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Design Choices and Adoption Processes: from Engineering Designed Products to Services

Alessandro Casagrande-Seretti

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Supervisors
Prof. Francesca Montagna
Prof. Claudia De Giorgi

Doctoral Examination Committee:

Prof. Niccolò Beccatini, Referee, Politecnico di Milano
Prof. Marzia Mortati, Referee, Politecnico di Milano
Prof. Marco Cantamessa, Politecnico di Torino
Prof. Beatrice Lerma, Politecnico di Torino
Prof. Federico Rotini, Università degli Studi di Firenze

Politecnico di Torino
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Alessandro Casagrande-Seretti
Turin, March 04, 2021

Summary

When designing new innovations, one mistake companies are led to make is to consider only the technical aspects related to the product or service being developed. In this respect, Design for Innovation means considering all the design issues relevant to adoption. This is equivalent to study the diffusion dynamics of new technologies in order to understand whether potential customers could adopt new products and services or not. The thesis aims to deepen the study of product and service diffusion and adoption and address the impact of design choices on the adoption process.

The literature has extensively investigated product diffusion, and first contributions date back to the 1960s. In addition to the mathematical models to trace the diffusion curves, contributions around the first steps of diffusion arose, such as the concepts of first-mover advantages and time-based competition. The idea here proposed is that rethinking time, defined as the time available to firms to redesign products according to the needs of upcoming customer segments, may be one of the moderating effects of first-mover advantages.

On the other side, service diffusion is a very underdeveloped topic. Despite studies about product diffusion date back many years, they neglected the existence of services mainly because, at the dawn of innovation diffusion theory in the 1960s, the service sector was far less developed than the product one. The advent of the internet in the 1990s was an incredible catalyst in developing new innovative services and aroused interest in the topic. Three kinds of services exist (i.e., subscription services, on demand services used several times in a medium/short period of time, and on demand services occasionally used over a long period of time); and three types of diffusion models are recognisable in the literature (i.e., Bass-type, Choice-type, and Grey models). In particular, Bass-type models require to collect given data and apply related metrics according to the kind of service under analysis. Hence, the thesis proposes a simple framework to choose the best-suited metric when the diffusion of a given type of service is under investigation.

'Diffusion' theories have been investigated together with 'adoption' theories since the 1960s. The adoption process has often been described as one of the diffusion process stages; in particular, it is the last one after awareness, interest, evaluation, and trial. However, as diffusion dynamics differ, the adoption process differs from products to services too.

The idea here is to investigate the factors behind adoption from an Engineering Design perspective. Firstly, a model to anticipate the market appreciation of innovative consumer products as a function of design decisions was presented. For analysis purposes, design decisions here represent functional modifications that occurred between two subsequent product generations and have been categorised in twelve variables.

However, this approach may result to be difficult to apply in service contexts. Indeed, contrary to products, services are usually characterised by intangible elements. The adoption of industrial designed products may represent an intermediate step since it is usually linked to elements related to the experiential process (e.g., affordance).

A model to anticipate the market adoption of innovative industrial designed products as a function of design decisions was presented. Again, design decisions represent functional modifications, and, indeed, the novelty lies in studying whether and to what extent functional features affect adoption when elements other than physical and technical ones usually drive these dynamics.

The analyses to develop the model were carried out on data from the surface material industry. The latter, even if it is a semi-finished products industry, has features that allow equating products from this industry to industrial designed products. Indeed, surface material industry products give some of the most important properties to the end products to which they are applied (e.g., countertops, chairs, cabinets, desks).

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1. Introduction

1.1. Design for Innovation

Over the years, many discussions around technological innovations have been presented in the literature, and have generated diverse classifications.

First of all, innovations can be defined as incremental or radical by looking at the functions and performance systems have (Dewar & Dutton, 1986). Incremental innovations are intended as minor improvements or simple adjustments in current technology; they introduce small changes that are aimed at improving performances, reducing costs, or enhancing desirability, but without affecting the technological trade-offs each system always poses. In contrast, radical innovations break trade-offs by introducing new functions that differentiate products or services from predecessors and represent revolutionary technology changes. For instance, a typical trade-off in the mobile phone industry can be found between performance (e.g., processor speed and functionalities) and portability. All the feature phones introduced in the 1990s and early 2000s were incremental innovations, which may be graphically represented by a series of nested s-curves corresponding to different product generations (Christensen, 1992). Instead, the first iPhone represented a radical innovation as it was the first smartphone – and, therefore, a mobile phone with much more functionalities but almost the same portability – to be commercially successful.

The distinction between radical and incremental innovations proposed by Dewar and Dutton (1986) actually is more natural to intuit than measure, as the same authors recognised. In the literature, the rise of a radical innovation has been closely associated with the emergence and diffusion of a new technological paradigm which in turn is linked to the presence of a dominant design, as proposed by Dosi (1982). A technological paradigm is a mixture of supply-side and demand-side elements that need to coherently mix together in order to favour its emergence. For instance, by providing encyclopaedic knowledge for free, Wikipedia understood that supply-side factors were being affected by the spreading of internet connections, while users were becoming different as well. People started to consult online contents, preferring real-time, almost infinite results, rather than traditional encyclopaedias' greater reliability. Similarly, Apple provided more functionalities without restricting portability, up to Amazon nowadays, that is assessing a drone-based delivery system. It is clear that also all the elements of the economic and social system independent from the technical performances determine the success or failure of a product or service.

The high market and technological uncertainty related to the emergence of a new paradigm make market and customer-based approaches hardly reliable. Therefore, it is interesting to investigate the technological and design elements that can underneath an innovation in this context. Adopting this perspective, differences between incremental and radical innovations have been deepened by observing two axes typically linked to the design choices: underlying technology and product architecture (Henderson & Clark, 1990). In particular, the latter consists of the main physical elements of a product and their mutual relationships. These relationships may represent either functional interactions, as well as proximity or even a general relation.

The concept of proximity within an architecture is so relevant that innovations can even be distinguished based on the locus of the product where they are incorporated (Gatignon, Tushman, Smith, & Anderson, 2002). In particular, it is referred to as core innovation when a design decision that leads to innovation is onto the core components of a product, while it is peripheral when minor elements are affected.

Regardless of the kind of technological innovation under analysis, when designing innovations, one mistake companies are led to make is to consider only the performances related to the product or service being developed, neglecting completely those technical aspects that affect adoption. In this respect, Design for Innovation (Cantamessa, Montagna, & Cascini, 2016) means considering those design issues that are related to user's needs within a multistakeholder context, as well as being able to identify customers who adopt innovative products at different timings along the diffusion curve (Montagna & Cantamessa, 2019). In fact, they are not homogenous segments but part of distinct market segments with different needs (Rogers, 1962); hence, companies should plan product development by defining a sequence of different requirements according to the successive market segments and designing products and services concepts accordingly.

1.2. Diffusion Dynamics and Design Variables – From Engineering Designed Products to Services, through Industrial Designed Products

Diffusion dynamics (i.e., how a system penetrates the market) are different with respect to the features of the system itself. Physical products are tangible and, usually, characterised by a set of technical and physical features that are rather measurable, and therefore their adoption, that can only be a binary decision (i.e., adopt / not adopt), is driven by such measurable features. Consequently, all design choices affecting these technical and physical features have a direct effect on diffusion. Instead, services are intangible by definition; they are made of processes often difficult to be evaluated. Hence, services can not be represented by the classic adoption process leading to a long-lasting binary decision. Adoption mechanisms are here more varied and can persist over time. Designing a service, therefore, means working on its intangible elements in order to define technical features that may have an impact on service perception and may promote its adoption by supporting experiential processes related to it.

This difference places limits on considering the diffusion dynamics of products and services as similar and may explain why service diffusion is a very underdeveloped topic in the literature (Libai, Muller, & Peres, 2009). Despite studies about product diffusion date back many years, they neglected the existence of services. Obviously, the reason lies in the fact that at the dawn of innovation diffusion theory in the 1960s, the service sector was far less developed than the product one. Nevertheless, the advent of the internet in the 1990s was an incredible catalyst in developing innovative services which acquired complete research streams in various literature fields, such as Operations Management and Quality Management, up to Service Design.

Diffusion dynamics are, in turn, linked to the concept of adoption. The latter is one of the two elements of the diffusion process, together with awareness (Bass, 1969). Adopting basically means purchasing a product or becoming a customer of a service provider (Rogers, 1976), and it occurs whenever the perceived value to a product or a service exceeds its selling price.

Apart from adoption definition, as diffusion dynamics differ from products to services, adoption processes differ too. As already said, when potential customers evaluate consumer goods, they usually take into consideration technical and physical measurable features, such as the fuel consumption for a car or the megapixel for a photo camera. Instead, services do not allow to assess benefits perceived by users so easily due to their intangible nature.

In studying adoption, *a possible solution to move from products to services is to distinguish between engineering designed and industrial designed products*. Engineering designed products represent those products characterised by an extensive engineering design process that provides them with functional features crucial for the adoption process. Examples can be either consumer goods such as Blu-ray player, smartphones or microwave ovens, or more complex systems such as an aeroplane. Whether assessed by quantitative or qualitative approaches, these features are usually strictly linked to technical and physical elements. Instead, industrial designed products result from an extensive industrial design process. They are usually characterised by hardly measurables features – again assessable with both qualitative and quantitative approaches – such as aesthetic aspects, as well as by design elements treating the product shape as an experiential element that drives the interaction with the product. The interaction and experience processes are as relevant as for services and, therefore, play a significant role in adoption. Examples could be the purchase of a furnishing accessory, a chair, or a coffeepot when elements such as comfort, style, or affordance can be crucial in the adoption process (Norman, 2013). Industrial designed products can be positioned halfway between engineering designed goods with their complete measurable set of features and intangible services. One of the latter's most important characteristics consists indeed in intangibility, i.e., the lack of physical attributes.

1.3. Research Aim and Objectives

The aim of the thesis, therefore, is to investigate the phenomena of diffusion and adoption process in the varied panorama of systems that can result from engineering or industrial designed processes, be they products or services, or be they characterised by easily assessable and measurable features or more intangible and experiential ones.

A review of the literature on product and service diffusion has led to identifying two gaps in the literature. The lack of a theory when companies have a limited time available to redesign products according to the needs of the upcoming customer segments; the lack in service diffusion studies of suggestions regarding the proper model to be applied when industrial products or services are under analysis.

The link between diffusion dynamics and adoption processes was deepened, in particular. The differences between products and services do not allow to treat the topic neglecting their distinctions. Therefore, products were further distinguished into engineering designed and industrial designed products.

The idea is that even when adoption is usually driven by qualitative or intangible elements, some intrinsic and measurable features could have an impact on customer adoption. Therefore, industrial designed products represent, as described above, an intermediate step between engineering designed products and services.

1.4. Research Questions

The discussion will be based on three main research questions:

RQ1: Given the existence of different customer segments, may companies gain advantages by rethinking products? And therefore, is it more advantageous being a first-mover or taking time to rethink and develop new products that must be marketed to an upcoming segment of potential adopters?

Indeed, it is widely demonstrated in the literature that being first movers determines an advantage from a competitive point of view (Lieberman & Montgomery, 1988). However, they usually focus on the specific needs of the early segments and neglect a more farsighted exploration of future segments, which exhibit quite different preferences and requirements (Schnaars, 1994). Hence, late entrants may focus their effort on developing products that suit subsequent adopters and trying to influence their needs (Carpenter & Nakamoto, 1989). Thus, a first-mover will likely be unsuccessful in the mass market when the time available to redesign the product is too short. However, the outcome could also be the opposite when a long time span may lead to better improvements, and organisational inertia may hinder forecasting and reacting to environmental changes and new threats (Vecchiato, 2015).

RQ2: Which diffusion models and metrics are the best suited to represent the diffusion of innovative industrial products and services?

The primary assumption here is that several kinds of services exist, and there are still no clear and unique indications as to which models can best simulate diffusion in these sectors. Several models have been so far proposed and can be ascribed to three typologies: Bass-type models (Libai, Muller, & Peres, 2009), Choice-type models (Landsman & Givon, 2010), and Grey models (Lin, 2013). These model typologies require different computational capacity and a different amount of data to be applied, and the data itself to be collected also varies from model to model.

RQ3: How do design new features, mainly enabled by a new technology, affect the adoption of engineering, industrial designed products, and services?

The idea is that systems architecture, to which technological paradigms are related, results from design decisions. It merely means that any radical innovation, and therefore any technological shift, is always the outcome of a given set of design choices. This research question investigates how design decisions may impact adoption and hence the diffusion of new technological paradigms, where design decisions have been analysed according to the extent to which they can affect customer perception.

In light of the research aim, objectives, and questions, the main elements of novelty are then represented by the attempt to revise the competitive advantage concept that derives from being a first-mover by adding a moderating effect, i.e., the rethinking time. Moreover, the thesis tries to address diffusion studies issues by distinguishing between engineering designed products and industrial designed products as an intermediate step to look for a link between engineering designed products and services. Finally, focusing on the adoption process behind diffusion, the novelty lies right in investigating whether functional and measurable features could be applied to the study of product and service, regardless of the type of product or service under consideration, also to those contexts where functional features are usually overlooked.

1.5. Research Structure

The thesis will be organised as follows. Chapter 1 presents a review of the literature on product and service diffusion together with observed shortages and the contributions addressing them. In particular, the first part focuses on the dynamics of product diffusion, a mature field with extensive literature whose study led to identifying the first research question. In the second part, service diffusion – a topic so far understated by literature – is deepened, and the second research question is determined. The chapter then presents an answer to the questions by proposing a new concept that affects product diffusion and describes the time span available for rethinking products, and two new frameworks that suggest the proper model and metric to outline service diffusion.

In Chapter 2, the connection between diffusion dynamics and adoption processes is treated, deepening the differencing concerning products and services.

Chapter 3 illustrates the theoretical background underlying previous research aiming to study inventive problems and anticipate new value profiles. In particular, two contributions – the Theory of Inventive Problem Solving (Terninko, Zusman, & Zlotin, 1998) and Blue Ocean Strategy (Kim & Mauborgne, Blue Ocean Strategy: How to Create Uncontested Market Space and Make the Competition Irrelevant, 2005) – resulted in being crucial for the proposal of a model that aims at describing the overlooked link between design decisions and products adoption (Borgianni, Cascini, Pucillo, & Rotini, 2013). Hence, in the chapter, the model is presented together with a further validation.

In Chapter 4, the adoption processes characterising an industry (i.e., the surface material industry) usually driven by hardly measurable elements have been investigated as an intermediate step between the study of adoption processes of products and services.

Conclusions will be finally presented together with the study limitations and the possible future research developments.

2. From Product to Service Diffusion

The chapter investigates diffusion related issues from various perspectives and is structured as follows.

1. It studies the diffusion models for products.
2. It analyses the diffusion models for services that are present in the literature.

Then, it investigates the role of time as a key variable when the design has to be rethought by answering whether:

3. Rethinking time may play a key role in diffusion and adoption studies.

Finally, it questions the role of industrial designed products on the three above mentioned topics.

2.1. Product Diffusion: Models and Relevant Theoretical Elements

Early scholars who studied diffusion phenomena followed two alternative routes, one focused on a negative exponential law (Fourt & Woodlock, 1960) and one focused on a logistic (s-shaped) curve (Mansfield, 1961). Frank Bass (1969) merged these two approaches and proposed a diffusion model that bears his name.

2.1.1. Bass Model

The Bass model posits that innovation and imitation are the two drivers of the diffusion of innovations (Bass, 1969). The innovative adoption is the result of the communication strategy executed by producers, combined with customers' willingness to adopt, and, at each time instant, it leads a fraction p of non-adopters into adoption. Instead, the imitative adoption depends on effects that are internal to the market, such as word of mouth. Because of imitative adoption, a fraction q of non-adopters – weighted by the fraction of adopters – adopts at each time instant. These two distinct phenomena can be combined in a differential equation:

$$n(t) = \frac{dN(t)}{dt} = p[M - N(t)] + q\frac{N(t)}{M}[M - N(t)] \tag{1}$$

where M is the target market, N(t) are cumulative sales, and n(t) are instant sales. Equation (1) can be easily integrated, leading to a closed-form solution for the diffusion process:

$$N(t) = M \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{2}$$

The hypotheses underlying the model are quite restrictive, and in the following years, variants of the model were introduced in order to relax some of them.

First of all, sales are those of the market as a whole; considering an individual firm is justifiable in the case of monopolies. Secondly, the model is valid for durable goods, without any substitution or additional sales. Thirdly, there must be no substitutes nor complements that affect the diffusion of the product being studied. Moreover, marketing actions must be constant throughout the diffusion phenomenon. Finally, customers can buy just one item, and no additional sales are allowed.

The model leads to different managerial implications according to the diffusion process in place. When innovative diffusion occurs, adoption choices are relatively frictionless, and this is typical of fast-moving and low-ticket consumable products. This kind of diffusion process can be stimulated, for instance, by advertising spending. Conversely, durable products require a significant outlay, and customers will hesitate and wait for confirmations of the product's validity coming from their peers. This process occurs in the case of mainly imitative diffusion, which can be influenced by marketing actions that encourage network externalities.

Whether a firm should prefer a rapid diffusion, as in the case of mainly innovative diffusion, or a slower one, as in the case of imitative, depends on the nature of the industry, the goods being sold, and the type of production capacity.

2.1.2. Variants of the Bass Model

As mentioned above, the Bass diffusion model is based on restrictive assumptions, and a number of variants have been developed over the years to relax them. A pair of them will be briefly discussed in the following.

2.1.2.1. Generalised Bass Model

Bass, Krishnan, and Jain (1994) proposed a generalisation of the Bass diffusion model that: (1) included decision variables, (2) presented a closed-form solution in the time domain, and (3) could be reduced to the standard Bass model under certain conditions.

The model is formulated as follows:

$$n(t) = [M - N(t)]\left[p + q\,\frac{N(t)}{M}\right]x(t) \tag{3}$$

The term x(t) represents the current marketing effort and reflects the effects of dynamic marketing variables on the adoption at time t. The authors also presented a specific functional form for x(t) by considering two decision variables (price and advertising), called mapping function:

$$x(t) = 1 + \beta_p \frac{\Delta \Pr(t)}{\Pr(t-1)} + \beta_A \frac{\Delta A(t)}{A(t-1)} \tag{4}$$

where Pr(t) is the observed price at time t, A(t) is the observed value of the advertising at time t, and β_p and β_A represent the coefficients reflecting the effectiveness of the price and advertising strategies over the simple time-based diffusion. Treating time as continuous, it is then possible to obtain n, the continuous time version of equation (4):

$$x(t) = 1 + \beta_p \frac{dpr(t)/dt}{pr(t)} + \beta_A \frac{dA(t)/dt}{A(t)} \tag{5}$$

If decision variables are constant for all t, the generalised Bass model reduces to the standard one.

2.1.2.2. Bass Model with Seasonality

Guidolin and Guseo (2014) proposed an extension of the Bass diffusion model in order to take into account the intra-year oscillations of sales (i.e., seasonality). Seasonality is a common phenomenon for a wide range of products and services. It has been defined as a “systematic, although not necessarily regular, intra-year movement caused by the changes of weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by the agents of the economy” (Hylleberg, 1992).

In particular, Radas and Shungan (1998) identified seven key factors that are at the base of seasonality effects: holidays, government actions, industry traditions, weather, social phenomena, summer, and school years. Examples may be sports seasons affecting sports equipment demand (industry traditions), weather patterns that influence the agriculture sector, or even Christmas holidays, which determine a higher consumption of sweets or greeting cards.

Collecting monthly or quarterly data allows to detect seasonal sales trends; conversely, working with yearly data may lead to a loss of information when a seasonal pattern characterises the diffusion process. Guidolin and Guseo (2014) recognised a lack in the literature and proposed a model to fill this gap. The authors found reasonable to model seasonality proportionally to the trend by introducing a multiplicative interaction that uncouples the trend T(t) from the seasonality S(t) and the accidental component ε(t):

$$y(t) = T(t) + S(t) + \varepsilon(t) = h(t)\,[M + A(t)] + \varepsilon(t) \tag{6}$$

where y(t) are instantaneous observed data, h(t) is a probability density function which describes the evolution of sales, M is a constant scale parameter, and A(t) is the pure seasonal effect.

In particular, h(t) has been defined starting from the simple Bass model (2) where F(t; p, q) is a cumulative distribution function:

$$F(t;p,q) = \frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{7}$$

The corresponding instantaneous process, f(t; p, q), may be efficiently approximated by:

$$f(t;p,q) \cong [F(t+0{,}5;p,q) - F(t-0{,}5;p,q)] \tag{8}$$

and authors assumed that (8) was equal to h(t), so:

$$T(t) = M\,h(t) = M\,[F(t+0{,}5;p,q) - F(t-0{,}5;p,q)] \tag{9}$$

where M now is the market potential as defined by the Bass model. All that remains was to specify the seasonal effect A(t), that was modelled as a linear combination of trigonometric functions (Wei, 1990; Bloomfield, 2000):

$$A(t) = \sum_{j=1}^{\left[\frac{s}{2}\right]}\left[a_j\cos\left(\frac{2\pi jt}{s}\right) + b_j\sin\left(\frac{2\pi jt}{s}\right)\right] \tag{10}$$

Finally, the authors proposed a simplified version of equation (10) and came up with the complete formula:

$$y(t) = \left[M + \left[a\cos\left(\frac{2\pi t}{s}\right) + b\sin\left(\frac{2\pi t}{s}\right)\right]\right][F(t+0{,}5;p,q) - F(t - 0{,}5;p,q] + \varepsilon(t) \tag{11}$$

2.2. Service Diffusion: Models and Relevant Theoretical Elements

What is certain is that physical goods and services have many differences. But what is a service? The period from the 1950s to the 1980s was an initial period of debate over the definition of services and their diversities from goods. However, the first attempts to define services do not give any information about their essential characteristics (Judd, 1964; Rathmell, 1966). One of the first and most employed lists of characterising features of services was suggested by Zeithaml, Parasuraman, and Berry (1985):

- Intangibility refers to the lack of physical attributes by services. This affects both the price choice and the quality assessment of the offer. Indeed, quality can be measured only ex-post, and the service is usually tested in the market rather than in R&D laboratories.
- Heterogeneity (or variability) refers to the uniqueness of the offer. Unlike products that can be mass standardised, services can not.
- Inseparability defines that services are simultaneously produced and consumed, unlike goods for which production is separated from consumption.
- Perishability means that services cannot be stored, returned, or resold once provided.

Moreover, services can be provided by a public or a private entity. The former is the case of governments, or, more generally, the public sector, which finances and provide services that should be available to everybody. Private services, instead, are provided by private companies and can be either profit or non-profit businesses.

2.2.1. Types of Services

For the purposes of the research carried out, it has been considered three types of services defines as follows:

- Subscription services: users must sign a provision contract, which may consist of a fixed or variable periodical subscription. Examples of fixed / flat-rate services are pay-TV (e.g., Sky), mobile phone plans, digital content platforms (e.g., Spotify or Netflix). Instead, services with a variable rate subscription include, for example, electricity supply services or insurance contracts. There also exist so-called multi-sided platforms that allow one side of a market to use the platform for free, while the other side has to pay and, hence, subsidise the first one. Examples are Google or Facebook, which allow individual users to use their services for free. On the other side of the platform, we then find governments, companies, or whatever entity that wants to be put in contact with end-users (potential customers) and approach them to convert them into actual customers.
- On demand services: users do not sign any provision contract but purchase the service from the provider whenever they want to use it. It is then possible to distinguish between services used several times in a medium/short period of time (e.g., Flixbus, Glovo, PayPal, etc.) and services occasionally used over a long period of time (e.g., UTravel).

2.2.2. Service Diffusion Models

Service diffusion is a very underdeveloped branch of marketing science, except for some scholars who focus on this topic since the 1990s. Although, as discussed earlier, studies of product diffusion date back many years, they have neglected the existence of services. This is mainly due to the fact that at the dawn of innovation diffusion theory in the 1960s, the service sector was far less developed than the product sector. In fact, the 1960s were characterised by an economic boom in many countries, and the manufacturing industry started again at full capacity after the decline experienced during the Second World War. As a result of the industrial development, more product innovations were achieved, and the academic world focused accordingly on product diffusion studies: there was no need for tools able to predict the diffusion of an innovative service. In the 1980s, the service sector started to grow at a faster pace than the product sector, and lately, in the 1990s, the advent of the internet was an incredible catalyst in the development of new innovative services. A secondary cause lies in the greater complexity of services, whose diffusion represents a conceptual problem more challenging to describe with a model.

2.2.2.1. Bass-Type Models

Therefore, scholars started to question how to estimate the diffusion of service innovation, and the first experiments are traceable to models in line with the Bass model but with slight adjustments due to the different context.

A first example is the research of Giovanis and Skiadas, who studied the mobile plans diffusion in EU countries (2007). Although classified among the Bass-type models, the model they developed does not follow Bass assumptions but takes as an example the ordinary differential equations of the second degree of the Bass model. The starting point is a standard logistic diffusion curve:

$$\frac{dN(t)}{dt} = \frac{b}{M} N(t)[M - N(t)] \tag{12}$$

where M is the target market or the number of potential adopters, N(t) are cumulative sales or customers who have already adopted the service at time t, and b is the growth rate of the number of adopters. The underlying hypotheses are that (a) service diffusion follows a modified logistic curve, and (b) the time-delay between the awareness phase and the adoption phase affects how a service diffuse. The reason is that a new customer has to sign a supply contract, which implies a more significant user commitment over time compared to buy a product. The typical service purchase process is less impulsive than product purchase; in the latter case, a potential customer, once aware of a new product, may purchase it quite simultaneously.

The authors have hence introduced the term $N_{t-\tau}$, i.e., the number of users that τ periods prior to the decision to subscribe (which occurs at time t) have become aware of the service.

$$\frac{dN(t)}{dt} = \frac{b}{M} N_{t-\tau}[M - N(t)] \tag{13}$$

It is needed to apply the Taylor series expansion to the expression $N_{t-\tau}$ to obtain an approximate solution:

$$N_{t-\tau} = N(t) - \tau \frac{d\,N(t)}{dt} \tag{14}$$

After a series of steps, it is possible to obtain:

$$\frac{d\,N(t)}{dt} = b^* \frac{N(t)[M - N(t)]}{M - (1 - \sigma)N(t)} \tag{15}$$

where b^* is equal to $\frac{b}{1+b\tau}$ and τb^* is equal to $1 - \sigma$. If the delay between awareness phase and adoption one tended to zero, i.e., for $\tau \rightarrow 0$, the value of σ would tend to 1, and the model would collapse to a standard logistic diffusion curve.

Another variation of the Bass model was proposed by Libai, Muller, and Peres (2009) in order to describe the effects of customer attrition on diffusion. The idea is that, in any time period, companies can acquire customers among those who have not yet adopted the service, among those who have already abandoned it, or among those who decide to switch from a competitor (churn). Alternatively, the firm can lose customers whether they decide to dismiss the service category or they decide to switch in favour of a competitor (churn), and the sum of these two components then defines customers attrition:

$$\begin{aligned} &Customer\ attrition \\ &= disadopting\ customers + churning\ customers \end{aligned} \tag{16}$$

Consequently, it is possible to compute the corresponding rate – customer attrition rate, CA(t) – as the sum between disadoption rate and churn rate:

$$CA(t) = \frac{disadopting\ customers(t) + churning\ customers(t)}{customers(t)} \tag{17}$$

Once the customer attrition rate has been defined, it could be helpful to specify also the customer retention rate, i.e., the percentage of customers that decided to continue to use the service.

$$CR(t) = \frac{customers(t) - new\ customers(t) - customers(t-1)}{customers(t-1)} \tag{18}$$

or:

$$CR(t) = 1 - CA(t) \tag{19}$$

The proposed model is subject to the same assumptions as of the Bass model, and the diffusion of the new service is given by the following equation:

$$\frac{d\,N(t)}{dt} = p\,[M - N(t)] + \frac{q\,(1-\delta)N(t)}{M}[M - N(t)] - \delta\,N(t) \tag{20}$$

where M, N(t), p and q are parameters already introduced by Bass, and δ is the disadoption rate. This term strongly affects imitative innovation since the positive word-of-mouth effect is spread only by those who have not dismissed the service. The closed-form solution is here defined as:

$$N(t) = M' \frac{1 - \ e^{-(p'+q')t}}{1 + \frac{q'}{p'}\ e^{-(p'+q')t}} \tag{21}$$

The formula has the same functional form as the Bass equation (2) but with different parameters: $M^{'} = M\frac{\Delta+\beta}{2q(1-\delta)}$, $p^{'} = M\frac{\Delta-\beta}{2}$ and $q^{'} = M\frac{\Delta+\beta}{2}$. In particular, due to the presence of the customer attrition rate, p' > p, q' < q and M' < M. Moreover, if the disadoption rate tends towards 0, then equation (21) converges with the Bass diffusion function. Finally, Δ and β are defined as follows:

$$\Delta = \sqrt{\beta^2 + 4q(1-\delta)}p \tag{22}$$

$$\beta \ = \ q(1 - \ \delta) - p - \delta \tag{23}$$

This model focuses on category-level growth; it shows how the category-level attrition (or disadopting customers) affects the growth of the service, so no competitive attrition (or churning customers) is here considered. The latter has been taken into account in a second model, which consists of a more detailed version of the just presented model, discussed by the authors in the same paper. One of the major limitations of this second model lies in the application difficulty as the amount of competition data required is huge, and this kind of data is often not available.

The greater limit of the first presented model instead concerns the absence of a negative imitation effect due to users who decide to abandon the service, who may share the reasons under their decisions with actual and potential customers. This may result in an overestimation of the diffusion curve obtained from equation (21).

2.2.2.2. Choice-Type Models

Choice-type models derive from Economy: the main difference with Bass-type models is that choice-type models focus on individual choices, which may have an impact on innovation diffusion. The choice process is represented by a tree diagram, where the nodes are the decisional steps, and the branches are the probabilities that the users make a specific choice.

Among the choice models, it is important to mention the one proposed by Landsman and Givon (2010). The model describes a two-stage service diffusion process. The first, modelled by a hazard function, is called the consideration stage, where the potential customers decide whether to join the service or not. The second is the choice stage and is modelled by a conditional multinomial logit model. Here the customers choose between the service alternatives and the no-choice option.

In particular, in the first stage, at $t = 0$, j new services are offered on the market and users do not even consider the possibility of subscribing to any of them (i.e., the so-called state “No Service No Consideration”). λ_{it} represents the transition rate from no consideration to consideration, and it is modelled as a hazard rate which is a function of two elements: (1) the time passed since the service has been introduced and (2) a set of covariates that describes the potential market. Authors, in order to decompose the hazard function, opted for the Proportional Hazard Model (Gupta, 1991; Helsen & Schmittlein, 1993; Seetharaman & Chintagunta, 2003):

$$h_t = h_{0t}\psi(X_t) \tag{24}$$

where h_{0t} is the baseline hazard function which can be decomposed employing the expo-power formula (Saha & Hilton, 1997; Seetharaman & Chintagunta, 2003):

$$h_{0t} = \gamma\alpha t^{\alpha-1}e^{\theta t^{\alpha}} \tag{25}$$

The second stage is modelled by a multinomial logit model. Once reached the choice stage, the probability that a customer chooses the alternative j at time t is given by:

$$P_{jt} = \frac{e^{V_{jt}}}{\sum_{j=0}^{J} e^{V_{jt}}} \tag{26}$$

where V_{jt} is the deterministic part of the utility obtained from choosing the alternative j at time t, and it is specified as follows:

$$V_{jt} = \beta' Y_t + \rho_s E C_{t-1} C_{jt-1} \tag{27}$$

The first component, Y_t, is a set of K covariates characterising the alternatives, the customers, or the alternative-customer combination. The second component instead represents what may affect current customers probability to remain in the same state during the next time period. The model is summarised and depicted in figure 1.

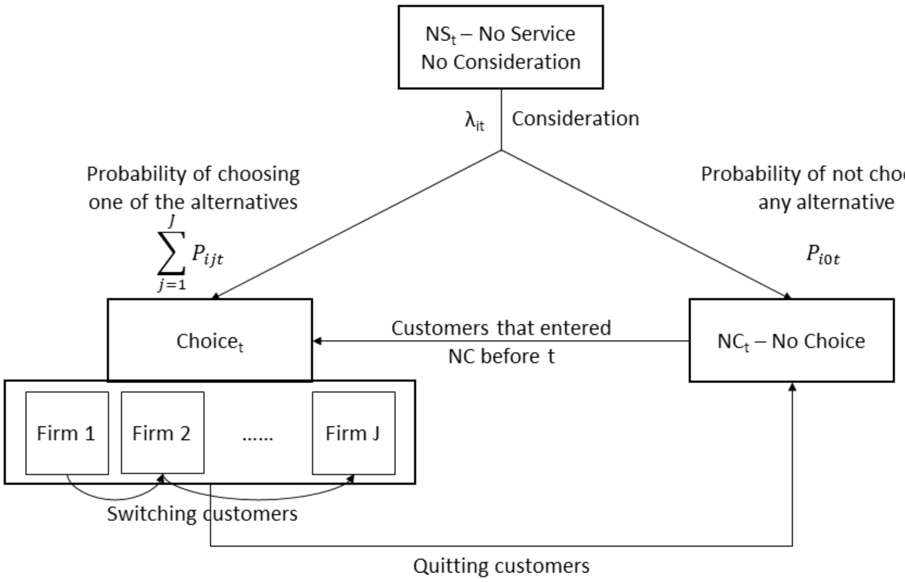

Figure 1. Landsman and Givon diffusion model (2010)

Another choice-type diffusion model was discussed by Shi, Chumnumpan, and Fernandes (2014). The authors considered N services competing each other; at each time period t, the i person is a customer of the service $l = 0 \dots N$, where $l = 0$ means that the person has not chosen any alternative yet and is a potential customer. Moreover, at each time period t, the same i person may choose to switch to another service $k = 0 \dots N$, where $k = 0$ means that the person dismisses the current service and goes back to being a potential customer. At each time period t, there are therefore five possible scenarios:

1. The potential customer i chooses the service k and utility is equal to $U_{i,t}^{k,0}$.
2. The customer i switches from service l to k and utility is equal to $U_{i,t}^{k,l}$.
3. The customer i decides to continue using service l and utility is equal to $U_{i,t}^{l,l}$.
4. The potential customer i decide not to use any service and utility is equal to $U_{i,t}^{0,0}$.
5. The customer i decide to dismiss service l and not use any service; utility is equal to $U_{i,t}^{0,l}$.

Utility is here defined as the combination of two terms:

$$U_{i,t}^{k,l} = V_t^{k,l} + \varepsilon_{i,t}^{k,l} \tag{28}$$

where ε is the error term, and $V_t^{k,l}$ is a deterministic term changing from scenario to scenario. In the first two, it is defined as follows:

$$V_t^{k,l} = V_0^k + \sum_{t'=1}^{t} \delta_{t'}^k V_0^k,\ l \neq k,\ k \neq 0 \tag{29}$$

where V_0^k is the utility associated with the service k at time $t = 0$, and it is equal to $\beta_0^k X_0^k$. X_0^k represents the service features, such as price, service quality, or network effect; β_0^k is the impact that these features have on the utility. Instead, since utility may grow or decrease over time, $\delta_{t'}^k$ represents this additional utility.

In the third scenario, the formula is equal to equation 29, plus a constant term p representing the extra utility gained by users that keep using the same service.

$$V_t^{k,l} = V_0^k + \sum_{t'=1}^{t} \delta_{t'}^k V_0^k + p, l \neq k, k \neq 0 \tag{30}$$

Finally, in the fourth and fifth scenario, the utility is assumed to be constant and given by abandoning the service.

$$V_t^{k,l} = c, k = 0 \tag{31}$$

Given the utility computation, the authors then defined the probabilities that a potential customer starts to use service k (i.e., $P_t^{First,k}$), and a customer of service l switches to service k (i.e., $P_t^{Existing,k,l}$).

$$P_t^{First,k} = \frac{e^{V_t^{k,0}}}{\sum_{k=0}^{N} e^{V_t^{k,0}}} \tag{32}$$

$$P_t^{Existing,k,l} = \frac{e^{V_t^{k.l}}}{\sum_{k=0}^{N} e^{V_t^{k,l}}} \tag{33}$$

As a consequence, the number of first users and switching users is defined as follows:

$$S_t^{First,k} = P_t^{First,k} M \tag{34}$$

$$S_t^{Existing,k,l} = P_t^{Existing,k,l} S_{l,t-1} \tag{35}$$

where M represents the potential market. Finally, the number of users of the service k at time t is given by the combination of the following terms:

$$S_t^k = S_{t-1}^k + S_t^{First,k} + \sum_{l=1;l\neq k}^{N} S_t^{Existing,l,k} + \sum_{l=0;l\neq k}^{N} S_t^{Existing,l,k} \tag{36}$$

2.2.2.3. Grey Models

A white system is characterised by the presence of all the information needed, and, on the contrary, there is no information in a black system. Clearly, a grey system is in the middle, and, indeed, the peculiarity of grey models is the applicability even in the presence of a minimal amount of data.

$GM(m, n)$ is the representation of a basic grey model, where m is the order of a differential equation, and n the number of variables. Lin (2013) used a first-order differential equation with one variable to propose a diffusion model based on a historical series of at least four data. A first-order differential equation is defined as follows:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{37}$$

where a is the sales growth coefficient, b is the grey influence coefficient, and $X^{(1)}$ is the vector of cumulative sales over time. Using the non-linear least square method, parameters a and b are estimated to get the curve of cumulative sales values finally:

$$\hat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \tag{38}$$

The major limitation of this model is due to the absence of an upper bound, which means that the diffusion curve tends to infinity. This is conceptually wrong because the market is, by definition, a finite set of users, and the fact that there is no upper limit can lead to misleading forecasts.

2.2.3. Development of a Model and a Metric Selection Framework

A framework has been proposed from literature analysis on service diffusion models to help choose the more suitable kind of model to estimate service diffusion. Two main dimensions have been identified that may influence the choice, i.e., data availability and computational capacity (see Figure 2).

Computational capacity / **Data availability**	**Low** closed formula	**Medium**	**High** simulation algorithms
Low - only number of users	Bass model / Grey type models	Grey type models	Grey type models
Medium	Bass model / Bass type models	Bass type models	Bass type models
High - number of users, competitors' data, control parameters	Bass model	Bass type models / Choice type models	Bass type models / Choice type models

Figure 2. Model selection framework

Focusing on Bass-type models, the aim is to understand which metrics are more suitable for each of the three kinds of service discussed above. The literature already suggests that the customer attrition rate is appropriate when subscription services are analysed (Libai, Muller, & Peres, 2009), so the study will focus on the two kinds of on demand services. Moreover, the choice fell on the Bass-type models because of the available data provided by two companies (i.e., an extra-urban transportation company and a travel company) and the necessity of working with a closed-form solution.

The former company offers a service based on a multi-sided platform for national and international mobility where end-users and regional transportation companies can find each other. The travel company instead offers an innovative service addressed to under 30. It is called blind booking, and it consists of choosing the dates of a trip, paying a fixed amount, and discovering the destination five days before departure. Both are on demand services, but the difference is that in order to be an actual customer of the transportation company, it is required to buy a ticket several times in a medium/short period of time (usually at least a couple of times a year); while the service provided by the travel company is usually bought occasionally over a more extended period of time.

In particular, the transportation company provided new monthly customers from July 2015 to December 2018, and the modified customer attrition is defined as follows: the number of customers that one year after the first purchase has not been made anymore.

Working with Bass-type models, it was first necessary to estimate the market potential. The country under analysis was Italy, where there are 38.7 million people aged between 18 and 64 (i.e., the age range to which the service is addressed). Individual income and job class information were then cross-referenced with data obtained from a questionnaire run by the company to obtain information about its customers. The potential market estimate was, therefore, revised from 38.7 million to 9.8 million. Finally, given the similarity between the Italian and German markets, the market share reached in the latter one in five years was set as a benchmark. So, potential market M was finally set at 7.9 million customers.

With the aim of finding adequate metrics for on demand services, the customer attrition rate was excluded. Indeed, the latter is a typical metric of subscription services where customers can unsubscribe and, hence, the company has an effective measure on losing customers. This does not apply to on demand services as customers can use the service whenever they need it.

The modified customer attrition described above has therefore been tested by starting from the differential equation (1) of the Bass model where however $\frac{dN(t)}{dt}$ has been defined as follows:

$$\frac{dN(t)}{dt} = \frac{dN'(t)}{dt} - \delta_t \frac{dN'(t-1)}{dt} \tag{39}$$

where δ_t is the modified customer attrition rate at time t. The rate, therefore, affects the diffusion, slowing it down. New monthly customers and customer attrition rate from July 2015 to December 2018, corresponding to forty-two time periods, together with the estimated potential market, were used to estimate Bass parameters p and q, by instructing the model, modified as seen in (39), with data from thirty out of forty-two time periods available.

The parameters were then used to estimate the diffusion curve, which was compared with all the forty-two time periods. In Table 1, p and q are reported, together with the mean percentage error and the R^2 of the estimated diffusion curve, while in Figure 3, real and estimated diffusion curves are presented.

parameter	**value**
p	0.003
q	0.042
MPE	1.28%
R^2	99.63%

Table 1. Outcome with Modified Customer Attrition rate as a metric

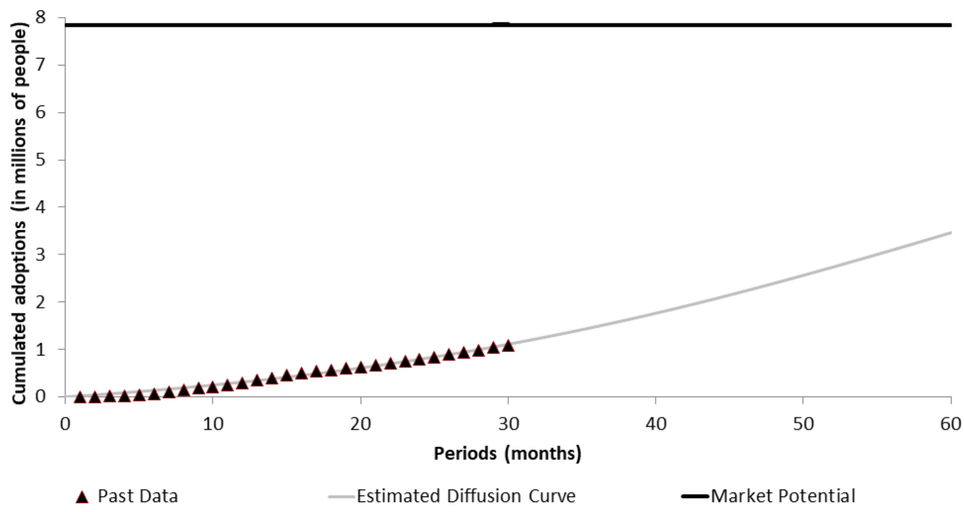

Figure 3. Real data and estimated one with Modified Customer Attrition

Once the modified customer attrition rate was tested, it was proposed a metric that reflected repeated purchases by customers. The reactivation rate, RR_t, has therefore been defined as the percentage of customers that, after the time period t, make another purchase. The differential equation (1) of the Bass model is then modified, assuming that $\frac{dN(t)}{dt}$ is equal to:

$$\frac{dN(t)}{dt} = \frac{dN'(t)}{dt} + \sum_{t=1}^{t-1} \left[(RR_t - RR_{t-1}) \frac{dN'(t)}{dt} \right] \tag{40}$$

The logic is that the number of new customers is added to the number of customers making a subsequent purchase. The CRM team provided data on the reactivation rate for fifteen months. In other words, the percentage of customers who had made a subsequent purchase in a given month, from one to fifteen months after the first one, was available. It was noticed that the reactivation rate converges to 53% around the fourteenth period, and it was supposed and tested that RR_t may be estimated with a logarithmic curve (see Figure 4), obtaining an R^2 equal to 97.20%.

$$y = 0.084 \ln x + 0.234 \tag{41}$$

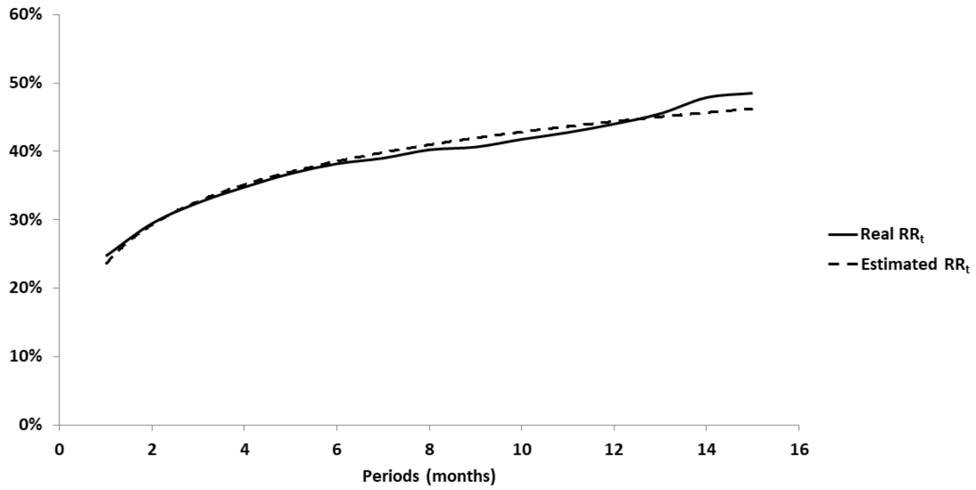

Figure 4. Real data and estimated one with RR_t

The curve obtained made it possible to estimate the average reactivation rate over each of the available periods, which was hence used to apply equation 40 and estimate p and q. They were estimated with data from thirty out of forty-two time periods available as before. Bass model with reactivation rate was then applied to estimate the diffusion curve obtaining data reported in Table 2.

parameter	value
p	0.004
q	0.053
MPE	2.35%
R^2	99.68%

Table 2. Outcome with Reactivation Rate as a metric

Figure 5 shows the real diffusion curve and the one estimated with the Reactivation Rate.

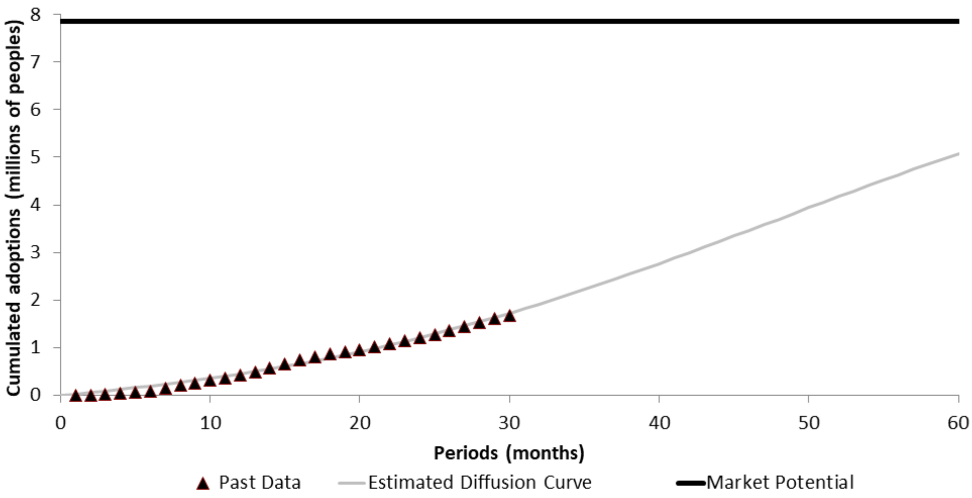

Figure 5. Real and estimated diffusion curves with Reactivation Rate

Finally, the same kind of analysis was replicated using the standard Bass model, and results were compared (see Table 3).

	standard Bass model	**Bass model with modified customer attrition rate**	**Bass model with reactivation rate**
p	0.003	0.003	0.004
q	0.042	0.042	0.053
MPE	1.50%	1.28%	2.35%
R^2	82.73%	99.63%	99.68%

Table 3. Outcome comparison

First of all, each model returned p and q values unbalanced towards the imitation parameter. Diffusion is hence much more influenced by network externalities and word-of-mouth effect than by advertising.

Modified Bass models showed better performances, i.e., a higher R^2, in estimating diffusion curve compared to the standard one; however, the Bass model with reactivation rate is characterised by a higher mean percentage error. This may be due to the limits of the metric as it has been calculated since it is the arithmetic mean of numerous values and was subject to several approximations.

The modified Bass models above introduced may not be suitable to study the diffusion process of other kinds of service. The absence of repeated purchases in a short period of time led us to the assumption that this kind of service, when dealing with diffusion curves, might be treated as durable products. A travel company service was then analysed to test the performances of the standard Bass model, together with the ones of the model with seasonality effects previously discussed. The latter was chosen given the peculiarity of the service under analysis, which is subject to a strong seasonal effect.

The only data required were the sales data made available by the company for the period from November 2018 to January 2020 equal to fifteen time periods. As before, the first step was to estimate the market potential. The registry office tells that the number of Italians under 30 is about 7 million; nevertheless, the service under analysis was addressed to university students. The two data were hence crossed, obtaining the value of 1.5 million students between 18 and 30. This data was revised as a result of the estimate of the penetration level of online travel bookings in Italy, which is equal to 21.5%. Market potential M finally resulted to be equal to 320 thousand people.

Bass parameters p and q were then estimated, and the forecasted diffusion curve was compared with the real one. The results are reported in Table 4 and Figure 6.

parameter	**value**
p	0.0002
q	0.1124
MAPE	26%
R^2	97%

Table 4. Outcome with Bass model

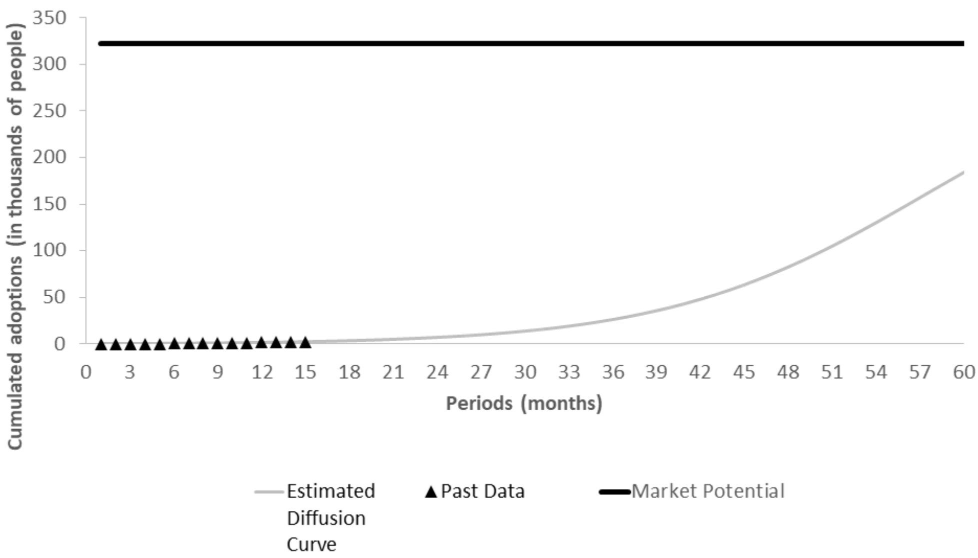

Figure 6. Real data and estimated one with the standard Bass model

Same kind of analysis was replicated for the Bass model with seasonality. First of all, it was necessary to set the period s introduced in equation (10). It was then assumed that the service under analysis was subject to the same seasonality effect of a comparable service offered by the same company. Sales data of four years (see Figure 7) suggested a periodicity equal to twelve months ($s = 12$).

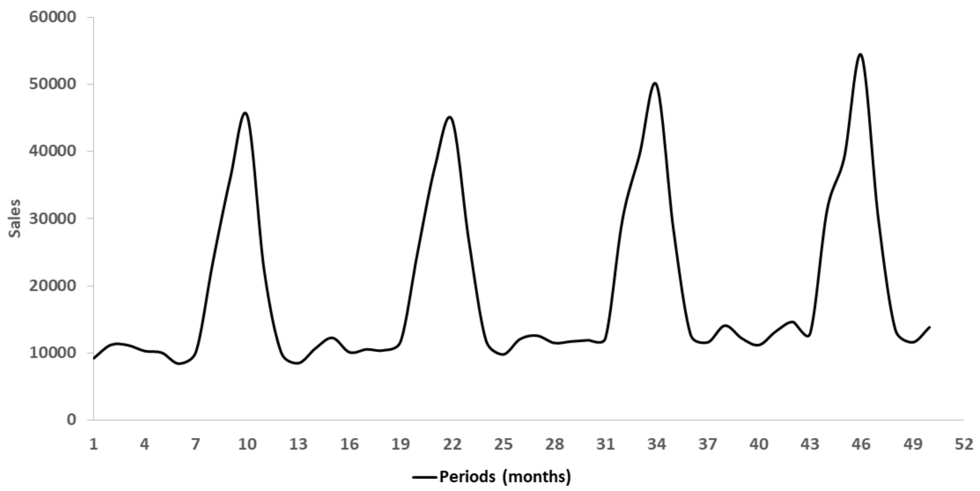

Figure 7. Sales data of the service reference

Then, Bass parameters, i.e., p and q, and seasonal ones, a and b, were estimated applying equation (11); and the same fifteen time periods as before were employed.

In Table 5, results are shown, and they are compared with the ones obtained applying the Bass model (see Figure 8).

	Bass model	**Bass model with seasonality**
p	0.0002	0.0002
q	0.1124	0.0969
MAPE	26.0%	14.0%
R^2	97.0%	99.5%

Table 5. Outcome comparison

The Bass model with seasonality outperformed the standard Bass model because of the detail it adds to the analysis by introducing the seasonality effect; however, both provided promising results in the estimation of the diffusion curve for this type of service. Both the Bass model and the Bass model with seasonality may represent a good solution to study the diffusion of services with these intrinsic characteristics, although they were originally developed to study product diffusion.

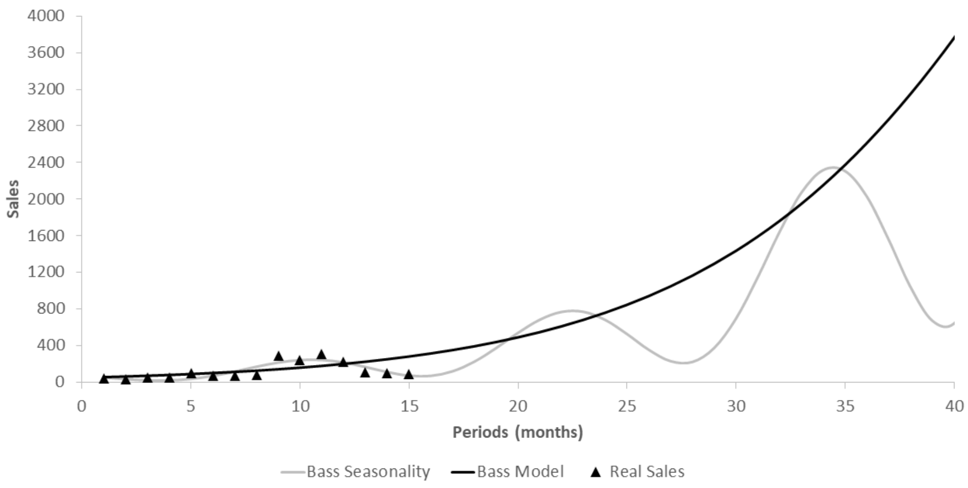

Figure 8. Real data and estimated one with the standard Bass model with seasonality

A second framework has been proposed suggesting, in the specific case of Bass type models, which metrics to adopt according to the type of service under consideration (see Figure 9).

Metrics / **Types of service**	**Attrition rate**	**Reactivation rate** / **Modified attrition rate**	**No metrics**
Subscription services	X		
On demand services used several times in a medium/short period of time		X	
On demand services used occasionally over a long period of time			X

Figure 9. Metric Selection Framework

In particular, the attrition rate resulted to be optimal for subscription services. Indeed, they are characterised by a number of subscribers that each month pay a fee, and companies can easily collect required data.

On demand services require different metrics instead depending on the use frequency. On demand services used several times in a medium/short period of time requires that customers make repeatable purchases and, hence, it is necessary to address this process. The reactivation rate and a modified attrition rate have been individuated as suitable metrics. The former allows to track customers that make repeated purchases and considers them as new customers; the latter considers lost customers who do not make any purchase after the first one for a given amount of time.

Instead, on demand services occasionally used over a long period of time do not require any metric, and their diffusion process can be represented by the standard Bass model. Indeed, the diffusion dynamics of this kind of services are comparable to the ones of durable goods. It is not necessary to buy a second time to be considered a customer because two possible subsequent purchases are generally very distant in time.

2.3. The Role of Rethinking Time on Product Diffusion

Diffusion dynamics of a given product or service have obviously an impact on how an industry will develop. Entry strategy can play a role as a source of advantage when a new product starts to diffuse in the market. The literature on entry strategy can be split into two parts, the former looking at first-mover advantages (FMAs), and the latter at the impact of development time on product success. The former is grounded in the field of Strategic Management, whereas the latter stems from Operations Management.

2.3.1. First-Mover Advantages and Disadvantages

The Strategic Management and Innovation Management literature have hosted intensive discussions about FMAs, and three broad streams of research were born from FMA theory (Suarez & Lanzolla, 2007).

First, researchers started to investigate isolating mechanisms, which allow first movers to be protected against late entrants. Spence (1981; 1984) demonstrated the existence of entry barriers created by learning effects, an example of which could be advantages gained by DuPont, thanks to the development of a new process for titanium dioxide (Ghemawat, 1984). Schmalensee (1982) suggested that buyers' habits cause the emergence of switching costs that may limit customers to switch from a product to another. At an early stage, researchers seemed to converge around the absolute effectiveness of these mechanisms, and several authors attempted to formalise them. Lieberman and Montgomery (1988) differentiated between technology leadership, preemption of scarce assets, and switching costs under uncertainty; Kerin, Varadarajan, and Peterson (1992) identified four kinds of factors that are economical, preemption, technological and behavioural; Golder and Tellis (1993) distinguished between producer-based and consumer-based FMA drivers. The major limitation of these early studies was the near absence of consideration on the firm and environmental factors, which has been later understood might play a crucial role in favouring or disfavouring the presence of these advantages.

Indeed, a second and more recent research stream has explored firm-level characteristics that may have an impact on FMAs. These studies hypothesize that, in order to benefit from early entry, companies need to rely on their assets and capabilities. For instance, Franco, Sarkar, Agarwal, and Echambadi (2009) have linked technological capabilities to early entry benefits, finding that pioneers have to be technically strong to survive in the market. Markides and Sosa (2013) explored the importance of business models both for first movers, to sustain their advantages, and late entrants, to attack pioneers. Vidal and Mitchell (2013) investigated whether owning the core technology and/or the complementary resources affect the likelihood for first movers and late entrants to survive in the market. However, even this stream did not explore issues related to the context in which the company operates.

Precisely the most recent stream has examined whether and how environmental features may affect companies trying to exploit their FMAs. For instance, Makadok (1998) investigated the role of low entry barriers and how to sustain first-mover advantages in such conditions. Lee, Smith, Grimm, and Schomburg (2000) examined whether and to what extent imitation affects the durability of first-mover advantages. Min, Kalwani, and Robinson (2006) discussed whether being a first mover and introducing incremental or radical innovations leads to different survival risks. Fosfuri, Lanzolla, and Suarez (2013) proposed to include new dimensions in FMAs theory, such as the strategies and business models of late entrants and insight from institutional theory or industry life cycle. The last two streams were particularly interesting because of their attention to elements previously overlooked that may add an additional level of detail to the analysis of this phenomenon.

2.3.2. Time-Based Competition and Time to Market

In the late 1980s, Stalk (1988) coined the expression "time-based competition" to highlight the role of time as a source of advantage in intensively competitive environments. In his work, Stalk recognised the importance of time-based competitiveness and investigated how the structure and practices of several parts of the organization change when firms adopt a time-based approach. In this context, a key strategy consists of reducing the time required for product development.

In the 1990s, several studies continued to investigate the implications of getting products to market faster. Time to market (TTM), defined as the elapsed time between product definition and product availability, has been increasingly recognised as one of the most critical factors across all industries (Vesey, 1991). Several contributions discussed the methods and tools to reduce TTM (Smith & Reinertsen, 1997), the benefits of achieving this reduction (Pawar, Menon, & Riedel, 1994), and the key factors which affect it (Lynn, Abel, Valentine, & Wright, 1999).

However, despite its popularity, this idea has not been entirely free of criticism. For instance, Meyer and Utterback (1995) showed that a shorter TTM is not necessarily correlated with expected commercial success, especially when technological and market uncertainties are high. Several other studies investigated and proved the existence of trade-offs between time to market, product performance, and development costs (Bayus, 1997; Crawford, 1992; Utterback, Meyer, Tuff, & Richardson, 1992).

Trying to quantify these trade-offs, Cohen, Eliasberg, and Ho (1996) derived an analytical model that determines the optimal TTM with respect to a product performance target, based on market features and firms' cost structure. Their findings suggested that if margins are high and the category demand is significant, companies should focus on product performance and delay product launch. Calantone and Di Benedetto (2000) refined this model by employing a flexible product development process, which includes overlapping stages between marketing, design, and manufacturing engineering that jointly work on performance improvement. In this way, design decisions and timing of entry are related. Again, in the late 1990s, new studies introduced factors related to the firm itself and the environment where it operates, which led to the rise of conflicting results around TTM. Therefore, in the 2000s, several authors continued to shed light on the conflicting findings about trade-offs on cost, speed, and quality (Kessler & Bierly, 2002; Chen, Reilly, & Lynn, 2005; Feng, Sun, Zhu, & Sohal, 2012). TTM continued to be of interest to studies (Zhong, Xu, Klotz, & Newman, 2017), and recently researchers focused on the impact that new techniques such as virtualization (Han, Gopalakrishnan, Ji, & Lee, 2015) and additive manufacturing (Macdonald, et al., 2014; Martin, et al., 2017) have on TTM.

2.3.3. Rogers' Market Segments and Rethinking Time

As previously mentioned, several factors impact obtaining or not advantages from a first-mover strategy. FMAs may specifically depend on the rate with which different customer segments are encountered over time and firms' subjective ability to deal with this evolution. In fact, customers who adopt at different timings are not homogenous but part of distinct market segments with different needs. As postulated by Rogers (1962), the various market segments – innovators, early adopters, early majority, late majority, and laggards – adopt innovations in sequence (see Figure 10). Moreover, a significant gap (or chasm) exists between the early adopters and the early majority segments (Moore, 1991), which may destabilise the competitive advantage that is temporarily enjoyed by early movers who decided to engage with the first adopting segments of the new market.

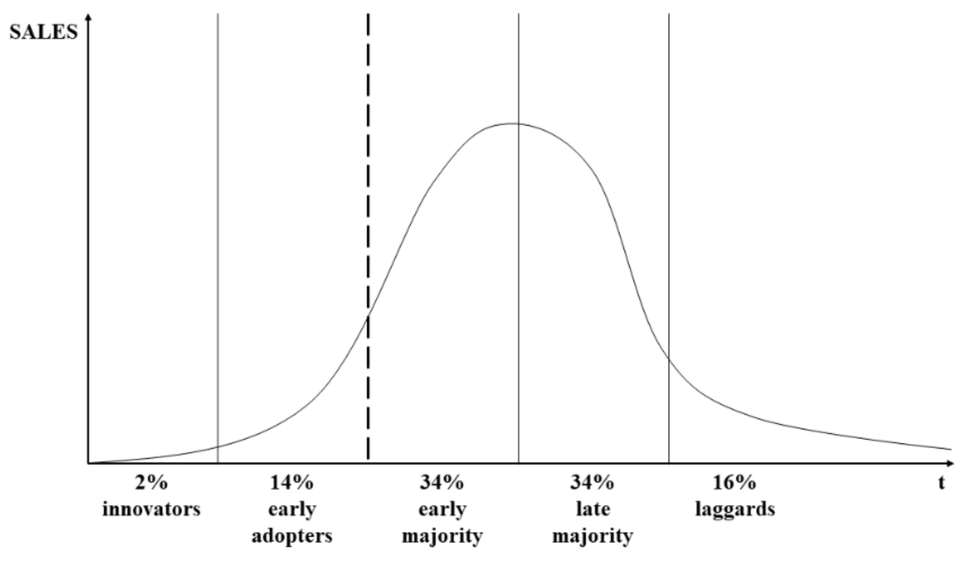

Figure 10. Rogers' market segmentation along the diffusion curve

Following this line of thought, a highly successful producer with early adopters could see its advantage relapse when the early majority segment kicks in. Indeed, products offered to successive market segments have to be different, and companies cannot neglect the time needed to identify future needs and develop products accordingly. Hence, in line with the most recent research streams related to TTM and FMAs, it was investigated the role of the time available for redesigning the product according to the needs of the upcoming segments on the survival of first movers.

The time window between the first sale to early adopters and the first sale to the early majority segments was referred to as the rethinking time available to firms to leap across the chasm. It represents the maximum time available for planning and developing the new products that will be marketed to the upcoming segment.

The idea is that the duration of rethinking time may significantly impact the development of new products addressing the early majority of a new market and, therefore, affect gaining or not first-mover advantages.

As discussed above, literature recognises the existence and relevance of a chasm between early adopters and early majority customers (Faiers & Neame, 2006; Goodwin, 2010; Sroufe, Curkovic, Montabon, & Melnyk, 2000). This chasm must be crossed in order to be successful in the mainstream market (Börjesson, Martinsson, & Timmerås, 2006; Jahanmir & Lages, 2015); however, none of the papers in literature makes any explicit reference to the possible link between this chasm and the strategies relating to the timing of entry. The rethinking time concept may represent the dimension that describes this link between the chasm and a time-based strategy. In the following, the expression crossing the chasm will be used for a firm that successfully maintains its competitive advantage when the diffusion curve moves from the early adopters to the early majority segment.

First movers usually focus on the specific needs of the early segments and neglect a more farsighted exploration of future segments' needs. Indeed, the product must first satisfy innovators and early adopters, who are relatively technology-aware and risk-prone, in contrast with later adopters, who exhibit quite different preferences and requirements (Schnaars, 1994). Late entrants may hence focus their effort on developing products that suit later adopters, try to influence their needs (Carpenter & Nakamoto, 1989), and make use of prior experience to easily reach the mass-market (Rayna & Striukova, 2009). Thus, a first mover will likely be unsuccessful in crossing the chasm when the rethinking time is too short, given that it will have less time available to obtain a better understanding of subsequent segments' needs, and redefine and redesign the product.

However, the expected impact of rethinking time could also be the opposite. Indeed, a first mover having a long rethinking time available may develop organizational inertia, binding it to the current segment and become unable to forecast and react to environmental changes and new threats, thus favouring late entrants (Vecchiato, 2015). If so, a short rethinking time might prevent first movers from developing such organizational inertia.

Moreover, since both the FMAs theory and the time-based competition literature investigated the environmental characteristics linked to entry strategies (Cohen, Eliasberg, & Ho, 1996; Suarez & Lanzolla, 2007), the possible effects of these exogenous characteristics are considered to be worth of interests. These features can be various – low barriers (Makadok, 1998), pace of technological change (Suarez & Lanzolla, 2007) – and can mitigate or emphasise an entry strategy's effect.

Suppose one looks at the status with respect to entry (i.e., incumbents vs new entrants), when dealing with innovations, incumbents may suffer from several disadvantages. Examples are lower incentives (Conner, 1988), the inertia of organizational routines (Henderson & Clark, 1990), or lock-in phenomena with respect to their current customer base (Klemperer, 1987). However, despite these disadvantages, incumbents usually have a better and broader understanding of the market and its segmentation (Chandy & Tellis, 2000). Customers also have greater confidence in incumbents, who can, therefore, leverage this trust to succeed in the market when innovations are being introduced (Obal, 2013). Moreover, incumbents often have investment capabilities and assets required to develop new technologies and face new entrants (Tripsas, 1997). It is possible to hypothesize that incumbents' superior understanding of the market might make it easier for them to develop successive products that are suitable for adjacent segments. New entrants, especially if forced to redesign their product in a short rethinking time, may instead be disadvantaged because they lack the broad market knowledge that would be needed to adapt their offerings successfully.

The other contextual characteristics taken into account involved the product itself. B2B markets have been set in opposition to B2C ones, and brown goods (i.e., small appliances such as an electric blender, electric shaver, toaster) have been compared to consumer electronics (e.g., tablet, smartphone, television) and white goods (e.g., laundry machines, refrigerators, microwave ovens). Indeed, both the dimensions mentioned above were taken into account in past product diffusion studies (Stremersch, Muller, & Peres, 2010; Tellis, Stremersch, & Yin, 2003) and, more generally, in research on possible differences between different product types, from buyers' behaviours to market structures (Anderson, Narus, & Narayandas, 2009). However, diffusion speed and status with respect to entry are expected to be more crucial to this phenomenon, at the cost of characteristics related to the product and the market.

The arguments mentioned above lead us to formulate the following hypotheses, summarised in Figure 11:

H1. All other things being equal, a shorter rethinking time will penalize (favour) first movers rather than followers in crossing the chasm.

H2. All other things being equal, first movers will more likely cross the chasm if they also are incumbents rather than new entrants.

H3. All other things being equal, first movers will more likely cross the chasm if they are incumbents and short rethinking times occur.

H4. All other things being equal, first movers will cross the chasm with the same probability regardless of the type of product under consideration.

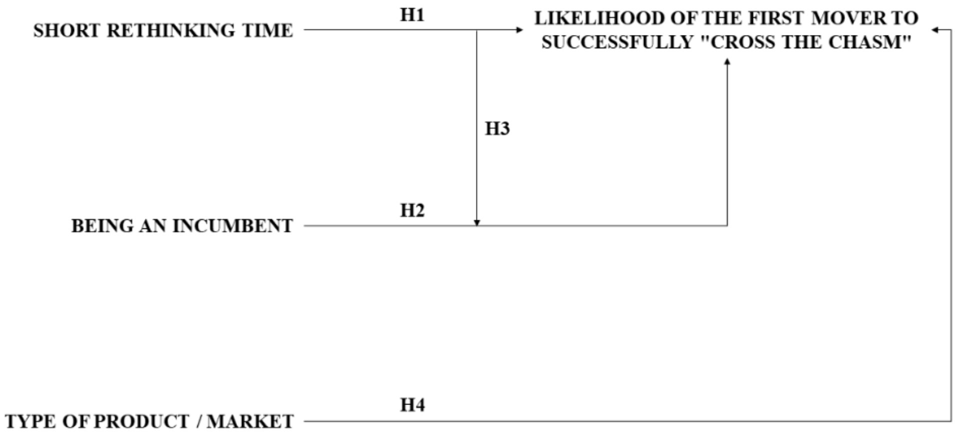

Figure 11. Hypotheses visualisation

2.3.4. The Role of Rethinking Time and Design Choices that Affect Diffusion

The rethinking time can be mathematically determined by relying on the well-known Bass model of technology diffusion (Bass, 1969). The model is known to suffer from several limitations inherent to its underlying hypotheses (Easingwood, Mahajan, & Muller, 1983; Golder & Tellis, 1998), but it easily lends itself to this purpose, in view of its widely accepted capability of fitting empirical data and because of the ease of estimating its parameters (Golder & Tellis, 1998).

Equation (2) can be normalised by considering $M = 1$ and rewritten in order to highlight the progression of customer segments. Specifically, if X_i is the portion of M that makes up the i-th customer segment and t_i is the time at which diffusion to that same segment ends, one can write $\sum_{i'=1}^{i} X_{i'} = {N(t_i)}/{M}$ to express that diffusion has reached saturation of segment i. This can be written as:

$$\sum_{i'=1}^{i} X_{i'} = \frac{1 - e^{-(p+q)t_i}}{1 + \frac{q}{p} e^{-(p+q)t_i}} \tag{42}$$

Customer segments X_i that successively adopt the product are depicted in Figure 12, where, for instance, the time period from t_1 and t_2 represents the time it takes to all customers in segment X_2 to adopt and, hence, the time between the start of adoption by two successive customer segments (X_2 and X_3 in this case). For the sake of simplicity, it was assumed that segments are mutually exclusive (i.e., no customers from X_i adopt the product before customers from X_{i-1} have all done so). It follows that, when moving from one segment to the other, producers have to offer completely redesigned products since they cannot rely on any stray customer from a previous segment.

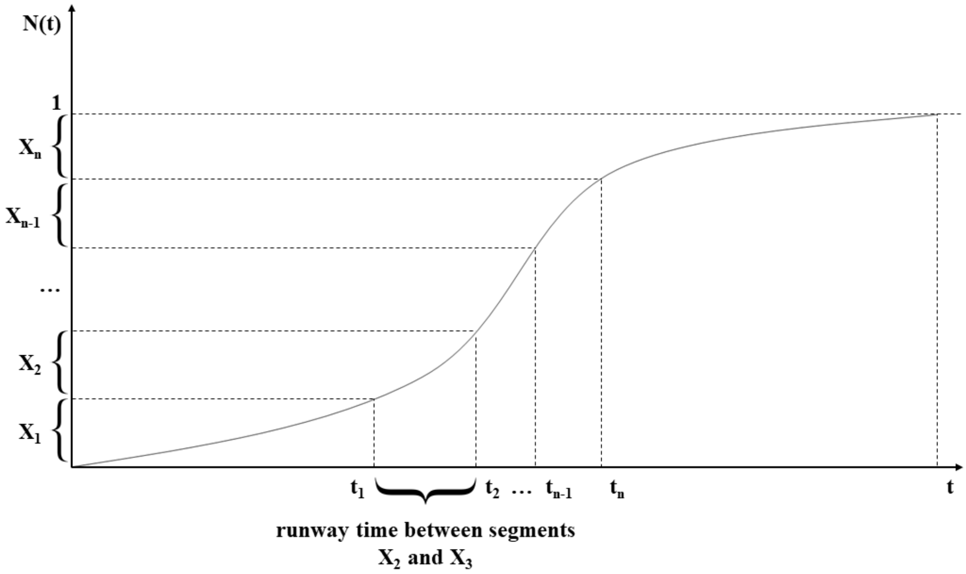

Figure 12. Rethinking time between subsequent segments

By setting $\beta = {}^{p}/_{q}$, the parameter embeds innovative adoption and imitative adoption parameters, which consequently are included in the calculation of rethinking time. β shows the relative weight of the innovative phenomenon over the imitative one, and by making explicit t_i, it is possible to obtain:

$$t_i = \frac{1}{q(\beta+1)} ln\left[\frac{\sum_{i'=1}^{i} X_{i'} + \beta}{\beta\left(1 - \sum_{i'=1}^{i} X_{i'}\right)}\right] \tag{43}$$

It was assumed that a firm maintains its competitive advantage throughout the diffusion curve if it is able to use the time horizon from t_{i-1} to t_i as a rethinking time to move from segment X_i to X_{i+1} successfully. Hence, firms have to understand the needs of segment X_{i+1} and fine-tune the product accordingly. The rethinking time between the segment i and the segment i-1 can be therefore calculated as:

$$t_i - t_{i-1} = \frac{1}{q(\beta+1)} \ln\left[\frac{\beta + \sum_{i'=1}^{i} X_{i'}}{\beta + \sum_{i'=1}^{i-1} X_{i'}} \frac{1 - \sum_{i'=1}^{i-1} X_{i'}}{1 - \sum_{i'=1}^{i} X_{i'}}\right] \tag{44}$$

Considering the segmentation proposed by Rogers (1962) and focusing on the chasm between early adopters and the early majority, the points can be assumed $\sum_{i'=1}^{i-1} X_{i'} = 0.025$ and $\sum_{i'=1}^{i} X_{i'} = 0.16$.

As a result, the rethinking time can be calculated as follow:

$$Rethinking\ time\ =\ \frac{1}{q(\beta+1)}\ln\left[\frac{\beta+\ 0.16}{\beta+\ 0.025}\ \frac{1-\ 0.025}{1-\ 0.16}\right] \tag{45}$$

The equation (45) has been used to compute rethinking time and test the hypotheses. A database of 70 historical cases – reported in Appendix 1 – of diffusion belonging to several industries was assembled, and, for each case, the Bass diffusion parameters p and q were identified. There are products of different ages in the database, from the 1920s – phonographs and refrigerators – to the 2000s – tablets and fitness tracker. If available, the parameters contained in past studies were used (Jiang, Bass, & Bass, 2006; Lee, Kim, Park, & Kang, 2014; Lilien, Rangaswamy, & De Bruyn, 2017). For instance, Golder and Tellis (1998) presented Bass parameters of several products ranging from clothes dryers to home VCRs. Otherwise, parameters were computed by using available cumulated sales data and the software "Bass forecasting" included in the tool "Marketing Engineering for Excel" developed by DecisionPro.

Besides diffusion data, other information about each case was collected. A historical narration describing the leading producers involved along the diffusion process was reviewed in order to identify the market leaders from the early majority phase onwards. Each product was then classified as brown good, consumer electronics product, white good, or other. The same argument was applied considering the type of market reached in the early majority phase, namely B2B or B2C. Then, the timing of entry was used to classify each of these companies as a first mover or late entrant. Finally, the prior experience of companies was used to distinguish between incumbents and new entrants.

These historical information were collected from various materials – from scientific papers (Golder, Shacham, & Mitra, 2009; Robinson, Kalyanaram, & Urban, 1994) to books (Schnaars, 1994) and internet sources (Business Insider or The Atlantic). Due to the risk of introducing subjective interpretations when identifying market leaders and their traits from historical reports, the process of case identification and analysis was supervised by two expert who, in case of misalignment, jointly discussed with the author until an agreed position was found. Table 6 reports the structure of the database.

Variable	Description
product	product name
p, q, β	Bass coefficients if available, parameters from literature were used otherwise, parameters were computed by using available cumulated sales data and the software Bass forecasting included in the tool Marketing Engineering for Excel developed by DecisionPro
rethinking time [years]	time between first and last sales to early adopters, equation (6) was used
brown good	binary variable equals to 1 if the product was a brown good

white good	binary variable equals to 1 if the product was a white good
consumer electronic	binary variable equals to 1 if the product was a consumer electronic product
other	binary variable equals to 1 if the product did not belong to the previous three classes
type of good	variable equals to 1 if the product was a brown good, 2 if the product was a white good, 3 if the product was a consumer electronic product, and 4 if the product did not belong to the previous three classes
B2C vs. B2B	binary variable equals to 1 if the product was sold in a B2B market
first mover	binary variable equals to 1 if the company leader in the early majority segment was the market pioneer
incumbent	binary variable equals to 1 if the company leader in the early majority segment was an incumbent

Table 6. Structure of the database

First of all, an exploratory analysis was conducted performing a preliminary ANOVA test in order to investigate whether successful first movers and successful late entrants were subject to different rethinking times. Table 7 suggests that first movers who cross the chasm (i.e., who remain leaders during the early majority segment) are found when diffusion exhibits a larger rethinking time, compared to the rethinking time that occurs when late entrants succeed. This difference has been confirmed by the ANOVA in Table 8, which shows that the p-value is equal to 0.011 and, hence, allows to reject the null hypothesis that the means of the two samples are equivalent. In other words, there is a statistically significant difference between the two average rethinking times. This allows providing preliminary support to the first of the two opposite options defining H1.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Successful late entrant	32	3.1875	1.9265	0.341	2.4930	3.8821
Successful first mover	38	4.6079	2.5022	0.409	3.7854	5.4304
total	70	3.9586	2.3522	0.281	3.3977	4.5195

Table 7. ANOVA test: descriptive table - timing of entry

	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	35.045	1	35.045	6.873	0.011
Within Groups	346.721	68	5.099		
Total	381.766	69			

Table 8. ANOVA test: ANOVA table - timing of entry

In order to deepen the study of the phenomenon, logistic regression models are employed, and Table 9 summarizes the results of all the models.

H1 was tested by estimating the chance that a first mover will reach the leadership position in the mass-market as a function of the rethinking time. As reported in Table 9 – Model 1, rethinking time positively correlates with the success of a first mover: in other words, if rethinking time increases, the probability of success for first movers increases too. Indeed, when rethinking time is short, the first movers might not have the time to redesign the product in order to leap across the chasm successfully. When instead rethinking time is longer, they are more at ease in developing products able to meet the early majority segment's needs and avoid the trap mentioned above. In particular, the likelihood of success for a first mover exceeds 50% if the rethinking time is between three and four years, and this success probability increases with rethinking time at a decreasing pace.

In order to test H2 and H3, new dimensions related to the role of the company within an industry were added to the analysis. It was respectively verified whether being an incumbent or a new entrant affects the probability that a first mover can successfully cross the chasm (H2) and that there might be a moderating effect due to rethinking time (H3).

Models 2 and 3 in Table 9 confirm that larger rethinking times will favour first movers to become leaders in the mainstream market. However, H2 cannot be confirmed; indeed, models 2 and 3 present two contrasting results and both with a p-value (0.104 and 0.180 respectively) above the 5% threshold of significance. Model 3 also shows that the probability of an incumbent first mover to cross the chasm successfully exists, but when short rethinking times occur, confirming H3. This effect is statistically significant, with a p-value equal to 0.023.

Finally, the last hypothesis – H4 – was tested by adding four product type variables to the model. As can be seen from Table 9 – Model 4, H4 was confirmed. In fact, whether B2C or B2B product, a white or brown good, or a consumer electronics product, there does not seem to be an impact on a first mover's likelihood of successfully crossing the chasm.

	Model 1	**Model 2**	**Model 3**	**Model 4**
rethinking time	0.292	0.240	0.561	0.537
	(0.016)	(0.054)	(0.011)	(0.017)
incumbent		-0.865	1.532	1.501
		(0.104)	(0.180)	(0.191)
incumbent X rethinking time			-0.697	-0.685
			(0.023)	(0.026)
B2C vs. B2B				-0.264
				(0.716)
brown good				-0.202
				(0.824)

white good				0.655
				(0.637)
consumer electronic				-0.201
				(0.781)
Constant	-0.949	-0.386	-1.615	-1.371
	(0.063)	(0.529)	(0.066)	(0.195)
Cox & Snell R square	0.093	0.127	0.201	0.208
Nagelkerke R square	0.124	0.169	0.269	0.278

Table 9. Logit models for successful first movers

This outcome confirms findings in the literature, which suggest that first movers usually focus on the specific needs of the early adopters and neglect later adopters, who exhibit quite different preferences and requirements (Schnaars, 1994). Hence, late entrants may focus their effort on developing products that suit later adopters (Carpenter & Nakamoto, 1989). Instead, when rethinking time is short, holding the incumbent position is a necessary condition for a fist mover to have a higher probability of being successful in the mass-market. These results are in line with the literature: incumbents have larger investment capabilities and assets (Tripsas, 1997), a better and broader understanding of the market and its segmentation (Chandy & Tellis, 2000), and can leverage on the trust they already obtained (Obal, 2013). All these factors contribute in part to successfully leap across the chasm despite a low rethinking time.

The contribution is twofold: from an academic point of view, it further investigates the dynamics occurring during the early phases of diffusion of new technologies, and it introduces a new and relevant factor in the discussion (i.e., the rethinking time). From a managerial perspective, it highlights the necessity of managing the timing of entry with great care when working within the early segments of diffusion curves since it is not universally true that being the first company to serve the market ensures long-term success.

When dealing with innovative products, market success does not only require the capability to operate quickly in the early phases of diffusion (something that is typically associated with new entrants) but also to operate with a significant breadth of view with respect to multiple market segments (something that – instead – may favour incumbents). In other terms, potential disruptions, as described by Christensen (1997), might not materialise if firms that initially engage with unmatched needs and underserved customers are then unable to understand how to leap across the chasm and – critically – do not have enough time to do it. Quite significantly, this inability has been found to be associated with entrants to the industry, which implies that inertia and competency traps can be tied not only to firm size but also to the narrowness of experience.

From a managerial perspective, the necessity of managing the timing of entry with great care was highlighted. When working within the early segments of diffusion curves, it is not universally true that being the first company to serve the market ensures long term success. Incumbents may still have the upper hand when leaping across the chasm. So, they might either wait for the early majority segment and leave entrants with the onus of opening the market for them or operate as first movers and stimulate diffusion in order to reach the early majority segment as soon as possible, thus leveraging on the superior knowledge they have of the broader market. Conversely, firms that do not enjoy incumbent status should take care in making an early entry in new markets, especially when dealing with goods that exhibit significant diffusion speed. In doing so, they should avoid the risk of fixating themselves on the initial customer segments and should actively look ahead for the key challenges they will find with the early majority segment.

The choice to limit the analysis only to durable products is because of a clear separation between product development and its commercialisation. This is not true for services; especially when adopting modern agile and experimental approaches, service development and diffusion progress in tandem. Specifically, agile development calls into question the traditional separation between product development and its subsequent diffusion (Beck, et al., 2001). Within this context, each product development iteration simultaneously incorporates the elicitation and satisfaction of current customer needs and the validation of the corresponding product/service performance but does not usually involve interaction with the customer segments that progressively appear along the diffusion curve (Cantamessa & Montagna, 2016). So, exploring the implications of rethinking time and entry decisions in agile contexts could be an important topic for further research, that responds to the need reported in the literature of new theoretical models able to study new evolutionary patterns of products and services (Bstieler, et al., 2018).

2.4. What About Industrial Designed Product and Their Diffusion?

Concerning product diffusion studies, the Bass model (Bass, 1969) and those derived from it (Bass, Krishnan, & Jain, 1994; Guidolin & Guseo, 2014; Niu, 2002) consider diffusion as a binary decision (i.e., adopt or not adopt) that consumers take and, once taken, it has a permanent effect on the diffusion process. In other words, when a consumer buys, for instance, a new smartphone, he/she is immediately recognised as an adopter by diffusion studies. This kind of diffusion models especially focuses on marketing, strategical and contextual variables, such as marketing expenditure, pricing strategy, or seasonality effects, and recognises a significant value to product performance metrics. Instead, all the elements that are hardly measurable (e.g., style) or related to the experiential process (e.g., affordance) have been neglected.

The same shortages apply to reflections around rethinking time. They are certainly well suited to the world of engineering designed products as the concept of rethinking time owes its mathematical definition to the Bass model, which poorly adapt to industrial designed products. However, the latter, exactly as engineering designed products, have to meet customer requirements that change over time in order to address the needs of the different subsequent segments. In other words, the experiential process around the adoption, that is related to the interactions between the variety of users and industrial designed products, may affect rethinking time, thus making it necessary to add a layer to the analysis of industrial designed products.

The literature on services and their diffusion recognises several peculiarities to services, such as intangibility in contrast to products tangibility (Zeithaml, Parasuraman, & Berry, 1985), that lead to differences in the diffusion process too. The various services diffusion models, be they Bass-type models, choice-type models, or Grey-models, for instance, consider no more the adoption as a binary decision. They agree that the adoption process may last over time for most of the services offerings and, therefore, it is required to collect customers information about subsequent purchases. However, none of them specifically address the experiential aspects related to the use or associated with intangible variables. Therefore, we can state that, despite peculiar characteristics have been recognised, service diffusion studies still need to implement them to understand the phenomenon better and deeper.

3. Relation Between Diffusion and Adoption

'Diffusion' and 'adoption' are twisted theories that researchers developed together since the 1960s (Bass, 1969; Rogers, 1962). Since the early years, theories on diffusion have been applied to various fields, spanning from textile chemicals (Lancaster & White, 1977) to steam engines (Atack, Bateman, & Weiss, 1980). They aimed at deepening diffusion dynamics in specific fields (Norton & Bass, 1987; Oren & Schwartz, 1988) or at proposing approaches to estimate diffusion curves (Schmittlein & Mahajan, 1982; Srinivasan & Mason, 1986), usually based on the standard Bass model (1969).

Whit respect to adoption, over the years, two opposite approaches have been used to study this process: a market-oriented vs a product-oriented approach. Market orientation has received most of the research attention (Kirca, Jayachandran, & Bearden, 2005; Langerak, Hultink, & Robben, 2004), and it is interested in promoting customers, competitors, and inter-functional coordination (Kohli & Jaworski, 1990). However, this perspective may prevent companies from proposing radical innovations (Moriarty & Kosnik, 1989; Slater & Narver, 1995). A product-oriented approach opposes it, and it is hence preferred when the aim is to improve product performances and reach technical superiority (Eng & Quaia, 2009).

Since the influence that diffusion and adoption processes have proven to have on innovation success in the market (Banytė & Salickaitė, 2008), studies on the topics have driven the attention of the Innovation Management literature too. McCormick, Steckler, and McLeroy (1995) proposed an adoption process, which included implementation and institutionalisation, for the diffusion of goods. Sethi, Prasad, and He (2008) investigated price and advertising effects on the adoption process by proposing a new product adoption model. Nakata and Weidner (2012), studying how to support the adoption processes for people living in developing countries, proposed a set of characteristics of product, social context and marketing approach that might help the adoption. Li, Zhang, and Wang (2015) seek to explore the relationship between product originality and product usefulness in respect of consumers' intention to adopt a new product. Baizal, Widyantoro, and Maulidevi (2016) proposed a new conversational recommender system to help customers in the adoption process. Jeong, Kim, Park, and Choi (2017) focused on the impact of consumers' domain-specific innovativeness wearable technology adoption, highlighting the importance of consumers' propensity to innovation for wearable devices to influence other consumers during the adoption process. All these studies have in common the proposal of strategies aimed at stimulating the adoption process by working on features related to the product or the market from an Innovation Management point of view.

Independently on that, the adoption process has often been described as one of the diffusion process stages. Rogers (1962) has given the most significant contribution by distinguishing between two stages: awareness and adoption. The former concerns becoming aware of the existence of a good and is an essential precondition for adoption to occur. It can happen either to play a passive role and become aware quite by accident (Coleman, Katz, & Menzel, 1967) or to expose actively to ideas related to one's interests, attitudes, or passions (Hassinger, 1959). Earlier knowers of an innovation share commonalities with innovators: they usually are more educated, reach a higher social status, and the like. However, they do not match: becoming aware of an idea is completely different from using it (Rogers, 2003). The latter instead consists of purchasing the product or using the service (Rogers, 1962).

The same author later introduced three more stages (see Figure 13) (Rogers, 2003), which separate awareness from adoption. In the second stage (i.e., after awareness), interest starts to grow, and the potential customer seeks new information. He/she starts to have a positive or negative attitude toward the innovation. At this stage, the potential customer is psychologically involved in the decision: previously, the activity was cognitive (knowing the innovation); here, an individual may, for instance, imagine how the new idea will affect his/ her situation.

Subsequently, a decision about adoption based on an evaluation of present and possible future situations must be made (Song & Chintagunta, 2003). A decision may be taken trying out the new idea on a partial basis; in other circumstances, a peer's trial may constitute a substitute for a first-hand trial. Opinion leaders are here of great importance and are used to speed up the adoption process (Magill & Rogers, 1981).

If the choice is to adopt, the potential customer wants the innovation. Although individuals have decided to adopt at this stage, they still have questions to find answers to. First of all, they must know where or how to acquire the good; and once obtained, they must understand how to use it and how to solve the first problems they may encounter using it. Once answered these questions and used the good for a more or less long period that depends on the nature of the good itself, the innovation is adopted, and the adoption process is finally considered ended.

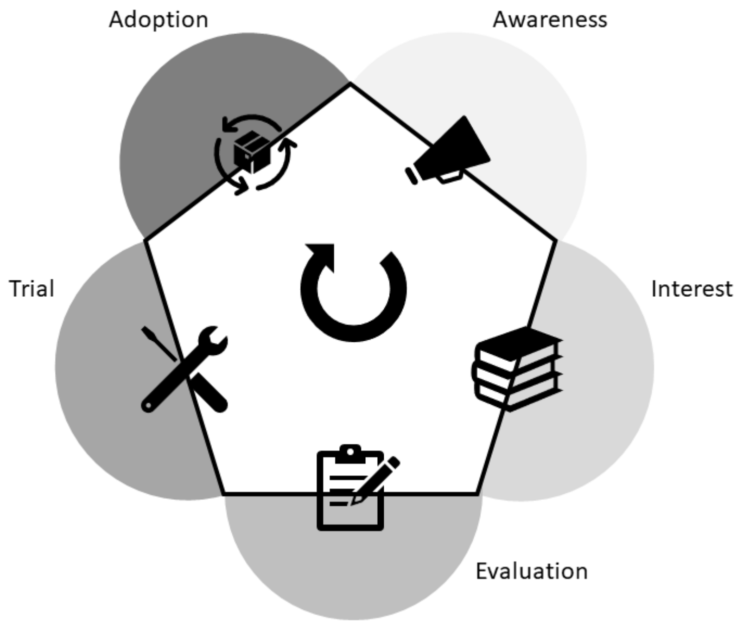

Figure 13. The stage of the diffusion process as represented in Rogers (2003)

It is therefore clear that the intrinsic characteristics of products and services, such as tangibility vs intangibility (Zeithaml, Parasuraman, & Berry, 1985), and the qualitative features of industrial designed products (Abidin, Sigurjonsson, Liem, & Keitsch, 2008) lead consequently to differences in the adoption process since they are directly tackled within the evaluation stage.

Although early proposals of diffusion processes did not provide for mechanisms other than a binary adoption choice and late proposals usually referred to products adoption, they can be easily adapted to services.

Let us take the case of a social media as an example. At the awareness stage, commercial campaigns or word of mouth enable the potential customer to become aware of the social media. At the interest stage, the potential customer starts to search for opinions, reviews, and specifications in order to get as much information as possible about the social media. Subsequently, he/she will evaluate whether the social media will provide benefits or not. Some of the critical factors in product evaluation are price, place, quality, and quantity. If we consider the consumer side in a typical social media, the service is free for use and provided everywhere and every time. A new social media should, therefore, at least satisfy these two needs to be positively evaluated. In the trial stage, the potential customer tries the social media and determines whether he/she will continue to use it. Finally, all the considerations above will lead the potential customers to adopt or not the social media.

The differences lie, first of all, in the reflections around adoption: depending on the kind of service offered, factors, such as the presence of a monthly or a yearly subscription, or the need to collect multiple purchases from the same customer, have an impact on the adoption stage.

Secondly, in the evaluation stage, factors that affect the adoption are hardly measurable. Returning to the example of social media, Mamonov and Benbunan-Fich (2017) explored the case of Facebook Gifts showing that factors such as privacy concerns and perceived social utility played a key role in their adoption.

3.1. The Adoption of Radically Innovative Products

The literature has widely recognised the differences between radical and incremental innovations adoption (Dewar & Dutton, 1986; Ettlie, Bridges, & O'Keefe, 1984), as described previously at the beginning of this thesis.

In the 2000s, contributions have started to focus on product features and the role customers with their specificities have on adoption.

Lam, Chiang, and Parasuraman (2008) discussed the impact of *consumer readiness* on technology adoption by studying the four single dimensions of the consumer-readiness construct (i.e., (innovativeness, optimism, discomfort, and insecurity).

Customer readiness is the 'condition or state in which a consumer is prepared and likely to adopt an innovation for the first time' (Meuter, Bitner, Ostrom, & Brown, 2005), and it is the twin construct of technology readiness, which is a well-known concept in the diffusion of innovations literature (Poushneh & Vasquez-Parraga, 2018). Also, Rakhi and Mala (2014) stressed the importance of consumer readiness as a whole by confirming its significant positive effect on adoption intention in a real case of radical innovation.

Chao, Reid, and Mavondo (2012) especially focused on *customer innovativeness*: authors aimed at deepening research around the existing relationship between consumer innovativeness and radically innovative product adoption. They distinguished between innate consumer innovativeness, domain-specific innovativeness, and vicarious innovativeness; only the second component resulted in directly affecting the adoption of radical innovations.

The former represents the bias for adopting new products without being influenced by other experiences (Midgley & Dowling, 1978). Domain-specific innovativeness refers to the predisposition to adopt new products within a specific domain of interest (Goldsmith & Hofacker, 1991). Vicarious innovativeness is the openness to advertising messages of all kinds, from word of mouth to mass media (Hirschman, 1980).

Customer innovativeness is particularly relevant and more difficult to manage when developing radical innovations since high customer innovativeness is linked to consumers who 'exhibit the ability to process information in a dominantly experimental way and that the interactions among such individuals will, in a new product development context, produce a radical innovation that mainstream consumers will find more appealing and be more likely to adopt relative to one that is developed by mainstream or innovative consumers' (Hoffman, Kopalle, & Novak, 2004). Consistently, from a product perspective, Reinders, Frambach, and Schoormans (2010) proposed that bundling radically innovative features with existing ones may represent a means in the hands of companies to affect adoption intention positively.

Precisely because of the difficulty in managing customer readiness in radically innovative contexts, it may be worth of interest to investigate whether and how designers affect the adoption process by making choices during product development that will reflect in functional modifications, and hence, to a certain degree, bypassing customers.

4. Design Choices and Adoption: New Model to Estimate Product Adoption

From the discussion conducted so far, it is possible to conclude that it is challenging for a company to successfully manage an adoption process, especially in the case of radical innovations characterised by highly uncertain environments and less customer readiness. Successfully managing this process has historically represented a solution to gain a temporary advantage both for large and small firms (D'Aveni & Gunther, 1994; Song & Montoya-Weiss, 1998; Tellis, Prabhu, & Chandy, 2009).

4.1. Market Research Cannot Drive Totally Adoption for Radical Shifts

However, since the path to achieve conditions favouring radical innovations success involves both high technology and market uncertainties, incumbents often fail to maintain market leadership since they are unable to interpret the potentialities of new technology (Christensen, 1997). Technological progress sometimes pushes radical innovations independently on the market, and adopters are not even aware of their needs (Norman & Verganti, 2014; Reinders, Frambach, & Schoormans, 2010). Often, a reference market does not exist yet, and companies are consequently unable to elicit needs from potential customers. Traditional market research may, therefore, result to be an inappropriate tool. S-curves result to be misleading (Cantamessa & Montagna, 2016) and consequently, firms suffer from the absence of reliable models by which evaluating the progress of the technology and predicting the market appraisal of radical innovations (Stevens & Burley, 1997; Birkinshaw, Bessant, & Delbridge, 2007). Investing decisions, moreover, are challenging in such fuzzy front-end contexts (Moenaert, De Meyer, Souder, & Deschoolmeester, 1995; Frishammar, Florén, & Wincent, 2011), and both idea generation and pre-development are carried on without precisely knowing the emerging technology (Khurana & Rosenthal, 1998; Kim & Wilemon, 2002; McLaughlin, Bessant, & Smart, 2008). In this milieu, design decisions are constrained by the emerging technology but often are made without having a clear idea of the effects on customer perception.

Over the years, scholars deeply investigated what makes an innovation radical (Henderson & Clark, 1990; Lee & Na, 1994; Atuahene-Gima, 1995; Balachandra & Friar, 1997; Kessler & Chakrabarti, 1999). Henderson and Clark (1990) stated that innovations could be analysed by looking at the product architecture and the underlying technology. The authors defined incremental and radical innovation: the former does not present any drastic change neither in underlying technology nor in product architecture, the latter modifies both. Atuahene-Gima (1995) distinguished between incremental and radical innovations by define first as improvements or modifications, and the latter as new product lines or new-to-the-world products. Balachandra and Friar (1997) stated that incremental innovations usually address a well-established market and present minor modifications to performance, flexibility, and appearance. In the case of radical innovation, the market may not exist at all, and the technology is considerably different from what is on the market. Moreover, Kessler and Chakrabarti (1999) claimed that radical innovations are characterised by higher complexity and risks, and require a greater number of information and people involved. All these studies agreed that innovations have to be subject to substantial modifications to be classified as radicals and that uncertainties are particularly high in these contexts.

Scholars also observed that radical innovation and the emergence of a new technological paradigm are twisted concepts: independently of where a radical innovation occurs (at system or component level), it is always related to the emergence of a new technological paradigm (Schilling, 2009). If it occurs at the component level, it will lead to a new paradigm shift for the associated technology, and it will contribute to the progress of the whole system. If it occurs at the system level, it will determine a paradigm shift associated with the system and, consequently, with components (Cantamessa & Montagna, 2016).

Correspondingly, literature contributions are usually aimed at identifying the requirements to explore new technological paradigms and enhancing the development of radical innovations. Some of these contributions relate to comprehending the enabling conditions, such as the technology evolution phases (Tushman & O'Reilly, 1997; Iansiti, 2000), discontinuous progress (Schilling, 2009), disruption possibilities and barriers (Antonelli, 1995; Christensen, 1997), as well as competition forces (Porter, 1985). These studies focus on the industry-level factors that firms can leverage to support the introduction of radical innovations.

Other authors investigated organisation and management strategies, such as the combination of internal and external knowledge (Cohen & Levinthal, 1990; Leiponen & Helfat, 2010), the balancing between exploration and exploitation approaches (Helfat & Raubitschek, 2000), ambidextrous behaviours (Tushman & O'Reilly, 1996; Gibson & Birkinshaw, 2004), visionary aptitude and shaping strategies (Hagel, Brown, & Davison, 2008), technology policies (Ettlie, Bridges, & O'Keefe, 1984), the ability to blend supply-side and demand-side elements together (Cooper & Kleinschmidt, 1990; Calantone, Di Benedetto, & Divine, 1993; Sainio, Ritala, & Hurmelinna-Laukkanen, 2012), and the choice of specific inter-firm integration configurations (Christensen, Verlinden, & Westerman, 2002; Lee & Veloso, 2008). This research stream stressed the importance and the impact of firm-level strategies have on radical innovations emergence. However, as in the previous stream, the attention was on favouring conditions for radical innovations, which led to overlook a design perspective aimed at support designers.

Many studies also explored antecedents to product success from different perspectives: organisational factors (Ayers, Dahlstrom, & Skinner, 1997; Sivadas & Dwyer, 2000), capabilities for gathering and using market information (Ottum &

Moore, 1997; Kam Sing Wong & Tong, 2012), cross-functional integration (Troy, Hirunyawipada, & Paswan, 2008). However, all of them focus on the conditions required to support the emergence of a new technological paradigm or on the preferred strategic and managerial orientation, neglecting how the design decisions underlying radical shifts can be supported. Shifting from an old technological paradigm to a new one, in fact, implies on the one side, strategic assessments and managerial actions, while leads on the other side, to design decisions and technology-related choices. Suppose a dominant design locks a technological paradigm (Tushman & Rosenkopf, 1992). Hence, a dominant design represents a specific emerged product architecture (Utterback & Abernathy, 1975), and any product architecture is the outcome of design choices which have to be consequently supported.

In particular, companies usually employ technological road-mapping (Paap, 1994; Geum, Lee, Kang, & Park, 2011; de Carvalho, Fleury, & Lopes, 2013) and forecasting techniques to estimate adoption of innovations (Firat, Woon, & Madnick, 2008). Qualitative approaches like scenario analysis (Clarke Sr., 2000) or expert opinions (Okoli & Pawlowski, 2004) are more frequently proposed because of the uncertainty surrounding radical situations. Nevertheless, quantitative methods could be employed to estimate the market adoption of technically superior new products (Salo & Cuhls, 2003) or to represent the state of progress as a point on the S-curve, in order to depict maturity and consequently the possible emergence of a new curve (Utterback & Abernathy, 1975; Foster, 1986; Utterback, 1994; Chandy & Tellis, 2000; Roy & Sivakumar, 2011). However, these models have limits mainly dependent on the performance indicator chosen as a driver of progress, or on time that is selected as the independent variable (Cantamessa & Montagna, 2016). As an additional help, companies adopt methods aiding them to define a business model (Osterwalder & Pigneur, 2004; Casadesus-Masanell & Ricart, 2010) or to assess project and competence portfolios (Cantamessa, 2005; Verganti & Pisano, 2008), in order to understand how the organisation can enable and support product changes.

All these methods are employed by companies to make strategic decisions on technology investments or company structure, but they do not provide any suggestions about the product features and technical decisions designers should make to provide successful products.

Designers, in fact, have to refer to other perspectives. On the one hand, methods aiming at investigating customer needs, such as Human-Centred Design (Norman & Draper, 1986) and Design Thinking (Brown, 2009; Cross, 2011) which are the two alternative main streams in this view. On the other hand, design-driven approaches (Verganti, 2009) that aim at avoiding customer involvement.

Methods from the former group have a common framework: an iterative cycle of investigation – analysis of user needs, search for technologies to satisfy them and prototyping – that leads to appropriate results only when design solutions address customer needs. If one adopts these approaches, problems precisely arise when companies are designing a radically innovative product. Indeed, customers do not know their needs yet (Zaltman, 2003), or do not recognize or understand the novelty of the innovation (Heiskanen, et al., 2007). Hence, the effort dedicated to initial market assessments is more and more limited when market and technology uncertainty becomes extremely large. Instead, it is usually preferred to offer a minimum value product progressively enriched (Smith & Reinertsen, 1997) or to employ a 'probe and learn' process based on several approximations (Lynn, Morone, & Paulson, 1996). Lean approaches (Ward, 2007), namely Agile in digital contexts, are more and more diffused, especially in the start-up contexts (Blank, 2013).

Instead, design-driven approaches (Verganti, 2009) try to avoid customer involvement entirely. According to these approaches, the adoption of radical innovations is based on the tacit interplay between the cultural and "emotional" new value proposed and the customers' perception. Such new cultural aspects are designed by the company and proposed to customers so that a specific path of adoption is designed.

Also studies of design cognition have addressed issues arising from design activities. For instance, designers may be fixated on early solution ideas and concepts (Jansson & Smith, 1991) and, therefore, may be unwilling to explore the problem and generate new design features. This kind of behaviour is ill-suited to the development of radical innovations, which often require new solutions. Proposing many alternative solutions is another behaviour found in actual practices but risks to lead to poor results (Fricke, 1996). Moreover, during the design process, especially when designers are fixated on existing solutions, creativity – defined by Cross (1997) as a bridge between the problem space and the solution space – plays a key role to generate solutions outside the existing domain.

In 2014, Norman and Verganti definitively combined human-centred and design-driven perspectives and agreed regarding the importance of eliciting user needs for incremental innovations, confirming the weaknesses of customer-driven approaches in radical innovation cases. In these latter cases, whether or not designers would involve potential users, they must consider that users are unaware of their needs, and consequently, opportunities for innovation and new product requirements must be validated independently of them.

Some attempts to address this last problem start being found within the Engineering Design literature. Some of them belong to the stream of Creativity and are devoted to supporting design divergence and the generation of alternatives (Bacciotti, Borgianni, & Rotini, 2016); some other instead focus on Design Management and try to face with the multiplicity of the design decisions in radical contexts and the related uncertainty (Yannou, Jankovic, & Leroy, 2011). Besides, additional contributions try to enhance the traditional design process and decisions by investigating the information on new features and functionalities that radical innovations call for. Borgianni, Cascini, Pucillo, and Rotini (2013), in particular, propose a TRIZ based systematic method for the development of radical solutions through a comparative analysis of successful and unsuccessful products with their predecessors in order to assess in advance the expected market appraisal of the alternative product profiles that are to be designed.

The idea is to position in the last stream of research focusing on radical innovations adoption and paradigm shifts and study the recommended and inadvisable actions that designers should perform to embrace new technological paradigms, making designers aware that not all design choices have equal consequences in terms of innovation. Therefore, it is clear that the aim is not to investigate neither the antecedents of product success nor the factors behind radical innovations, as well as the ones behind the emergence of technological paradigms according to the traditional criteria of Innovation Management literature. Instead, it looks at the problem from a complementary perspective deriving from the Engineering Design domain.

4.2. Design Variables to Estimate Adoption

Borgianni, Cascini, Pucillo, and Rotini (2013) proposed a model based on 12 design variables able to assess in advance the expected adoption of alternative product profiles that are to be designed. The model was grounded on concepts from the Theory of Inventive Problem Solving and Blue Ocean Strategy, here introduced and discussed.

4.2.1. TRIZ - Theory of Inventive Problem Solving

4.2.1.1. History

TRIZ is the Russian acronym for *теория решения изобретательских задач* and can be translated as Theory of Inventive Problem Solving (Terninko, Zusman, & Zlotin, 1998). It is a methodology developed by Genrich Altshuller, born in 1926 in the former Soviet Union.

After the Second World War, he started to work as an invention inspector; his role was to help inventors find creative solutions to their technical problems. He had the idea that some sort of inventive trend might exist, and he started to collect and study thousands of patents. His studies firstly led him to classify inventions from less to more innovative. The lowest level was assigned to patents showing minor changes in the original system; higher levels were assigned when more substantial changes were present.

In 1948, Altshuller and Saphiro – his friend and colleague – expressed their doubts about the future of innovation in the Soviet Union to Stalin, and they gave suggestions to improve it. As an answer, both were sentenced to 25 years of imprisonment. After the death of Stalin, 1953, both were released, but only Altshuller continued the studies.

During the next decade, the studies of Altshuller started to attract more and more professionals from different disciplines and to be known as TRIZ. Its principles were applied to various fields, from scientific problems to managerial ones. In more than 30 years, Altshuller and his colleagues studied, theorised, and developed many principles. The most important are:

- Level of invention
- Contradictions
    - Technical
        - The 40 Inventive Principles (1956-1971)
        - The 39 Technical Parameters
    - Physical
        - The 4 Separation Principles
- Ideality (1956)
- Standard solutions
- Laws of Engineering System Evolution
- Algorithm of Inventive Problem Solving (ARIZ) (1959-1985)
- Su-field analysis (1977)

Some of them will be briefly discussed in the following paragraphs.

4.2.1.2. Laws of Engineering System Evolution

TRIZ theorised that any artefact evolves by following repeatable patterns. These patterns were recognised and proposed by Altshuller in his book Creativity as an Exact Science: The Theory of the Solution of Inventive Problems (1984). They were named Laws of Engineering System Evolution, and represent the laws that govern the development of technical systems, just like natural laws regulate the development of biological systems (Cascini, 2012).

The first is the law of the completeness of parts of the system. Four elements are the main components of every technical system (see Figure 14): Tool (i.e., the functional element delivering the function), Engine (i.e., the element providing the energy), Transmission (i.e., the element transmitting energy from Engine to Tool) and Control (i.e., the element governing at least one of the previous elements).

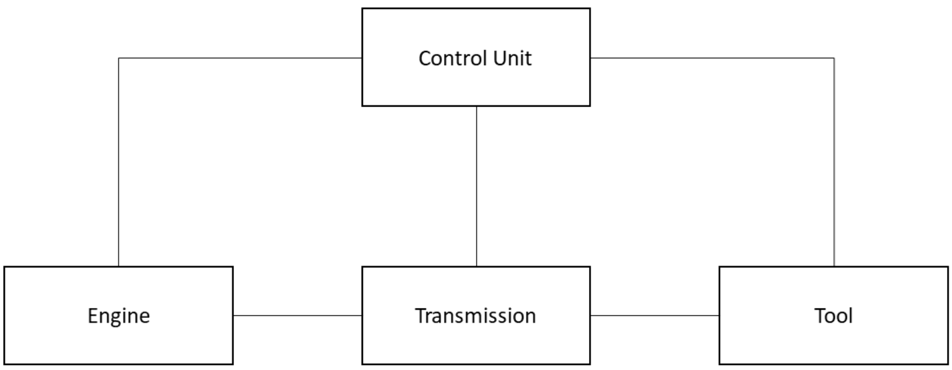

Figure 14. Main parts of technical systems

As an example, to achieve the function "clean teeth", a technical system requires a toothbrush as a tool, the muscles as the engine, arm and hand as transmission, and the nervous system as a control unit. If one of the four parts missed, the required function would not be any more accomplished.

A corollary of this law is that technical systems progress to the reduction of human involvement. Technical systems are developed by people to save time and to dedicate themselves to intellectual works. For example, washing clothes initially was a labour-intensive process; when first washing machines were introduced, they required reasonable manual labour; finally, the modern washing machines further reduced human involvement.

The second is the law of energy conductivity (2) and states that the unhindered passage of energy through all parts of the system is a necessary condition for the life capability of the technical system, an example of which is the data transmission speed in smartphones (i.e., from 2G to 5G).

The third, known as the law of harmonising the rhythms (3), refers to the elements of a technical system that should be coordinated amongst themselves to improve how they interact with the system and the object and go beyond current limits. An example of the implementation of this law is the electric toothbrush, which has gradually refined the teeth cleaning process.

The law of increasing the degree of idealness of the system (4) states that systems development seeks to maximise the degree of ideality. The concept of ideality can be described by a simple equation, $I = E/C$, where E represents the user benefits and C the costs of the system. The ideal system provides benefits without any expenses, but it represents just a standard for comparisons because it is not possible to get the costs down to zero.

The fifth is the law of uneven development of parts of a system (5). Every technical system is subject to the development of its subcomponent, and there is always one of them that holds back the technical system from its further progress. This part is known as a bottleneck, and it gives rise to sharp contradictions. For example, aeroplanes performances are linked to several parts of the vehicle, and concentrating most of the development efforts on just some of them might lead to the rise of bottlenecks.

The sixth is known as the law of the transition to a super-system (6). When all the subcomponents of a technical system are fully developed, the technical system is integrated into a super-system, that is a wider system that comprises the one under consideration as a sub-system and drives the technology forward. Usually, a system evolves according to the following logic: mono-system, bi-system and poly-system, moving from delivering only one function to various functions. For example, a simple blue pen is a mono-system; a staple gun able to remove paper clips represents a bi-system.

The law of the transition from a macro to a micro level (7) states that the elements of a system are initially improved at a macro level, to be further broken into micro-level processes. This transition still represents how modern technical systems typically progress, and usually is followed by a radical shift in the S-curve. As an example, record playing devices moved from having a mechanical contact to an optical system with a laser.

The last is the law of increase of the Substance-Field (Su-Field) involvement (8) which specifies that, in any technical system, the number of constituent elements and interactions between them tends to increase. If one considers modern disposable razors, they incorporate multiple blades and lubricated strips that interact with each other and with the skin, providing hence a safer and smoother shave.

The best practice to use these laws is to analyse the current system taking into consideration all the laws. An overview of the current status of each law applied to the system will give suggestions about the possible future evolution patterns (see Figure 15).

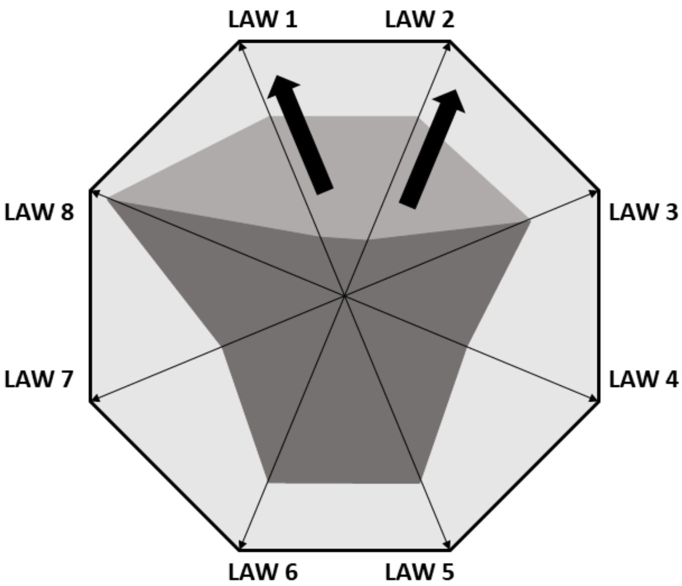

Figure 15. State of development of a technical system

4.2.1.3. Useful Functions, Harmful Functions and Resources

Technical systems are characterised by tools, functions, and objects receiving a function (see Figure 16). The former is the element responsible for providing the function which is adequately defined if it can be expressed as a combination of one among four verbs – increase, decrease, change, stabilise – and the name of an object property. Examples of properties are size, colour or shape. Functions can be useful (i.e., desired actions), or harmful if the action is undesired. This kind of representation is used to understand the current situation better and, for instance, to identify existing conflicts that should be overcome.

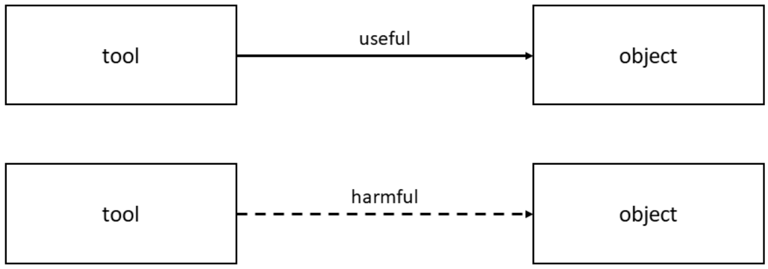

Figure 16. Useful and harmful functions

Resources instead represent everything that can be applied to solve a problem and improve a system without significant expenses. For instance, time, space and energy are resources. Resources should be easily attainable, free or low cost, and they can be internal or external to the system. TRIZ suggests looking at how the initial system uses resources, what resources are underused, or which ones may be further exploited to make the technical system more efficient.

4.2.2. Blue Ocean Strategy

Kim and Mauborgne firstly introduced the concept of Blue Ocean Strategy (2005). They described the market as a bloody battlefield, a red ocean, in which companies battle for market share, trying to outperform their rivals. In a red ocean, every player knows the boundaries and the rule of the games, and, usually, profits continue to decline.

The solution the authors found is making the competition irrelevant by creating the so-called blue oceans of uncontested market space; essentially, creating an industry that does not exist today. In blue oceans, competition is irrelevant because the company that created it is the only one to swim in it.

A blue ocean can be created starting from an existing industry that is struggling to earn profits; this is the case of Cirque du Soleil, which innovates the circus system introducing new factors from the theatre and other industries (DeLong & Vijayaraghavan, 2002). Alternatively, a company introducing a blue ocean can create a new industry, as Apple did when they introduced the iPhone, creating the smartphone industry (Yoffie & Slind, 2008).

Blue oceans are crucial for companies that want to make new profits and gain a temporary or permanent advantage against their competitors, but their theorisation does not mean that red oceans will disappear. Many practical cases and studies supported the validity of the importance of blue oceans. For example, the authors found that most of the revenues and profits are generated by new blue oceans even if they accounted for only 14% of total launches; the remaining 86% were incremental improvements (see Figure 17).

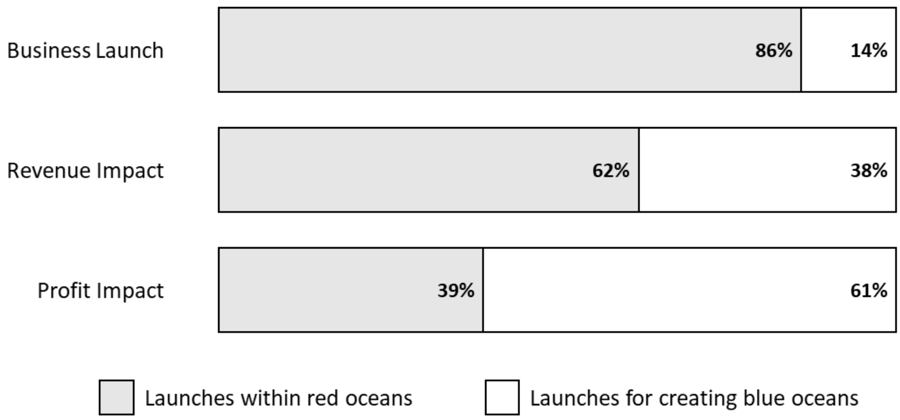

Figure 17. The profit and growth consequences of creating blue oceans (Kim & Mauborgne, 2005)

Understanding the basic unit of analysis was the first problem Kim and Mauborgne faced. Trying to figure out if visionary companies that continuously outperform the market exist, they analysed cases from In Search of Excellence (Peters & Waterman Jr.., 1982) and Built to Last: Successful Habits of Visionary Companies (Collins & Porras, 1994). They recognised that industry performances have a higher impact on outperforming the market rather than the performances of a single company. Hewlett-Packard, for instance, outperformed the market while the entire computer industry was quickly progressing too. The authors concluded that the company was not the right unit of analysis.

Moreover, history has taught that new industries always arise, and industries today existing will disappear in the future. For instance, the smartphone industry was unknown thirty years ago. The conclusion was that even the industry was the wrong unit of analysis. The authors hence concluded that the right unit of analysis was the strategic move. The difference between losers and winners is their approach to strategy. Losers try to beat the competition and stay in a defensive position against competitors; winners do not use the competition as their benchmark but pursue value innovation, i.e., they try to raise value for buyers and the company itself. Value innovation, as the name suggests, focuses both on value and innovation. Value without innovation tends to focus on value creation; innovation without value tends to be technology-driven, market pioneering or futuristic, forgetting that this kind of innovation might be too far ahead for customers.

Value innovation is usually achieved by driving cost down and value up for buyers, i.e., companies pursuing value innovation do not accept one of the most commonly accepted dogmas of competition-based strategy: the value-cost trade-off. Indeed, organisations that seek to create blue oceans pursue differentiation and low cost simultaneously; value innovation is achieved only when utility, price and cost activities are correctly aligned. In contrast, innovations, such as ones in production plants, may lower the cost structure to reinforce an existing cost leadership strategy or gain a cost leadership position without changing the offer.

The blue ocean is a dynamic concept. A new blue ocean will attract more and more competitors until it will become a red ocean. No blue ocean is forever, but the switch from blue to red can be delayed by distancing from potential imitators. In this way, the blue ocean strategy presents a dynamic and iterative process to build uncontested market space across time.

4.2.2.1. Strategy canvas

The authors also introduced various tools to help companies facing blue oceans. The most famous is the strategy canvas (an example in Figure 18).

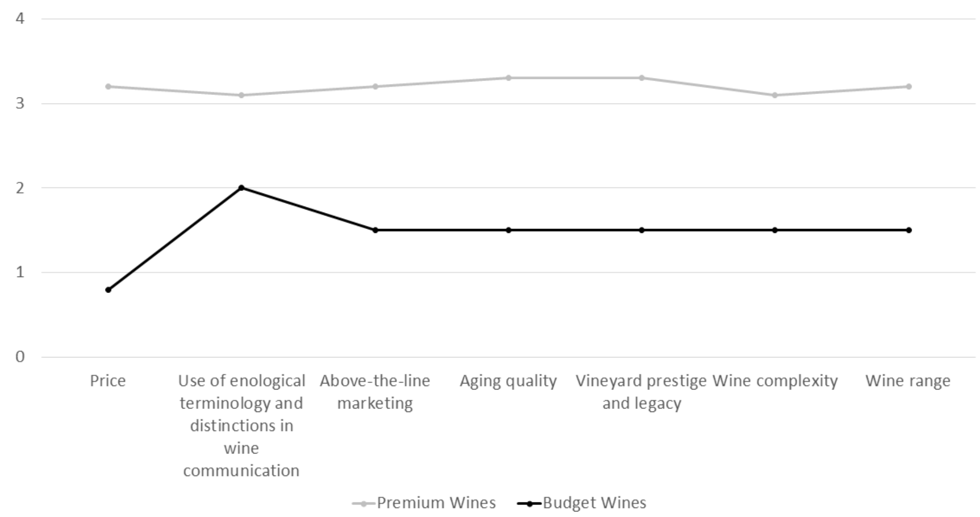

Figure 18. The strategy canvas of the U.S. wine industry in the late 1990s (Wischnewski, 2017)

This tool captures the current position of a company in its industry, depicting it in a curve called the value curve. The latter is a graphic performance comparison between two or more offerings across several industry factors of competition. Strategy canvas allows businesses to understand where competitors are currently striving.

4.2.2.2. Four actions framework

The four actions framework is a tool meant to help companies in proposing a new value curve. Authors proposed four key questions companies need to answer:

1. Which of the factors that the industry takes for granted should be eliminated?
2. Which factors should be reduced well below the industry standard?
3. Which factors should be raised well above the industry standard?
4. Which factors should be created that the industry has never offered?

The first two questions allow companies to focus on how to drop their cost structure. The second two make companies realise how to create new demand.

Eliminate and create are particularly crucial because push companies to go beyond traditional competition factors pursuing value innovation.

For example, Casella Wines – a wine company based in Australia – produce [yellow tail], a wine whose strategic profile broke from the competition and created a blue ocean consisting of wine accessible to everyone. Casella Wines acted on all four actions – eliminate, reduce, raise, and create – to unlock uncontested market space that changed the face of the U.S. wine industry in a span of two years. They created three new factors in the U.S. wine industry – easy drinking, easy to select, and fun and adventure – because they want the wine to become a social drink accessible to everyone and, in so doing, enlarge their customer base. The result was stealing sales from competitors and bringing non-wine drinkers into the wine industry. Moreover, to keep the cost structure down, they eliminated or reduced everything else – tannins, oak, complexity, and ageing.

4.2.3. A Framework Based on Design Variables

Principles from the Theory of Inventive Problem Solving and Blue Ocean Strategy have been borrowed by Borgianni, Cascini, Pucillo, and Rotini (2013) to propose a two-dimensional space to classify design modifications occurred. These modifications mainly depend on the Design Object and the Design Process (Borgianni, Cascini, Pucillo, & Rotini, 2013).

On the one hand, in fact, products differ for features. Engineering Design associates these features with functionalities according to the extent these characteristics address product functions and affect user satisfaction. Borrowing the function definition and the concept of the ideality of a technical system from the Theory of Inventing Problem Solving, these features can be classified as follows:

- properties that directly benefit users and stakeholders and, hence, deliver a useful function (UF attributes).
- Features seeking to eliminate unwanted outputs or diminish harmful side effects provoked by the system (HF attributes).
- Characteristics involving a reduction of the consumption of the resources in charge of any stakeholder (RES attributes).

On the other hand, products differ because different design decisions are made on them. The four actions framework (Kim & Mauborgne, 2005), initially introduced for depicting the matching between business modifications and value generated, can be adapted to products to describe the possible design choices. Here, the unit of analysis is no longer the strategic move; instead, the focus is on the design choice. This classification allows to stress which are the usual actions designers perform to obtain new products:

- introducing a property overlooked by that specific industry until then (action Create);

- improving a feature on which, so far, the company and its competitors have been competing with each other (action Raise);
- worsening the performance of a known property, and as a result, diminishing customer satisfaction (action Reduce);
- removing a given characteristic from the set of competing factors (action Eliminate).

The crossed interrelationships among actions and functional features gave rise to the definition of 12 variables to classify design modifications: Create UF, Create HF, Create RES, Raise UF, Raise HF, Raise RES, Reduce UF, Reduce HF, Reduce RES, Eliminate UF, Eliminate HF, and Eliminate RES.

Figure 19, hence, depicts this model conceptualisation that focuses on the one hand on the object of design (i.e., the product), assessing functional characteristics that differentiate the product from its predecessors, while on the other hand, investigates the design process and the adopted choices of modification.

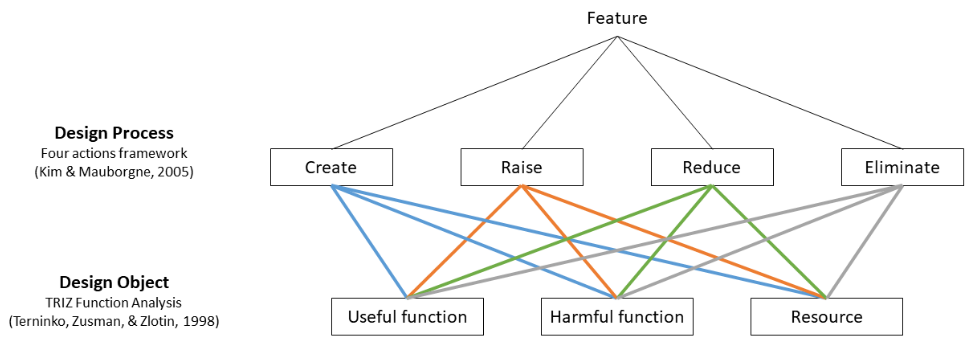

Figure 19. Conceptual model definition

4.3. TRIZ-Based Model to Estimate Product Adoption

In order to test whether these variables can describe the actions that designers could do, and, if so, to what extent those actions affect customer adoption and the probability of product success, it was necessary to identify past cases of successful and unsuccessful radical innovations. An existing database of 92 case studies (Borgianni, Cascini, Pucillo, & Rotini, 2013), both products and services, both successful and unsuccessful, was the starting point. Market failures consisted of the goods rejected by consumers or products which have not reached the expected market penetration, especially if the advertisement campaign was massive and increased the expectations. Success stories consisted of a new generation of products with an impressive commercial result.

The analysis was then limited only to physical products since they observe adoption rules entirely different from services ones (Pujol, 2010). As a result, the initial database was reduced to 71 records (see Appendix 2). Subsequently, academic and technical journals and websites were investigated to identify additional 39 cases to be included, to finally come up with 110 cases equally divided between successful products and market failures (see Appendix 3).

According to the conceptual framework previously described, each of the 110 cases was investigated to find out the differences from its predecessors at the architectural, modular and component levels. These changes had to be documented by more than one author in scientific and/or technical sources without any conflicting indication. These changes were then classified to assign to each of them one of the twelve categories described above. Moreover, information about success or failure has been collected, where success stories comprise products showing remarkable commercial results, together with information regarding firm maturity and nationality. The case evaluation process was supervised by two experts who aimed to reach a mutually agreed solution when ambiguities rose. In Table 10, the structure of the database is described together with all the variables collected.

Variable	Description	Domain and collection
Success	A binary variable representing success or failure of a product	1: success 0: failure
Create UF	Introduction of a feature that provides a positive outcome to users	Number of occurrences [0, +∞)
Create HF	Introduction of a property that limits drawbacks	Number of occurrences [0, +∞)
Create RES	Introduction of a characteristic that reduces the consumption of the resources in charge of any stakeholder	Number of occurrences [0, +∞)
Raise UF	A property that provides benefits is improved compared to industry standard	Number of occurrences [0, +∞)
Raise HF	A characteristic that restricts drawbacks is improved	Number of occurrences [0, +∞)
Raise RES	A feature that limits the consumption of the resources is enhanced	Number of occurrences [0, +∞)
Reduce UF	Worsening of a characteristic that benefits any stakeholder	Number of occurrences [0, +∞)
Reduce HF	A feature that restricts drawbacks had worsened compared to industry standard	Number of occurrences [0, +∞)
Reduce RES	A property diminishing the consumption of the resources had worsened compared to standard	Number of occurrences [0, +∞)
Eliminate UF	A feature that provides a positive outcome is removed	Number of occurrences [0, +∞)

Eliminate HF	Elimination of a feature that diminishes drawbacks	Number of occurrences [0, +∞)
Eliminate RES	Disposal of a characteristic reducing the consumption of the resources	Number of occurrences [0, +∞)
Firm maturity	A binary variable distinguishing between mature firms and start-ups	1: mature firms 0: start-ups
Nationality	A binary variable describing where firms are based	1: firms based outside the US 0: US-based firms

Table 10. Variables description

An example of a past successful case was the iPhone (see Table 11). Laugesen and Yuan (2010) and West and Mace (2010) affirmed that the browser and a large touchscreen are two key factors that differentiate the iPhone from its predecessors. Engineer designers created two distinct attributes that provide a positive outcome to the user – create and useful functions. The same contributions agreed on eliminate actions that occurred: iPhone, unlike most competing smartphones, lacked a user-changeable battery and memory expandability. Both attributes are resources. The first one involves increasing maintenance time because of the inability to replace the battery when a failure occurs easily. The second one because it affects the ease of upgradeability when the internal storage is full.

Parameter definition	**C | R | R | E**	**UF | HF | RES**
Browser web, based on personal computer standard	Create	Useful function
Cool design	Create	Useful function
Large touchscreen	Create	Useful function
Ease of use	Raise	Resource
Cheapness	Reduce	Resource
Memory card support	Eliminate	Resource
Required purchase of a mobile data service plan	Eliminate	Resource
User-replaceable battery	Eliminate	Resource

Table 11. Analysis of the Apple iPhone

The resulted database was then split into two portions randomly selected in order to use the first one to develop the statistical model and the second one to cross-validate it (Picard & Berk, 1990), according to the two-thirds rule as suggested in the literature (Harrell Jr., Lee, & Mark, 1996). Logistic regression was then used due to its capability in predicting the probability of an event – and product success represents such kind of event here – by modelling the dependence of a binary response variable – success vs failure – as a function of more explanatory variables (Bewick, Cheek, & Ball, 2005). The analysis regression was carried out through the IBM SPSS Statistics® module, which makes use of the maximum likelihood estimation criterion. Three models have been proposed: the first one includes only design variables, while the others include the control variables mentioned before – firm maturity and nationality. The results are reported in Table 12.

	Model 1 Only design variables	**Model 2 DV + firm maturity**	**Model 3 DV + nationality**
Constant	- 0.490	1.644	- 0.206
Design variables			
Create UF	1.842***	1.858**	1.799**
Create HF	0.535	1.064	0.419
Create RES	2.130**	1.854*	1.816**
Raise UF	0.658	0.805*	0.420
Raise HF	1.182	1.121	0.678
Raise RES	1.047**	1.109**	0.863*
Reduce UF	- 0.941**	- 0.882**	- 0.916**
Reduce HF	- 1.596	- 2.432	- 2.165
Reduce RES	- 1.768***	- 1.643***	- 2.310***
Eliminate UF	- 1.284**	- 1.759**	- 1.284**
Eliminate HF	- 6.624	- 6.099	- 6.318
Eliminate RES	- 1.101	- 0.807	- 0.928
Control variables			
Firm maturity		- 2.699	
Nationality	- 0.490		- 0.206*
Note. ****p-value < .01; **p-value < .05; *p-value < .1*			

Table 12. Internal models comparison

First of all, the outcome of the three models are similar, and, in particular, the sign and orders of magnitude of the coefficients are still comparable. This evidence confirms the existence of the relation between the 12 possible modifications and the product success, definitively proving the relevance of design variables.

Moreover, considering the first model, the results show that six design variables are significant at a 0.01 or a 0.05 significance level. The result remained largely unchanged when the dummy variables were included in the analysis. Indeed, both the coefficients of the explanatory variables and the statistical significance of the outcome are in line with the ones obtained by employing only the design variables.

The two additional binary logistic regression analyses provide further insights into how product success is influenced by other variables such as nationality and firm maturity. Even if it is not statistically significant, the latter confirmed what is known from the literature (Chandy & Tellis, 2000): incumbents deal with difficulties when they have to face radical innovations. It follows that they may be disadvantaged in successfully introducing that kind of innovations.

Going into detail of the first model (see Table 13), it correctly classifies 90.9% of successful cases (i.e., sensitivity). Specificity instead (i.e., the proportion of market failures correctly predicted) is 87.9%. False positives (11.8%) predict that a case would be a success when it did factually not. False negatives (9.4%) would be predicting that a case would fail when it factually did succeed.

Metric	Value
The overall percentage of correctly predicted products	89.4%
Sensitivity	90.9%
Specificity	87.9%
False positives	11.8%
False negatives	9.4%

Table 13. Model accuracy

The fit of the model was then tested looking at Cox & Snell R-square and Nagelkerke R-square values. These tests approximate the coefficient of determination R-square and indicate how useful the explanatory variables are in predicting the response variable (Menard, 2000). Values here are, respectively, equal to 0.539 and 0.719 and, hence, there is a good relationship between predictors and the prediction. In addition, the Hosmer and Lemeshow (2013) test investigates the extent predicted values are close to the observed ones for different subgroups. Here, a p-value equal to 0.314 was obtained, which is over the suggested threshold equal to 0.05. These results are summarised in Table 14.

Test	Value	Threshold
Hosmer – Lemeshow test	0.314	> 0.05
Cox & Snell R-square	0.539	Higher the value, better
Nagelkerke R-square	0.719	the model predictability

Table 14. Model reliability summary

The model coefficients were then used to develop the following predictive equation formula to cross-validate the model according to the data-splitting rule (Arboretti Giancristofaro & Salmaso, 2007; Picard & Berk, 1990). Indeed, validating by using only the modelling data means over-estimating its performance (Park, 2013).

$$\begin{aligned} z = -0.490 &+ 1.842\,CREATEUF + 0.535\,CREATEHF \\ &+ 2.130\,CREATERES + 0.658\,RAISEUF \\ &+ 1.182\,RAISEHF + 1.047\,RAISERES \\ &- 0.941\,REDUCEUF - 1.596\,REDUCEHF \\ &- 1.768\,REDUCERES - 1.284\,ELIMINATEUF \\ &- 6.624\,ELIMINATEHF - 1.101\,ELIMINATEHF \end{aligned} \tag{46}$$

Actions ‘Create’ and ‘Raise’ add or improve functions and, therefore, positively impact customer satisfaction, while it goes the other way when designers perform actions such as ‘Reduce’ or ‘Eliminate’. That means that ‘Create’ and ‘Raise’ always add functionalities, while ‘Reduce’ and ‘Eliminate’ do the opposite. Hence, the introduction of a new interface of a digital good represents a 'Create' action, while the choice to prevent users from removing the battery from iPhone leads to 'Eliminate'. Even if it is grounded in deeply assessed design trade-offs and other generated benefits balance it, this action negatively affects the perceived performance by the customer when considered on its own. Instead, other activities, such as reducing the space occupied by components or operation time, lessening of the amount of material waste, reducing costs (that leads to lowered prices), etc. constitute a way to increase customer satisfaction. Hence, this kind of action must be accordingly interpreted as actions of 'Create' or 'Raise' (e.g., increased cheapness). Wikipedia, for instance, among several new properties, differentiated itself from other online encyclopaedias by eliminating advertisements from the website. As a result, customers enjoyed a better user experience (Kim, Mauborgne, & Ling, 2011), and this action constituted a 'Create' action since they introduced a way to reduce a drawback, in this case, distraction.

Moreover, there may be design choices that imply both positive and negative effects. These situations were managed by taking into account both effects. For instance, implementing a battery that lasts longer and weighs more means modifying two different kinds of resources; designers raise durability and reduce portability.

The coefficients can be interpreted as indications to designers about design actions to perform during the definition of radical innovations, and z represents the logit function used to predict the probability of success:

$$Success\ probability = \frac{e^z}{1 + e^z} \tag{47}$$

Hence, the remaining portion of the database was used by computing the success probability through (47) for each case. A case is considered as a predicted success when the success probability is higher than 50%. The model turns out to effectively highlight 38 cases out of the 44 used in the validation process. More in detail, sensitivity is equal to 82%, and specificity is equal to 91%.

The reliability of the present model must finally be compared to other previous ones that have similar purposes. This comparison is made considering precision and recall (Maroco, et al., 2011), F-measures (Powers, 2011), and the Matthews correlation coefficient (Bendtsen, Nielsen, von Heijne, & Brunak, 2004), as Table 15 shows.

Index	**Present model**	**Borgianni et al. (2013) log reg**	**Borgianni et al. (2013) neural networks**	**EBONSAI (Yada, Ip, & Katoh, 2007)**
Precision	0.90	0.79	0.87	0.62
Recall	0.82	0.83	0.87	0.87
F-measure	0.86	0.81	0.87	0.72

Matthews correlation coefficient	0.73	0.61	0.77	0.26

Table 15. External models comparison

Our model results to be a remarkable improvement compared to the one developed by Borgianni, Cascini, Pucillo, and Rotini (2013) through logistic regression (since precision, F-measure, and Matthews correlation coefficient are higher and only recall slightly decreased) and to provide similar results to the one developed through Neural Networks. Furthermore, compared to Neural Network, logistic regression shows its potential, which is the capability to estimate the impact of the individual variables. Finally, the presented model outperforms a decision support tool, named EBONSAI (Yada, Ip, & Katoh, 2007). Even if it has not been mentioned previously, EBONSAI has been chosen as a relevant benchmark given the similarity of its goal (i.e., the anticipation of product market success).

The main implication is that, even in the absence of customers' indications, designers receive hints about the impact of their specific choices on product success. Hence, the model results particularly appropriate when market needs cannot be elicited (i.e., in radical innovation cases). However, the model parameters are industry-dependent and must be opportunely calibrated by developing specific models able to detect the peculiarities of each sector. Conversely, the presented model was developed around several industries defining its wide-ranging theoretical applicability, and therefore it is not applicable in a real setting.

5. Studying the impact of Design Choices for Industrial Designed Products

The model presented in the previous chapter was required to be calibrated by collecting industry-specific cases, but even more, to take a further step towards the study of services, an industry halfway between engineering designed products and services was investigated.

It was not easy to find test-beds for the industrial designed products industry because it was necessary to find an industry where decisions were usually associated with experiential elements. Simultaneously, products had to own assessable physical and measurable features to apply the quantitative model. The opportunity to study a semi-finished industry occurred, and this industry was the surface material industry, which, however, has particular characteristics that allow treating its products as industrial designed products, especially if one considers the variables of interest in the study.

First, despite most of the companies in the surface material industry manufacture and propose semi-finished products, it is precisely semi-finished products that give some of the most important properties to the end products to which they are applied (e.g., countertops, chairs, cabinets, desks). Secondly, these properties precisely confer the product the features, such as textures, that play a key role in the experiential process leading to adoption. As an example, Figure 20 shows a variety of textures proposed by Abet in the 1980s.

Figure 20. Some examples of Abet laminate textures in the 1980s (from Domus 612)

Such as for every product, functional features result from the design process and, hence, from the design choices leading to them. However, as previously mentioned, these features do not usually guide the potential customer decision-making process, but still innate characterize each of these products.

Therefore, the novelty lies in studying whether and to what extent models thought to study functional and measurable features can be used to study the adoption and the consequent emergence of new paradigms in industries usually linked with intangible elements (i.e., service industry) or those related to the experiential aspects of the adoption process.

5.1. Research Setting

5.1.1. Context: Surface Material Industry

The industry in analysis (i.e., surface material) includes all those materials used with a mainly decorative function to cover an underlying structural substrate. The materials families studied are various, from resilient materials to woods, from ceramic tiles to high-pressure laminates, from terracotta claddings to composite panels, and others. The fields of application are also different, and in particular, the panels covering floors and furniture and those applied in ventilated façades have been taken into consideration.

In this industry, there are a lot of diverse companies operating in terms of products and services offered. For example, some companies focus mainly on a single material; Arpa Industriale is an example of a company manufacturing mainly high-pressure laminates. Besides having only one material in their portfolio, others also focus on a single application area, as is the case of Trespa who offers ventilated façades. Other companies offer products directly to the consumer, for example Kährs, which produces wooden floors ready for quick and easy installation by the end-user. In contrast, others need intermediaries to process its materials, such as Renewed Materials which offers kitchen tops solutions. Finally, some companies have an extensively diversified portfolio; an example is Wilsonart, which produces from high-pressure laminates to solid surfaces, and from veneers to quartz surfaces.

Given the high degree of diversification within it, an aggregate overview of the whole industry would be challenging to obtain. Numbers are, in any case, significant also focusing on the individual markets that compose the industry. The laminate floorings, for instance, generate around one billion dollars a year in the United States alone (Catalina Research Institute, 2020). Still in the US, the ventilated façade market in 2015 was valued at around fifteen billion dollars (Statista Research Department, 2016). The same year, the market value of aluminium composite panels in the United States was around eight hundred million dollars. In terms of volumes, the global market size for decorative surfacing materials on wood-based panels reached twenty-one billion square metres in 2015 (Pöyry Management Consulting, 2016).

5.1.2. Case Company: Abet Laminati S.p.A.

Abet Laminati is an Italian company based in Bra that operates in the surface material industry and produces decorative laminates, solid surfaces, and sandwich panels (Lecce, 2014). It was founded as Anonima Braidese Estratti Tannici (A.B.E.T.) in 1946 to produce tannins; but, following a crisis that hit the sector in the 50s, the company had the idea to convert the production line. Given the growing interest in high-pressure laminate, after some market research, in 1957, Abet started to produce it, gradually dismissing tannin production. The idea of starting a production conversion was definitely driven by the market of plastic materials and synthetic fibres, which seemed to have more future than the one of leather. The first years were useful to obtain an adequate production experience and gradually enter the Italian market. During the 60s, the company started to invest in innovative products in order to focus on more qualitative and remunerative market segments, thus succeeding in gaining a strong image in the Italian market. This leading position was achieved mainly thanks to technological advances, such as the development of a finish that completely changed the laminate perception by the market (i.e., *finitura SEI*), and the nascent collaborations with architects, artists, and designers. For example, to launch *finitura SEI*, the company asked five architects and designers to create an interior where everything, from the walls to the furniture, was made of laminate. This kind of initiative, particularly appreciated and employed by Abet, targeted typically young designers and aimed to promote high-pressure laminates.

The company, which was then moving towards laminate innovation, introduced other innovations over the years, such as the silk-screen printing laboratory at the end of the 1960s, which offered designers the possibility to work on the laminate surface with customised decorations. This idea was born as a result of the collaboration with Ettore Sottsass Jr., who represented one of the most important and brilliant partners of Abet among the collaborations with the design environment.

In the 1970s, a new luminescent laminate (Figure 21) sees the light from a collaboration with Clino Trini Castelli. Presented in 1974, it was the first real case in Abet of a product developed jointly with a designer. Moreover, it represented a major step forward for the industry since no innovative laminates were presented in the previous twenty years. In 1981, from another collaboration, Abet developed a new laminate with an innovative embossed surface (i.e., *Reli-tech*, Figure 22) as a result of several researches carried out in the field of tactile perception of materials.

Figure 21. Picture of an exhibition of Lumiphos at Eco '74 in Turin

Figure 22. Advertising insert from 1980 of the Abet laminate 'Relitech'

In the 1980s, also thanks to the collaboration with Ettore Sottsass, Abet achieved an outstanding international resonance, particularly in the United States, reaching a prominent role in the field of design. In Figure 23, the first proposals by Ettore Sottsass and Abet to use serigraphy to obtain custom textures are shown as an example of an outstanding result of that collaboration that helped Abet to reach a leading position. In the following years, the innovations introduced were various: *Straticolor* in 1984, a laminate for ventilated façades (i.e., Material Exterior Grade, *MEG*) in 1986, the first transparent laminate (i.e., *Diafos*) in 1987, a laminate obtained from recycled manufacturing wastes (i.e., *Tefor*) in 1993. At the end of the 1990s, a crucial turning point was given by the introduction of the digital printing technique, thanks to which it became possible to realise very elaborated patterns even for small quantities.

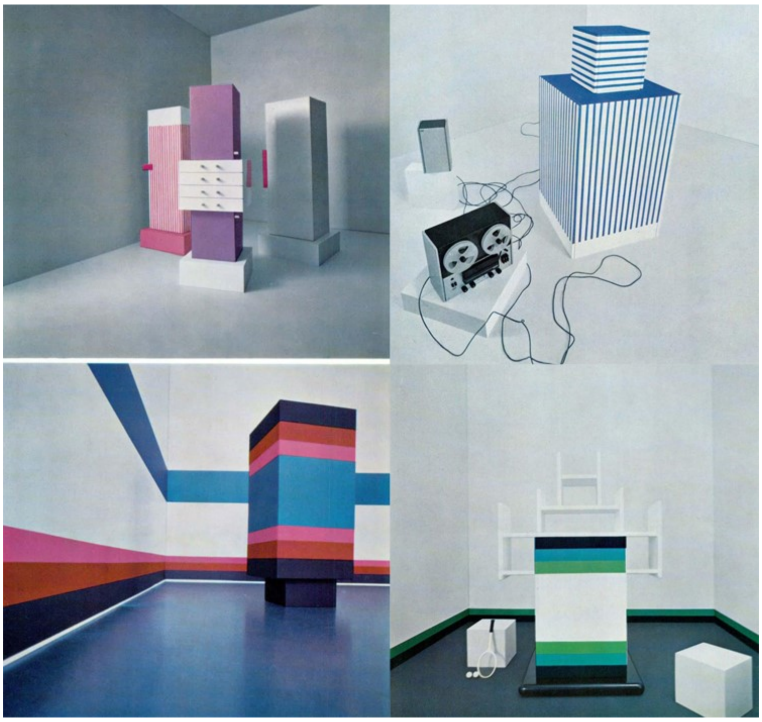

Figure 23. Furniture designed by Ettore Sottsass with Abet laminates from "Katalogo Mobili 1966" (from Domus 449)

In recent years, the industry has been affected by the entry into the market of more and more companies from countries with lower labour costs, causing a process of commoditisation of the product. Moreover, as already happened in the 1970s, technological innovation has been at a standstill for several years now, and it is not yet clear what direction it will take in the future.

Therefore, it has been decided to adopt a quantitative approach to the problem and apply the model introduced in the previous chapter, thus studying the design variables typical of the industry in which Abet Laminati operates to try to estimate the adoption of a new product, in this case a new laminate.

5.1.3. Data Collection

In order to apply the model introduced in the previous chapter, it was necessary to find and analyse a set of innovative products within the reference industry (i.e., surface material). After a detailed analysis of the literature conducted primarily in several field books such as Smart Materials (Ritter, 2006), Materiology (Kula &

Ternaux, 2013), Transmaterial 2 (Brownell, Transmaterial 2: A Catalog of Materials That Redifine Our Physical, 2008), Transmaterial 3 (Brownell, 2013) and Material Revolution (2011) and trade journals such as Domus, 112 innovative products introduced between the end of the 1980s and the beginning of the 2010s were initially identified. It was necessary to introduce this timeframe mainly for three reasons: 1) there could be several difficulties in finding objective data on products introduced in years before those considered; 2) due to technological advances and intrinsic changes in market dynamics, considering products introduced previously could be misleading for the purposes of the analysis; 3) it was not possible to consider more recent products as it would not have been possible to make assumptions about adoption in such a short period of time.

Following the identification of these products, the same sources mentioned above plus brochures from manufacturers, websites of these companies, blogs and websites where these products were presented and forums where these products were discussed, were used to find the information needed to develop the model. These information concerned the functional differences between the products under analysis and those identified as predecessors on the market. An example could be the bamboo flooring introduced by MOSO under the name Bamboo Supreme in 2002, which has been compared with hardwood flooring. These differences were later classified using the framework introduced in the chapter "A Framework Based on Design Variables".

At the end of the analysis, further entries were removed from the dataset either because of the scarcity of information on them or because of the reflections arising from a further study leading to their exclusion. The dataset was therefore composed of 77 products (see Appendix 4) introduced by 71 different companies, divided as follows: 21 products for flooring, 23 products for ventilated façades, and 33 products for indoor use such as kitchen tops, tables, shutters, etc. 58 of them have been successful while 19 have represented failures. The oldest product taken into consideration is Volkern G2 (later Meteon), a high-pressure laminate panel for ventilated façades introduced by Trespa in 1987; while the most recent is HYLITE, a composite panel for indoor use introduced by 3A Composites in 2016.

The structure of the database is the same as before, and is represented in Table 17.

Variable	**Description**	**Domain and collection**
Success	A binary variable representing success or failure of a product	1: success 0: failure
Create UF	Introduction of a feature that provides a positive outcome to users	Number of occurrences [0, +∞)
Create HF	Introduction of a property that limits drawbacks	Number of occurrences [0, +∞)
Create RES	Introduction of a characteristic that reduces the consumption of the	Number of occurrences [0, +∞)

	resources in charge of any stakeholder	
Raise UF	A property that provides benefits is improved compared to industry standard	Number of occurrences [0, +∞)
Raise HF	A characteristic that restricts drawbacks is improved	Number of occurrences [0, +∞)
Raise RES	A feature that limits the consumption of the resources is enhanced	Number of occurrences [0, +∞)
Reduce UF	Worsening of a characteristic that benefits any stakeholder	Number of occurrences [0, +∞)
Reduce HF	A feature that restricts drawbacks had worsened compared to industry standard	Number of occurrences [0, +∞)
Reduce RES	A property diminishing the consumption of the resources had worsened compared to standard	Number of occurrences [0, +∞)
Eliminate UF	A feature that provides a positive outcome is removed	Number of occurrences [0, +∞)
Eliminate HF	Elimination of a feature that diminishes drawbacks	Number of occurrences [0, +∞)
Eliminate RES	Disposal of a characteristic reducing the consumption of the resources	Number of occurrences [0, +∞)

Table 16. Variables description

Generally speaking, all the variables associated with the action eliminate presented few occurrences; especially, no occurrences have been counted for the variable eliminate HF. This may be due to the peculiarities of the products in question. Indeed, their functional features are usually associated with physical characteristics, such as resistance to wear, that can not be eliminated but can be subject to a performance decrease.

5.1.4. Empirical Analysis

The resulting database was entirely used to develop the statistical model since the limited size of the database did not allow to employ data-splitting techniques. Logistic regression was again used due to its capability in predicting the probability of an event – and product success represents such kind of event here – by modelling the dependence of a binary response variable – success vs failure – as a function of more explanatory variables (Bewick, Cheek, & Ball, 2005). The analysis regression was carried out through the IBM SPSS Statistics® module, which makes use of the maximum likelihood estimation criterion. The results are reported in Table 18.

parameter	value
Constant	- 0.894
Design variables	
Create UF	- 0.011
Create HF	0.964•
Create RES	20.8615
Raise UF	1.310**
Raise HF	0.649•
Raise RES	1.200*
Reduce UF	- 1.200**
Reduce HF	- 1.802***
Reduce RES	- 1.584•
Eliminate UF	- 22.086
Eliminate RES	- 1.787•
Note. ****p-value < .01; **p-value < .05; *p-value < .1; •p-value < .3*	

Table 17. Parameters of the model

First of all, it is possible to notice that the action eliminate HF is not present anymore since, as mentioned before, no occurrences have been counted. Four variables (i.e., raise UF, raise RES, reduce UF, and reduce HF) have reached the significance threshold (at a .01 or at a .05). Create HF, raise HF, and reduce RES have instead obtained a significance level slightly higher than the threshold but with a result in line with the expected one. Indeed, in this specific case, the problem may lie in the small sample size. However, the remaining four variables present some critical issues. Create UF obtained a very high significance and a sign coefficient contrary to that hypothesised; create RES and eliminate UF presented high significance levels, and coefficients with a very large value; eliminate RES, instead, seems to be less critical but the low number of occurrences counted led to include it with the set of critical variables. It is precisely the low number occurrences that the critical variables have in common.

The predictive accuracy of the logistic regression model was then assessed. The sensitivity of the model resulted to be equal to 93.1%, while the proportion of market failures correctly predicted (i.e., specificity) was 57.9%, reaching an overall percentage of cases correctly predicted equal to 84.4%. False positives are equal to 14.8%, and false negatives to 36.4% (see Table 19).

Metric	Value
The overall percentage of correctly predicted products	84.4%
Sensitivity	93.1%
Specificity	57.9%
False positives	14.8%
False negatives	36.4%

Table 18. Model accuracy

Cox & Snell R-square and Nagelkerke R-square values are then employed to assess the fit of the model. Values are, respectively, equal to 0.372 and 0.553 and, hence, the relationship between predictors and the prediction, even if it is not optimal, is satisfying. Hosmer and Lemeshow (2013) test, instead, returned a p-value equal to 0.863 was obtained, which is over the suggested threshold equal to 0.05. These results are summarised in Table 20.

Test	Value	Threshold
Hosmer – Lemeshow test	0.863	> 0.05
Cox & Snell R-square	0.372	Higher the value, better
Nagelkerke R-square	0.553	the model predictability

Table 19. Model reliability summary

As before, it is possible to use the coefficients of the model to develop a predictive equation:

$$\begin{aligned} z = &-0.894 - 0.011\,CREATEUF + 0.964\,CREATEHF \\ &+ 20.8615\,CREATERES + 1.310\,RAISEUF \\ &+ 0.649\,RAISEHF + 1.200\,RAISERES \\ &- 1.200\,REDUCEUF - 1.802\,REDUCEHF \\ &- 1.584\,REDUCERES - 22.086\,ELIMINATEUF \\ &- 1.787\,ELIMINATEHF \end{aligned} \tag{48}$$

The latter presented results in line with those previously obtained (see Table 21). Obviously, the impact that the variables may have on the adoption is changed due to the dynamics that are specific for this industry. Some variables have lost statistical significance in favour of others, but the link between them and product adoption has been proved. However, larger sample size may give more precise indications, especially for those variables that are located around the significance threshold or are widely underestimated due to scarce occurrences.

Index	Industry-specific model	General-purpose model	Borgianni et al. (2013) - log reg
Precision	0.87	0.90	0.79
Recall	0.93	0.82	0.83
F-measure	0.90	0.86	0.81
Matthews correlation coefficient	0.56	0.73	0.61

Table 20. External model comparison

The novelty lies in studying whether and to what extent functional features affect products diffusion, and hence the customer adoption, in an industry where intangible elements usually drive these dynamics. The surface material industry indeed has been chosen since it presents characteristics dissimilar to one of typical consumer goods. Here adoption is usually linked to experiential factors rather than tangible and physical performance variables.

5.2. Takeaways for Studying Service Diffusion

The latter model represents a further step to move from studying product adoption to service adoption. Indeed, it showed that functional elements are not restricted to engineering designed product studies.

The design decision classification used for the analysis has proven to have wide applicability: both engineering designed products and industrial designed products present modifications to functional features that can be interpreted as design choices made during product development.

It may be hence worth of note to apply the same design decision framework to services and develop service-specific models. It is obvious that, again, model parameters are industry-dependent, and, hence, they have to be appropriately calibrated. Both the parameter sign and module depend on the properties of the industry, the market, and the customers, and even the statistical significance of each parameter can be heavily affected.

6. Conclusions

The thesis aims to deepen the study of product and service diffusion and adoption and addresses the impact of design choices on the adoption process.

Product diffusion has been extensively investigated by the literature, and two of the most important stream of research focus on the mathematical models to trace the diffusion curves (Bass, 1969; Guidolin & Guseo, 2014) and on the first stages of diffusion (Lieberman & Montgomery, 1988; Stalk, 1988). The latter stream stressed the importance of serving first, or in any case as soon as possible, the market (Golder & Tellis, 1993; Vesey, 1991), neglecting that companies may need time to redesign products according to the needs of upcoming customer segments (Moore, 1991; Rogers, 1962). This time span has been here defined as 'rethinking time' and has been tested to assess whether it could be considered a moderating effect of first-mover advantages.

Specifically, in terms of mathematical models, they trace the diffusion curves and are typically applied to study product diffusion (Bass, 1969; Guidolin & Guseo, 2014; Niu, 2002). Indeed, their underlying assumptions usually limit the applicability to consumer goods, neglecting all those products and services where the experiential process becomes relevant for adopting. With respect to the latter, there is some attempt to deepen the process, including some of the innate features services have (Libai, Muller, & Peres, 2009; Lin, 2013).

Service diffusion studies, for example, introduce models that include parameters that would revise the concept of binary adoption; however, do not suggest any parameter to apply when diffusion curves are under analysis. A literature review on service diffusion models and empirical analysis on two service providers (i.e., an extra-urban transportation company and a travel company) led to propose a framework that can guide the decision on which data to collect, and hence which parameter to apply when the diffusion of a given type of service is under investigation (i.e., subscription services, on demand services used several times in a medium/short period of time, and on demand services occasionally used over a long period of time).

At their turn, diffusion dynamics are linked to the adoption process. The latter has often been described as one of the diffusion process stages; in particular, it is the last one after awareness, interest, evaluation, and trial.

The idea here is to investigate the factors behind adoption from an Engineering Design perspective, keeping in mind, however, that the diffusion process of industrial designed products and services is usually analysed by looking at qualitative and intangible features.

Borgianni, Cascini, Pucillo, & Rotini (2013) proposed a model to anticipate the market adoption of innovative products as a function of twelve design actions. The main implication of this model is that, even in the absence of customer indications, designers receive hints about the impact of their specific choices on customer adoption. Hence, the model results particularly appropriate when market needs cannot be elicited (i.e., in radical innovation cases). However, this approach may result to be difficult to apply outside the engineering designed product contexts. Indeed, the adoption processes of industrial designed products and services are mainly driven by intangible elements or experiential factors (e.g., affordance).

The novelty lies in studying whether and to what extent design decisions related to modifications to functional features affect the emergence of a new paradigm in an industry where intangible elements or experiential factors usually drive customer adoption and product diffusion. Such a kind of industry is represented by the ones related to industrial design. Hence, the surface material industry has been chosen as a case study since, even if most of the companies offer semi-finished products, they play an important role in the adoption process since they confer to the finished products some of the most important properties related to the experiential process. Past cases of successful and unsuccessful products in the surface material industry were analysed to classify them through the design variables introduced by Borgianni, Cascini, Pucillo, & Rotini (2013). Logistic regression was employed to develop an industry-specific model that allows concluding that the design decision classification used for the analysis is widely applicable, having been applied both to engineering designed products and industrial designed products.

Moreover, the model has proved that it is possible to identify the effect that modifications to functional features have on the adoption probability even when industrial designed products are under investigation. It is therefore plausible to assume that this kind of finding may also be extended to the study of service adoption. However, the impact design decisions have on adoption is industry-dependent, so the numerical results obtained with the model cannot be generalised.

The major limitation of the study consists of the sample size required to instruct the model. Building a database with an adequate number of innovation cases from a given industry could represent an obstacle. It may also happen to analyse an industry in which a given design action represents a rare occurrence, as it was the case of 'eliminate' actions for the surface material industry, and many data would be needed to measure its impact.

A further step will be to extend the findings to service by developing service-specific models which, however, would require a more intensive and challenging process to track functional features modifications. Again, model parameters will be industry-dependent, and, hence, they have to be appropriately calibrated.

The same goes for rethinking time which, following diffusion studies evolution pattern, has been studied in engineering designed contexts. It may be worth of interest to deepen the effect of rethinking time on the diffusion of industrial designed products and services, particularly when modern agile approaches call into question the traditional separation between product development and its subsequent diffusion (Beck, et al., 2001).

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Appendix

Appendix 1

tablet	electric toothbrush	videogames
ct scanner	microwave ovens	laser printer
motorised lawn mower	sram	copying machines
vcr's	electric blender	fax machines
electric dishwasher	personal computer	phonograph
disk drive	iPod	electric iron
colour television	sat nav	camcorder
digital watches	supercomputer	electric vacuum cleaner
mainframes	room air conditioners	smartphone
freezer	toaster	answering machines
disposable diaper	cellular phone	water softener
commercial jet aircraft	portable dictation machine	handheld / pocket calculator
cd player	usb drive	tractors
electric can opener	ATM	telephone
electric clothes washer	typewriter	food processor
universal product code	safety razor	mammography
Nintendo Wii	trash compactors	instant camera
leaf blower	anti-lock braking system	eBook reader
ultrasound imaging	laserdisc player	automatic drip
coffee maker	food waste disposer	Walkman
fitness trackers	8-bit microprocessor	fibre optic cable
styling mousse	pager	blank video cassettes
slow cooker	elevators	calculator
electric shaver	nylon cord	

Appendix 2

Cases in the database by Borgianni, Cascini, Pucillo, & Rotini (2013). Cells in grey represent the services removed from the analysis.

[Yellow Tail] wines	Federal Express' Zap Mail	Pepsi AM
Amphicar	Ford Edsel	Pepsi Crystal
Apple iPod	Ford Model T	Pfizer Viagra
Apple Lisa	Formule 1	Philips Alto bulbe
Apple Newton	Geox	Philips CD-i
Barnes & Noble booksellers	Gerber Singles	Pink Taxi
Bert Claeys Kinepolis	Herman Miller Aeron Chair	Planet Hollywood
Bloomberg	Home Depot	Polaroid Polavision
BMW C1 motorbike	Hubspot	Polo Ralph Lauren (compared with haute couture)
Body Shop cosmetics	IBM PC jr	QB House barbershops
Bratton's New York Transit Police	IKEA	Quadraphonic Sound
Cadillac Cimarron	Intuit Quicken ™ (compared with financial softwares)	Rasna Limited's Oranjolt
Callaway Golf "Big Bertha"	iTunes (compared with CD stores)	RedBull
Campbell's Souper Combo	JCDecaux	RIM's Blackberry
Canon copiers	Joint Strike Fighter F-35	RJ Reynolds Premier smokeless cigarettes
Cirque du Soleil	Kellog's Cereal Mates	SAP R/2
CNN	La Femme	Sony Betamax
Compaq in Server Industry (1992-1994)	Lynx barber shop	Sony Minidisc
Croc's	Maxwell House ready-to-drink coffee	Sony Walkman
CueCat	Mc Donalds' Arch Deluxe	Sony's Godzilla
Curves fitness company	Microsoft BOB	Southwest Airlines
Dell's Web PC	Motorola Iridium	Swatch
Digital Audio Tape	NetJets	Telecom Italia FIDO
Direct Line	New Coke	The Hot Wheels/Barbie computer
Dive Restaurant	Nintendo Virtual Boy	Thirsty Cat! and Thirsty Dog!
Dreamcast	Nintendo WII	Toyota Prius

DuPont's Corfam	Nokia N-Gage	Unilever Persil Power
Earring Magic Ken	Novo Nordisk Novopen®	Virgin Atlantic
EFS - Corporate Foreign Exchange	OK Soda	Voice Pod
Evilla Sony	OS/2	Youtube
Facebook	Outlet Villages	

Appendix 3

Cases in the database used for the analysis of the general-purpose model.

[Yellow Tail] wines	GoPro	Pepsi Crystal
Amazon Fire Phone	Herman Miller Aeron Chair	Pfizer Viagra
Amazon Kindle	HP Touchpad	Philips Alto bulbe
Amphicar	Hubspot	Philips CD-i
Apple II	IBM PC jr	Pink Taxi
Apple iPad	IKEA	Polaroid Polavision
Apple iPhone	Intuit Quicken ™ (compared with financial softwares)	Polaroid SX-70
Apple iPod	iTunes (compared with CD stores)	Polo Ralph Lauren (compared with haute couture)
Apple Lisa	JCDecaux	Rasna Limited's Oranjolt
Apple Newton	Joint Strike Fighter F-35	RedBull
Apple Pippin	Kellog's Cereal Mates	RIM's Blackberry
Blu-ray Disc (compared to HD DVD)	Kodak Funsaver single-use camer	RJ Reynolds Premier smokeless cigarettes
BMW C1 motorbike	Kodak Instamatic	SAP R/2
Body Shop cosmetics	La Femme	Sony Betamax
Cadillac Cimarron	Maxwell House ready-to-drink coffee	Sony Minidisc
Callaway Golf "Big Bertha"	Mc Donalds' Arch Deluxe	Sony Playstation
Campbell's Souper Combo	Microsoft BOB	Sony Walkman
Canon copiers	Microsoft Kin	Sony's Godzilla
Compaq in Server Industry (1992-1994)	Microsoft Kinect	Swatch
Concorde	Microsoft Mira Smart Display (compared to desktop and laptop)	Tata Nano
Croc's	Microsoft SPOT Watches	Tesla Roadster
CueCat	Microsoft Zune	The Hot Wheels/Barbie computer
Curves fitness company	Motorola Iridium	Thirsty Cat! and Thirsty Dog!
Dell's Web PC	NetJets	TiVo
Digital Audio Tape	New Coke	TomTom Go
Digital calculator	Nikon F	Toyota Corolla
Dreamcast	Nintendo NES	Toyota Prius

DuPont's Corfam	Nintendo Virtual Boy	Transistor radio
Dyson DC01	Nintendo WII	TwitterPeek
Earring Magic Ken	Nokia N-Gage	Unilever Persil Power
Evilla Sony	Novo Nordisk Novopen®	Voice Pod
Federal Express' Zap Mail	Oakley Thump	Volkswagen Beetle
Ford Edsel	OK Soda	Wikipedia
Ford Model T	OS/2	Wow! Chips
Geox	Pebble	Xerox 914
Gerber Singles	Pepsi AM	Zipcar
Gizmondo		

Appendix 4

Cases in the database used for the analysis of the industry-specific model.

company	product	company	product
Pergo	TitanX	Onyx Solar	Photovoltaic Ventilated Facades
MOSO	Bamboo Supreme	Casalgrande Padana	Bios Self Cleaning Ceramics
Carpet Burns	Heat Treated Carpet	ROCKWOOL	REDAir
Gruppo Ceramiche Gambarelli	Oxygena	LAMINAM	HYDROTECT
Kährs	Upofloor Zero	Bellotti	Nomex® Decore™
Rieder	fibreC	Yemm & Hart	Origins
MOSO	density	Cosentino	Silestone
UPM ProFi	UPM ProFi Deck	Abet Laminati	Tefor
Dalsouple	DalNaturel	LG Hausys	HI-MACS Acrylic Solid Surface
Alulife	Alulife	Investwood	Valchromat
Global Enginerring	Fotofluid	Meld USA	Extreme Concrete
Cotto d'Este	Kerlite Plus	KlipTech Technologies	PaperStone
E-Green Building Systems	Strong Enviroboard	Environ Biocomposite	Dakota Burl
Gage	Planium	LitraCon	LitraCon Classic
Kebony	Kebony	Weidmann	Maplex
Mondo	Mondoflex II	Renewed Materials	ALKEMI-polyester
Oltremateria	Ecomalta	Columbia Forest Products	PureBond Hardwood Plywood
Wicanders	Hydrocork	3form	Chroma
Chenna	Chylon	Meld USA	EcoX
G.tecz Engineering	Quantz	Kraftplex	Kraftplex
Lapitec	Lapitec	3form	100 Percent
Trespa	Volkern G2 (poi Meteon)	Kokoshout	Cocodots
KME	TECU	Coverings Etc	Bio-Glass
3A Composites	DIBOND	Luminoso (Litwork)	Luminoso
VMZINC	QUARTZ-ZINC	Ecoplan	Ecomat
SierraPine Ltd. - poi venduta a Roseburg	Medite FR MDF	TetraPak	Tectan board
Italcementi	TX Active	Dekodur | Resopal	RE-Y-STONE
NBK	TERRART BAGUETTE	HEXPOL	Lifocork

MOEDING	ALPHATON	Corian	DeepColor technology
Duralmond	Duralmond	Arpa Industriale	FENIX NTM
AltusGroup	CarbonCast	APR-In	Concreo
NOVOWOOD	NOVOWOOD	Alfatherm	AECORE
VMZINC	PIGMENTO	3A Composites	HYLITE
Cymat	Alusion	Richlite	Richlite
Accoya	Accoya	Bencore	Starlight
Evonik	ccflex	Durat	Durat
Silvadec	Atmosphere	Environ Biocomposite	BioFiber Wheat
Everlite Concept	DANPALON BRV	La Casa Deco	Flexipane
Porcelanosa	KRION		