together and, to some degree, coordinate their shopping. The virtual market learning lab's households are composed of shoppers, inventories, and consumers, as shown in Figure 2.

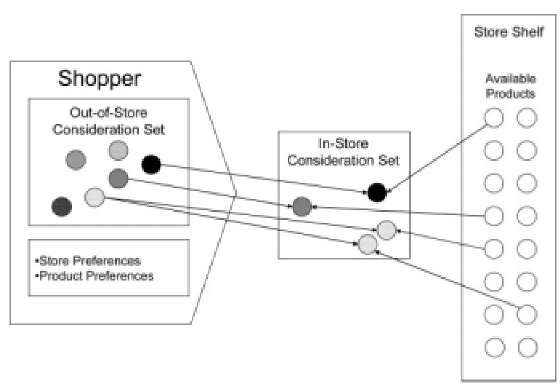
Virtual market learning lab shoppers purchase goods. A virtual market learning lab household can have any number of shoppers. Typically, each household has a primary shopper and possibly a secondary shopper. Shoppers purchase goods from retail stores and then place the goods into one of their household's inventories. Shoppers choose stores on the basis of their individual store preferences, which can evolve over time depending on the shopper's experiences in each store. Shoppers select goods on the basis of consideration sets.

Consideration sets are based on Miller's [31] well-known observation that normally people can remember and cognitively process at most, "seven plus or minus two items at one time." There are two kinds of shopper consideration sets: an in-store consideration set (ISCS) and an out-of-store consideration set (OSCS).

An OSCS represents the products, or abstractions of products, consumers have in mind when they shop. It contains weighted elements that model abstracted, but critical, features of store shelf items or stock-keeping units (SKUs). The critical features contained in each OSCS element are determined by the hierarchy of characteristics for the product category being considered. For example, each laundry detergent OSCS element contains a brand, a form (e.g., liquid or powder), and a benefit (e.g., bleach). The weights are used to account for advertizing exposure, advertizing decay, product usage experiences, and other issues or activities outside the retail stores.

An ISCS represents the short list of retail store SKUs that are candidates for purchase during the current shopping trip. The ISCS contains weighted lists of SKUs. The list of SKUs is generated by each shopper on each shopping trip, as shown in Figure 3. The generation process involves applying user-defined filters to match the shopper's OSCS elements to the SKUs available on the shelf of the retail store where the shopper is shopping. Filters, shown in Figure 4, allow model users to specify exactly how each shopper in a given category selects items from a store shelf. Filters are user input data that can be changed as needed by model users. Each shopper's filters are defined by using a filter sequencer and a tree of filter steps. The filter steps act as qualifiers. If a filter is executed successfully, then all of the "child" filters below it in the tree are also executed; otherwise, the child filters are ignored. Each filter step itself offers a highly configurable matching process that supports many kinds of individual examinations of and matches among store shelves, the OSCS, and the ISCS. Filter steps also allow SKUs to be added to, removed from, and reweighed within the ISCS. In addition, filter steps can modify the shopper's likelihood of purchasing a product on the current shopping trip. Any purchases made are stored in the appropriate inventory.

FIGURE 3



Virtual market learning lab shopper and store shelf.

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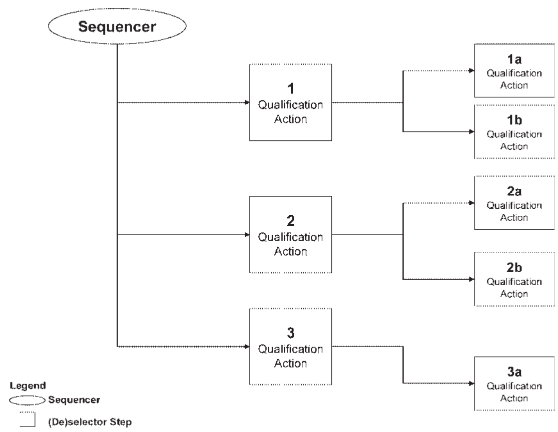
FIGURE 4



Virtual market learning lab shopper filters.

Household inventories represent the product stock kept within a given household. Households always have at least one inventory, but they may have more than one (e.g., an extra inventory for special stocks, such as snacks for invited guests). Inventories can be drawn down in several ways (e.g., sequential or parallel use of all stored items), depending on the category being modeled. Like shopper filters, inventory policies are user input data that can be changed as needed by model users. Inventory levels and other factors are factored into each shopper's purchase decisions. Multiple shoppers may contribute to each inventory (e.g., primary and secondary shoppers may supply the main household inventory). Each inventory, in turn, may act to supply multiple consumers.

Virtual market learning lab household consumers use the products stored in inventories on the basis of a flexible set of user-specifiable consumption amount distributions (e.g., a normal distribution). Virtual market learning lab household consumers are different than standard market consumers in the sense that standard market consumers purchase, store, and use products, while household consumers only use products. The purchasing and storage activities of standard market consumers are represented by shoppers and inventories, respectively. Like shopper filters and inventory policies, consumption behavior is user input data that can be changed as needed by model users.

Retail stores represent locations for purchasing goods in the given category. They are associated with stocked store shelves, advertizing flyers, product displays, temporary price reductions (sales), optional inventories, and other features. Retail stores are grouped into neighborhoods. Each neighborhood contains a set of competing stores, a population of shoppers who visit the stores, and a representative for each retail channel. As each retail channel may have a different number of stores (e.g., there are many more drug stores than club stores in the United States), individual stores may be in more than one neighborhood. Store membership in multiple neighborhoods creates the potential for networks of neighborhoods to form. The constraints for neighborhood formation are specified by the user within the input data.

Retail neighborhoods are grouped to form retail regions. Regions are used to reflect varying store stocks, promotions, features, preferences, etc. on a broad geographic basis. The number of regions used depends on the category and area being modeled.

Each retail store belongs to one of several retail channels. Each retail channel represents either a type of retailer (e.g., food stores) or a specific retailer. Channel-level data are used when there is a large number of small retailers that have similar stores and strategies or when higher-level results are needed. Data for specific named retailers are used when there are a small number of large retailers or when detailed results are needed. Hybrid combinations of channel-level and named retailers can also be used when mixtures of results are needed. In all cases, the retailer channel information is provided as user-defined input data.

Virtual market learning lab retail channels, regions, and stores can operate in one of two modes: scripted mode or rules mode. In scripted mode, stores follow a prespecified plan for stocking shelves, sales, etc. All channel, regional, and store behaviors can be activated through scripts. Scripts are normally specified as detailed input data. Scripted mode is useful for model calibration, some types of model verification and validation, simulation warm-up, and tests of specific situations of interest. In rules mode, retail channels, regions, and stores react to their current conditions by using individualized sets of strategies. Their reactions can be a function of various factors, such as recent profits, recent sales volumes, or selected targets. The reactions can include price changes, sales, promotions, or stocking changes at the channel, regional, or store levels. The virtual market learning lab retail channel, region, and store can move back and forth between scripted mode and rules mode during a simulation run as directed by model users through the input data.

Manufacturers function similarly to retail channels except that they produce rather than resell products. Like retail channels, they operate in both scripted and rules modes and can move between these two modes as directed by input data. Scripted mode can be used to activate any manufacturer behavior. Rules mode allows manufacturers to respond interactively to their environment and

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to change their behavior depending on the results they experience. Manufacturers have a variety of ways to react to their environments, including changes in offered SKU portfolios, advertizing, wholesale pricing, and trade support.

3.2. Virtual Market Learning Lab Usage

The virtual market learning lab is not intended to predict the future behaviors of market participants (e.g., the responses of P&G's competitors), and it is not intended to precisely predict future market outcomes (e.g., next year's market shares). Rather, it is intended to support testing of the robustness of market strategies and to allow an exploration of the potential drivers for trends. A competitive advantage can be gained by using the virtual market learning lab because it helps ensure that strategic decisions are made with a clear knowledge of the benefits and risks associated with each option.

As mentioned, the virtual market learning lab is intended to support robustness testing of market strategies. For example, imagine that a company is hypothetically considering reducing the price of one of its leading brands. The virtual market learning lab cannot determine if a competitor will reduce the price of its brand in response. However, it can automatically generate a range of potential response scenarios, each describing a possibility of what might happen in response to the initial price cut. If a large number of diverse response scenarios were executed and all of them were favorable, one might conclude that a price reduction would be relatively safe. However, if many of the runs were moderately unfavorable or a few runs were extremely unfavorable, one might conclude that a price reduction would be risky. Again, the virtual market learning lab would not predict market outcomes. It would simply allow a diverse range of potential market outcomes to be explored in an efficient and objective manner.

In addition to helping users analyze a possible marketing strategy, the virtual market learning lab is designed to help users explore the potential causes of trends. For example, imagine that there were several competing opinions on why one kind of coupon distribution schedule tends to increase sales much more than other kinds of coupon distribution schedules. It might be difficult and expensive to test these opinions in actual markets. The virtual market learning lab provides an efficient platform for testing each opinion. To complete the tests, input scenarios and possibly agent software that represented each of the candidate explanations could be configured and executed in the virtual market learning lab, often through many stochastic replications. The results from the model runs could then be compared to the observed market effects. If there were significant mismatches between the model results and the real market outcomes for a given opinion, one might conclude that that opinion is probably not correct, at least for the range covered by the observed data. The reverse may or may not be true since the model results might match the real world data for coincidental reasons other than the correctness of the opinion.[2] Of course, reproducing one market outcome does not guarantee that the theory is correct. However, this approach turns out to be powerful in practice. The virtual market learning lab has been used to demonstrate that several strongly held ideas about consumer behavior do not successfully reproduce observed market outcomes. This was accomplished by showing that each idea's predicted system-level consequences do not obtain from the agent-level hypotheses.

4. MODEL CALIBRATION, VERIFICATION, AND VALIDATION

For purposes of reference, model calibration, verification, and validation can be briefly summarized as follows:

1. Calibration fits a model's parameters to data from the real system.
2. Verification checks a model against its specifications.
3. Validation checks a model against observations of the real system.

For more detailed coverage of these topics, see Refs. [11, 32].

It is important to emphasize that there is no perfect model. In the famous words of George Box, "all models are wrong, but some models are useful." With regard to calibration, verification, and validation, this statement means that for practical purposes, each activity is a function of a model's intended purpose. Thus, practical models can never be universally correct but instead have the potential to be calibrated, verified, and validated for a given usage.[3] Thus, a critical issue for model calibration, verification, and validation is to define clearly the intended usage or usages of the model.

As previously discussed, the virtual market learning lab is being developed for the specific purpose of providing a

[2] *This is more generally known as the "model uniqueness problem," which is a philosophical challenge for all types of modeling.*

[3] *Even models from well-understood areas in the physical sciences and engineering have these limits. Consider the simple example of a civil engineering model that simulates the stresses on buildings by using specialized classical mechanics. Such a model may work well enough to allow complete buildings to be fully designed in silico. However, it is almost certainly invalid for simulating extremely small objects, since it lacks quantum mechanics, or very large or very speedy objects, since it lacks general relativity.*

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robust strategic planning test bed for brand management teams. Efforts testing the virtual market learning lab focused on calibration, verification, and validation for this usage.

4.1. Major Model Calibration, Verification, and Validation Methods

There are a variety of ways to calibrate, verify, and validate models. As the virtual market learning lab is a simulation, this section and later sections emphasize methods that support simulations. The major methods include design walkthroughs, code walkthroughs, manual tracing, manual comparisons, automated unit testing, and automated system testing.

Design walkthroughs involve presenting software designs (e.g., flowcharts) to domain experts or independent designers (i.e., designers who did not develop the modules under examination) and then manually stepping through example executions of the design. They allow domain experts and independent designers to confirm or refute the correct operation of the design. Code walkthroughs are much like design walkthroughs, except that they involve presenting software code to domain experts or independent programmers (i.e., programmers who did not write the modules under examination) and then manually stepping through example executions of the code. As with design walkthroughs, they allow the examiners to evaluate the code.

Manual tracing involves (1) executing a model line by line in a debugging program and confirming the correctness of the operation of the simulation or (2) logging the line-by-line execution of a model and then examining the resulting data in great detail. Manual comparisons involve logging the end results of model execution and then comparing these results to expected values derived from the model's specifications or against observed data from the real system.

Automated unit tests allow individual modules of software to be automatically executed independent of the rest of the model. As a result, the actual programmed behavior of software components can be checked against the behavior expected on the basis of the component's specifications or observed data from the real system. Similar to automated unit tests, automated system tests allow full programs to be automatically executed and checked against target data. Thus actual programmed behavior of complete programs can be checked against the behavior expected on the basis of the software's specifications or observed data from the real system.

4.2. Virtual Market Learning Lab Calibration, Verification, and Validation

Because of the virtual market learning lab's potential strategic influence, there is an extremely strong need for calibration, verification, and validation. In fact, all major releases of the model normally undergo an extensive and well-documented calibration, verification, and validation process that is made up of more than 60 steps. This process has three major phases: model development verification, model development calibration and validation, and model pilot study validation. Each of these activities is outlined in the sections that follow.

4.3. Testing Phase 1, Model Development Verification

In the verification phase, a model is checked against its specifications. The virtual market learning lab verification process involves the use of design and code walkthroughs, manual tracing and comparisons, and automated unit and system testing. In particular, major model releases are subjected to about 30 well-documented verification checks. The exact details of the verification checks are documented in the virtual market learning lab integrated testing plan (ITP) spreadsheet. The content of this spreadsheet is discussed in sections 4.1 to 4.5.

4.4. Testing Phase 2, Model Development Calibration, and Validation

In the calibration stage, a model's parameters are fitted to data from the real system, while in the validation phase, the model is checked against observations of the real system. In particular, major model releases are subjected to about 10 well-documented calibration steps and about 20 well-documented validation checks. Many of the tests are quantitative. The tests include manual tracing and comparisons and automated system testing. Furthermore, many of the quantitative checks have acceptance thresholds within 1–10%. An example verification check that compares virtual market learning lab results to the expected theoretical values is shown in Figure 5. This figure shows as a percentage on the *X*-axis the amount of a product that is used by a consumer normalized by the amount that was recommended by the manufacturer. One hundred percent means consumers use exactly the manufacturer's recommended amount. More than 100% means consumers use more than the recommended amount. The *Y*-axis shows the probability of each normalized usage level within a given sample population. The R^2 fit value between the 81 virtual market learning lab data points and the theoretically expected product usage distribution is 0.996. These results show that the model is correctly reproducing consumer product usage levels.

The data used for calibration and validation include the following:

- Household panel data that include detailed time-series purchase histories from hundreds of shoppers covering multiyear periods. The shoppers' identities are made suitably anonymous to avoid privacy issues.

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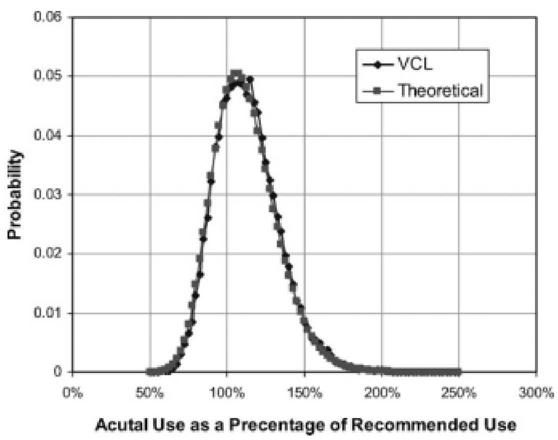
FIGURE 5



Verification check comparing virtual market learning lab results to theoretically expected product usage results ($R^2 = 0.996$).

- Scanner data from store checkout counters at a variety of retail stores. Again, the shopper's identities are made suitably anonymous to avoid privacy issues.
- Aggregate and time-series industry statistics, including market shares, sales volumes, and advertizing trends.
- Detailed industry data, including information on retail store shelf stocks, product pricing numbers, and product promotion counts.

The virtual market learning lab was calibrated and validated against two full sets of the above-mentioned data from independent sources. The sources were the two major companies that collect retail data: Nielsen and Information Resources Inc. (IRI). The following calibration and validation work was done:

1. A full set of IRI data for the laundry detergent and dentifrice categories were successfully used by Argonne and by P&G separately for calibration and validation, as outlined earlier.
2. A full set of Nielsen data for the laundry detergent and dentifrice categories were successfully used by Argonne and by P&G separately for calibration and validation, as outlined earlier.

The exact details of each calibration step and validation check have been fully documented in a virtual market learning lab ITP spreadsheet that is delivered with each major version of the model. The content of this spreadsheet is discussed in sections 4.1 to 4.4.

4.5. Testing Phase 3, Model Pilot Study Validation

In addition to undergoing the Phase 1 and 2 verification, calibration, and validation steps discussed above, the virtual market learning lab was tested during pilot applications for both the laundry detergent and dentifrice categories. These pilot application tests were conducted by P&G. The tests included manual tracing and comparisons and involved the following steps:

1. Virtual market learning lab input data were set up to reflect realistic scenarios of special interest to the P&G brand teams.
2. The model's ability to reproduce the conditions of interest observed in the real system was demonstrated to the brand teams.
3. Narratives of possible future scenarios and/or explanations for observed but otherwise unexplained or misunderstood market phenomena were provided to the teams.

When new explanations were provided for observed market phenomena, they were analyzed by brand team members and other domain experts. After investigation the explanations held up to scrutiny. Several have even been accepted within the virtual market learning lab user community as being genuinely "new learning" about the categories under study.

5. MODEL USE

In addition to being used to obtain new information about the categories under study, the virtual market learning lab was successfully applied by P&G to several challenging business problems. In these situations, it directly influenced managerial decision making and produced substantial cost savings. Furthermore, the model was recently calibrated to be used in an additional category.

6. CONCLUSIONS AND FUTURE WORK

As previously discussed, consumer markets have been studied extensively by means of a wide range of tools. Although many of these tools have been very successful with regard to achieving their particular purpose, they have generally not been able to provide enough detail on the interdependent behavior of consumers, retailers, and manufacturers. This gap has created a need for holistic models of consumer markets. As demonstrated by the virtual market learning lab, agent-based modeling is an approach that can be used to successfully create such models.

The next steps for virtual market learning lab development include increasing the level of geographic fidelity and moving to multiple product categories. These steps can allow the model to represent an even more comprehensive view of consumer markets.

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REFERENCES

1. Hahn, J.I.; North, M.J. Methods of creating and using a virtual consumer packaged goods marketplace; US Patent and Trademark Office Patent Application Number 20,080,086,364, 2006.
2. Leeflang, P.S.H.; Wittink, D.R. Building models for marketing decisions: Past, present, and future. Int J Res Mark 2000, 17, 105–126.
3. Little, J.D.C. Models and managers: The concept of a decision calculus. Manage Sci 1970, 16, 466–485.
4. Ehrenburg, A.S.C. Repeat Buying Theory and Application. North Holland Publishing Company, Amsterdam, 1972.
5. Nakanishi, M.; Cooper, L.G. Simplified estimation procedures for MCI models. Mark Sci 1982, 1, 314–322.
6. Guadagni, P.M.; Little, J.D.C. A logit model of brand choice calibrated on scanner data. Mark Sci 1983, 2, 203–238.
7. Chatfield, C.; Ehrenberg, A.S.C.; Goodhardt, G.J. Progress on a simplified model of stationary purchasing behavior. J R Stat Soc 1966, 129, 317–367.
8. Bucklin, R.E.; Lehmann, D.R.; Little, J.D.C. From decision support to decision automation: A 2020 vision. Mark Lett 1998, 9, 235–246.
9. Rogers, G.; Renken, T. The importance of shelf presentation in choice-based conjoint studies. Proceedings of the Sawtooth Software Conference, San Diego, CA, Sawtooth Software, Sequim, WA; October 2004; pp 137–144.
10. Dorner, D. The Logic of Failure: Recognizing and Avoiding Error in Complex Situations. Metropolitan Books: New York, 1996.
11. North, M.J.; Macal, C.M. Managing Business Complexity: Discovering Strategic Solutions with Agent-based Modeling and Simulation. Oxford University Press: Oxford, England, 2007.
12. Padgett, J.F.; Ansell, C.K. Robust action and the rise of the Medici, 1400-1434. Am J Sociol 1993, 98, 1259–1319.
13. Padgett, J.F.; Lee, D.; Collier, N. Economic production as chemistry. Ind Corp Change 2003, 12, 843–877.
14. Cederman, L.-E. Modeling the co-evolution of states and nations. Workshop on Simulation of Social Agents: Architectures and Institutions, Chicago, Illinois; Sponsored by Argonne National Laboratory, Argonne, Illinois, 1997.
15. Cederman, L.-E. Endogenizing geopolitical boundaries with agent-based modeling. Proc Natl Acad Sci USA 2002, 99, 7296–7303.
16. Stephan, C.; Sullivan, J. Growth of a hydrogen transportation infrastructure. Agent 2004 Conference Proceedings, Conference on Social Dynamics: Interaction, Reflexivity and Emergence, ANL/DIS-05-6; Co-sponsored by Argonne National Laboratory and the University of Chicago, October 7–9, 2004.
17. North, M.J.; Thimmapuram, P.R.; Macal, C.; Cirillo, R.; Conzelmann, G.; Koritarov, V.; Veselka, T. EMCAS: An agent-based tool for modeling electricity markets. Agent 2003: Conference on Challenges in Social Simulation, Argonne National Laboratory, The University of Chicago, Chicago, IL, October 2–4, 2003.
18. Casti, J. BizSim: The world of business—In a box. Complexity Int 2001, 8, 6.
19. Adjali, I.; Dias, B.; Hurling, R. Agent based modeling of consumer behavior. Abstract in Proceedings of the 2005 North American Association for Computational Social and Organizational Science Annual Conference, University of Notre Dame, Notre Dame, Indiana, 2005.
20. Brannon, E.; Ulrich, P.; Anderson, L.J.; Presley, A.B.; Thommesen, S. Agent-based simulation of the consumer's apparel purchase decision. National Textile Center Report I98-A09-A1, 2000.
21. Schenk, T.A.; Löffler, G.; Rauh, J. Agent-based simulation of consumer behavior in grocery shopping on a regional level. J Bus Res 2007, 60, 894–903.
22. Janssen, M.A.; Jager, W. Simulating market dynamics: The interactions of consumer psychology and structure of social networks. Artif Life 2003, 9, 343–356.
23. Jager, W. Simulating consumer behaviour: A perspective. In: Environmental Policy and Modeling in Evolutionary Economics; Faber, A.; Frenken, K.; Idenburg, A.M., Eds.; Netherlands Environmental Assessment Agency, 2006, Groningen, Netherlands. pp. 1–27.
24. Jager, W.; Janssen, M.A.; Vlek, C.A.J. Consumats in a commons dilemma: Testing the behavioural rules of simulated consumers. COV Report No. 99-01, Centre for Environment and Traffic Psychology, University of Groningen, 1999.
25. Said, L.B.; Bouron, T.; Drogoul, A. Multi-agent based simulation of consumer behaviour: Towards a new marketing approach. Proceedings of the International Congress on Modelling and Simulation (MODSIM 2001), Canberra, Australia. December 2001.
26. Said, L.B.; Bouron, T.; Drogoul, A. Agent-based interaction analysis of consumer behavior. Proceedings of the First International Joint Conference on Autonomous Agents and Multi-Agent Systems, Bologna, Italy, 2002.
27. Collings, D.; Reeder, A.A.; Adjali, I.; Crocker, P.; Lyons, M.H. Agent based customer modeling: Individuals who learn from their environment. Proceedings of the 2000 Congress on Evolutionary Computation, La Jolla, California, 2000.
28. North, M.J.; Collier, N.T.; Vos, J.R. Experiences creating three implementations of the Repast agent modeling toolkit. ACM Trans Model Comput Simulation 2006, 16, 1–25.
29. ROAD. Repast Organization for Architecture and Development (ROAD). Available at: http://repast.sourceforge.net. Accessed on 1 June 2009.
30. North, M.J.; Howe, T.R.; Collier, N.T.; Vos, J.R. Repast Simphony runtime system. Proceedings of the Agent 2005 Conference on Generative Social Processes, Models, and Mechanisms, ANL/DIS-06-5, Argonne National Laboratory, The University of Chicago. Chicago, IL, October 13–15, 2005.
31. Miller, G.A. The magic number seven plus or minus two. Psychol Rev 1956, 63, 81–97.
32. Law, A.M. Simulation Modeling and Analysis, 4th edn. McGraw-Hill: New York, 2006.

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