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Pharmaceutical market dynamics and strategic planning: a system dynamics perspective†

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Abstract

Competitive pressures are forcing pharmaceutical companies to develop even more effective product-based strategic plans, which have traditionally been derived from unarticulated mental models about the individual diseases and the role of various decision-makers within them. The industry is blessed with a wealth of patient- and physician-level data, but often this information is not leveraged to its full extent. System dynamics provides an operational framework for understanding and analyzing how the interaction of patient flow dynamics, physician prescribing/product adoption behavior, and the evaluation of therapy options drive marketplace behavior. By evaluating the response of such an integrated model to possible marketing initiatives, pharmaceutical firms can develop and ultimately execute more cost-effective strategic plans for their products. Copyright © 2011 System Dynamics Society.

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Effective models are those that help make better decisions, and people use such models every day – often without realizing it. Did you take an alternative route to work this morning to avoid traffic? Your revised path was the result of a mental simulation that predicted you could get to work faster with a "back roads" strategy. Have you ever reprimanded a child? Doing so is likely the product of a mental model that forecasts the long-term positive effects on the child's future behavior. Brushing your teeth, attending college, exercising—all are actions done with the expectation of a desired result sometime in the future. Though rarely explicitly represented or analyzed, mental models are often the implicit basis in our decision-making processes.

The situation is no different in the pharmaceutical world, where marketing strategies are developed based on expectations of their effects on drug sales, market penetration, perceived quality, etc. Such strategies are often the product of cross-functional teams working with implicit mental models. But mental models are difficult to communicate, impossible to analyze or quantify, and hard to evaluate (Forrester, 1971). As such, they often result in suboptimal decisions when it comes to strategy development and brand planning in the pharmaceutical industry, where profit maximization of new chemical entities (NCEs) is of increasing importance.

System dynamics models represent an operational way to translate mental models from the implicit to the explicit, allowing for a set of specific business questions to be addressed and analyzed. Many of our pharmaceutical clients find themselves asking strategic questions such as:

- How can we develop a more effective brand plan?
  - Should we grow the market, steal share from competitors, or create new markets?

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  - What key market segments are crucial to success of the NCE?
- How can we better leverage the wealth of data and institutional knowledge about the disease indication, patient behavior, and physician preferences?
  - How can our marketing programs impact the observed behavior of these important stakeholders in the disease marketplace?
  - What vital knowledge of marketplace dynamics is missing from our current information sources?
- How can we sanity check existing commercial assessment methodologies?
  - How likely are various forecasting outcomes?
  - What key assumptions drive the expected sales trajectory of the NCE?
- How can we design an integrated tool to link the results of proposed strategies to impact on the NCE's commercial assessment?
  - Is there a way to evaluate how potential marketing efforts will affect the disease marketplace?

Each of these questions boils down to gaining a better operational understanding of the fundamental processes driving the expected evolution of an indication marketplace. System dynamics models go beyond statistical correlations or regression algorithms to address the fundamental processes and interrelationships that define future results—the link between the *structure* of a system and its resulting *behavior* (Forrester, 1961; Richmond and Peterson, 1996). Understanding these key dynamic relationships is essential to effective strategic decision making and resource allocation in the pharmaceutical industry and beyond.

Understanding of the structure of an indication marketplace allows decision makers to formulate a better, more effective set of strategies for operating within it. Knowing the uptake trajectories of previously released compounds in the indication or isolated data on epidemiology, treatment paradigms, physician attitudes, and competitive products is not enough. Rather, an integrated approach that combines the effects of these operational factors can not only explain the sales trajectories for product analogs, but also provides a means to quantify such key dynamic questions as:

- How many patients are newly diagnosed each year?
- How many patients are switching treatments?
- What drugs are they switching from and to?
- How are changing patient demographics and/or epidemiology likely to affect the key patient dynamics?
- How quickly do physicians progress through stages in their acceptance of a new compound?
- How do marketing levers affect the speed at which that diffusion takes place?
- How do evaluations of current and future therapies impact overall marketplace behavior?

Answering questions such as these depends on a clear understanding of marketplace dynamics and the structure/behavior paradigm—links that are pervasive but often unexamined in the pharmaceutical industry. To address these types of questions, we have developed a basic but expandable framework that combines aspects of patient flow dynamics, doctor adoption of pharmaceutical products, and the perceived treatment attractiveness of the therapy options within a disease marketplace, as shown in Figure 1.

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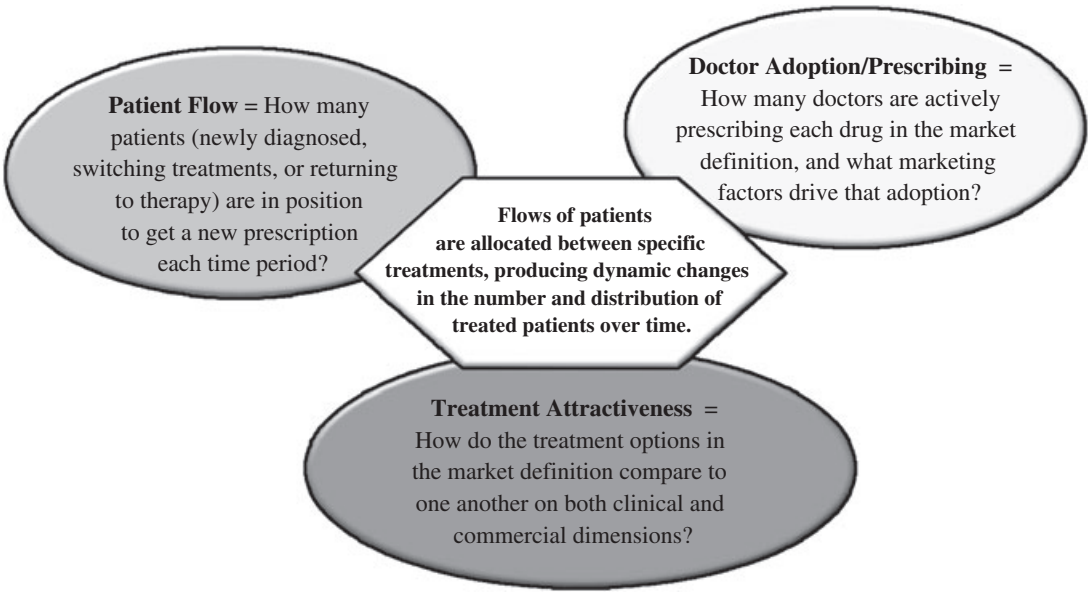

Fig. 1. Three components of integrated framework for pharmaceutical markets (Reproduced from Paich *et al.*, 2009, by permission)

These components are populated with data from epidemiology and a wide variety of physician and patient databases to ensure a robust representation of actual market dynamics. Merging these three structural pieces into a simulation model determines what drugs patients receive, how long they remain on treatment, how they transition between therapies, how rapidly doctors accept newly released compounds, and the evaluation of available treatments in the marketplace. Leveraging this knowledge in an operational simulation environment provides the means for pharmaceutical firms to test the effects of various strategic initiatives.

Patient flow

From a business perspective, the operating principle for pharmaceutical products is getting patients to try and continue to use a particular drug therapy. Pharmaceutical firms often obtain data on the number of prescriptions written and/or filled, as prescriptions can be translated into a revenue estimate for a particular drug in a given indication. Early commercial assessments of NCEs often employ statistical analysis to produce projections of the numbers of prescriptions in an indication marketplace through time. Quite often, however, forecast methodologies do not address the underlying factors that determine how prescriptions are created in the marketplace. From an operational or causal standpoint, patients generate prescriptions when they:

- initiate prescription treatment for the first time;
- switch from one treatment to another;

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- return to treatment after having been not treated for a certain time;
- refill their existing prescriptions periodically.

These treatment opportunities represent the flow of patients in a given indication over a specific period of time. There is a famous saying that getting an education at MIT is like trying to take a sip from a fire hose. The same principle applies in a pharmaceutical context, but relates to the flow of patients moving within a marketplace and the number of those patients captured by individual compounds. *Operationally, the volume of patient flows and their allocation between various treatment options in a marketplace fundamentally determine how the magnitude and associated shares of patients/prescriptions/revenues will change over time.* From a strategic standpoint, the questions for brand planning teams become: "How big are the relevant patient flows, how might the volume of such flows be influenced, how many patients might each treatment option capture, and what are the cost/benefit tradeoffs for strategies that might influence any of these dynamics?"

To capture these dynamics, we have developed a stock/flow framework (Figure 2) incorporating epidemiology, treatment options, and compliance/persistence metrics to evaluate and analyze patient behavior in individual indication marketplaces. Diseases integrating well into this framework tend to be chronic (lifetime diseases with no cures, only treatments), have defined pharmaceutical treatment options (data are available on what types of treatment patients receive), and exhibit high rates of patient churn (patients often discontinue, reinitiate, and/or switch treatments during the course of therapy).

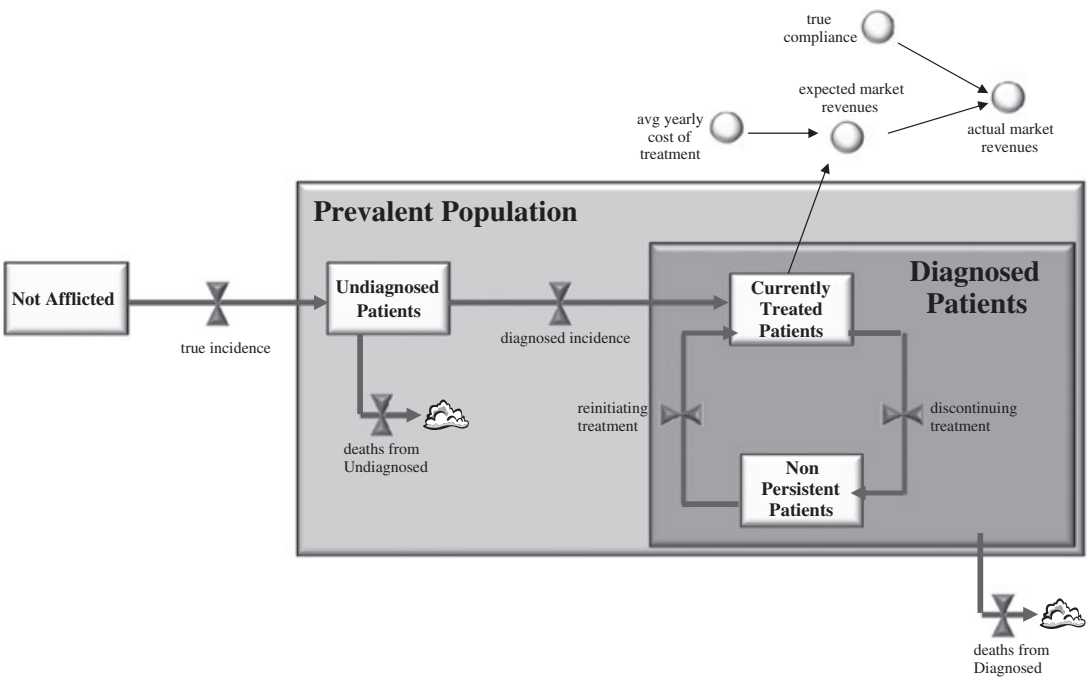

Fig. 2. Market revenue calculation using basic patient flow structure (Reproduced from Paich *et al.*, 2009, by permission)

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Epidemiology

Epidemiology reports often center on concepts of prevalence and incidence (Milstein *et al.*, 2007). In the stock/flow language of system dynamics, the former represents where patients exist *at a single point in time*, and prevalence is therefore a stock concept. Prevalence is often expressed either as a percentage of the population that has a particular disease at a point in time, or as an absolute number of people with that condition.[1]

The concept of point prevalence can be further divided according to prevailing diagnosis rates, which categorizes patients as either undiagnosed and diagnosed. Projections of disease epidemiology vary by methodology, so some triangulation may be necessary to understand differences in epidemiology forecasts. Some published research uses sophisticated trend analysis to project changes in demographic segments such as age, race, and gender, to which segment-specific prevalence rates are applied to produce an integrated forecast of disease prevalence.

A distinct advantage of a system dynamics model is the integration of forecasts with a stock/flow framework, which when coupled with mortality rate information allows the associated epidemiology flows to be determined by filling out the basic epidemiology picture.

The inflow to the stock of Prevalent Population is, by definition, *true incidence*—the number of patients that develop a particular disease over a period of time (usually a year). Patients generally develop a chronic disease physiologically before being diagnosed, so *true incidence* is an inflow to the stock of Undiagnosed Patients. Two things can subsequently happen to these patients after some period of time. One, they can die before being diagnosed, as is represented by the first outflow of *deaths from Undiagnosed*. Alternatively, they can be diagnosed with the disease and enter the stock of Diagnosed Patients through the flow labeled *diagnosed incidence*. In chronic diseases, a diagnosed patient is "red-flagged" for life—once a diabetic, for example, always a diabetic. Without the possibility of true recovery from the illness, the only way to exit the Diagnosed Patients stock, unfortunately, is to die and exit the system through the *deaths from Diagnosed* outflow.

Although prevalence forecasts rarely include estimates of incidence, these very important flows can be back-calculated fairly easily with disease-specific mortality data. The operational accounting of the system dynamics approach means that if a stock (such as Diagnosed Patients) is projected to increase by 20,000 over a forecast interval, then the cumulative inflows (*diagnosed incidence*) must have exceeded cumulative outflows (*deaths from Diagnosed*) by 20,000 over that time frame. Such incidence calculations are often a simple yet insightful output of even a very basic patient flow model.

Compliance and persistence

Compliance and persistence are frequently used terms in the pharmaceutical industry, sometimes interchangeably and often inconsistently. In general, these words are intended to imply the "falloff" that occurs when attempting to translate epidemiology into revenue dollars. However, there is an important dynamic and psychological distinction between compliance and persistence that static analyses often ignore.

Stock/flow structure depends on precise definitions, and the vagueness surrounding an aggregate compliance/persistency term requires clarification. Compliance is a continuous measure of the therapy volume a treated patient actually uses versus the amount prescribed. For example, a diabetic patient taking five pills in 10 days for a drug

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prescribed as a once-a-day therapy would have a 50 percent compliance rate. A 50 percent compliance rate cuts expected drug revenues in half, as prescriptions intended for monthly refill are instead refilled every 60 days. In strict terms, compliance relates to treated patients that are still revenue generating (albeit at a reduced rate) and true compliance rates can easily be determined from analysis of longitudinal patient databases.

The term *persistence* represents the average time a patients stays on a particular drug, and it encompasses two different dynamics: either switching drugs or discontinuing therapy entirely. To address the latter, the model introduces a concept of Non Persistent Patients: those who are no longer taking *any* form of prescribed medication.

The dynamics surrounding Non Persistent Patients are important in many chronic indications, and many companies focus on patients *discontinuing treatment*. However, the flow labeled *reinitiating treatment* is often neglected but is quite important dynamically. If patients only discontinued treatment (all else being equal), the stock of Non Persistent Patients would increase over time. In fact, for the distribution of the stocks to be fairly constant over time (a situation called steady state), the magnitude of the *discontinuing treatment* and *reinitiating treatment* flows need to be roughly equal. Depending on the relative rates of therapy switching versus discontinuation, the *reinitiating treatment* flow often represents a large opportunity for capturing patients as they return to therapy.

By definition, true compliance should apply only to the Currently Treated Patients stock, as the dynamic structure has explicitly accounted for the Non Persistent Patients who are taking no medication. Auxiliary variables and connectors can now be incorporated to augment the stock/flow diagram. The auxiliary variables dealing with *avg yearly cost of therapy* and *true compliance* metrics allow for market revenues to be easily calculated. Recall that the simulation model is not limited to yearly averages, however, and actually computes monthly (or even weekly) revenues based on the dynamics in the system.

Explicitly capturing the operational differences between patient compliance versus treatment persistence often helps identify key strategic levers for pharmaceutical firms. Cases in which patients remain on therapy but do not take all of their daily medication may suggest a compliance program strategy designed to track compliance of patients and enact marketing programs designed to increase this metric. Conversely, identification of low true persistency rates may suggest a strategy designed to keep patients from discontinuing treatment entirely.

Segmenting

The final piece to the structure is the disaggregation of Currently Treated Patients into various categories, such as age, gender, disease severity, and form of treatment. Current simulation software can easily handle this segmentation process in a wide range of dimensions, and the wealth of data in the pharmaceutical industry can be used to support these efforts. From a dynamic perspective, however, the key disaggregation deals with the various forms of treatment options. This expansion of the model:

- categorizes and tracks patients according to a defined set of therapy options;
- quantifies therapy change dynamics that often prove to be major drivers of market performance;
- forecasts individual drug revenue specific to an indication.

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To include individual treatment options, a defined set of currently available and pipeline therapies (including possible combinations) must be established. We have found that the concept of a Mutually Exclusive, Collectively Exhaustive (MECE) competitive set (popularized by McKinsey & Company; Rasiel, 1999) provides the clearest and most robust way to categorize therapy options. MECE means that the treatment option set completely covers the spectrum of possible therapy choices, but does not allow patients to be on more than one treatment option at any given time.

MECE designations are important for a number of reasons, as they:

- provide a framework for consistent data collection and analysis;
- avoid double counting of patients (a problem that often plagues forecasting efforts);
- reflect actual practice by treating combinations as individual therapy options;
- allow the dynamics of therapy changes to be categorized and quantified;
- incorporate data collected at the patient level;
- support the projection of patient-level data to overall epidemiology information.

The stock/flow model structure can now be disaggregated to accommodate this newly established MECE set. First, the stock of Currently Treated Patients is broken down into segments, creating "slots" for each element in the treatment option set. Diagrammatically, the stock takes on a three-dimensional appearance indicating the presence of treatment segments are shown in Figure 3. (Note that the flows into and out of each disaggregated/segmented stock will be broken down into the same dimensions; these details, as well as the mortality flows, are not shown for the sake of diagram simplicity.)

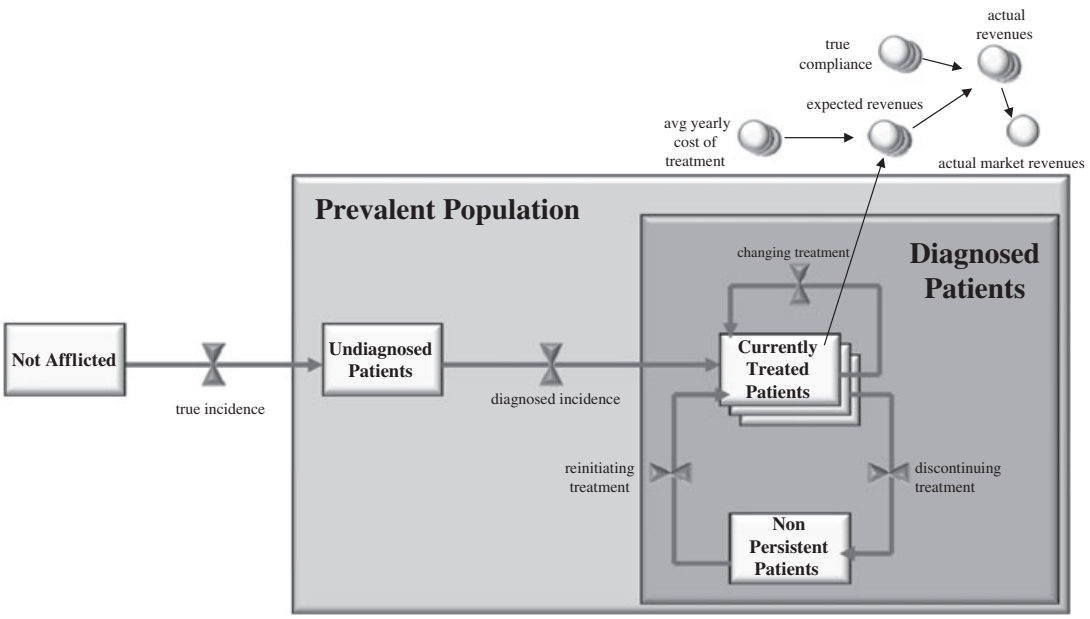

Fig. 3. Treatment option revenue calculating using disaggregated patient flow structure (Reproduced from Paich *et al.*, 2009, by permission)

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The number of elements or "stacks" is not limited by software technology, but rather by the ability to collect and analyze data in a model that is both useful and usable. In our experience, 15–20 treatment options in the MECE set represent the practical upper limit for the number of therapy choices.

With the MECE set established, the important dynamic of therapy changes can be included. Operationally, changes in treatment represent opportunities to capture patients and direct them to a specific therapy option. Recall that the stock of Currently Treated Patients is the basis for generating revenues in pharmaceutical marketplaces. A basic tenet of system dynamics, however, is that the number and distribution of Currently Treated Patients change as the result of the relative magnitude of the flows attached to it. Clearly, categorizing and quantifying these therapy changes is of vital importance from both a forecasting and strategic planning perspective. Establishing a MECE set and integrating it with the stock/flow structure allows the model to capture the operational dynamics that ultimately drive patient (an hence prescription/revenue) numbers.

Some points to notice in this expanded diagram include the following:

- The stacked stock labeled Currently Treated Patients shows that patients are being tracked according to individual treatment options.
- The curious flow labeled *changing treatment* allows patients to move between elements in the MECE treatment set. In other words, these patients remain Currently Treated, but are transitioning from one therapy option to another.
- Each of the auxiliary variables can now be segmented by the treatments included in the MECE set. Treatment-specific data such as *avg yearly cost of therapy* and *true compliance* can be used to calculate *actual revenues* for the individual drugs, which can then be summed up to arrive at *actual market revenues*.

The *changing treatment* flow occupies a small portion of Figure 3, yet captures some very important dynamics that ultimately drive market evolution. Patients *changing treatment* can go *from* any treatment option in the MECE set *to* any other option over a given time period. These treatment change dynamics can be conceptualized in a two-dimensional matrix or grid, and this flow of therapy transitions is often the primary driver of patient shares and marketplace evolution (particularly in well-established indications).

With this basic patient flow structure established, our attention can now turn towards how these flows are actually allocated between options in the MECE choice set. Doing so requires us to investigate the role of physicians, and their evaluations of treatment options for the disease, to get a fully integrated model.

Doctor adoption of pharmaceuticals

In pharmaceutical markets, newly released treatments must first be accepted by prescribing physicians before they can reach the hands of interested consumers. In effect, doctors are an intermediary and rate-limiting step in the diffusion of products into the marketplace. In many pharmaceutical markets, historical data can be analyzed to determine how quickly drugs in a particular indication were adopted by prescribing physicians. Prospectively, market researchers often collect data on awareness of drugs that have yet to be launched and conduct surveys on doctors' expectations regarding their future prescribing patterns. This

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information, while useful, does not explicitly capture the mechanisms at play in both past and future adoption of pharmacological treatments by doctors, nor does it indicate how such dynamics might respond to various marketing initiatives.

Our approach utilizes a physician adoption structure that is well documented in the system dynamics literature and can be used to analyze the historical behavior of various drug analogs for a particular indication. This methodology establishes a visual, operational representation of the doctor adoption process, and involves a translation/extension of the popular Bass diffusion model (Bass, 1969). The framework first breaks up the universe of possible consumers (physicians, in this case) into those who have adopted the product and those who have not yet done so.[2] Bass diffusion models then further investigate the influencers of adoption (as shown in Figure 4), which in broad terms can be grouped as:

1. *internal influence*: word of mouth within the population;
2. *external influence*: the effects of advertising, promotion, marketing, etc.

In this formulation, the *word-of-mouth factor* variable represents the strength or effect of Adopters on the *adopting* flow. In essence, this variable says: "How many Potential Adopters does each Adopter persuade to purchase the product each time period?" Though not explicitly shown, the *external influence* variable can itself be driven by different types of marketing initiatives, such as detailing (sales representatives spending time with individual doctors), sampling (distributing free trial samples to physicians) and medical education (large symposia attracting prescribing physicians).

Doctor adoption frameworks often begin with general analyses of physician behavior that can then be disaggregated into more detailed doctor segments along lines of specialty, geography, and even disease-specific characteristics. For example, general practitioners (GPs) may be accounted for separately from specialists in an indication, including word-of-mouth or referral patterns between these two groups of potential treating physicians. System dynamics models often include adoption of drugs specific to certain patient segments—a feature which is especially useful for indications in which physicians may readily accept a new treatment for their most severe patients, for example, but not for patients suffering from

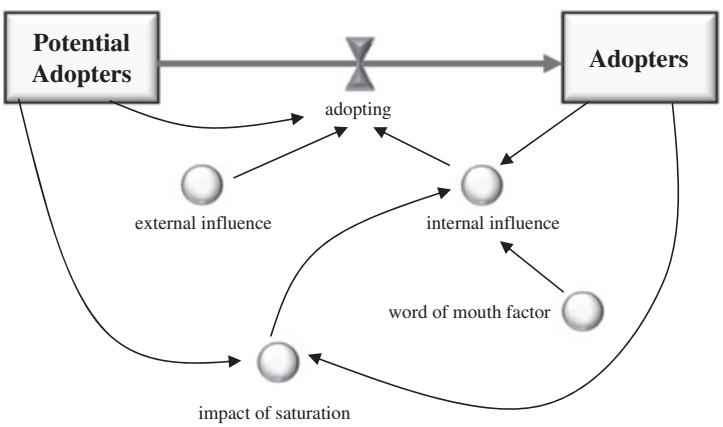

Fig. 4. Basic stock/flow structure of Bass diffusion model (Reproduced from Paich *et al.*, 2009, by permission)

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only mild symptoms. The ability to incorporate and test the adoption behavior of different physician segments provides a more realistic and detailed picture of how effective marketing strategies related to physician acceptance of products can best be developed.

The simple structure shown in Figure 3 can now be expanded to account for historical behavior of pharmaceutical offerings in a particular market. By including the dimensions of product recognition and prescribing behavior, the stock/flow representation replicates the metrics of awareness, trial, and usage (sometimes abbreviated as ATU) commonly collected and analyzed by many pharmaceutical companies. The framework is segmented to track physicians' adoption of specific treatment options in order to match the MECE designation of therapy choices outlined previously, as shown in Figure 5.

The *awareness target* variable in Figure 5 is usually a time-based scenario concerning company goals regarding overall product awareness. Operationally, the concept of awareness over time is generated by the rate at which a pharmaceutical firm can enable physicians to *become aware* minus the rate at which they forget about a certain product and return to the Unaware category (for diagram simplicity, this flow is not shown). The adoption metrics of *external* and *internal influence* remain from the generic Bass diffusion structure, and can easily be extended to account for various marketing levers at a pharmaceutical firm's disposal.

Some definitions related to Figure 5 are necessary to ensure proper interpretation:

- The stock/flow structure is intended to represent the entire universe of doctors who might prescribe a particular drug for a specific indication.
- The stock labeled Aware/Prescribe on a Trial Basis represents doctors who know about the product, might occasionally give out a sample or prescribe the drug on an experimental basis, but are not active prescribers of the drug.
- Prescribers are physicians who actively use the drug to treat some, but not all, of their patients suffering from a particular indication. In other words, this designation does not

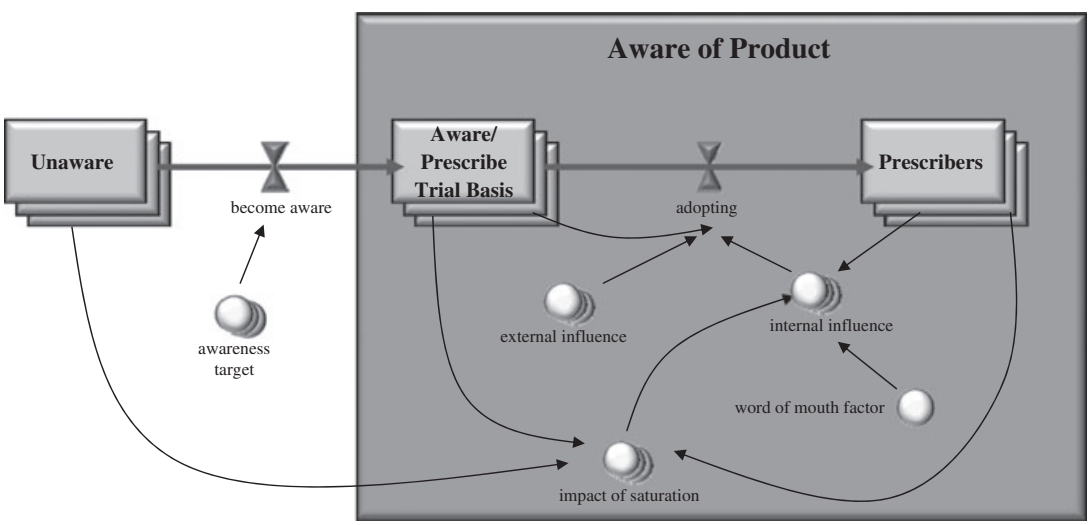

Fig. 5. Extended Bass diffusion model of adoption of pharmaceutical products by physicians (Reproduced from Paich *et al.*, 2009, by permission)

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imply that physicians must be exclusive prescribers of a particular drug, but only that the drug in question is in their consideration set and thus a viable option when choosing a pharmaceutical treatment for their patients.

The stock/flow structure relating to doctor adoption of pharmaceuticals allows for analysis of previously released products in a particular indication. Often such investigations are completed with the aim of forecasting expected adoptions of soon-to-be released NCEs and/or to determine the factors contributing to successful launches of previously released compounds. Doing so provides marketing teams with a better understanding of this important dynamic in pharmaceutical markets, a tool to forecast expected adoption (based on historical analogs) in a specific indication, and a structure that can be easily integrated into the basic patient flow framework. This process allows a marketing team to formulate more effective strategies related to physicians, as well as to understand the impact of those initiatives on the disease marketplace.

Our clients often use a doctor adoption framework to address various strategic options, such as:

- Would higher awareness early in the launch of an NCE result in faster adoption on the part of prescribing physicians?
- How would changing the expected marketing mix affect the speed and magnitude of the diffusion path?
- How strong is the word-of-mouth (the auxiliary variable *internal influence*) dynamic in the adoption process, and are there any strategic levers to affect it?
- How important is the overall Prescriber status when this component is integrated with patient flow and treatment attractiveness dynamics?

These questions, framed and ultimately answered using system dynamics, can be of extreme importance in establishing an effective strategic plan for the launch of an NCE, resulting in a more effective allocation of limited marketing resources.

The final component of an integrated system dynamics model of pharmaceutical marketplaces includes physicians' evaluations of treatment options for a particular disease.

Treatment attractiveness and choice modeling

Pharmaceutical markets are interesting in that physicians evaluate and then choose between available products but patients are the ultimate end-users of the chosen therapy option. Since in most cases doctors make the decision regarding the appropriate prescription regimen for their patients, treatment attractiveness should be viewed through the eyes of prescribing physicians. Direct-to-consumer (DTC) advertising efforts, the evolving role of nurse practitioners or pharmacists, and wider access to prescription drug information are slowly influencing this paradigm, but physicians are still the primary drivers in the prescribing decision.

Treatment attractiveness is an overall metric of utility that can be a function of product attributes such as safety, side effects, and price. As such, it can be viewed as the means through which doctors make prescribing decisions. The evaluation of attractiveness can also be tied to specific patient segments or physician specialties in order to more closely replicate differential evaluations in a complex pharmaceutical market. However, to

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incorporate concepts of attractiveness/utility of various pharmaceutical offerings for a given indication, we must depart from the operational "physics" of stock/flow structures to a slightly more calculation-based approach.[3] First, the overall utility of each treatment option needs to be determined using objective criteria. This process of determining the individual treatment attractiveness scores for each element of an MECE treatment option set has one goal in mind: *an evaluation of utility for each therapy regimen on a consistent, bounded scale.* These scores (typically on a scale of 0–100) can then be incorporated into a choice algorithm that determines the allocation of the flows of patients in the integrated model.

Determining treatment attractiveness

Pharmaceutical products rarely have published or agreed-upon metrics of product utility, so in most cases marketing teams need to come up with such evaluations internally. Typically the approach involves input from key opinion leaders (KOLs), market researchers, and the firm's own clinical and medical teams. A number of factors can impact the aggregate utility evaluation for treatment options in a given indication, such as:

- safety;
- efficacy;
- side effects;
- tolerability;
- mode of administration;
- onset of action.

The relative importance of these causal factors is vital in determining aggregate treatment attractiveness. A therapy's safety profile, for example, may be a hugely important issue if drug toxicity problems plague the current treatment landscape. In other markets with well-established and comparable products in terms of efficacy, the side effect attribute may be the key determinate of overall treatment attractiveness. Assigning importance to each treatment attribute will establish what percentage each factor plays in the weighted average calculation of aggregate evaluation of utility, as shown for a hypothetical NCE in Table 1.

Pharmaceutical teams must also assign relative rankings by treatment attribute for each therapy in the MECE set. In our experience, team members from various company functions have access to different data sources and perspectives that can help provide a much more comprehensive evaluation of utility. For example, market share information may provide a

Table 1. Example treatment attractiveness calculation for hypothetical pharmaceutical product[a]

Treatment attribute	Weighting	Rating	Calculation
Efficacy	30%	50	15
Safety	30%	80	24
Onset of action	25%	40	10
Side effects	15%	20	3
Total			52

[a]Reproduced from Paich *et al.* (2009), by permission.

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rough estimation of how products are being accepted in the marketplace. Clinical trial data often provide valuable product comparisons across dimensions of attractiveness such as efficacy or side effects. Also, primary market research may have data on the strengths and weaknesses of drug options in the market. Incorporating this knowledge from each function allows for a more accurate view of the treatment landscape to emerge.[4]

The hypothetical evaluation calculation (shown in Table 1) indicates that the overall treatment attractiveness score for this particular drug is just about average: 52 on a 0–100 scale.[5] This process is repeated for every treatment option in the MECE set, resulting in a complete universe of utility metrics that can now be integrated into a choice algorithm which will drive physicians' prescribing distributions.

Choice modeling

In order to integrate treatment attractiveness scores into the described patient flow and doctor adoption frameworks, we need to establish an algorithm to translate calculated utility into physician behavior. There are myriad choice models to be found in the marketing literature (Lilien *et al.*, 1992), but in our experience a logit choice formulation is often the most useful.

Readers might experience bad flashbacks to college calculus courses, but in fact the calculations behind a logit choice model are not too onerous, as shown in Eq. 1:

Equation 1: Logit Choice Formulation

$$S_n = e^{x*U_n} / \sum e^{x*U_n}$$

where S_n is the share for treatment n, e is Euler's number (~2.718), x is a constant to be solved for (in order to calibrate to historical data), U_n is the utility/treatment attractiveness score for treatment n, and $\sum e^{x*U_n}$ is the sum of all utility scores multiplied by some constant (x) when used as a power of e.

In effect, the logit formula uses exponents to accentuate the differences in utility scores as they are converted into physician choices. A small value of x translates into equal shares for all treatment options, while a large value of x indicates that minor differences in treatment attractiveness result in major differences in the resulting physician choice shares. Typically x is determined statistically through an analysis of historical data and/or primary market research regarding physician responses to product profiles. For modeling purposes, the derived treatment attractiveness scores can be plugged into this logit choice formulation to determine the distribution of therapy choices within the universe of prescribing physicians. These two components, when integrated with the patient flow framework, begin to give a robust, operational picture of the key components driving behavior in a particular disease area.

Integrating patient flow, doctor adoption, and treatment attractiveness/ choice algorithm

The components of patient movement, physician prescribing patterns, and therapy evaluations (translated through a logit function) can now be combined to form an integrated system dynamics model of the pharmaceutical market for a given disease (as shown in Figure 6).

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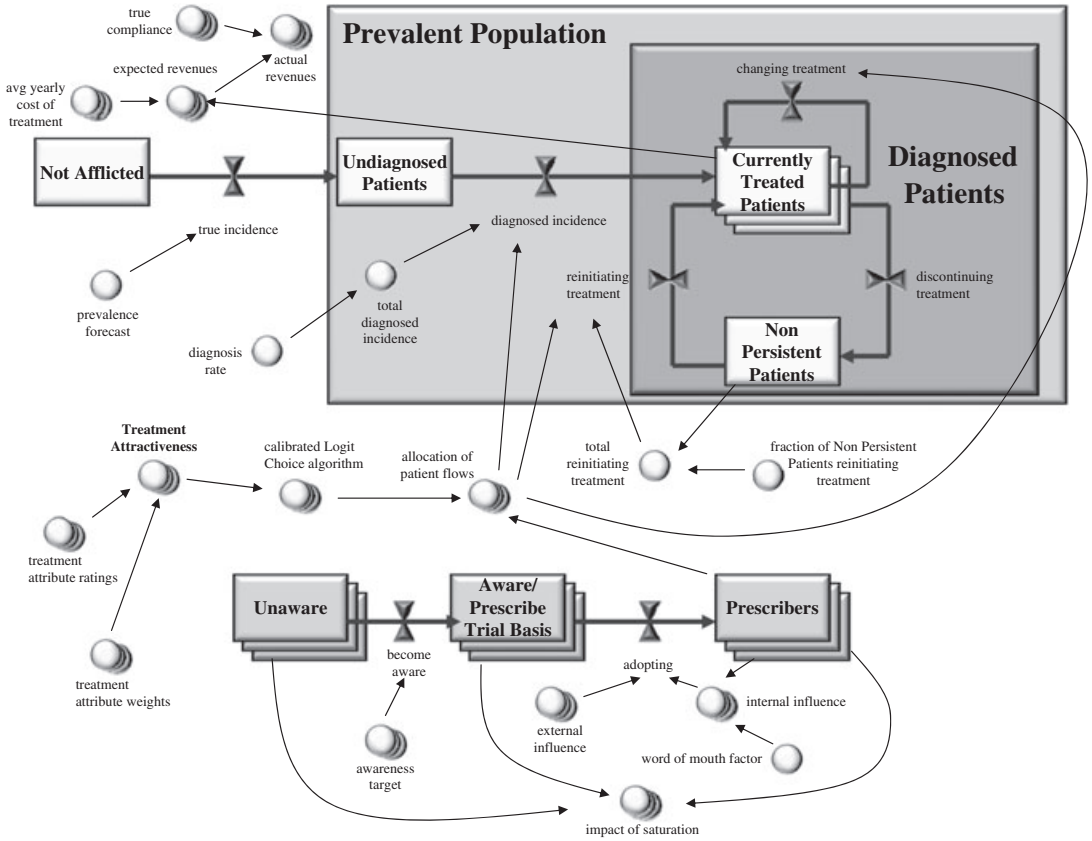

Fig. 6. Integrated model of three main components found in pharmaceutical markets (Reproduced from Paich *et al.*, 2009, by permission)

In our experience, pharmaceutical teams appreciate the visual/operational nature of such models (which helps render their collective mental models) as well as the fact that these structures can be simulated to test the response of the marketplace to various strategic initiatives. Doing so provides a low-cost "virtual testing ground" for developing more effective marketing campaigns. For example, teams often develop a set of "best guess" or "most likely" input parameters to populate such an integrated model, and then test the response when the magnitude, timing, sequencing, and/or combinations of these causal factors is changed. Figure 7 shows the results of a very simple set of experiments, which can begin to help pharmaceutical teams understand the driving forces in the marketplace.

Typically the first round of testing simply involves the response of the model to alternative assumptions in order to find areas of high sensitivity——places where small changes to one or more model components results in dramatic shifts in simulated outputs. Next, pharmaceutical teams evaluate the feasibility of affecting those portions of the model through their strategic marketing initiatives. Some components of this integrated system dynamics model are not really influenceable—prevalence of the disease, for example. But many input parameters can in fact respond to external influence, such as

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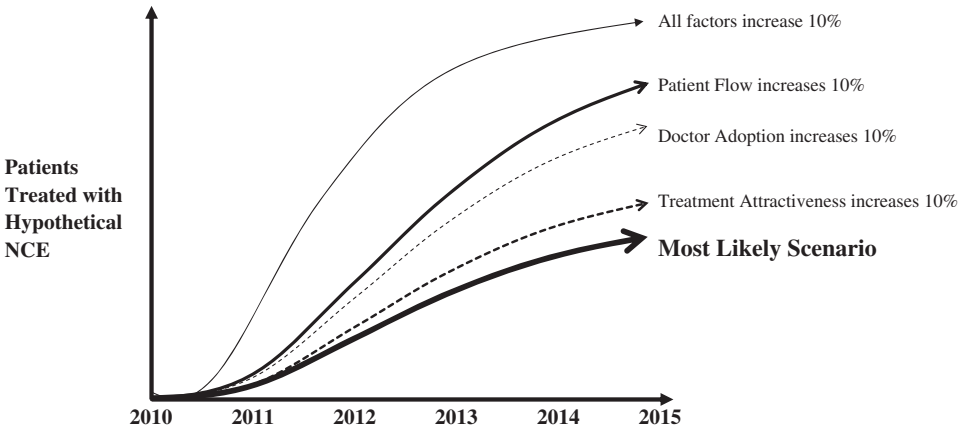

Fig. 7. Impact of changes in magnitude of three main components on model results (Reproduced from Paich *et al.*, 2009, by permission)

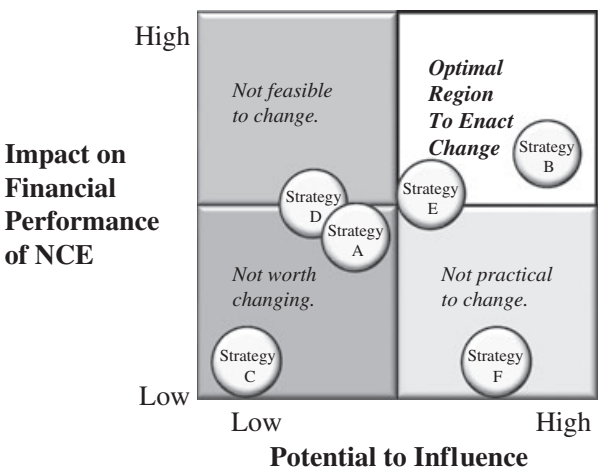

Fig. 8. Framework for evaluating model results for the purposes of strategy development (Reproduced from Paich *et al.*, 2009, by permission)

patient behavior (compliance, persistence, switching between treatments), physician adoption (subject to marketing levers such as detailing, medical education), and even treatment attractiveness (changing the perceived utility of an NCE). Finally, the pharmaceutical team can assess the expected cost of changing a set of sensitive input parameters to develop a cost/benefit analysis of various strategic initiatives. Effective marketing plans are designed to target model components that are easy and/or inexpensive to change, but that have a significant impact on model results. As shown in Figure 8, using the integrated system dynamics approach can help pharmaceutical teams arrive at a set of cost-effective, high-leverage strategies that can then be implemented through their strategic marketing campaign for an NCE.

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Conclusion

Over the past 20 years, we have helped over a dozen major pharmaceutical clients develop integrated system dynamics models based on the basic but expandable framework detailed here. Current versions of this approach have become much more complex, given the increased availability of patient and physician data, as well as the improved sophistication of simulation and analytic tools. However, the basic principles of the interaction between patient flow dynamics, doctor adoption of therapy options, and treatment attractiveness evaluations remain the same. By translating implicit mental models into an operational framework and then integrating those structures based on the wealth of data available in the pharmaceutical world, our clients are making better decisions about resource allocation, strategy development, and marketing initiatives. Also, by understanding the link between the structure of pharmaceutical marketplaces and their resulting behavior (particularly in response to external influences), pharmaceutical marketing teams are developing more cost-effective strategic plans. In an environment of rising development costs, mounting price pressure, and growing uncertainty regarding the future of health care, improved decision-making based on the system dynamics framework is more important than ever.

Notes

1. Readers familiar with epidemiology will note there are actually a variety of prevalence metrics for various diseases. For the purposes of this analysis, we are using point prevalence; the number of people with a particular affliction at a single time point. Period or lifetime prevalence formulations are easy extensions.
2. This framework is explained more extensively by Sterman (2000).
3. Interested readers are encouraged to investigate Cook (2006) for a comprehensive account of utility evaluations.
4. Utility scores for therapy options can be further broken according to physician characteristics (specialty, geography, etc.) and patient segmentation (age, gender, disease severity, etc.) in order to match the characteristics tracked in the patient flow sector of the model.
5. Typically such calculations are extended over the forecast interval, such that attribute weightings and ratings (as well as the overall evaluation of treatment attractiveness) are changing over time.

Biographies

Mark Paich has a doctorate degree in System Dynamics from MIT, a master's degree in Economics from the University of Colorado, 20+ years of teaching experience at Colorado College and MIT, and is recognized as one of the premier minds in System Dynamics over the last quarter century. In addition to his role as a modeling practitioner, Mark has been instrumental in fostering and developing the talent of an inordinate number of people in the field.

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Corey Peck holds a BA magna cum laude in Economics from The Colorado College and has been a System Dynamics practitioner for over 15 years. Corey's career has spanned a wide range of client engagements, focusing on training others in the principles behind, and application of, the System Dynamics approach to problem-solving. He is currently the Managing Director of Lexidyne, LLC– a role that values approaching new directions, emphasizing learning and yield.

Jason Valant holds a BA cum laude in Economics from The Colorado College and is one of the founding partners of Lexidyne, LLC. With almost 20 years of business experience and a decade of intense focus on System Dynamics, Jason is widely regarded as one of the most knowledgeable practitioners in the pharmaceutical industry. He specializes in integrating patient- and physician-level data into System Dynamics frameworks for the purposes of forecasting and strategy development.

References

Bass F. 1969. A new product growth for model consumer durables. *Management Science* **15**: 215–227.

Cook A. 2006. *Forecasting for the Pharmaceutical Industry: Models for New Product and In-Market Forecasting and How to Use Them*. Gower: Farnham, UK.

Forrester J. 1961. *Industrial Dynamics*. MIT Press: Cambridge, MA. (Now available from Pegasus Communications, Waltham, MA)

Forrester J. 1971. Counterintuitive behavior of social systems. *Technology Review* **73**(3): 52–68.

Lilien G, Kotler P, Moorthy KS. 1992. *Marketing Models*. Prentice-Hall: Upper Saddle River, NJ.

Milstein B, Jones A, Homer J, Murphy D, Essien J, Seville D. 2007. Charting plausible futures for diabetes prevalence in the United States: a role for system dynamics simulation modeling. *Preventing Chronic Disease* **4**(3). Available: http://www.cdc.gov/pcd/issues/2007/jul/06_0070.htm [13 December 2010].

Paich M, Peck C, Valant J. 2009. *Pharmaceutical Product Branding Strategies: Simulating Patient Flow and Portfolio Dynamics*. Second Edition. lnforma Healthcare: London.

Rasiel E. 1999. *The McKinsey Way: Using the Techniques of the World's Top Strategic Consultants to Help You and Your Business*. McGraw-Hill: New York.

Richmond B, Peterson S. 1996. *An Introduction to Systems Thinking*. iseesystems: Lebanon, NH.

Sterman J. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. McGraw-Hill: New York.

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