A Decision Support Model to Assess Technological Paradigms

Abstract

Envisioning the emergence of a new technological paradigm involves several issues, spanning from strategic assessments and managerial actions to design decisions and technology related choices. The present study focuses on this latter perspective, by proposing a model that estimates the success probability of innovative products as a function of design actions. This focus on the design decisions that underlie radical shifts is not conflicting, but complementary to the more traditional perspectives of forecasting that consider environmental variables or process management factors. The model is based on a database of past successful and unsuccessful innovations, which are used to build a logistic regression model, whose evidences can assist both designers and managers. The former get advice on how specific design choices affect product perception and innovation adoption, while the latter are supported in identifying the most promising projects. The model is illustrated through two cases of digital products.

Keywords: *radical innovation, technology paradigm emergence, product success, design decisions.*

Introduction

Companies are seeking new opportunities for growth and advantage over competitors (Hitt et al., 1998), and this condition results even more demanding in digital industries which are characterised by products with shorter life cycles (Steffens, 1994). Introducing radical innovations has always represented a solution both for large and small firms (Song and Montoya-Weiss, 1998; Tellis et al., 2009). When an industry moves from the old technological trajectory to a new one, in fact, new paradigms emerge, and this shift provides a temporary advantage (D'Aveni, 1994).

Technological paradigm is a powerful concept since it definitively states that improved technical performances are not enough to have successful products and services. Wikipedia, for instance, by providing encyclopaedic knowledge for free, understood that supply-side factors were being affected by the spreading of internet connections, while users were becoming different as well. People were starting to consult online contents, preferring real-time and almost infinite results, rather than the greater reliability offered by traditional encyclopaedias. Similarly, Apple provided more functionalities without restricting portability, up to Amazon nowadays that is assessing a drone-based delivery system, etc. Several other examples would be worthy of note, and all of them would prove that the consistency of supply-side and demand-side elements, associated in some cases with the emergence of one dominant design, represents a mandatory requirement for the emergence but also the stability of a technological paradigm (Dosi, 1982).

However, the path to achieving this condition of emergence involves both high technology and market uncertainties for companies. 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, or sometimes adopters are not aware of their needs (Norman and Verganti, 2014). Often, a reference market does not exist yet, and companies are consequently unable to elicit needs from potential customers.

Hence, traditional market research is an inappropriate and misleading tool in these cases, S-curves are often misleading (Cantamessa and 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 a new technological paradigm (Stevens and Burley, 1997; Birkinshaw et al., 2007). Investing decisions, moreover, are difficult in such fuzzy front-end contexts (Moenart et al., 1995; Frishammar et al., 2011), and both idea generation and pre-development are carried on without knowing exactly the emerging technology (Khurana and Rosenthal, 1998; Kim and Wilemon, 2002; McLaughlin et al., 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.

Hence, this paper explores some research questions: is it possible to understand the value of a technical change, without models that elicit information from customers? How does designing some new product features, mainly enabled by new technology, affect product success?

This paper deals with such technological forecasting issues from a different perspective: it does not study the problem by a traditional managerial point of view, but instead, it strives for complementing this view with a Design-oriented one.

This research, in fact, is based on the premise that technological paradigms are always the result of design choices and consequently tries to investigate how these design choices have an impact on adoption and on the probability of success of new technological paradigms. It is therefore clear that the present study does not investigate either the antecedents of product success or 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. Rather, it looks at the problem from a complementary perspective deriving from the Engineering Design domain.

The idea is to make designers aware that not all design choices have equal consequences in terms of innovation and, on the contrary, to provide managers a complementary view that ties success of products to variables that are endogenous to the process of development, as complement to the exogenous ones (see the traditional forecasting models) and to management practices (i.e. Cooper and Kleinschmidt, 1990).

The next section illustrates the theoretical background underlying the present research, whose analysis leads to the research aim described in section 3. The model and results are proposed in section 4. Two digital cases are then discussed since they represent an interesting illustrative occasion. Conclusions are finally provided in section 5.

Theoretical background

Over the years, scholars investigated what makes an innovation radical (Henderson and Clark, 1990; Lee and Na, 1994; Atuahene-Gima, 1995; Balachandra and Friar, 1997; Kessler and Chakrabarti, 1999). Meanwhile, other authors 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 technology associated with it and will contribute to the incremental progress of the whole system. If it occurs at the system level, it will determine a shift of the paradigm associated with the system, and consequently, in turn, with components (Cantamessa and Montagna, 2016). Correspondingly, contributions are aimed at identifying what are the requirements to explore new technological paradigms and to enhance the development of radical innovations.

Some of these relate to comprehending the enabling conditions, such as the technology evolution phases (Tushman and O' Reilly, 1997; Iansiti, 2000), discontinuous progresses (Schilling, 2009), disruption possibilities and barriers (Antonelli, 1995; Christensen, 1997), as well as competition forces (Porter, 1985). Some others investigate organization and management strategies, such as the combination of internal and external knowledge (Cohen and Levinthal, 1990; Leiponen and Helfat, 2010), the balancing between exploration and exploitation (Helfat and Raubitscheck, 2000), ambidextrous behaviours (Tushman and O'Reilly, 1996; 2004; Gibson and Birkinshaw, 2004), visionary aptitude and shaping strategies (Hagel et al., 2008). Technology policies (Ettlie et al., 1984), the ability of blending supply-side and demand-side elements together (Cooper and Kleinschmidt, 1990; Calantone et al, 1993; 1995; Sainio et al., 2012), and the choice of specific inter-firm integration configurations (Christensen et al., 2002; Lee and Veloso, 2008) are studied as well. Therefore, definitively, antecedents to product success have been widely explored from different perspectives: organizational factors (Ayers et al., 1997; Sivadas and Dwyer, 2000), capabilities for gathering and using market information (Ottum and Moore, 1997; Kam Sing Wong and Tong, 2012), cross-functional integration (Troy et al., 2008), etc.

Nevertheless, this study faces the problem from a complementary point of view. It focuses neither on conditions required to support the emergence of a new technological paradigm nor on the preferred strategic and managerial orientation; it investigates how the design decisions that underlie 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. If the dominant design locks a technological paradigm (Tushman and Rosenkopf, 1992), in its turn, a dominant design represents a specific emerged product architecture (Utterback and Abernathy, 1975) and any product architecture is the outcome of design choices, and those choices can be consequently supported.

In respect with methods, companies usually employ technological road-mapping (Paap, 1994; Geum et al., 2011; Carvalho et al., 2013) and forecasting techniques to estimate adoption or diffusion of innovations (Firat et al., 2008). Qualitative approaches like scenario analysis (e.g. Clarke Sr., 2000) or expert opinions (e.g. Okoli and Pawlowski, 2004) are more frequently proposed, because of the uncertainty that characterizes radical situations. Nevertheless, quantitative methods could be employed to estimate the market adoption of technically superior new products (Sahlo and 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 and Abernathy, 1975; Foster, 1986; Utterback, 1994; Chandy and Tellis, 2000; Roy and Sivakumar, 2010). However, also these models have limits mainly dependent on the performance indicator that is chosen as a driver of progress, or on time that is selected as the independent variable (Cantamessa and Montagna, 2016). As an additional help, companies adopt methods aiding them to define a business model (Osterwalder, 2004; Casadeus-Masanell and Ricart, 2010) or to assess project and competence portfolios (Cantamessa, 2005; Pisano and Verganti, 2008), in order to understand how the organization can enable and support product changes.

However, all these methods are used by companies to make strategic decisions on technology investments or company structure, but they do not provide any suggestion about the product features and technical decisions designers should make to provide success 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 and 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 radically innovative product, since customers do not know their needs (Zaltman, 2003), or they do not understand the novelty of the product (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 and Reinertsen, 1991) or to employ a ‘probe and learn’ process based on several approximations (Lynn et al., 1996).

Lean approaches (Ward, 2007), namely Agile in digital contexts, are more and more diffused especially in the start-up contexts (Blank, 2013).

Finally, design-driven approaches (Verganti, 2009) try to avoid customer involvement entirely. In these cases, 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.

In 2014, Norman and Verganti definitively combined the two 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 support design divergence and the generation of alternatives (e.g. Bacciotti et al., 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 et al., 2011). Besides, additional contributions try to enhance traditional design process and decisions by investigating the information on new features and functionalities that radical innovations call for. Borgianni et al., (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 present paper is positioned in this last stream of research. In particular, it enriches that contribution both methodologically (i.e. product and services are distinguished) and with respect to the model robustness and the statistical significance of the results. Nevertheless, this paper adopts a broader and more management-oriented perspective in the functional definition of a product. That way makes our goal closer to the ones of traditional technological forecasting techniques, meant as models which are used to anticipate and to understand the potential direction of technological change (Firat et al., 2008). Nevertheless, the idea of borrowing the method of investigation from another stream of research, such as that of Engineering Design, gives the paper originality and can provide useful food for thought for the more traditional innovation literature.

Research Objectives

This research is therefore based on the premise that technological paradigms are the result of design decisions. It simply means that any radical innovation, and therefore any technological shift, is also always the outcome of a given set of design choices. In particular, this research tries to investigate how these design decisions, which are analysed according to the extent they can affect customer perception, have an impact on adoption and hence on the probability of success of new technological paradigms.

Accordingly, the paper focusing on radical innovations and paradigm shifts aims at providing an answer to the following questions: *which are the recommended and inadvisable actions that designers should perform to embrace new technological paradigms? To what extent do those actions affect customer adoption and the probability of product success*?

Actually, Engineering Design scholars know that technical systems do not evolve by chance, but they follow specific evolution laws (Altshuller, 1984). Indeed, according to the Theory of Inventive Problem Solving (TRIZ), recognisable design decisions can be associated with repeated patterns in innovations. For instance, systems evolve because they integrate all the elements that constitute the system to reduce active human involvement; or they proceed from macro to micro-level, since technology evolution moves from system architecture to the surrounding technologies at the component level. As an example, printing machines have been through many generations of transition to micro-level, from lithography which employed huge stones, to laser printers which use light to sensitise the paper and fine powder to print (Rantanen et al., 2008).

Therefore, technology changes affect single components or the entire architecture (Henderson and Clark, 1990), but in any case, any new product can be interpreted as a set of modifications to the previous system, which makes a difference if functionally compared to their predecessors. Independently of the level at which these changes occur (namely architectural or component level), variated functional features affect customer perception and adoption. One contribution in this stream of research states, for instance, that three functional changes are just enough to make product perceived as innovative, and hence definitively affect adoption (Borgianni et al., 2013).

Therefore, this paper proposes a model that, by comparing such functional differences between new products and their predecessors, investigates the design choices that generated these functional modifications and aims at providing a link between those choices and the success those products reached. This link in fact is due to common patterns, whose existence was stated by Altshuller; if one recognises these patterns into the design choices made, part of the decisional uncertainty results consequently addressed.

The derived implications are significant. Theoretically, forecasting methods are complemented by new models that concern endogenous variables to development. From a practical point of view, implications are for managers and designers.

At first, managers are provided with an additional decision support tool to envision product success to be employed when market needs are barely recognisable. The use of such kind of aid allows having an estimate of the chance of success for each product belonging to the company product portfolio. Furtherly, the results can be used to address resources to the most promising projects.

Secondly, even in the absence of indications from customers, designers can receive hints about the impact of their specific choices on product success. Hence, they have an overview of the actions that might increase and decrease the chance of success, acquiring a perception of the consequence of their choices on innovation dynamics. Change decisions can be made accordingly.

Digital products represent an interesting occasion of illustration. Their radical impact in fact has been often studied in literature (e.g. iPhone, Farris et al., 2008; Campbell and La Pastina, 2010; West and Mace, 2010). Without looking for a comparison of the evidence; the idea is to provide a complementary perspective on the phenomenon.

Methodological Approach

Therefore, innovative products are compared with their predecessors with the aim of recognising repeatable patterns and investigating the design modifications occurred. Products history in term of customer appreciation is known, and a product, accordingly to other contributions in the literature, can be considered successful if diffusion has occurred (Goldenberg et al., 2001; Garber et al., 2004). The hypothesis to be proved hence states:

Is there one or a several sets of design choices common to many successful products?

A two-dimensional space can be used to analyse how a set of products differs from predecessors. These differences are mainly dependent on the Design Object and the Design Process (Borgianni et al., 2013).

On the one hand, in fact, products differ for features. Engineering Design associates these features with functionalities (Pahl and Beitz, 1988; Ulrich and Eppinger, 1995), according to the extent these characteristics address product functions and affect user satisfaction. That extent can be thought as the proximity of a technical system to "ideality" (Ilevbare et al., 2013) and can be operated mainly by three attributes:

- properties which 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, initially introduced by Kim and Mauborgne (2005) for depicting the matching between business modifications and value generated, can be adapted to products (Borgianni et al., 2012) to describe the possible design choices. 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).

Actions "Create" and "Raise" add or improve functions and therefore have a positive impact on 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". This decision, even if it is grounded in deeply assessed design trade-offs and other generated benefits balance it, in itself negatively affects the perceived performance by the customer. 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 actions 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 (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 which 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.

Figure 1, hence, depicts this model conceptualisation that focuses on the one hand on the object of design (i.e. the product), assessing functional characteristics which differentiate the product from its predecessors, while on the other hand investigates the design process and the adopted choices of modification.

The crossed interrelationships among the three kinds of attributes and the four types of actions give rise to the definition of 12 decisional design modifications, which can be used to investigate the occurred product changes when a paradigm shift has happened or has failed to happen. Those 12 categories of modification are used to empirically test the original hypothesis through a set of historical cases of product successes and failures.

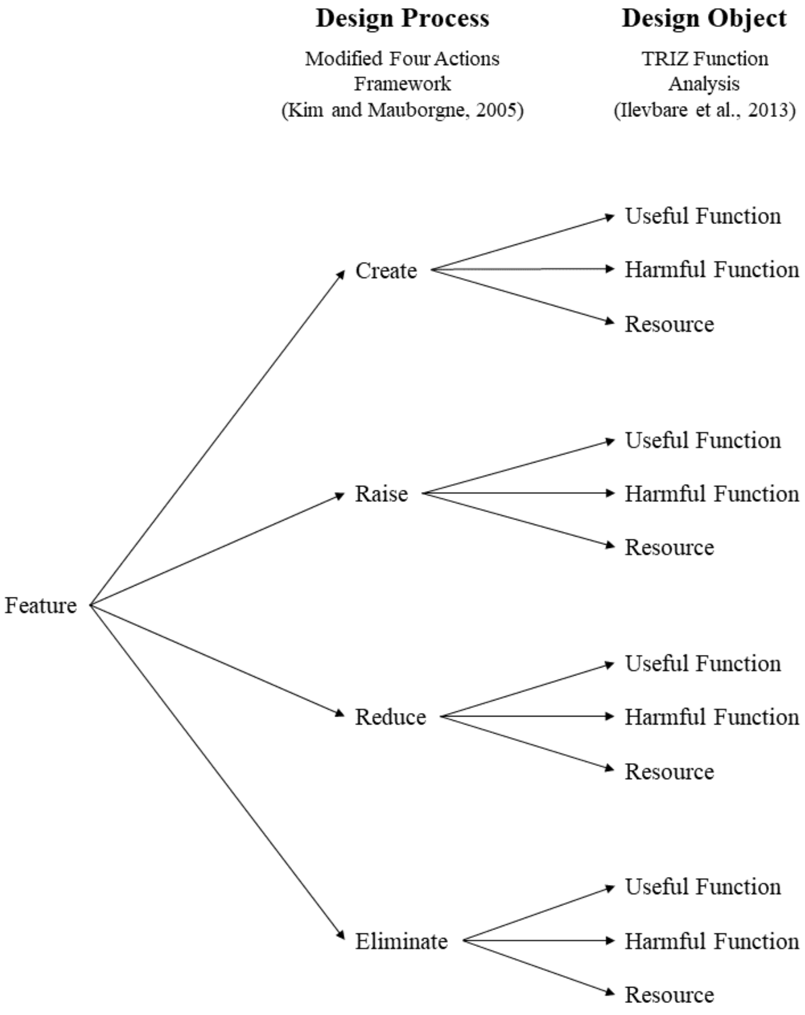

Figure 1. Conceptual model definition

Other attempts of anticipating the success of products exist in the literature (e.g. Ayers et al., 1997; Szymanski et al., 2007; Song and Di Benedetto, 2008; Troy et al., 2008; Yang et al., 2012) and among them, logistic regression has been used to estimate the potential of a new concept (e.g. Goldenberg et al., 2001; de Jong and Vermeulen, 2006). Logistic regression, in fact, allows 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 et al., 2005); accordingly, logistic regression is here employed to estimate the potential of a new concept. The main difference to the other previous attempts is represented by the micro-level perspective adopted: the source of the idea or the newness to the firm is not taken into account here, while the 12 categories of modification are considered as the explanatory variables.

Table 1 describes the 13 described variables and defines their domain, and it clearly shows that the variables are conceptually defined regardless of the environmental conditions, industry typology, specific strategies, etc. The present study, in fact, wants to investigate the effectiveness of those design decisions that are linkable to repetitive patterns of product evolution. This defines the wide-ranging applicability of the model among the various industries, although the parameters of the model, which are industry dependent, must be opportunely calibrated.

Table 1. Variables description

Name	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, +∞)*

Empirical Analysis

Data Collection

We started from an existing database in the literature, the one proposed by Borgianni et al. (2013), which consisted of 92 case studies, be it products or services, collected by investigating journal papers, books, websites and forums. Products and services there were selected independently on the industry, but so that functional features were easily recognizable. Starting from this database, we decided, to focus our analysis just on products; this choice was made in order to achieve a higher methodological consistency. Indeed, services and products observe adoption rules that are entirely different – if one thinks for instance to freemium services (Pujol, 2010) – and, hence, their probability of success depends not surely on comparable functional variables. Consequently, purely functional approaches, such as the ones introduced by TRIZ, are not applicable. As a result, the initial database was reduced to 71 records.

Subsequently, further academic and technical journals and websites were investigated to identify additional 39 cases to be included, as reported in Table 2. In the end, 110 cases equally divided between successful products and market failures were collected. The subset of success stories comprises products showing remarkable commercial results and with a diffusion which was publicly recognised.

Table 2. New case studies and sources

Successful innovations	Kindle, Apple II, iPad, iPhone, Blu-ray Disc, Digital calculator, Dyson, GoPro, Kodak Funsaver, Kodak Instamatic, Nikon F, NES, Palm Pilot, Pebble, Polaroid SX-70, Sony PlayStation, Tesla, TiVo, TomTom, Corolla, Transistor radio, Volkswagen Beetle, Wikipedia, Xerox, Zipcar
Market failures	Fire Phone, Apple Pippin, Concorde, Gizmondo, HP Touchpad, Microsoft Kin, Kinect, Mira Smart Display, SPOT Watches, Zune, Oakley Thump, Tata Nano, TwitterPeek, Wow! Chips
Sources	ACM Interactions, Bloomberg, Business Insider, California Management Review, Claremont McKenna College thesis, Communications of the ACM, Design Studies, Fast Company, Forbes, Electric Vehicle Waves of History: Lessons Learned about Market Deployment of Electric Vehicles (InTech), Film International, Fortune, Harvard Business Review, IEEE Annals of the History of Computing, IEEE Computer Society, IEEE Journal of Solid-State Circuits, IEEE Pervasive Computing, IEEE Transactions on Engineering Management, Independent, Industrial and Corporate Change, Information, Communication & Society, International Journal of Design, International Journal of Engineering Business Management, Journal of Commerce & Business Management, LUISS thesis, MIT Management Sloan School, MIT thesis, New Products Management (McGraw-Hill), Performance Measurement and Metrics, Proceeding of New Interfaces for Musical Expression, Proceeding of Ninth International Conference on Mobile Business, Research Policy, Smithsonian Magazine, Strategic Management, Telecommunications Policy, The Invisible Future: The Seamless Integration of Technology Into Everyday Life (McGraw-Hill), The New York Times, The Wall Street Journal, Time, Universidade Católica Portuguesa thesis, Universität St. Gallen thesis

Data Analysis

Each of the 110 cases was investigated to find out the differences from its predecessors at architectural, modular and component level according to the conceptual framework previously developed. These changes had to be documented by more than one author in scientific and/or technical sources without any conflicting indication. In order to ensure continuity to the previous study and to obtain at the end comparable evidence, those products that were subjected to at least three net functional modifications were considered innovative. The process of evaluation and validation was iteratively carried on by a multidisciplinary team made of three design experts and two managerial figures. The process consisted in a voting procedure aimed at reaching at the end a mutually agreed solution.

Figure 2 reports an excerpt of the 110 x 13 matrix that resulted from this evaluation procedure. As an example, the Fire Phone worsened in terms of user-friendliness and price compared to existing smartphones. These two properties depend directly on design choices which negatively affect customer satisfaction (action Reduce) and involve the consumption of resources, namely time and money.

	CREATE UF	CREATE HF	CREATE RES	RAISE UF	RAISE HF	RAISE UF	REDUCE UF	REDUCE HF	REDUCE RES	ELIMINATE UF	ELIMINATE HF	ELIMINATE RES	SUCCESS
[Yellow Tail] wines	**1**	**0**	**1**	**1**	**0**	**1**	**2**	**0**	**1**	**2**	**0**	**0**	**1**
Amazon Fire Phone	**2**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**3**	**0**	**0**	**0**	**0**
Amazon Kindle	**2**	**0**	**0**	**0**	**0**	**2**	**1**	**0**	**0**	**0**	**0**	**0**	**1**
Amphicar	**2**	**0**	**0**	**0**	**0**	**0**	**3**	**1**	**3**	**0**	**1**	**0**	**0**

Figure 2. Excerpt of the matrix reporting the 110 cases and their classification

Statistical Analysis

The resulted database then was split into two portions in order to use the first one to develop the statistical model, and the second one to cross-validate it (Picard and Berk, 1990), according to a two-thirds rule as suggested in the literature (e.g. Harrell et al., 1996).

The analysis regression was carried out through IBM SPSS Statistics® module, which makes use of the maximum likelihood estimation criterion. Logistic regression returned coefficients used to develop the following predictive equation formula:

$$
\begin{aligned}
z = & -0.490 + 1.842\, CREATE_{UF} + 0.535\, CREATE_{HF} + 2.130\, CREATE_{RES} + 0.658\, RAISE_{UF} \\
& + 1.182\, RAISE_{HF} + 1.047\, RAISE_{RES} - 0.941\, REDUCE_{UF} - 1.596\, REDUCE_{HF} \\
& - 1.768\, REDUCE_{RES} - 1.284\, ELIMINATE_{UF} - 6.624\, ELIMINATE_{HF} \\
& - 1.101\, ELIMINATE_{HF}
\end{aligned}
$$

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

In detail, delivering a new useful function, such as the capability of the first PlayStation for playing audio CDs, or introducing a new property that reduces consumption of the resources (e.g. energy, space, time, etc.) are actions that more positively affect the chance of success of new products. Their coefficients 1,842 and 2,130 are in fact positive in the equation, and they are the highest ones. If one compares these coefficients with the ones of the actions that correspond not to introductions, but just to improvements – for instance for reducing drawbacks (e.g. the mechanical resistance of a photo camera) – one can observe that those actions are suggested as well. Besides, improving an existing characteristic could be easier than introducing an entirely new one. On the other hand, new properties diminishing drawbacks, like the wireless charger of the HP touchpad, or improved features providing a benefit, like the larger screen of the Microsoft Zune, contributes on a slighter extent to the probability of success. Hence, designers should ponder whether working in this direction, and companies should be careful not to propose products involving these kinds of modifications as the major elements of differentiation. Finally, all the actions negatively influencing customer satisfaction are equally inadvisable; in particular, removing an attribute that diminishes drawbacks has six times the magnitude of other actions and is the worst action to perform.

The developed model predicts a successful product when it returns a value higher than 50% and vice versa for market failures. As a result, almost 90% of the subset used was correctly predicted by the metric.

With respect to control variables, by analysing previous studies, three variables have been recognised as interesting: B2B vs B2C (Ma et al., 2012), firm maturity (Rothaermel et al., 2006), and nationality

(Johnson et al., 2009). The former variable was not included in the analysis due to the very high number of B2C products which would make useless the deepening. Concerning the second, we distinguished between mature firms and startups, and the latter were defined as newly created companies with no operating history (Giardino et al., 2016). Finally, due to the high number of US-based firms, we distinguished between companies site in US or not. Table 3 shows a comparison between the original model and the ones obtained including dummy variables in the analysis.

Table 3. Model comparison

	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			- 0.206*

Note. ***p-value < .01; **p-value < .05; *p-value < .1

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, besides strategic, managerial and organisational ones in product success. For sure, indication on the chance of success for each product belonging to the company product portfolio can be valuable for designers, but also for managers in addressing resources to the most promising projects.

Moreover, considering the first model, the results show that six design variables are significant at a .01 or at a .05 significance level. The result remained largely unchanged when the dummy variables were included in the analysis. Finally, the two additional binary logistic regression analyses we conducted provide further insights into how product success is influenced by other variables such as the nationality and the firm maturity. The latter, even if it is not statistically significant, confirmed what is known from literature (Chandy and Tellis, 2000), that is incumbents deal with difficulties when they have to face radical innovations.

Model Validation

The empirical model was then tested both by considering the fitting and its statistical significance and regarding the model's performance (Picard and Berk, 1990).

For the former testing, Cox & Snell R-square and Nagelkerke R-square values approximate the coefficient of determination R-square and indicate how useful the explanatory variables are in predicting the response variable (Menard, 2000). In our case, values 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 (2000) test investigates the extent predicted values are close to the observed ones for different subgroups. In our case, the nine identified groups were considered significantly close with a p-value of 0,314, that is over the suggested threshold equal to 0.05. These results are summarised in Table 4.

Table 4. Model reliability summary

Test	Value	Threshold
Hosmer – Lemeshow test	0.314	> 0,05
Cox & Snell R-square	0.539	Higher the value, better the model predictability
Nagelkerke R-square	0.719	

Finally, according to the rules of data-splitting (Arboretti Giancristofaro and Salmaso, 2007), we validated the model by using the coefficients of the Logistic Regression to evaluate the model's performance on data other than those used to develop it. Indeed, validating by using only the modelling data means over-estimating its performance (Park, 2013). As reported in Table 5, the model correctly predicts 86% of the data of the validation sample. In addition, the percentage of correctly predicted success cases is 91% while the percentage of correctly predicted market failures is 82%.

Table 5. Validation summary

	Correctly predicted success cases	Correctly predicted market failures	Overall success percentage
Modelling Sample	87.9%	90.9%	89.4%
Validation Sample	90.9%	81.8%	86.4%

The reliability of the present model must 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 et al., 2004), as Table 6 shows.

Table 6. Index comparison

Index	Present model	Borgianni et al. (2013) log reg	Borgianni et al. (2013) neural networks	EBONSAI (Yada et al., 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

Our model results to be a remarkable improvement compared to the one developed by Borgianni et al. (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, when compared to Neural Network, logistic regression shows its potential, that is the capability to estimate the impact of the individual variables.

Finally, the presented model outperforms a decision support tool, named EBONSAI (Yada et al., 2007), too. Even if it has not been mentioned previously, it has been chosen as a relevant benchmark given the similarity of its goal, i.e. the anticipation of the market success of products.

Illustrative Case #1

Since other cases in the literature evaluated the radical impact that iPhone had in the mobile phone industry (Farris et al., 2008; Campbell and La Pastina, 2010; West and Mace, 2010), we decided to face with it accordingly. Comparison of the evidence was not the aim since the variables investigated refer to complete different perspectives; rather the idea was to provide a more-design oriented view on the phenomenon. When Steve Jobs and Apple marketed the iPhone in 2007, they were able to capture changing consumer, corporate and environmental factors (Laugesen and Yuan, 2010), and, as a result, they created a new technological paradigm.

First of all, they were able to anticipate the need for increased capabilities of mobile phones (Funk, 2004) by developing a browser-based on personal computer standard, and by introducing large touchscreens. Even cultural factors influence the adoption of the iPhone; indeed, its design helped to make it a status symbol (Laugesen and Yuan, 2010). These features provided different kinds of benefits to users, both material and emotional, and were introduced to the mobile phone industry by Apple. Moreover, the initial iPhone provided a more user-friendly mobile interface than competitors (West and Mace, 2010), which is another property directly linked to the consumption of a given resource, namely the time and skills required to interact with the product.

However, on the other hand, for market positioning reasons, the company initially set a high price, which corresponded to a resource that was negatively affected during the redefinition of the product. Furthermore, even if users were not ready to pay for a mobile data service plan (Laugesen and Yuan, 2010), the technology on which the first iPhone was built required it. Hence, a mobile phone, for the first time, was not anymore independent of that kind of service, and this decision represented the elimination of a resource, namely the independence from other service sources.

The iPhone case can be summarised as in Table 7. At this stage, we applied our model according to the identified design choices, and, in particular, we obtained $z = 1.012$, which allowed to estimate a chance of success equal to 73%.

Table 7. Apple iPhone analysis

Action	Feature	Functional analysis
CREATE	Browser Web based on personal computer standard	UF
CREATE	Cool design	UF
CREATE	Large touchscreen	UF
RAISE	Ease of use	RES
REDUCE	Cheapness	RES
ELIMINATE	Memory card support	RES
ELIMINATE	Required purchase of a mobile data service plan	RES
ELIMINATE	User-replaceable battery	RES

Illustrative Case #2

The revolution started by GoPro in the photographic industry was one more case we analysed. Woodman marketed the GoPro in 2004 because he belonged to a niche, namely the action sports community, which was overlooked by the major players of the photographic industry (Shannon, 2016). By understanding new supply-side and demand-side circumstances, he did not just renovate the product but was able to introduce a new technological paradigm.

He exploited more recent knowledge and technologies to improve a key performance such as the portability and introduced a feature – resistance to impact – fundamental to film first-hand extreme sports. Concerning the previous categorisation, portability can be classified as a resource since it is linked to the space required to use and store the product, while the resistance to impact is related to a common drawback of the camera and, as such, can be defined as a harmful function.

At the same time, Woodman gave customers the possibility to record and shoot what they love doing (Berardinetti, 2016). Partnering with accessories manufacturers and allowing people to install GoPro almost anywhere pursued this strategy. More in detail, the ability to mount the camera everywhere was a new feature that provided benefits to final users, so can be classified as a useful function which was created. Accessories availability can be defined as a useful function as well, but, instead, it was merely an improvement.

On the basis of this assessment, the design choices characterising the GoPro case can be summarised in Table 8, and, based on them, the model estimated a success probability equal to 97%.

Table 8. GoPro analysis

Action	Feature	Functional analysis
CREATE	Ability to mount the camera almost everywhere	UF
CREATE	Resistance	HF
RAISE	Accessories availability	UF
RAISE	Cheapness	RES
RAISE	Ease of use	RES
RAISE	Portability	RES
REDUCE	Quality	UF
ELIMINATE	Controllability	UF

Discussions and conclusion

Shifting from an old technological paradigm to a new one implies strategic assessments and managerial actions, but also design decisions and technology related choices.

The present study focuses on this latter perspective. It does not investigate either condition required to support the emergence of a new technological paradigm and radical innovation or the preferred strategic and managerial orientation, according to the traditional criteria of Innovation Management literature; rather, it looks at the problem from a complementary perspective deriving from Engineering Design. The focus on the design decisions that underlie radical shifts is not conflicting, but complementary to the more traditional perspectives. This viewpoint aims at opening the black-box of technology and adding the possibility of micro-level investigations of the phenomenon.

Therefore, the present paper proposes a model to anticipate the market appreciation of innovative products as a function of design actions. Designers in fact through their actions give rise to properties that significantly characterise products and determine their appreciation, but on the other side, design decisions follow specific patterns of technology evolution. The effectiveness of design decisions, hence, can be evaluated by exploring the link each decision (effective or not) has with repetitive patterns of product evolution.

The proposed model predicts almost 90% of the subset used correctly. Moderating factors have also been studied, and the relevance of design variables in product success remains confirmed. Design choices can definitively affect product success, besides the traditional factors investigated by the management literature.

Moreover, the model outperforms previous models with similar purposes (Yada et al., 2007; Borgianni et al., 2013). This is likely due both to the more rigorous methodological background on which the model is grounded and to the managerial perspective that complemented the technical one in the functional analysis of the products.

The derived implications are significant. At first, managers are provided with an additional decision support tool to be employed when market needs are barely recognisable. The use of such kind of aid allows estimating which are the most promising projects, avoiding waste of money, time and resources resulting from the development of poor-valued projects.

Secondly, even in the absence of indications from customers, designers receive hints about the impact of their specific choices on product success; hence, engineer designers can use it to extract advice about what kind of features modify to increase prospects of product success. Therefore, the model results particularly appropriate when market needs cannot be elicited and hence in radical innovation cases.

However, it is evident that the proposed model needs to be further validated by analysing additional case studies for both obtaining more reliable results and specifying the term of application. Investigating the effectiveness of design decisions that are linkable to repetitive patterns of product evolution defines the wide-ranging applicability of the model among the various industries, although the parameters of the model, which are industry dependent, must be opportunely calibrated. With this respect, collecting more and more cases, it would be possible to develop industry-specific models, able to detect the peculiarities of each sector.

Finally, each new feature describing a new paradigm was examined in the time lapse with respect to their actual impact on the product use. Actually, innovations could affect a product when using it or even when not in use. The first is the case of a car reducing noise while driving it; the latter is the case of a folding chair allowing to save space when not in use. Hence, in order to complete the study, it is essential to extend our analysis also to those cases which were subjected to innovations affecting them when they are not used.

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