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REVIEW

# Empirical generalizations in management science: Theory and modeling

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Empirical generalizations refer to a repeating pattern or a set regularity that repeats itself over different conditions of a system. In this paper, our goal is to reinforce the growing perspective mentioned above. Specifically, we highlight the concept of empirical generalizations in the field of management (marketing) science, which avers that the phenomena of theory-building and data generation should go hand in hand in order to build higher-order theories. We begin with the discussion of the scientific approach and mathematical model building. The concepts of empirical generalizations are then discussed to elaborate on their role in theory-building and research. We discuss 2 salient approaches to developing empirical generalizations—(i) First theory, then data, or (ii) First data, then theory. We then use the Bass diffusion model as a base to develop the case for the greater use of empirical generalizations in the field of management. The objective of a diffusion model is to generate a life-cycle sales curve of a new product/service based on a small number of parameters. The parameters may be estimated based on the consumer pre-tests, an analogy with the sales pattern of similar products in the past, or by early sales returns as the new product enters the market. Starting from the seminal paper by Bass, a vast amount of literature has been produced in the diffusion modeling. Finally, we provide a product/service diffusion example of the performing arts company as an extension of the Bass model.

**Keywords:** empirical generalizations, diffusion modeling, bass model, innovation, theory building

## Introduction

The evolution of strategies to enhance managerial decision-making has become a significant area of interest in both academic research and mainstream business literature. Theory-building for the various organizational phenomena has consistently been a fundamental focus in the academic field of organizational theory. However, it is a common reality that many experienced and astute business professionals continue to have confidence in their managerial decisions based simply on the quarterly data available to them. While the significance of managerial experience, intuition, and data cannot be overstated, there has been undeniable substantiation emerging over the past few decades in support of incorporating the utilization of both theory and mathematical modeling in the business world (1).

In this paper, our goal is to reinforce the growing perspective mentioned above. Specifically, we highlight the concept of empirical generalizations in the field of management (marketing) science, which avers that the phenomena of theory-building and data generation should go hand in hand in order to build higher-order theories.

Management science as a field encompasses a wide variety of disciplines and methodologies, which are aimed at understanding and improving the management of organizations. Management science uses empirical research extensively to help develop a theory and assist in managerial problem-solving and taking decisions. The empirical generalizations are crucial in empirical research, as they reveal underlying relationships or relationships in real-world data.

Some of the important functions of empirical generalizations in management science are listed below:

- Initial step in theory-building—The underlying relationships and patterns in the data provide suitable starting point in developing hypotheses and the relevant theories.
- Confirmation of existing theories—The tendency of the patterns detected by the extant data to consistently indicate in the direction of a theory corroborates to validation of the theory.
- Guiding managerial decision making—Empirical generalizations provide evidence-based insights. Managers can use these to make more informed choices and improve organizational outcomes.

## Literature review

### *Scientific approach*

Science is a systematic process of inquiry. Through the scientific approach, we seek answers to the questions of our interest, and, over a period of time, we devise more and more effective methods to answer the questions. As the process of inquiry becomes more scientific, we are likely to obtain correct answers to our questions of interest.

Bass and Wind (2) further define science as a process in which theory and data interact, leading to generalized explanations of disparate types of phenomena. These phenomena are called empirical generalizations and are the building blocks of science. The development of an inventory of generalizable findings helps advance both science and managerial knowledge.

The scientific approach, or scientific method, is a systematic and logical process that scientists and researchers use to investigate natural phenomena, acquire new knowledge, and test hypotheses. It is a fundamental basis for conducting research and is characterized by some key principles and steps, which are described below:

- Observation: The scientific process begins with making observations about a particular phenomenon or asking questions about the natural world.
- Research: Scientists gather existing information and conduct a thorough literature review to understand what is already known about the topic of interest.
- Hypothesis: Based on their observations and existing knowledge, scientists formulate a hypothesis. A hypothesis is a proposition which is testable and falsifiable, and helps provide a plausible explanation for the phenomenon being investigated.
- Experimentation: Scientists design and conduct experiments to test the hypothesis. These experiments are carefully controlled and manipulated to isolate specific variables and gather data.
- Data Collection: During the experiments, data is collected through measurements, observations, and other means. It's essential to collect reliable and unbiased data.
- Analysis: The collected data is analyzed using statistical and other analytical methods to determine whether it supports or refutes the hypothesis.
- Conclusion: The relevant data analysis leads to the conclusions. If the data shows evidence in favor of the hypothesis, it is seen as a valid explanation for the proposition taken; else the hypothesis is considered rejected, and a new hypothesis is proposed.
- Peer Review: In the field of science, the outcomes are often published in the research journals, which have been reviewed by expert peers in the field to certify the quality and correctness of the results.
- Replication: To enhance the reliability of the findings, other researchers attempt to replicate the experiments and obtain similar results independently.
- Theory or Law: During the course of the ongoing research, a hypothesis may be supported by a number of studies. Then, it is judged to have undergone meticulous testing, and is designated as a scientific theory or law.

This approach to the development of science is dynamic and repetitive in nature, with frequent revisions and refinements in the theories based on the additional data becoming available. Thus, science progresses in a rigorous and self-correcting manner over time.

### *Model building*

When examining a system of sufficient complexity, it has been observed by the past researchers that the complexity increases over time. Finally, it reaches a point that it is no longer feasible to deal with the complexity in its entirety, for which a model of the system is used. A model is a simplified representation of reality or the real-world complex system. The model describes, analyzes, and predicts the behavior of the system under various conditions. The use of mathematical models is pervasive in the fields of science, engineering, economics, and social sciences.

Models can be of different kinds. These include verbal models, graphical models, conceptual models, or mathematical models. In this paper, our focus is on the mathematical models, which use mathematical symbols to denote variables and equations/inequalities to denote relationships among variables.

In light of the above explanations, it can be inferred that the mathematical models create mathematical representations of the real-world systems, which helps to understand, analyze, predict, and simulate the behavior of the system.

Mathematical model building involves the following key steps:

- Problem Formulation: This involves defining of the problem under study and identifying the key variables, objective function, parameters, and constraints.
- Assumptions: As the real-world systems can be quite complex, the role of assumptions becomes quite crucial in mathematical modeling. While it makes the model tractable in solution, at the same time, it also retains the essential features of the complexity of the real-world systems.
- Variable and Parameters: Variables are the entities that change in the system, while parameters are given or fixed values (i.e., constants) that determine the scope of the system.
- Equations: The equations or inequalities represent the association between the different variables and parameters. These relations are extracted on the basis of the empirical data collected by the researcher.
- Solution Methods: On the basis of the complexity of the model, appropriate mathematical techniques are chosen to solve the model. These may range from analytical closed-form solutions to numerical methods of simulation.
- Validation: This step involves validating the model by comparing its predictions to real-world data or observations. When needed, the model is adjusted to improve its accuracy.
- Sensitivity Analysis: This step is undertaken to analyze how changes in different parameters affect the outcomes of the model. This helps prioritize the most critical features of the system.
- Model Interpretation: In this step, the outcomes or model results are interpreted in terms of the real-world system. The model interpretation helps in informed decision-making by the system's manager.

Mathematical modeling is applicable to a wide variety of systems. These vary from straightforward physical processes to highly complex systems such as biological, economic and environmental systems. The choice of mathematical techniques and the level of detail in the model depend on the specific problem and the goals of the analysis.

## *Empirical generalizations in management (marketing)*

We now discuss the concept of empirical generalizations in management. As an example, we will focus on the function of marketing in management. However, the ideas delineated here are similarly pertinent to the different functions of management, like finance or H.R.M. Over the last several decades, the field of marketing has matured to a point that it is almost inevitable to witness the use of data and modeling in marketing. Increasingly, this use of data and modeling in the function of marketing has been known as a special field of marketing science. The holding of annual marketing science conferences and the establishment of a Marketing Science Institute have been concomitant with the evolution of the field of marketing science. Thus, by the year 1993, it was felt that a stock of the status of the marketing science discipline be taken in terms of empirical generalizations.

Empirical generalizations refer to a repeating pattern or a set regularity that repeats itself over different conditions of a system. As enunciated by Bass (3), this explanation does not refer to a direction of causality. It only requires that there be a pattern, not a pattern that is universal across all circumstances. Further, the more precise generalizations are more useful than the less precise ones. Thus, "y increases exponentially with x" is more useful than "y increases with x."

Empirical generalizations are only approximate in nature, and there will be instances in which they may not hold. However, the discovery of such conditions in which the generalization may not hold will lead to a higher-level understanding, or theory. In this paper, we present an example from product diffusion theory (based on Bass Model(4)), which holds well as an empirical generalization in a number of product settings. We also present a case where the Bass (4) model may not hold but works well in conjunction with a new theory.

In February 1994, a workshop was organized at the Wharton School on the topic "Empirical Generalizations in Marketing," which can be reckoned as the genesis of this topic in the field of marketing science. In that workshop, a general consensus emerged that empirical generalization reflects a pattern of results which recurs. This may be possible, but not necessarily predicted by prior theory. The method of deriving such a generalization could "eyeballing," meta-analysis, pattern recognition, or any other method. A specific theory, on the other hand, refers to a "story" which is consistent with the past data. Beyond this, a general higher-level theory is consistent with the past data and applies beyond past data.

A pertinent question that was considered in the 1994 workshop was "Data First or Theory First?" There are examples and arguments supporting both sides of this question. Examples of the former (data first) include experience curve effects in the costs of producing new technologies, while the example of the latter (theory first) includes the Bass model (1969), which predicted the diffusion empirical generalization. There was a general agreement to the statement that science is a process in which data and theory interact to produce higher-level explanations.

In continuation of the above question, a cryptic question was considered as "ETET or TETE?," where ETET refers to (i) establishing some empirically well-grounded theory (as in EtT, that is, empirical-then-theoretical), (ii) testing the theory more widely (the second E), deducing new conjectural theory (the second T), testing that widely, and continuing. Many fields of science progress through the ETET route.

As opposed to the above approach of ETET, instances are also found in the literature of the TETE approach. Under this approach, the empirical does not always precede theory. In other words, the theory already exists or is deduced. The distinction is important because the theory may have other empirical implications beyond the immediate empirical generalization. Thus, in the first instance in this approach, the proper term assigned is TiI, that is, theory in Isolation. Subsequently, empirical observations, or E commence, and the process of TETE ensues. Bass (4) model exemplifies the TETE approach, which is discussed next. Some recent applications of the Bass model are given in Fibich et al. (5), Di Lucchio and Modanese (6), and Jafari et al. (7).

# Methodology

## Diffusion modeling

The objective of a diffusion model is to generate a life-cycle sales curve of a new product/service based on a small number of parameters. The parameters may be estimated based on the consumer pre-tests, an analogy with the sales pattern of similar products in the past, or by early sales returns as the new product enters the market. Starting from the seminal paper by Bass (4), a vast amount of literature has been produced in the diffusion modeling. In fact, Bass's (4) model has been built on the foundation laid by two previous works, namely Fourt and Woodlock (8) and Fisher and Pry (9).

## A Pure Innovative Model

One of the earliest market penetration models was an exponential model proposed by Fourt and Woodlock (8). Their model has the following functional form:

$$dX/dt = \alpha\,(N - X) \tag{1}$$

where,

$X$ = total sales till time '$t$'

$\alpha$ = coefficient of innovation

$N$ = market potential

As per the model in Equation 1, the instantaneous sales per time period, $dX/dt$, are a function of the population remaining to adopt the product ($N$–$X$). Thus, in each time period, a small fraction $\alpha$ of the remaining population will adopt the product based on their innovativeness.

## A Pure Imitative Model

The underlying assumption of Fisher and Pry (9) model is that when a new product penetrates the market, the rate of adoption is proportional to an interplay between 2 groups of customers: (i) adopters of the product and (ii) non-adopters of the product.

Fisher and Pry (9) model is specified as follows:

$$dX/dt = \beta * X * (N - X) \tag{2}$$

where,

$\beta$ = coefficient of imitation

As per the model in Equation 2, the instantaneous sales per time period, $dX/dt$, are a function of the interaction, or word-of-mouth, that takes place between adopters and non-adopters of the new product, ($X^*(N$–$X)$).

## Innovative and Imitative Model

While Fourt and Woodlock (8) is a pure innovative model, the Fisher and Pry (9) model is a pure imitative model. In an important integrative step in the marketing field, Bass (4) combined Equations (1) and (2) to provide the following version of the Bass (4) model:

$$dX/dt = (\alpha + \beta * X) * (N - X) \tag{3}$$

Note that Equation (3) has both innovative and imitative effects combined in a single equation.

The shapes of the cumulative (or total) sales curve ($X$) and instantaneous sales curve (i.e., new adopters, $dX/dt$) are as shown in **Figure 1**. Thus, $X$ has a classical S-shaped curve, while $dX/dt$ has a bell-shaped curve. Mahajan et al. (10) report the typical values of $\alpha$ and $\beta$ when time t is measured in years. The average value of $\alpha$ has been estimated as 0.03, with a typical range between 0.01 and 0.03. The average value of $\beta$ has been estimated as 0.38, with a typical range between 0.3 and 0.5.

A large number of follow-up articles have been published on the basis of the Bass model (11). The model usually works well in terms of fitting to the adoption data. Jeuland (12) showed that the Bass model works well for the 35 data sets examined for different product categories. The $R^2$ values usually exceeded 0.9. Thus, the Bass model can be considered as an empirical generalization.

The Bass model has also resulted in a variety of real-world applications of the Bass model. Lawrence and Lawton (13) analysis shows the range for ($\alpha + \beta$) to be between 0.3 and 0.7. Sultan et al. (14) examined 213 published results of the Bass model's extensions and found the average values of $\alpha$ and $\beta$ to be 0.03 and 0.38, respectively. The previous research also shows that $\alpha$ is often quite small, around 0.01. $\beta$ has been found to be relatively greater, between 0.3 and 0.5. The distribution based on historical data and parameter values provides useful generalizations to be used when no data is available for an innovation (i.e., a new product). The Bass model has resulted in several extensions, such as successive generations of technologies, decision variable

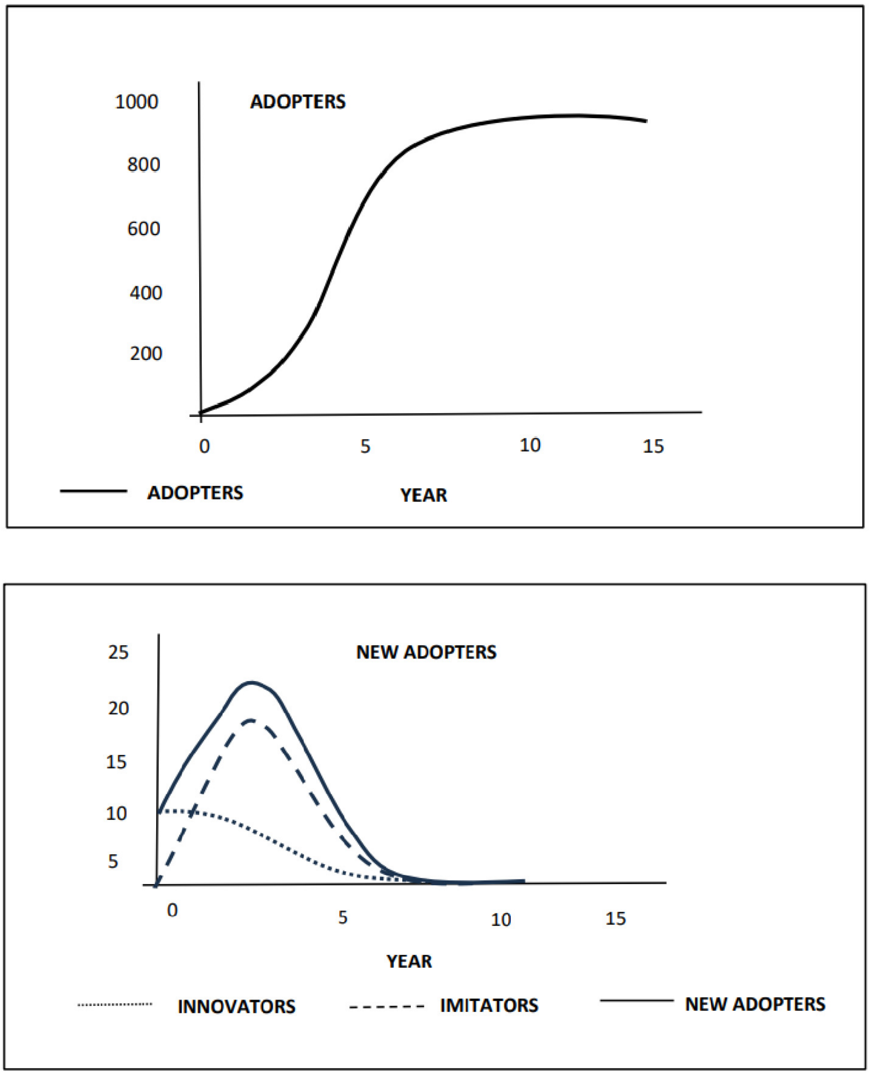


**FIGURE 1 |** The shapes of *X* and *dX/dt* as per the model by Bass (4). Source: https://en.wikipedia.org/wiki/Bass_diffusion_model.

incorporation, patent infringements, normative value of a business, and so on (10). We next present an extension of the Bass model to the category of services of performing arts, namely, symphony orchestra.

## Rogers' theory

Rogers (15) defines innovation as an idea, practice, or project that is perceived as new by an individual or other unit of adoption. The novelty characteristic of an adoption is more related to the 3 steps (knowledge, persuasion, and decision) of the innovation-decision process. Uncertainty is an important obstacle to the adoption of innovations. To reduce the uncertainty of adopting the innovation, individuals should be informed about its advantages and disadvantages to make them aware of all its consequences. Moreover, Rogers claimed that consequences can be classified as desirable versus undesirable (functional or dysfunctional), direct versus indirect (immediate result or result of the immediate result), and anticipated versus unanticipated (recognized and intended or not).

Rogers (15) further defines communication as a process in which participants create and share information with one another in order to reach a mutual understanding. This communication occurs through channels between sources. Rogers states that diffusion is a specific kind of communication and includes these communication elements: an innovation, 2 individuals or other units of adoption, and a communication channel. Mass media and interpersonal communication are 2 communication channels. Interpersonal channels are more powerful to create or change strong attitudes held by an individual. In interpersonal channels, the communication may have a characteristic of homophily, that is, the degree to which two or more individuals who interact are similar in certain attributes, such as beliefs, education, socioeconomic status, and the like, but the diffusion of innovations requires at least some degree of heterophily, which is the degree to which two or more individuals who interact are different in certain attributes.

Rogers (15) argues that including the time dimension in diffusion research illustrates one of its strengths. The innovation-diffusion process, adopter categorization, and rate of adoptions all include a time dimension.

The social system is the last element in the diffusion process. Rogers (15) defined the social system as a set of interrelated units engaged in joint problem solving to accomplish a common goal. Since the diffusion of innovations takes place in the social system, it is influenced by the social structure of the social system.

# Results or finding

## Case study – Booking curve prediction of a symphony orchestra

In this section, we discuss the modeling of the consumer behavior for a new symphony orchestra arts event based on the approach of the Bass model and specifically incorporating the phenomenon of limited seat availability on the ticket booking curve. Several studies have extended the Bass model by adding key elements to the basic model (16–18).

## Problem statement

We examine the instance of an arts organization that is publicizing a new upcoming event, for example, a symphony orchestra event. The planning horizon of the sale of tickets is of length T. The tickets are sold until time T, or before when all seats are booked. Suppose there are N potential customers in this market, and the theater's seating capacity is a fixed constant, m.

**Figure 2** depicts the conceptualization of the problem statement. The figure demonstrates that the typical two elements of diffusion modeling (based on the Bass model) affect customer ticket purchase behavior at a time are (1) the innovation effect and (2) the imitation effect. Swami and Khairnar (19) propose an additional factor, the scarcity effect, that can accelerate ticket purchase behavior. This effect comprises the following components: (i) limited quantity and (ii) time-based deadline (20).

With a limited-numbers strategy, a customer is notified that a limited number of seats are available for an arts event, and they may be booked soon. In the time-deadline strategy, a consumer's ability to acquire the ticket is restricted by the day of the event.

## Booking curve model

The demand is modeled based on the benchmark Bass model, which has the following form:

$$x'(t) = \frac{dx(t)}{dt} = \alpha(N - x(t)) + \frac{\beta}{N}x(t)(N - x(t)). \quad (4)$$

where $x(t)$ is the total sales till date, $N$ is the size of the market, and $\alpha$ and $\beta$ are the innovation and imitation coefficients, respectively.

This benchmark model considers innovation and imitation factors, $\alpha$ and $\beta$, to be fixed over time. However, when modified to account for the scarcity effect, $\alpha$ and $\beta$ may be accelerated and become a function of time, denoted as $\alpha(t)$ and $\beta(t)$ below:

$$\alpha(t) = \alpha_0 + \alpha_1\frac{t}{T} + \alpha_2\frac{x(t)}{m} + \alpha_3\frac{t}{T}\frac{x(t)}{m} \quad (5)$$

$$\beta(t) = \beta_0 + \beta_1\frac{t}{T} + \beta_2\frac{x(t)}{m} + \beta_3\frac{t}{T}\frac{x(t)}{m} \quad (6)$$

As shown above, the innovation and imitation coefficients are functions of fraction of time to event deadline, $t/T$, and fraction of seats sold to capacity, $x(t)/m$, and an interaction between the 2 fractions. It is clear that as $t$ approaches $T$, the event date and total sales $x$ approach $m$, the innovation and imitation coefficients are accelerated. Based on Equations 5 and 6, Equation 4 can be simplified to (dropping the subscript t):

$$y = \frac{dx}{dt} = A + B\,x + C\,x^2 + D\,x^3 + E\,t + F\,tx + G\,tx^2 + H\,tx^3 \quad (7)$$

In Equation 7, coefficients A-H are functions of the original parameters $N$, $m$, $T$, $\alpha$, and $\beta$. This general model has weekly sales depending on both cumulative adoption $x$ and time $t$. Several sub-models of Equation 7 can be generated as shown below. Their results are shown in the next section.

(i) Bass model (Benchmark) $y = A + B\,x + C\,x^2$
(ii) $y = A + B\,x + C\,x^2 + D\,x^3$
(iii) $y = A + B\,x + C\,x^2 + D\,t$
(iv) $y = A + B\,x + C\,x^2 + D\,tx$
(v) $y = A + B\,x + C\,x^2 + D\,tx^2$

## Data description

To assess the demand model's forecasting ability, we estimate regression coefficients using the sales data for the Vancouver Symphony Orchestra in Canada between 1985 and 1987. During this time, this orchestra was amongst Canada's top three symphony orchestras, performing nearly 130 concerts per year. These include a number of events such as classical, light classical, pops, family matinee, children's series, community outreach series, and a number of special events with globally celebrated artists.

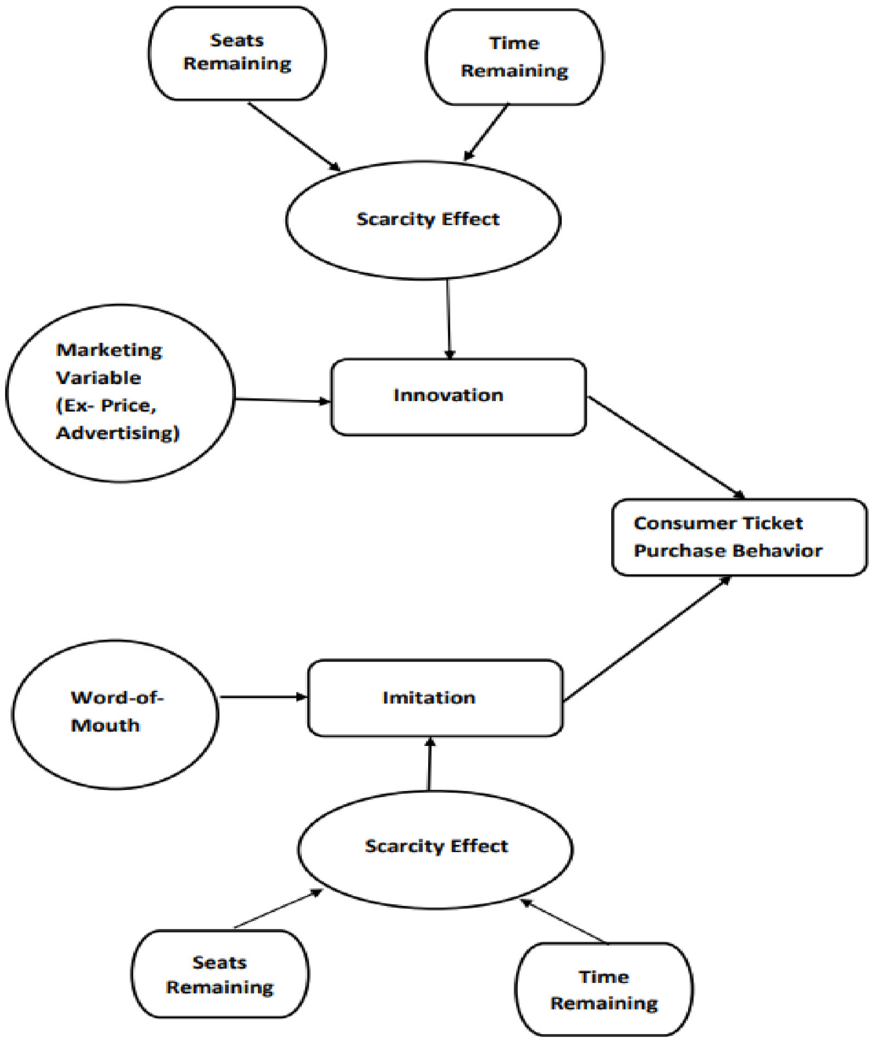


**FIGURE 2 |** Conceptualization of consumer behavior for ticket purchase. Source: Swami and Khairnar (19).

## Estimation results

We report the estimation results for eight data series of 1985-87 seasons in **Table 1**.

We make the following key observations from the results:

1. The relatively high $R^2$ values show that the proposed models provide a good fit to the concert seat sales data. The nested F-values denote the incremental impact of the parameter D over and above the parameters A, B, and C of the benchmark Bass model. Thus, in most cases, the additional effects of time deadlines and limited quantity are quite significant.
2. In case of some data series, like Series 4, the proposed models provide nearly equal fits to the classical Bass model. In such cases, the extended model reduces to the Bass model, a desirable property of an extension.
3. The proposed models show significant improvement over the Bass model, ranging from 3% to 53%.

# Discussions

## Recent related research in this area

Narain et al. (21) use Bass's diffusion model to examine both the evolutionary and control elements of the management of artificial superintelligence. The authors explore the distribution pattern of those advanced technologies that can be considered precursors to the acceptance of artificial superintelligence using empirical study (ASI). The authors present many dynamic models of superintelligence's likely future progression, including diffusion models, predator–prey models, and antagonism models. Additionally, the authors conduct an empirical investigation of the application of diffusion modeling to three technologies from the manufacturing, communication, and energy industries that can be viewed as potential antecedents to the evolution of ASI.

da Silva et al. (22) provide insight into the distributed photovoltaic generation technology diffusion in the

**TABLE 1 |** Multiple regression results for sales data of Vancouver Symphony Orchestra (period: 1985–1987).

| Coeff.\ model | (i) Bass | t-stat | (ii) | t | (iii) | t | (iv) | t | (v) | t |
|---|---|---|---|---|---|---|---|---|---|---|
| | y=A+Bx+ Cx$^2$ | | y=A+Bx+ Cx$^2$+Dx$^3$ | | y=A+Bx+ Cx$^2$+Dt | | y=A+Bx+ Cx$^2$+Dtx | | y=A+Bx+ Cx$^2$+Dtx$^2$ | |
| | | | | | **Series 1** | | | | | |
| A | 927.67 | 1.53 | −2963.67 | −1.65 | 3935.45 | 3.65 | 2049.35 | 4.08 | −1021.77 | −3.02 |
| B | −3.79 | −1.70 | 18.99 | 1.84 | −16.18 | −3.69 | −5.26 | −3.65 | 8.88 | 4.61 |
| C | 0.00 | 2.03 | −0.04 | −2.03 | 0.01 | 4.30 | −0.01 | −1.73 | −0.02 | −5.76 |
| D | | | 0.00 | 2.24 | 478.75 | 3.00 | 0.86 | 3.31 | 0.00 | 7.12 |
| $R^2$ | 0.66 | | 0.83 | | 0.88 | | 0.89 | | 0.97 | |
| F# | - | | 5 | | 9.17* | | 10.45* | | 51.67** | |
| | | | | | **Series 2** | | | | | |
| A | −583.08 | −1.70 | −2072.63 | −1.34 | −250.45 | −0.39 | −69.02 | −0.11 | −362.19 | −1.08 |
| B | 2.12 | 1.74 | 10.16 | 1.24 | 0.85 | 0.35 | 0.42 | 0.20 | 2.07 | 1.92 |
| C | 0.00 | −1.52 | −0.02 | −1.09 | 0.00 | −0.39 | 0.00 | −0.74 | 0.00 | −2.28 |
| D | | | 0.00 | 0.99 | 19.22 | 0.62 | 0.07 | 1.03 | 0.00 | 1.54 |
| $R^2$ | 0.65 | | 0.72 | | 0.69 | | 0.73 | | 0.78 | |
| F | - | | 1 | | 0.52 | | 1.19 | | 2.36 | |
| | | | | | **Series 3** | | | | | |
| A | −65.49 | −0.15 | 587.39 | 0.19 | 671.81 | 0.65 | 882.48 | 0.93 | 726.19 | 1.04 |
| B | −0.11 | −0.07 | −3.44 | −0.22 | −2.55 | −0.75 | −3.02 | −1.01 | −2.04 | −1.05 |
| C | 0.00 | 0.52 | 0.01 | 0.24 | 0.00 | 0.94 | 0.00 | 1.21 | 0.00 | 0.82 |
| D | | | 0.00 | −0.22 | 17.39 | 0.80 | 0.05 | 1.11 | 0.00 | 1.36 |
| $R^2$ | 0.89 | | 0.89 | | 0.90 | | 0.92 | | 0.92 | |
| F | - | | 0 | | 0.4 | | 1.5 | | 1.5 | |
| | | | | | **Series 4** | | | | | |
| A | 453.53 | 3.60 | −571.06 | −0.89 | 808.71 | 5.47 | 831.69 | 4.22 | 448.82 | 4.16 |
| B | −4.25 | −4.41 | 7.75 | 1.04 | −7.82 | −5.66 | −7.13 | −4.75 | −2.94 | −2.67 |
| C | 0.01 | 5.99 | −0.03 | −1.25 | 0.01 | 7.86 | 0.01 | 7.72 | 0.00 | 0.03 |
| D | | | 0.00 | 1.62 | 47.86 | 2.92 | 0.23 | 2.21 | 0.00 | 1.79 |
| $R^2$ | 0.95 | | 0.97 | | 0.98 | | 0.98 | | 0.97 | |
| F | - | | 3.33 | | 7.5* | | 7.5* | | 3.33 | |
| | | | | | **Series 5** | | | | | |
| A | −37.98 | −1.12 | 24.52 | 1.01 | 50.72 | 0.94 | 48.00 | 1.45 | −61.01 | −1.61 |
| B | 1.08 | 3.28 | −0.75 | −1.70 | 2.79 | 3.05 | −3.18 | −2.68 | 2.85 | 1.95 |
| C | 0.00 | −2.25 | 0.01 | 4.03 | 0.00 | −2.86 | 0.00 | −4.91 | −0.03 | −1.28 |
| D | | | 0.00 | −4.60 | −34.18 | −1.97 | 0.37 | 3.65 | 0.00 | 1.24 |
| $R^2$ | 0.63 | | 0.88 | | 0.74 | | 0.84 | | 0.68 | |
| F | - | | 20.83** | | 4.23 | | 13.13** | | 1.56 | |
| | | | | | **Series 6** | | | | | |
| A | −60.78 | −1.43 | 51.11 | 1.47 | −67.94 | −1.61 | 36.14 | 0.70 | −53.55 | −1.46 |
| B | 0.82 | 2.42 | −1.15 | −2.53 | 1.92 | 2.04 | −1.07 | −1.38 | 1.80 | 3.64 |
| C | 0.00 | −1.37 | 0.01 | 4.48 | 0.00 | −1.74 | 0.00 | −2.54 | −0.02 | −2.53 |
| D | | | 0.00 | −4.89 | −14.99 | −1.24 | 0.12 | 2.63 | 0.00 | 2.45 |
| $R^2$ | 0.55 | | 0.84 | | 0.59 | | 0.70 | | 0.69 | |
| F | - | | 23.56** | | 1.26 | | 6.5* | | 5.87* | |
| | | | | | **Series 7** | | | | | |
| A | −3.02 | −0.19 | 49.61 | 3.25 | −2.24 | −0.16 | 33.44 | 1.48 | −1.01 | −0.08 |
| B | −0.04 | −0.17 | −2.04 | −4.56 | 2.91 | 2.34 | −1.49 | −2.06 | 0.85 | 2.59 |
| C | 0.00 | 5.93 | 0.02 | 5.68 | 0.00 | −0.82 | 0.00 | 4.73 | −0.02 | −2.91 |

*(Continued)*

**TABLE 1** | Continued

| Coeff.\ model | (i) Bass | t-stat | (ii) | t | (iii) | t | (iv) | t | (v) | t |
|---|---|---|---|---|---|---|---|---|---|---|
| | $y=A+Bx+Cx^2$ | | $y=A+Bx+Cx^2+Dx^3$ | | $y=A+Bx+Cx^2+Dt$ | | $y=A+Bx+Cx^2+Dtx$ | | $y=A+Bx+Cx^2+Dtx^2$ | |
| D | | | 0.00 | −4.76 | −19.55 | −2.41 | 0.08 | 2.09 | 0.00 | 3.28 |
| $R^2$ | 0.95 | | 0.98 | | 0.96 | | 0.96 | | 0.97 | |
| F | - | | 24** | | 4 | | 4 | | 10.67** | |
| | | | | | **Series 8** | | | | | |
| A | −12.66 | −1.01 | −3.27 | −0.20 | −1.79 | −0.12 | 37.43 | 1.57 | −23.42 | −1.98 |
| B | 0.38 | 2.25 | 0.10 | 0.31 | 0.87 | 2.02 | −1.83 | −1.95 | 1.50 | 3.28 |
| C | 0.00 | 1.51 | 0.00 | 1.19 | 0.00 | −0.34 | 0.00 | 0.08 | −0.03 | −2.56 |
| D | | | 0.00 | −0.94 | −3.67 | −1.24 | 0.10 | 2.39 | 0.00 | 2.60 |
| $R^2$ | 0.88 | | 0.89 | | 0.89 | | 0.91 | | 0.91 | |
| F | - | | 1.81 | | 1.81 | | 6.67* | | 6.67* | |

Source: Swami and Khairnar (19)

residential sector. Brdulak et al. (23) acknowledge that, in light of present ecological challenges, such as the impact of transportation and mobility on the greenhouse effect, policymakers find a solution in electric vehicles (EVs). Bass's innovation diffusion concept was utilized to estimate whether and when EVs could eventually replace combustion engine vehicles in their research. Gunduc (24) investigates the innovation diffusion of two rival products. The primary objective has been to comprehend the consequences of a competitive dynamic market on innovation diffusion.

## Results

To summarize, the results augur well for the use of the proposed model to the symphony orchestra seat sales data. Although the Bass model also works well for this data, the proposed models provide even better fits to the data in many instances. Thus, the proposed models can be represented as a general case of the Bass model in such areas of application.

## Conclusion

In this paper, we introduce the concept of empirical generalizations in the field of management science. Using the seminal Bass's (4) diffusion model as a benchmark framework, we present the approach of empirical generalization in the diffusion theory literature. This approach underscores the importance of theory in the research process. Finally, we present a case study of a symphony orchestra performing arts company as a generalization of the Bass (4) model. The ideas presented in this paper can be used to propose further empirical generalizations in the field of management science. Some potent areas of current research that could benefit by the identification of empirical research are big data and analytics, behavioral economics and psychology, sustainability and Corporate Social Responsibility, digital transformation, cross-cultural management and its impact on leadership, communication, and teamwork; remote work and organizational adaptation, and artificial intelligence and robotics. The present study has certain limitations. The study provides an overview of exemplar work done in the area of diffusion modeling. However, it will be interesting to examine these implications on the current data in the digital era. Further, it will be useful to extend these results to a multi-country scenario.

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