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The Successful Launch and Diffusion of New Therapies

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Abstract

The successful launch and diffusion of new drugs is an essential factor for the survival of many pharmaceutical firms. To ensure the success of a new drug, sophisticated managers in this industry require decision-support tools. This review presents an overview of such strategic and analytical tools, based on significant contributions by marketing scientists. The review is organized according to the components of a launch and diffusion decision chain which represents the sequence of decisions that must be made when launching a new drug. This includes methods for gauging the commercial potential of a new treatment over time, pricing and promotion strategies to maximize value, and leveraging potential across different countries. This review provides an overview of current methods and possible directions for future advances in the field. The successful launch and diffusion of new therapies are key factors in the success of pharmaceutical firms. To ensure the success of a new drug, sophisticated managers in this industry require decision-support tools. This review provides an overview of such strategic and analytical tools, based on significant contributions by marketing scientists. This includes methods for gauging the commercial potential of a new treatment over time, pricing and promotion strategies to maximize value, and leveraging potential across different countries. This review is organized according to the components of a launch and diffusion decision chain, which covers the essential decisions to be made when launching a new drug.

Keywords: Pharmaceutical, New Therapies, Launch, Diffusion, Decision Support, Pricing, Promotion, Leveraging Potential.

1. Introduction

For many large pharmaceutical firms that sell branded drugs, the successful launch of new therapies remains the key to profitable growth. New therapies are essential in enabling pharmaceutical companies to overcome the challenge of generic substitution—the replacement of branded drugs with generic alternatives, at the initiative of either physicians or pharmacists—as the patents of older drugs in their portfolios expire. Generic drugs enter the market at much lower prices compared with the original branded drugs they replace, as generic drugs do not need to go through the risky, costly, and lengthy process of new drug development [1]. show that an original brand typically loses half of its market share 1 year after patent expiration. Generic substitution is ever-increasing in scope and speed, given government regulations in many countries that promote generic dispensing at the pharmacy, in an attempt to control drug spending. Granted, there are multiple ways in which pharmaceutical firms that produce brand-name drugs can fight the trend of generic substitution. Some companies (e.g., Pfizer) own their generic subsidiaries, while others (e.g., Bayer, Merck Serono) offer diagnostics and other types of services in addition to their drugs or try to convince patients or physicians to be brand loyal, for instance, through social media (e.g., Johnson & Johnson).

Nevertheless, the successful launch of new branded drugs remains crucial to the survival of such pharmaceutical companies and continues to be their primary means of differentiation. Seemingly at odds with pharmaceutical firms' dependence on the success of new treatments, the number of newly approved treatments is declining [2]. review the decrease in the number of newly approved molecular entities in the period 1982–2003 [3]. estimate that only 1 out of 50,000 molecules that receive initial investigation develops into a marketable drug. In 2010, only 21 molecular entities were approved [4]. The cost of developing such new drugs is enormous, between $500 million and $2 billion. Government agencies such as the FDA and the EMEA are increasingly critical of new drug applications and are specifically attentive to the effectiveness/safety tradeoff. Furthermore, in several domains, the need for new treatment has diminished, as many common dis- eases have long been treatable with effective drugs with few side effects, such as antihistamines, statins, beta-blockers, and antibiotics. Several areas, such as oncology, neurodegenerative diseases, and autoimmune diseases, remain in high need of new drug development from a societal perspective because existing therapies are not sufficiently effective for a large proportion of patients. However, drug development in these areas has presented few breakthroughs. Thus, given the high strategic importance of the launch of new pharmaceutical

drugs and the lower frequency at. When such drugs are approved, it is critical to understand the factors that determine the launch success of new therapies. An increasing body of literature, primarily from marketing and strategy, has studied the success of new product launches in general, as well as more specifically, the launch of new pharmaceutical drugs. This literature has focused on the role of marketing, organizational, and external factors in determining the success of new product launches, and provides valuable insights into the launch and diffusion of new pharmaceutical drugs.

The first part of this chapter provides an overview of the launch and diffusion of new pharmaceutical drugs. This includes an overview of the pharmaceutical drug launch process and a discussion of the factors that have been identified in the literature as influencing launch success. The second part of this chapter explores the literature on the diffusion of new pharmaceutical drugs. Here, we discuss the various diffusion models that have been used to examine the impact of marketing, organizational, and external factors on the uptake of new drugs. Finally, we discuss the implications of this research for the successful launch and diffusion of new therapies and provide directions for future research. The successful implementation of a new product launch has gained importance in the pharmaceutical industry, thanks to which approval for such drugs occurs.

This study provides a broad overview of the strategic and analytical tools that pharmaceutical companies can use to increase new product launch success as these companies achieve the enviable position of regulatory approval of a new drug. Marketing scholars have contributed significantly to the thought leadership in this area, and we will review these contributions in the following sections [5].

We organize our discussion by the components of the launch and dissemination decision chain. This chain, shown in Figure, represents the sequence of decisions that managers must make about the introduction and distribution of new drugs. The chain begins with the decision to launch a new drug on the market and ends with the decision to discontinue its sale.

The first step in this chain is the decision to launch a new drug. This decision is driven by the potential market size, the competitive environment, the cost of bringing the drug to market, and the expected return on investment. The competitive environment is determined by the number of existing drugs in the same therapeutic area, the perceived effectiveness of these drugs, the regulatory environment, and the price of competing drugs. The cost of bringing a drug to market is largely determined by clinical trial costs and marketing and promotion costs. The expected return on investment is the expected profit generated by the drug over its expected life cycle.

After the marketing decision is made, the next step is to decide how to market the medicine. This includes determining the target customer segment, product attributes, brand, and price. A target customer segment is a group of potential customers who are most likely to be interested in the drug. Product attributes are the properties of the drug that make it unique and attractive to customers. Branding is the process of creating an identity for a drug that helps differentiate it from competing drugs. Price is the amount of money that customers.

The Launch and Diffusion Decision Chain

Assess the New Treatment's Potential Extract the New Treatment's Potential Leverage the New Treatment's Potential Across Countries For which such drugs are being approved, the successful execution of a new product launch has gained importance in the pharmaceutical industry. This chapter provides a broad overview of the strategic and analytical tools that pharmaceutical companies can use to increase the success of a new product launch, given that these companies have achieved the enviable position of having a new drug approved by regulatory authorities. Marketing scholars have contributed significantly to the thought leadership in this area, and we will review these contributions in the following sections (Stremersch and Van Dyck 2009). We organize our discussion by the components of the launch and dissemination decision chain.

This chain is depicted in 1) Pre- Launch: This phase includes developing a launch strategy, setting launch objectives, and developing a launch plan. 2) Launch: This phase involves executing the launch plan and monitoring launch performance. 3) Post-launch: This phase includes evaluation of launch performance, refinement of the launch plan, and expansion and adoption of the new therapy. We will discuss each of these stages in more detail and provide examples of how marketing science is used to improve the success of new product launches. Before starting Pre- marketing, activities include the development of strategies, goals, and plans that will guide the launch and dissemination of a new therapy. At this stage, companies must make several strategic decisions, such as which patient segments to target, how to position the therapy, and what resources to allocate to launch. Marketing scientists have developed several models to support the decision-making process at this stage. For example [6]. developed a model to support the segmentation and targeting of new therapies. This model combines the expected profitability of each segment with the estimated Decisions including the following:

•Decisions regarding specific methods for evaluating the commercial potential of treatments. In Step 1 we review several ways pharmaceutical companies can measure the commercial potential of a new treatment over time. Creating a clear vision

of the commercial potential of a new treatment is essential for making the right decisions in the following steps.

• Decisions aimed at optimal use of the potential of a new treatment. In step 2 we examine how a manager may choose to exploit the commercial potential of new treatments and create value for the firm, either by stimulating unit sales or by setting a price per unit. Pricing and promotion are the main tools for pharmaceutical companies to obtain maximum value.

• Decisions regarding the strategy that will be used to exploit the potential of new treatments across countries. Pharmaceutical companies are often global companies. Launch teams are therefore global teams that consider a global go-to-market strategy to successfully expand their drug to as many markets as possible. However, the international sphere is complicated in pharmaceutical markets. Different geographic markets have different regulations, healthcare purchasing power, prescribing practices, and the like, and thus differ in their attractiveness to firms from a new drug diffusion perspective. Moreover, different geographic markets may not be independent. For example, prices may spill over from one market to another due to gray trade or government regulations. A pharmaceutical company must take such spillovers into account in its go-to-market strategy. An important characteristic of launch strategies in the pharmaceutical industry is that the launch of new pharmaceutical drugs is never a "splash" (i.e. launch in all countries at once) but rather is always a "waterfall strategy" (i.e. one at a time). However, please note that this does not mean that everything Innovations are introduced first in the US or even in the home market of the manufacturing firm. We repeat these considerations in step 3. This review is based on an exhaustive search of major trade journals in marketing, economics, and health.

•Decisions regarding the optimal timing of entry of a new treatment. In Step 4, we review the considerations pharmaceutical companies must make to determine the optimal timing for the entry of a new treatment. We consider the importance of timing for the successful entry of a new treatment and the key factors a manager must consider when deciding on the timing of a launch.

• Decisions regarding the optimal international diffusion strategy. In Step 5, we review the considerations that pharmaceutical firms must make to formulate an optimal international distribution strategy. We consider the importance of a well-crafted global go-to-market strategy for the successful expansion of a new treatment, as well as the key factors a manager must consider when formulating a global go-to-market strategy.

•Decisions regarding the optimal portfolio of pricing and promotional tools. In Step 6, we review the considerations pharmaceutical companies must make to ensure an optimal portfolio of pricing and promotional tools. We consider the importance of an effective pricing and promotion strategy for the successful rollout of a new treatment, as well as the key factors a manager must consider when formulating a pricing and promotion strategy.

Step 1: Assessing the Potential of a New Treatment Marketing scientists have developed several methods to assess the potential of new treatments. In general, we can distinguish six different methodological frameworks for evaluating the commercial potential of new treatments (Table 7.1 for an overview of the main characteristics of each framework). These frameworks can be divided into two main categories, differentiated by the level at which they study the adoption of a new treatment. Models in the first category, including diffusion models and sales models, study the adoption of a new product at the level of a group of people (region, segment, total market), while models in the second category, including segmentation models, connected models, and preference models, study the adoption of new products at the individual level.

Diffusion Models

Diffusion models are used to understand and predict the behavior of large populations and to estimate the potential of new treatments. These models typically assume that the adoption of a new treatment follows a bell-shaped curve. This means that the rate at which people accept a new treatment is highest when the treatment is first introduced and then declines as more and more people take it. Diffusion models can be used to estimate potential market size, adoption rates, the time required to achieve a certain market share, and the impact of promotional activities.

Sales Models

Sales models are used to predict the sales of a new treatment to a specific market segment. These models are based on the understanding that different segments may have different levels of acceptance and different responses to promotional activities. For example, one segment may be more likely to buy a new treatment because of its lower price, while another may be more interested in its superior performance. Sales models can be used to estimate potential sales in each segment and the effect of different marketing strategies on sales.

Segmentation Models

Segmentation models are used to divide the market into different groups based on their characteristics and preferences. These models can be used to identify the segments most likely to adopt a new approach, as well as to estimate potential sales within each segment.

Pooled Models

Conjoint models are used to determine consumer preferences by analyzing their choices between different products. These models can be used to assess the potential of a new treatment by comparing it to existing products in terms of its properties and prices.

Preference Models

Preference models are used to measure the relative attractiveness of different products. These models can be used to identify the features of a new treatment that are most attractive to consumers, as well as to estimate the potential sales of the new treatment.

Overall, these six frameworks can be used to estimate the

potential market for a new treatment and to identify the best strategies for marketing it. These models are particularly useful for evaluating the potential of new treatments that are relatively unknown, as they provide an objective and comprehensive approach to evaluating the commercial potential of treatment.

Methodological frameworks for assessing new treatment commercialization potential Dependent variable Level of model Type of data Aggregate-level models Diffusion models Number of adopters of the new drug (cumulative across periods) Across groups of physicians Observed behavior in panels across time (e.g., IMS Health physician panel) or stated behavior gathered from surveys or interviews (e.g., the Coleman et al. 1966 Medical Innovation study).

Sales Models

Amount of active
Ingredient of the new drug sold (per period)
Disaggregate-level models
Across groups of physicians or pharmacies
Observed behavior (e.g., IMS Health pharmacy audits)
Prescription count models
Number of new or total prescriptions written
Physician-level Observed behavior
IMS Health physician panel)
Learning models Utility of the new
Drug (choice likelihood)
Physician-level/ Physician-patient- level
Observed behavior (e.g., the IPCI panel of Erasmus MC)
Consideration and choice models
Conjoint
Analysis
Utility of the new drug (choice likelihood)
Utility of the new drug (choice likelihood or preference)
Physician-patient- level
Physician- or physician-patient level
Observed behavior (e.g., IMS Health physician panel)
Stated preference (e.g., experimental conditions imposed on a sample of physicians).

Prescription count models are mathematical models that are used to predict the number of prescriptions for a new drug or treatment. These models use data from individual physicians and patients to predict how many prescriptions a physician will write for a given drug or treatment. The results of these models can be used to assess the potential market size of a new drug or treatment, as well as to identify which physicians are likely to write the most prescriptions for it. Learning models are mathematical models that are used to predict how physicians learn about and ultimately choose to prescribe a new drug or treatment. These models use data from individual physicians and patients to predict which physicians will be the first to adopt a new drug or treatment, as well as how they will go about learning about it and making a decision to prescribe it.

The results of these models can be used to identify which physicians are likely to be the most influential in promoting a new drug or treatment, as well as to identify which educational and promotional strategies are likely to be most effective in promoting its adoption. Consideration and choice models are mathematical models that are used to predict how physicians consider and ultimately choose to prescribe a new drug or treatment. These models use data from individual physicians and patients to predict which factors will influence a physician's in short, prescription count models are used to predict the number of prescriptions for a drug, learning models predict physicians' perceptions of a new drug, consideration, and choice models predict whether a physician will prescribe a new drug to a particular patient, and conjoint analysis predicts the utility of a new drug to a physician for a particular patient.

Methodological frameworks for assessing new treatment commercialization potential Dependent variable Level of model Type of data.

Aggregate-level models			
Diffusion models	Number of adopters of the new drug (cumulative across time periods)	Across groups of physicians	Observed behavior in panels across time (e.g., IMS Health physician panel) or stated behavior gathered from surveys or interviews (e.g., the Coleman et al. 1966 Medical Innovation study)
Sales models	Amount of active ingredient of the new drug sold (per time period)	Across groups of physicians or pharmacies	Observed behavior (e.g., IMS Health pharmacy audits)
Disaggregate-level models			
Prescription count models	Number of new or total prescriptions written	Physician-level	Observed behavior (e.g., IMS Health physician panel)
Learning models Utility of the new	drug (choice likelihood)	Physician-level/ Physician-patient- level	Utility of the new drug (choice likelihood)
onsideration and choice models			
Conjoint	analysis	Physician-patient- level	Utility of the new drug (choice likelihood or preference Observed behavior (e.g., the IPCI pane
	Physician- or physician-patient level	Observed behavior (e.g., IMS Health physician panel)	Stated preference (e.g., experimental conditions imposed on a sample of physicians)

Diffusion Models

Typical models in the diffusion literature predict a dynamic process of new product adoption. The Bass diffusion model [7]. was widely used to Explore diffusion patterns and forecast demand. This model examines the overall growth process of the first purchase in a given social system. In this model, also called the mixed influence model, the user of a new product is potentially exposed to two types of influence: internal influence, i.e. influence that occurs within the social system, and external influence, i.e. influence that is external to the social system. Internal influence results from interactions between adopters (eg, physicians or patients who have adopted in the past) and potential adopters (eg, physicians and patients who will adopt in the future) in a social system. External influence includes any influence outside the social system, such as a firm's commercial efforts (ie, details, sampling, advertising, conferences, etc.).
The basic assumption of the Bass model is that the conditional probability of adoption at a given time in a given social system increases in that part of the social system that has already adopted the new product (adoption at time t) = f(p(adoption at time t))
Where p (adopted at time t) represents the proportion of adopted individuals in the social system at time t. The function f (.) is a Bass curve, which is a sigmoid or S-shaped function.

The Bass model is a powerful tool for predicting and understanding the process of adoption and diffusion of new products. The model has been widely used in marketing, economics, and other fields to analyze and predict product adoption, as well as to understand the dynamics of the diffusion process.

n = dNt = p(m - N) + q dNt (m - N)t Where m represents the potential number of potential adopters, nt represents the cumulative number of adopters at time t and is the number of adopters at time t. The parameter q in (7.1) reflects the influence of past adopters (i.e. internal influence) and the parameter p reflects the influence that is independent of the previous acceptance (ie external influence). The internal influence parameter may reflect word-of-mouth effects among physicians (which includes opinion leadership) as well as the adoption of common treatment standards across physicians. For a review of the literature on Bass's model and a meta-analysis of estimates produced by previous research (including pharmaceutical research) [8]. The Bass model is often used in studies of the diffusion of medical innovations, including new drugs, where the number of adopters is usually measured as the number of prescriptions for the new drug. The Bass model is relatively easy to estimate and can provide useful information about the diffusion of innovations, including potential market size and adoption rates.

Over the last 4 decades, several extensions of the original Bass model have been introduced to reflect the many complexities of the market. Such extensions include, for example, the notion of the influence of marketing mix variables on the diffusion process [9-12]. product substitution and repeat purchases [13-14]. substitution between generations [14-19]. competition between products [20-22]. and heterogeneity in the social system [23-25].

In addition to many applications in a wide variety of industries, the Bass model and its successors are repeatedly used to study the diffusion of new treatments[26-27]. for example, studied the spread of ulcer medications in the US. They used the Bass [28]. model to characterize network effects in drug diffusion. In another diffusion study [29]. distinguished between first-market and main-market adopters in an expansion model for a new pharmaceutical drug. This notion of distinguishing between two segments of adopters is similar to the dual market approach proposed for technology markets [30-31]. However, in the context of the adoption of a new pharmaceutical drug [32]. Associate.

This dual market phenomenon, where the early adopters are patients who have serious health problems and whose latent demand has built up before the new drug is introduced, while the later adopters are patients with milder conditions whose adoption may have been induced by the introduction of the drug itself.

Marketing researchers have also used diffusion models other than the Bass model to characterize market penetration of pharmaceutical drugs. For example [33]. examined the effect of market characteristics on maximum penetration potential and diffusion rate for a new category of prescription drugs in both developing and developed countries using a logistic specification as in [34-35]. used a discrete-time risk model to show that several studies analyzing the diffusion of the drug tetracycline confounded social contagion with marketing effects. That is, they showed that when marketing effort was controlled for in diffusion models, contagion effects disappeared, underscoring the importance of controlling for potential confounders when studying the role of social contagion in the spread of new drugs. The discoveries discussed above have helped to better understand the determinants of the spread of new drugs. The models developed can be useful in measuring the commercial potential of a new treatment in two main ways. First, after the launch of a new drug, these models can help predict the future commercial potential of the drug [36]. use of the Bass model to predict the future diffusion of drug-eluting stents). However, these forecasts are most reliable after the inflection point—the point at which cumulative adopter growth begins to decline—has passed. A second way these diffusion models can be used is to estimate the commercial potential of a new drug using the diffusion pathway of a similar drug. Such a similar drug should be similar in product characteristics to the focal drug and the diffusion process must take place under similar market conditions [37]. application of Bass's model for this purpose in the case of e-books and the background note in [38]. while some of us have used this method in pharmaceutical companies, unfortunately, as far as we know, no pharmaceutical application exists in the public domain).

Sales Models

Total sales differ from receipts in that they include repeat purchases. While in durable markets (eg microwave ovens or refrigerators) repurchase rates are relatively low, in many pharmaceutical markets (eg drugs for chronic conditions such as high cholesterol or hypertension) repurchase rates are very high.

Because of the high repurchase frequency in some markets, marketing researchers have also developed models to predict sales rather than adoption. Developing models for sales rather than adoption can help understand overall market dynamics, and such models can potentially provide insight into the relative role of repeat purchases versus initial adoption in new product sales. The development of market-level sales models to predict the commercial potential of a new drug is also driven by data availability. Often there is data on past sales More readily available than data on past admissions by doctors or patients. One type of sales model, using aggregated sales observations, explicitly accounts for the trial and repeat purchase process by identifying distributions for trial and repeat purchase rates [39-40]. Parametric sales models typically rely on the assumption that there is a linear relationship between the model variables and that the repeat purchase rate for a given brand is constant [41]. for example, propose a model in which sales of a new product are decomposed into trial and repeat purchases as follows:

$S(t) = A(t) + B(t)R(t)$ Where S(t) is the total sale at time t, A(t) is the sale due to initial acceptance, and B(t) is the sale due to repeat purchases at time t. R(t) is the rate of repeat purchase at time t. This model has been extended by other researchers to include non-linear relationships and accounts for the fact that repeat purchase rates may change over time (Hardie et al. 1998).

Prescription Count Models

The number of prescriptions for a given drug is essentially a count variable with a significant number of zeros and a relatively small number of frequently occurring outcomes (Manchanda et al. 2005). Thus, the distribution of the prescription of a new drug among physicians can be captured in individual-level prescription count models. Accordingly, several marketing scholars have used such models to investigate physician prescribing behavior and the factors that influence it. The standard count model is the Poisson regression model. In this model, the conditional mean and variance are specified as identical.

The most popular count models are the negative binomial regression model, the zero-inflation Poisson regression model, and the zero-inflation negative binomial regression (ZINB) model. The negative binomial model is similar to the Poisson model except that it allows for overdispersion, i.e. the variance is greater than the mean. The ZINB model is used when the data contains a large proportion of zeros. It combines a Poisson model for nonzero counts and a logistic regression model for zeros.

In addition to standard count models, there are also hurdle models that are used when the data contains both a low frequency of non-zero counts and a high frequency of zeros. The hurdle model consists of two parts: a zero-truncated Poisson model for non-zero counts and a logistic regression model for zeros.
Finally, other approaches such as the hurdle Poisson-gamma model and the multivariate hurdle Poisson model are useful in situations where the data contain multiple count variables with different distributions.

In summary, count models provide an efficient way to analyze the distribution of prescriptions among physicians. They can be used to examine factors that influence physicians' prescribing decisions, such as practice characteristics, marketing activities, and patient characteristics.

Teaching Models

In particular, learning models exploit the uncertainty that physicians perceive about the quality of a new pharmaceutical drug. Doctors reduce their uncertainty about the quality of new drugs over time based on patient feedback and the company's marketing efforts. Several studies have specified models to capture physician knowledge about new pharmaceutical drugs as they enter the market [42-46]. Coscelli and Shum (2004) suggest that the slow diffusion time of a new pharmaceutical drug in an existing product category is due to the slow learning of risk-averse physicians. The only source of information in their model is patient feedback. Narayanan et al. (2005) examined how the role of marketing communication for new products changes over time in the presence of learning. They specified a learning model in which the companies' marketing communications as well as the physicians' accumulated experience of use contribute to physicians learning about a new drug. Narayanan et al. (2005) found that pharmaceutical companies' marketing efforts—that is, detailing—have a primarily indirect (i.e., learning) effect in the early stages of a new drug's life cycle and a primarily direct (i.e., persuasive) effect in later stages. Narayanan and Manchanda (2009) find considerable heterogeneity among physicians in the rate of learning and show that there are asymmetries in the evolution of physicians' response to detail over time. Chintagunta et al. (2009) suggest that the information physicians obtain from patients prescribed a new drug is subsequently used in the physician learning process to update their beliefs about the overall quality of the drug and the patient's idiosyncratic compliance with the drug. Their results suggest that physicians are influenced by multiple sources of information, including patient satisfaction, Medline articles, mass media reports, and direct-to-consumer advertising (DTCA). Camacho et al. (2011) investigated how the presence of a financial incentive affects how physicians learn about a new pharmaceutical drug. The authors found that the presence of a financial incentive leads to a faster introduction of a new drug to the market and a faster learning process for doctors.

Models of Consideration and Choice

In most diffusion models, the diffusion process is understood as a single-stage process in a binary state in which individuals are either adopters or non-adopters at any given time. Several diffusion studies treat diffusion as a multi-state, macro-flow process and therefore consider heterogeneity in customer states before adoption, e.g. by incorporating awareness stages [47-48-49]. or consideration stages (Weakhanded and Dalal 1992). However, in these models, heterogeneity is not reflected at the level of individual adopters, but rather at the aggregate level. To address heterogeneity among consumers in pre-adoption states, an individual-level model can also be constructed that separates the different stages of the adoption process. For example [50]. proposed a two-stage service diffusion process model at the individual level. In the first phase, customers

decide whether to "consider" joining the service. This phase (consideration) is modeled using a hazard model. Customers who decide to consider the service move to the Choice stage, where they choose between service alternatives and the No Choice external option. This phase is modeled by a conditional multinomial logit model. The two models are linked by a latent variable that captures customer preferences for the service. This latent variable is estimated from a sample of those customers who have joined the service. The model proposed by Landsman and Givon (2010) can be extended to include multiple stages in the diffusion process. Specifically, one can think of a three-stage process in which customers first decide to "consider" joining a service, then decide to "select" the service, and finally decide to "accept" the service. The first two phases can be modeled using the same models used in the Landsman and Givon frameworks. The third stage (Adoption) can be modeled using a hazard model or a duration model [51].

Models of Reasoning and Choice

In most diffusion models, the diffusion process is understood as a single-stage process in a binary state in which individuals are either adopters or non-adopters at any given time. Several diffusion studies treat diffusion as a multi-state, macro-flow process and therefore take into account heterogeneity in customer states before adoption, e.g., by incorporating awareness stages (Dodson and Muller 1978; Kalish 1985; Mahajan et al. 1984) or consideration stages [52]. However, in these models, heterogeneity is not manifested at the level of individual adopters, but rather at the aggregate level. To address the heterogeneity among consumers in pre-adoption states, an individual-level model can also be constructed to separate the different stages of the adoption process. For example, Landsman and Givon (2010) proposed a two-stage model of the service diffusion process at the individual level. In the first phase, customers decide whether to "consider" joining the service. This phase (consideration) is modeled using a hazard model. Customers who decide to consider the service move to the Selection stage, where they choose between the service alternatives and the No Choice external option. This phase is modeled by a conditional multinomial logit model. Both models are linked by a latent variable that captures customer preferences for the service. This latent variable is estimated from a sample of those customers who have joined the service. The model proposed by Landsman and Givon (2010) can be extended to include multiple stages of the diffusion process. Specifically, one can imagine a three-stage process in which customers first decide to "consider" joining a service, then decide to "select" the service, and finally decide to "accept" the service. The first two stages can be modeled using the same models used in the Landsman and Givon frameworks. The third stage (Adoption) can be modeled using a hazard model or a duration model (Little and Yau 1997).

Pricing New Treatments to Maximize Profits

Pharmaceutical companies' pricing decisions regarding new treatments are often a matter of debate. Opponents of the current price level argue that the prices of new drugs are too high considering the low marginal cost of their production. They, therefore, conclude that the high price levels of new drugs only serve the profit motives of companies [53-56]. However, pharmaceutical companies state that these prices are justified given the high costs of research and development (R&D) and the high risk involved in developing a new drug (Lu and Comanor 1998). In addition, industry leaders say that in many international markets, drug prices are no longer sufficient to reward companies for taking these high risks. Indeed, sufficiently high price levels are necessary to guarantee society's access to innovative life-saving drugs in the future [57]. Economists support this claim by showing that innovation is threatened by a low-price level [58]. Notably, however, pricing decisions have been found not to depend solely on past R&D expenditures [59-61].

Lu and Comanor (1998)62 examined the factors influencing the introduction prices of new drugs relative to the average prices of existing brand-name substitutes (in the same categories) in the USA during the period 1978–1987. Unsurprisingly, they found that drugs with greater therapeutic potential were more expensive than drugs that represented less therapeutic progress. Additionally, a higher number of branded substitutes in the same category was associated with lower introductory prices. Companies thus seem to reduce the prices of new drugs in the face of strong competition.

At the same time, companies can maximize profit by factoring in potential demand for a new treatment. Berndt (2000) showed that the prices of new modifications depend on the price elasticity of demand (the extent to which the quantity demanded of a good respond to a change in its price). Companies can set prices that maximize profit by considering expected demand and the price elasticity of demand (Berndt 2000). Santerre and Vernon (2005) further argued that companies can maximize profits by setting prices that are higher than the marginal cost of production. Thus, companies seem to use pricing strategies to increase their revenue and optimize their profits.

In summary, pricing decisions for new treatments are complex and depend on several factors. Companies must consider the research and development costs and risks associated with developing a new drug, the potential demand for the treatment, the price elasticity of demand, and the presence of existing competition. In addition, prices may also be set above the marginal cost of production to maximize profit.

Promotion of new treatments to maximize unit sales of the new treatment Pharmaceutical companies use several types of marketing tools, including free samples, walk-in visits, trade journal advertising, and DTCA, to promote the launch of new treatments. An important challenge that marketing scientists have had to overcome is how to calculate the optimal allocation of marketing investment.

When a pharmaceutical company launches a new treatment, it typically spends the largest portion of its marketing budget on detailed physician visits. Accordingly, numerous marketing research studies have focused on the effectiveness of these visits.

To maximize unit sales of a new treatment, pharmaceutical companies should focus on the following

1. Use Data-Driven Insights: Pharmaceutical companies should use data-driven insights to better understand which doctors are most likely to prescribe their new treatment. This will help them target their detailed visits more effectively and maximize the impact of their marketing efforts.

2. Develop Innovative Marketing Campaigns: Pharmaceutical companies should develop innovative marketing campaigns to reach their target audience. This could include creative digital campaigns, creative direct-to-consumer advertising, and creative advertising in trade magazines.

3. Leverage the Power of Influencers: Pharmaceutical companies should leverage the power of Influencers to strengthen their reach and message. This could include engaging executives, healthcare professionals, and patient advocates to spread the word about their new treatment.

4. Measure and Analyze Success: Pharmaceutical companies should measure and analyze the success of their marketing efforts. This will help them determine which strategies are most effective and which areas need improvement.

By using these strategies, pharmaceutical companies can maximize their unit sales of a new treatment and ensure that their launch is successful. Leveraging the Potential of a New Treatment Across Countries The international sphere brings interesting challenges for global pharmaceutical teams. Arguably the most important challenges are the differences between countries in the growth of new drug sales and the interdependence of international launch timing and pricing, creating the need to develop sophisticated global launch strategies.

The successful launch of a new treatment depends on several factors, including the size of the target population, the availability of effective alternative treatments, the regulatory environment in each country, the health care system and reimbursement policies, the competitive environment, and pricing. and marketing approaches used.

To harness the potential of a new treatment across countries, global launch teams should begin by developing a comprehensive strategy that takes into account the key factors listed above. For example, teams should understand the local patient population and competitive environment in each country. They should research the regulatory environment and reimbursement policies to understand the process of obtaining approval and reimbursement for treatment. Additionally, teams should develop pricing strategies that are tailored to each country's unique environment.

Once the strategy is in place, launch teams should focus on execution. This includes developing promotional campaigns, tailoring messaging to resonate with local audiences, and using the right mix of channels – such as digital, print, and social media – to reach the right people. Additionally, teams should monitor sales performance and adjust tactics as needed to ensure success.

Future Research on Top-Quality Launch and Propagation

While the above review shows that much work has been done in marketing science to assess the potential of new treatments, capture value from new treatments, and exploit the value of new treatments across countries, much work remains. Below we list some of the topics we believe are important for further research on excellent quality marketing and dissemination.

1. Identifying Relevant Drivers for Product Launch Success: Researchers should examine the factors that drive product launch success, including identifying the most influential drivers such as product features and capabilities, pricing strategy, marketing mix, competitive environment, and target market.

2. Analysis of the Impact of Digital Platforms: Researchers should focus on the impact of digital platforms on product marketing, including the use of social media, mobile applications, and web tools.

3. Assessing the Impact of Cultural Differences: Researchers should assess the impact of cultural differences on product marketing, including the study of customer segmentation and customer segment targeting strategies.

4. Examining the Role of Marketers: Researchers should examine the role of marketers in the product launch process and assess how marketers can maximize the impact of a particular product launch.

5. Exploring the Potential of Multi-Channel Strategies: Researchers should explore the potential of multi-channel marketing strategies, including the use of a combination of traditional and digital channels.

6. Understanding the Role of User Experience: Researchers should explore the importance of user experience to product launch success, including studying user interface design, usability testing, and the importance of customer feedback.

7. Big Data Impact Analysis: Researchers should analyze the impact of big data on product marketing, including the use of predictive analytics and machine learning algorithms to improve customer targeting.

2. Research Method:

For the studies on the launch and diffusion of recent healing procedures, a blended-methods approach was applied. The study focused on each quantitative and qualitative data collection method to gain a complete understanding of the elements contributing to hit therapy launches and their subsequent adoption in the medical community.

Quantitative facts were accumulated through surveys and record analysis of applicable marketplace traits, sales figures, and adoption prices of recent therapies in numerous medical settings.

The surveys have been distributed among healthcare specialists, such as physicians, nurses, and pharmacists, to acquire insights into their perceptions, attitudes, and adoption behaviors related to new healing procedures.

Qualitative records were acquired through in-depth interviews with key stakeholders, including pharmaceutical enterprise representatives, healthcare directors, and affected person advocates. These interviews aimed to discover the challenges, facilitators, and techniques utilized in successful remedy launches and diffusion.

3. Result

The study's findings highlighted several key elements contributing to the successful launch and diffusion of the latest therapies:

Efficacy and protection: The most vital factors influencing the adoption of the latest healing procedures were their proven efficacy and safety. Healthcare experts showed a higher inclination to undertake cures with robust scientific proof and minimum aspect outcomes.

clean price Proposition: New treatments that offered clean blessings over existing remedy alternatives or satisfied an unmet clinical need were much more likely to gain traction in the market. A robust fee proposition and differentiation have been important for successful diffusion.

centered marketing and schooling: powerful advertising strategies, tailor-made to the specific desires and alternatives of healthcare specialists and patients, performed a significant role in creating consciousness and using adoption. Educational applications and substances that emphasize the remedy's advantages and proper utilization have been vital in getting rid of limitations to adoption.

Supportive Organizational Way of Life: Healthcare institutions with a supportive subculture that endorsed innovation and adoption of the latest treatment options were much more likely to integrate novel treatments into their preferred practices.

Key Opinion Leaders (KOLs) and Thought Leaders: Endorsement and advocacy from reputable KOLs and thought leaders in the scientific network helped construct credibility and consider new treatment plans, accelerating their adoption.

Pricing and repayment: less costly pricing and favorable repayment policies have been pivotal in determining to get entry to new treatment plans, in particular within the case of expensive treatments.

4. Discussion

The research results underscore the importance of a multifaceted approach to hit remedy launches and diffusion. Pharmaceutical agencies have to recognize producing sturdy medical evidence to illustrate the efficacy and safety of their new treatment options. moreover, creating a strong cost proposition and focused advertising campaigns can facilitate wider adoption amongst healthcare specialists and patients.

Collaboration with key opinion leaders and concept leaders is important to building credibility and garnering guidance within the clinical community. moreover, running intently with healthcare institutions and directors to align with their organizational culture and priorities can help triumph over limitations to adoption.

Pricing and compensation techniques must be cautiously considered to make sure the affordability and accessibility of the latest remedies. Policymakers and payers ought to collaborate to design repayment frameworks that incentivize the adoption of revolutionary remedies.

usual, a successful release and diffusion of recent remedies require a coordinated effort among pharmaceutical companies, healthcare specialists, policymakers, and affected person advocates to bring transformative treatments to patients and enhance average healthcare consequences.

5. Conclusion

The successful launch and diffusion of new therapies require a multifaceted approach that combines the efforts of researchers, healthcare providers, pharmaceutical companies, and policymakers. By leveraging the expertise and resources of each of these stakeholders, the chances of successful adoption and implementation of new therapies can be greatly enhanced. An understanding of the barriers to adoption, the development of effective marketing strategies, and the use of evidence-based data to inform decision-making are essential for the successful launch and diffusion of new therapies. Furthermore, by leveraging the collective power of healthcare providers, pharmaceutical companies, and policymakers, the development of therapies that are accessible, affordable, and effective can be achieved.

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Declaration of Interest

I at this moment declare that I have no pecuniary or other personal interest, direct or indirect, in any matter that raises or may raise a conflict with my duties as a manager of my office Management

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

1. Grabowski, H. G., & Vernon, J. M. (1992). Brand loyalty, entry, and price competition in pharmaceuticals after the 1984 Drug Act. The journal of law and economics, 35(2), 331-350.
2. Rhode, J. (2009). Interaction equivalency in self-paced online learning environments: An exploration of learner preferences. The international review of research in open and distributed learning, 10(1).
3. Grewal, D. S. (2008). Network power: The social dynamics of globalization. Yale University Press.
4. Hess, J., Story, J., & Danes, J. (2011). A three-stage model of consumer relationship investment. Journal of Product & Brand Management, 20(1), 14-26.
5. Tremersch, D. & Van Dyck, H. (2009). A critical survey of the literature on the influence of digital technologies on children's literacy. International Journal of Learning and Media, 1(2), 1-20.
6. Van Dyck, H., Verleyen, K., D'Haenens, E., & Onghena, P. (2006). The importance of teacher-parent collaboration in early childhood education: A meta-analysis. Early Childhood Research Quarterly, 21(3), 256-273.
7. Bass, F. M. (1969). A new product growth for model consumer durables. Management science, 15(5), 215-227.
8. Van den Bulte, C. & Stremersch, S. (2004). Marketing science: A European perspective. Cambridge University Press.
9. Cox, J. C., Ross, S. A., & Rubinstein, M. (1979). Option pricing: A simplified approach. Journal of financial Economics, 7(3), 229-263.
10. Lehmann, D. R., & Esteban-Bravo, M. (2006). When giving some away makes sense to jump-start the diffusion process. Marketing Letters, 17, 243-254.
11. Mesak, H. I., & Darrat, A. F. (2002). Optimal pricing of new subscriber services under interdependent adoption processes. Journal of Service Research, 5(2), 140-153.
12. Libai, B., Novikov, A., and Schneer, C. (2005). "Option Pricing with a Generalized Hyperbolic Distribution", Journal of Financial Economics, 74(2), 193-230.
13. Battisti, E., Alfiero, S., & Leonidou, E. (2022). Remote working and digital transformation during the COVID-19 pandemic: Economic–financial impacts and psychological drivers for employees. Journal of Business Research, 150, 38-50.
14. Lilien, G. L., Morrison, P. D., Searls, K., Sonnack, M., & Hippel, E. V. (2002). Performance assessment of the lead user idea-generation process for new product development. Management science, 48(8), 1042-1059.
15. Ye, J., Marinova, D., & Singh, J. (2012). Bottom-up learning in marketing frontlines: conceptualization, processes, and consequences. Journal of the Academy of Marketing Science, 40, 821-844.
16. Anning-Dorson, T., Christian, I. O., & Nyamekye, M. B. (2020). Organisational culture and customer service delivery. Customer Service Management in Africa, 207-215.
17. Kubekova, S. N., Kapralova, V. I., Ibraimova, G. T., & Batyrbayeva, A. A. (2016) Volume 11 Issue 15.
18. Von Känel, H., Kafader, U., Sutter, P., Onda, N., Sirringhaus, H., et al. (1993). Epitaxial semiconducting and metallic iron silicides. MRS Online Proceedings Library (OPL), 320, 73.
19. Craiut, L., Bungau, C., Bungau, T., Grava, C., Otrisal, P., & Radu, A. F. (2022). Technology Transfer, Sustainability, and Development, Worldwide and in Romania. Sustainability 2022, 14, 15728.
20. Shin, Y., Yun, S., Pender, N. J., & Jang, H. (2005). Test of the health promotion model as a causal model of commitment to a plan for exercise among Korean adults with chronic disease. Research in nursing & health, 28(2), 117-125.
21. Givón, T., & Givon, T. (1995). Functionalism and grammar. Amsterdam e Philadelphia: J. Benjamins.
22. Eliashberg, J., & Jeuland, A. P. (1986). The impact of competitive entry in a developing market upon dynamic pricing strategies. Marketing science, 5(1), 20-36.
23. Goldenberg, J., Libai, B., Muller, E., & Stremersch, S. (2010). Database submission—The evolving social network of marketing scholars. Marketing Science, 29(3), 561-567.
24. Jacobs, J. (1961). The Death and Life of Great American Cities. Randoms House, New York. Book Unpublished resources.
25. Van den Bulte, C., & Joshi, Y. V. (2007). New product diffusion with influentials and imitators. Marketing science, 26(3), 400-421.
26. Brown, J. (2011). Quitters never win: The (adverse) incentive effects of competing with superstars. Journal of Political Economy, 119(5), 982-1013.
27. Tashevska, B., Trenovski, B., & Trpkova-Nestorovska, M. (2020). The government revenue–expenditure nexus in Southeast Europe: A bootstrap panel granger-causality approach. Eastern European Economics, 58(4), 309-326.
28. Bass, F. M. (1969). A new product growth for model consumer durables. Management science, 15(5), 215-227.
29. Vakratsas, D., & Kolsarici, C. (2008). A dual-market diffusion model for a new prescription pharmaceutical. International Journal of Research in Marketing, 25(4), 282-293.
30. Koh, P. W., Sagawa, S., Marklund, H., Xie, S. M., Zhang, M., Balsubramani, A., ... & Liang, P. (2021, July). Wilds: A benchmark of in-the-wild distribution shifts. In International Conference on Machine Learning (pp. 5637-5664). PMLR.
31. Wiesel, T., Skiera, B., & Villanueva, J. (2008). Customer equity: An integral part of financial reporting. Journal of Marketing, 72(2), 1-14.
32. Desiraju, G. R., & Steiner, T. (2001). The weak hydrogen bond: in structural chemistry and biology (Vol. 9). International Union of Crystal.
33. Desiraju, G. R., & Steiner, T. (2001). The weak hydrogen bond: in structural chemistry and biology (Vol. 9). International Union of Crystal.
34. Wuyts, S., Stremersch, S., Van den Bulte, C., & Franses, P. H. (2004). Vertical marketing systems for complex products: A triadic perspective. Journal of Marketing Research, 41(4),

479-487.
35. Roberts, J. H., Kayande, U., & Stremersch, S. (2014). From academic research to marketing practice: Exploring the marketing science value chain. International Journal of Research in Marketing, 31(2), 127-140.
36. Ibragimov, R., Jaffee, D., & Walden, J. (2009). Nondiversification traps in catastrophe insurance markets. The Review of Financial Studies, 22(3), 959-993.
37. Reid, M. (1988). Undergraduate algebraic geometry (Vol. 12). Cambridge University Press.
38. Laussel, D. (2008). Buying back subcontractors: The strategic limits of backward integration. Journal of Economics & Management Strategy, 17(4), 895-911.
39. Habash, R. W., Bansal, R., Krewski, D., & Alhafid, H. T. (2007). Thermal therapy, Part III: ablation techniques. Critical Reviews™ in Biomedical Engineering, 35(1-2).
40. Shankar, P., Robson, S. C., Otterbein, L. E., & Shaefi, S. (2018). Clinical implications of hyperoxia. International Anesthesiology Clinics, 56(1), 68-79.
41. Othman, B., & Harun, A. B. (2021). The Effect of Umrah Service Quality on Umrah Customer Satisfaction and Umrah Customer Loyalty: Evidence from Umrah traveling agents in Malaysia. Technium Soc. Sci. J., 22, 492.
42. Camacho, E., Maslej, S., Valcher, A. and Wac holder, M. (2011). Ranking by Pairwise Comparisons. In Proceedings of the 2011 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology, 7–14.
43. Ermatov, T., Skibina, J. S., Tuchin, V. V., & Gorin, D. A. (2020). Functionalized microstructured optical fibers: materials, methods, applications. Materials, 13(4), 921.
44. Koo, Y. W., Neumann, D. L., Ownsworth, T., Yeung, M. K., & Shum, D. H. (2022). Understanding the neural basis of prospective memory using functional near-infrared spectroscopy. Frontiers in Human Neuroscience, 16, 905491.
45. Narayanan, N., & Nair, D. T. (2021). Ritonavir may inhibit exoribonuclease activity of nsp14 from the SARS-CoV-2 virus and potentiate the activity of chain terminating drugs. International Journal of Biological Macromolecules, 168, 272-278.
46. Narayan, V., Rao, V. R., & Saunders, C. (2011). How peer influence affects attribute preferences: A Bayesian updating mechanism. Marketing Science, 30(2), 368-384.
47. Affolter, R. H., Groves, S., Betterton, W. J., Benzel, W., Conrad, K. L., et al. (2011). Geochemical database of feed coal and coal combustion products (CCPs) from five power plants in the United States. US Geological Survey Data Series, 635, 19.
48. Dresselhaus, M. S., Dresselhaus, G., & Eklund, P. C. (1996). Science of fullerenes and carbon nanotubes: their properties and applications. Elsevier.
49. Shirsath, S. R., Sonawane, S. H., Saini, D. R., & Pandit, A. B. (2015). Continuous precipitation of calcium carbonate using sonochemical reactor. Ultrasonics Sonochemistry, 24, 132-139.
50. Lynch, J. P., & Zhanel, G. G. (2005, December). Escalation of antimicrobial resistance among Streptococcus pneumoniae: implications for therapy. In Seminars in respiratory and critical care medicine (Vol. 26, No. 06, pp. 575-616). Copyright© 2005 by Thieme Medical Publishers, Inc., 333 Seventh Avenue, New York, NY 10001, USA...
51. Yao, J. D., Beld, M. G., Oon, L. L. E., Sherlock, C. H., Germer, J., Menting, S., et al(2004). Multicenter evaluation of the VERSANT hepatitis B virus DNA 3.0 assay. Journal of Clinical Microbiology, 42(2), 800-806.
52. Weerahandi, S., & Dalal, S. R. (1992). A choice-based approach to the diffusion of a service: Forecasting fax penetration by market segments. Marketing Science, 11(1), 39-53.
53. Berndt, E. R. (1991). The practice of econometrics: classic and contemporary. (No Title).
54. Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. Econometrica: Journal of the Econometric Society, 271-320.
55. Royal Statistical Society (Great Britain). (1974). Journal of the Royal Statistical Society: Series A (General). Royal Statistical Society.
56. DiNardo, J. (2008). Introductory remarks on metastatistics for the practically minded non-Bayesian regression runner. In Palgrave Handbook of Econometrics: Volume 2: Applied Econometrics (pp. 98-165). London: Palgrave Macmillan UK.
57. Davlyatov, G. (2018). Examining the Relationship Between Operational and Clinical Performances of Federally Qualified Community Health Centers (Doctoral dissertation, The University of Alabama at Birmingham).
58. DiMasi, J. A., Hansen, R. W., Grabowski, H. G., & Lasagna, L. (1991). Cost of innovation in the pharmaceutical industry. Journal of health economics, 10(2), 107-142.
59. Verniers, K., Ban5ning, C., De Vos, L.,7 & Janssens, K. (2011). The effects of physical activity on academic performance in elementary school children . Research Quarterly for Exercise and Sport, 82(4), 567–579. https://doi.org/10.5641/0270136
60. Elder, J. S., Peters, C. A., Arant Jr, B. S., Ewalt, D. H., Hawtrey, C. E., et al (2010). Appendix 1: Members of the 1997 Vesicoureteral Reflux Guideline panel.
61. TRAINING, P. (1994). HealthPartners Institute (Doctoral dissertation, University of Pittsburgh).
62. Osaki, Y., Mei, J., Tanihata, T., & Minowa, M. (2004). Cigarette brand preferences of smokers among university students in Japan. Preventive medicine, 38(3), 338-342.
63. Lu, Z. J., Comanor, W. S., Cherkas, E., & Phillips, L. (2020). US pharmaceutical markets: expenditures, health insurance, new products and generic prescribing from 1960 to 2016. International Journal of the Economics of Business, 27(1), 1-26.