Applied Science & Engineering Journal for Advanced Research
ISSN (Online): 2583-2468
Volume-1 Issue-3 || May 2022 || PP. 34-42 DOI: 10.54741/asejar.1.3.6

Technology Paradigm Assessment using a Decision Support Model

Dr. Mukesh Mishra
HOD, Department of Mechanical Engineering, B.B.S. Institute of Engineering Technology, Allahabad, Uttar Pradesh, India

Corresponding Author: m*ishra_mukesh@gmail.com*

Received: 16-04-2022	Revised: 30-04-2022	Accepted: 23-05-2022

ABSTRACT
Thinking about the coming of a new technology paradigm means thinking about a number of things, from managerial decisions and strategic evaluations to design choices and technology-related choices. In order to address this latter viewpoint, the current study puts forth a model that calculates the likelihood that creative goods will succeed based on design choices. The emphasis on the design choices that give rise to significant changes is not antagonistic but rather a supplement to the conventional forecasting viewpoints that take environmental or process management aspects into account. The model is built on a database of previous inventions that were successful and failed. This information is used to construct a logistic regression model, the results of which can be useful to managers and designers alike. The former receive guidance on how certain design decisions impact innovation uptake and product perception, while the latter receive assistance in determining which initiatives hold the greatest promise. Two digital product cases serve as examples of the model.

Keywords: *paradigm, design decision, product cases, creative goods, innovation*

I. INTRODUCTION

Businesses are constantly looking for ways to develop and gain an advantage over rivals, and this demand is exacerbated in the digital sector, where goods have shorter life cycles. For both large and small businesses, implementing radical innovations has always been a solution. In reality, new paradigms arise as an industry transitions from the previous technology trajectory to the current one, and this change offers a transient advantage.

The technological paradigm is a potent idea because it unequivocally asserts that successful products and services require more than just enhanced technical performance. Wikipedia, for example, recognized that the proliferation of internet connections was changing consumers while also impacting supply-side variables by offering encyclopedic knowledge for free.

People were beginning to reference internet content instead of traditional encyclopedias, which had higher trustworthiness, since they preferred real-time and nearly endless results. Similar to how Apple increased functionality without compromising portability, Amazon is currently evaluating a drone-based delivery system, among other things. There are a number of other noteworthy examples that demonstrate the necessity of supply-side and demand-side elements being consistent, which is sometimes linked to the emergence of a dominant design, for both the emergence and stability of a technological paradigm.

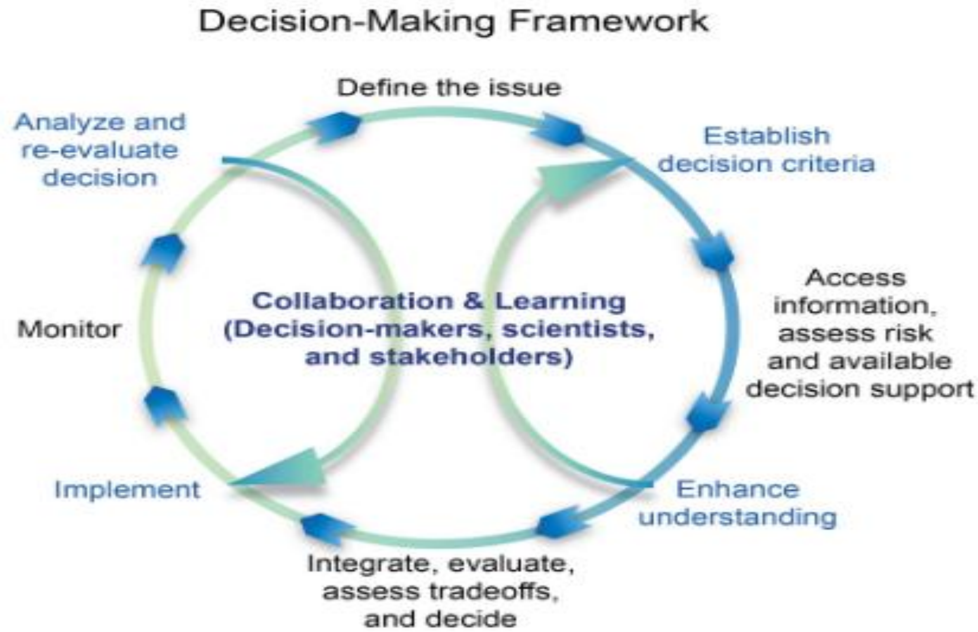

Figure 1: Decision-Making Framework
Source: https://nca2014.globalchange.gov/report/response-strategies/decision-support

Nevertheless, organizations must navigate significant technological and market uncertainty in order to reach this state of emergence. Because they are unable to recognize the promise of new technologies, incumbents frequently lose their position as market leaders (Christensen, 1997). Sometimes radical ideas are independently pushed onto the market by technological advancement, and other times adopters are unaware of their own demands (Norman and Verganti, 2014). A reference market is frequently absent, making it difficult for businesses to identify the demands of prospective clients.

Because of this, S-curves are frequently misleading, making traditional market research an inappropriate and misleading tool in these situations. As a result, businesses suffer from the lack of trustworthy models for assessing technological advancement and forecasting the market's assessment of a new technological paradigm. Furthermore, in such hazy front-end contexts, investing decisions are challenging. Moreover, pre-development and idea generation are conducted without precise knowledge of the emerging technology. In this context, design choices are influenced by new technologies, but they are frequently chosen without considering how they will affect how customers view the product.

Therefore, the purpose of this study is to investigate a few research questions: can the worth of a technical improvement be determined in the absence of models that collect data from customers? What impact does product success have on the design of some new features, mostly made possible by new technology?

This work approaches such technology forecasting problems from a different angle, aiming to augment the typical managerial point of view with a design-oriented one through the analysis of the topic.

In actuality, this research is predicated on the idea that design decisions always produce new technology paradigms, and it thus seeks to ascertain how these decisions affect the likelihood of new technological paradigms being adopted and succeeding. It follows that, in accordance with the conventional standards of the literature on innovation management, the current study does not examine the causes of either the establishment of technological paradigms or the radical breakthroughs that precede product success. Instead, it approaches the issue from a different angle that comes from the Engineering Design field.

The intention is to alert designers to the fact that not all design decisions will have the same impact on innovation. Conversely, it aims to offer managers an alternative perspective that links product success to endogenous development process variables in addition to exogenous variables (refer to conventional forecasting models) and management practices (e.g. Cooper and Kleinschmidt, 1990).

The theoretical framework for the current study is presented in the next part, and its analysis leads to the section 3 research goal. In section 4, the model and findings are presented. We then go over two digital situations because they provide an intriguing example. Section 5 offers conclusions at last.

II. GOALS OF THE RESEARCH

Thus, the foundation of this research is the idea that design choices lead to the development of technology paradigms. It basically indicates that a particular set of design decisions always results in every radical innovation, and hence any technological shift. This research specifically looks into how these design choices, which are evaluated based on how much they might influence customer perception, affect adoption and, thus, the likelihood that new technological paradigms will succeed.

Thus, the goal of this study is to address the following concerns regarding radical innovations and paradigm shifts: what are some best practices and worst practices for designers embracing new technological paradigms? How much of an impact do those efforts have on the likelihood that a product will succeed and be adopted by customers?

As technical systems adhere to certain evolution laws rather than evolving randomly, engineering design academics are aware of this. In fact, repeating patterns in innovations can be linked to identifiable design choices, according to the Theory of Inventive Problem Solving (TRIZ). Systems, for example, change throughout time because they integrate all of the components that make up the system to minimize the need for active human engagement. Alternatively, systems evolve from a macro to a micro level because technology evolves from system architecture to surrounding technologies at the component level. For instance, lithography, which used large stones, gave way to laser printers, which utilize light to sensitize paper and fine powder to print, as well as several generations of transition to micro-level printing equipment.

As a result, technological advancements can impact individual parts of the architecture or the entire system (Henderson and Clark, 1990). Nevertheless, any new product can be understood as a collection of changes to the prior system, which has an impact on how it functions in relation to its predecessors.

Different functional features influence customer perception and acceptance regardless of the level at which these changes happen (i.e., architectural or component level). A research contribution in this area suggests, for example, that a product only needs to undergo three functional modifications to be seen as innovative, which will have a significant impact on adoption.

In order to establish a connection between the design decisions that led to these functional adjustments and the success those goods had, this research suggests a model that compares these functional differences between new products and their predecessors. This connection is actually the product of common patterns, the existence of which Altshuller acknowledged; if these patterns are taken into account while making design decisions, then some of the decisional uncertainty is subsequently resolved.

The implications that follow are important. Theoretically, new models that address endogenous determinants to development augment forecasting techniques. Managers and designers will find consequences from a practical standpoint.

Initially, managers are given an extra tool for decision support to foresee the success of their products, which they might use when market needs are hardly discernible. Utilizing this type of assistance makes it possible to determine the estimated likelihood of success for each product in the company's product portfolio. The outcomes might also be utilized to allocate funds to the most promising projects.

Second, designers can get clues about how their particular decisions will affect the success of their products even if they don't receive direct feedback from consumers. As a result, they are aware of the steps that could both raise and lower their chances of success, giving them a sense of how their decisions will affect the dynamics of innovation. Decisions about changes can be made appropriately.

Digital goods offer an intriguing opportunity for illustration. In reality, the research has extensively examined their dramatic influence. The goal is to offer a contrasting viewpoint on the phenomenon without attempting to compare the facts.

III. ANALYTICAL EMPIRICISM

We commenced with an extant database in the literature, the one suggested by Borgianni et al. (2013), comprising 92 case studies pertaining to products or services, gathered through an examination of journal articles, books, websites, and discussion boards. There, goods and services were chosen autonomously based on industry standards, although with clearly identifiable practical aspects. We chose to start with this database and narrow the scope of our research to simple products in order to increase methodological consistency. As an example, consider freemium services (Pujol, 2010). In fact, services and products follow quite distinct adoption patterns, and as a result, their likelihood of success is not always dependent on similar functional characteristics. As a result, TRIZ's proposed strictly functional strategies are inappropriate. The original database was thus downsized to 71 records.

Following that, more academic and technical periodicals and websites were examined in order to find 39 more cases that should be included. Ultimately, 110 instances were gathered, split evenly between those that succeeded and those that failed on the market. Products with notable commercial outcomes and widely acknowledged dissemination are included in this subgroup of success stories.

3.1 Analyzing Data

Each of the 110 examples was compared to the conceptual framework that had already been built to see how it was different from the ones that came before it at the architectural, modular, and component levels. Multiple authors' documentation of these modifications in technical and/or scientific sources was required, with no contradicting evidence. In order to stay consistent with the results of the previous study and get similar evidence at the end of the investigation, products that went through at least three net functional modifications were thought to be novel. Three design specialists and two managers comprised the interdisciplinary team that iteratively carried out the evaluation and validation procedure. A vote technique was used in the process to find a solution that both parties could agree upon at the end.

A sample of the 110 x 13 matrix produced by this review process is shown in Table 1. For instance, in comparison to other smartphones, the Fire Phone's pricing and user friendliness declined. These two attributes are directly influenced by design decisions that have a detrimental effect on customer satisfaction (action reduction) and require the expenditure of resources, such as money and time.

Table 1: Summary of the 110 instances and their categorization from the matrix

	Yellow Nails Wine	**Amazon Fire Phone**	**Amazon Kindle**	**Amphicar**
Create UF	1	2	2	2
Create HF	0	0	0	0
Create RES	1	0	0	0
Raise UF	1	0	0	0
Raise HF	0	0	0	0
Raise UF	1	0	2	0
Reduce UF	2	1	1	3
Reduce HF	0	0	0	1
Reduce RES	1	3	0	3
Eliminate UF	2	0	0	0
Eliminate HF	0	0	0	1
Eliminate RES	0	0	0	0
Success	1	0	1	0

3.2 Analytical Statistics

After that, the database was divided into two parts using a two-thirds rule as recommended by the literature (e.g., Harrell et al., 1996), with the first part being used to create the statistical model and the second to cross-validate it (Picard and Berk, 1990).

The maximum likelihood estimation criterion was used in the analysis and regression by the IBM SPSS Statistics® module. The following prediction equation formula was created using the coefficients that logistic regression returned:

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

where z is the logit function used to guess the chance of success and the coefficients are suggestions to designers for what they should do when they are coming up with radical new ideas.

More specifically, adding a new feature that lowers the consumption of resources (e.g., energy, space, time, etc.) or providing a new, practical function (e.g., the first PlayStation's capacity to play audio CDs) are acts that more positively affect the possibility of success of new products. In reality, their maximum coefficients in the equation, 1,842 and 2,130, are positive.

When one compares these coefficients to those of the actions that only relate to improvements rather than introductions, like lowering a photo camera's mechanical resistance, one can see that those actions are also recommended. Furthermore, it might be simpler to enhance an already-existing trait than to introduce a completely new one. On the other hand, new features that make up for flaws, like the HP touchpad's wireless charging feature, or better features that offer a benefit, like the Microsoft Zune's bigger screen, only slightly raise the chances of success. Therefore, designers ought to consider whether to proceed in this direction, and businesses ought to exercise caution when suggesting products that

Applied Science & Engineering Journal for Advanced Research
ISSN (Online): 2583-2468
Volume-1 Issue-3 || May 2022 || PP. 34-42 DOI: 10.54741/asejar.1.3.6

incorporate these kinds of changes as the primary means of differentiating themselves. Ultimately, any action that lowers customer happiness is bad advice. Removing a feature that minimizes a negative aspect is the worst option because it has six times the impact of other actions.

When a product returns a value greater than 50%, the established model predicts that it will be successful; when it does not, it predicts market failure. In turn, this meant that the metric accurately predicted nearly 90% of the subgroup chosen.

By looking at past research, three interesting control variables have been found: nationality (Johnson et al., 2009), firm maturity. Because there are so many B2C products, the study did not include the former variable because it would have rendered the deepening ineffective. With regard to the latter, we made a distinction between startups and mature organizations, with the latter being described as recently established businesses without a track record of operations (Giardino et al., 2016). Finally, we made a distinction between corporations that are based in the US and those that are not, given the large number of US-based firms. A comparison of the original model and the models that were derived with dummy variables included in the analysis is presented in Table 2.

Table 2: Model Comparison

	Model 1	**Model 2**	**Model 3**
	Only Design Variables	**DV + Firm Maturity**	**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

First of all, there are similarities between the three models' results, especially when it comes to the sign and orders of magnitude of the coefficients. This data unambiguously demonstrates the importance of design variables—apart from organizational, managerial, and strategic ones—in product success by establishing a relationship between the 12 potential adjustments and the product's success. Undoubtedly, designers and managers alike can benefit from knowing the likelihood of success for each product in the company's portfolio when allocating resources to the most promising initiatives.

Furthermore, based on the initial model, the findings indicate that six design factors exhibit significance at either the.01 or.05 significance levels. When the dummy factors were incorporated into the analysis, the outcome mostly stayed the same. Ultimately, our two additional binary logistic regression analyses shed more light on the ways in which business maturity and nationality, for example, affect the success of a product. The latter supported what is known from literature, even though it is not statistically significant: incumbents struggle when faced with radical changes.

Validation of Models

The empirical model was then evaluated in terms of the model's performance as well as the fit and its statistical significance.

In the previous testing, the explanatory factors' predictive power for the response variable was indicated by the Cox & Snell R-square and Nagelkerke R-square values, which approximate the coefficient of determination R-square (Menard, 2000). In this instance, the values are identical to 0.539% and 0.719%, respectively, indicating a strong correlation between the predictors and the forecast. Furthermore, the Hosmer and Lemeshow (2000) test examines the degree to which expected values for certain subgroups are similar to the observed ones. In this instance, the p-value of 0.314, which is higher than the recommended cutoff of 0.05, indicated that the nine groups that were found to be statistically similar Table 3 provides a summary of these findings.

Table 3: Model Reliability Summary

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

Finally, we verified the model by assessing its performance on data other than the ones used to construct it using the coefficients of the logistic regression, in accordance with the guidelines of data splitting (Arboretti Giancristofaro and Salmaso, 2007). In fact, overestimating the model's performance results from verifying just from the modeling data (Park, 2013). 86% of the data in the validation sample is properly predicted by the model, as shown in Table 4. Furthermore, 82% of accurately expected market failures are incorrectly predicted, compared to 91% of correctly predicted success situations.

Table 4: Validation Summary

	Correctly predicted	Correctly Predicted	Overall Success
	Success Cases	Market Failures	Percentage
Modelling Sample	87.9%	90.9%	89.4%
Validation Sample	90.9%	81.8%	86.4%

It is necessary to compare the current model's dependability to other earlier models that served comparable functions. This comparison looks at the Matthews correlation coefficient, and precision and recall (Maroco et al., 2011). These can be seen in Table 5.

Table 5: Index Comparison

Index	Present Model	Borgianni et al. (2013)	Borgianni et al. (2013)	EBONSAI
		log reg	neural networks	(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	0.73	0.61	0.77	0.26
Correlation				
Coefficient				

The results of our model are similar to those of the neural networks model and much better than the logistic regression model used by Borgianni et al. (2013), as precision, F-measure, and Matthews correlation coefficient are all higher and recall is only slightly lower. Furthermore, logistic regression demonstrates its potential—that is, its capacity to calculate the individual variable's impact—in contrast to neural networks.

Lastly, the model that has been described also performs better than the EBONSAI decision assistance tool. Though it hasn't been brought up before, it was picked as a pertinent benchmark since its objective—the expectation of product success on the market—is similar to this one.

3.3 First Illustrative Case

We chose to approach it in light of the fact that other cases in the literature assessed the revolutionary influence that the iPhone had on the mobile phone sector. Comparing the evidence wasn't the point because the factors being studied come from very different points of view. Instead, the goal was to give a more design-oriented understanding of the phenomenon. By marketing the iPhone in 2007, Steve Jobs and Apple were able to capitalize on shifting corporate, consumer, and environmental forces. This led to the development of a new technological paradigm.

First of all, by creating a browser based on the PC standard and introducing huge touchscreens, they were able to foresee the demand for mobile phones to have more capabilities (Funk, 2004). Cultural factors also have an impact on how well-liked the iPhone is; in fact, the device's design contributed to its status as a status symbol (Laugesen and Yuan, 2010). These innovations, which Apple introduced to the mobile phone business, offered users a variety of rewards, both material and emotional. In addition, the first iPhone offered a more user-friendly mobile interface than rival models. This is another attribute that is closely related to the utilization of a certain resource, namely the time and abilities needed to utilize the product.

On the other hand, the corporation initially established a high price for reasons related to market positioning, which badly impacted a resource during the product's redefinition.

Moreover, the technology upon which the first iPhone was based necessitated a mobile data service plan, even in cases when customers were unwilling to pay for one. As a result, a mobile phone was no longer independent of that type of service for the first time. This choice signified the removal of a resource, namely the ability to receive services from other sources independently.

Table 6 provides a summary of the iPhone case. At this point, we used our model in accordance with the determined design options, and in particular, we were able to determine a 73% chance of success by obtaining z = 1.012.

Table 6: Apple iPhone analysis

Action	Feature	Functional analysis
CREATE	Browser Web based on personal	UF
	computer standard	
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	RES
	data service plan	
ELIMINATE	User-replaceable battery	RES

3.4 Second Illustrative Case

Another scenario we examined was the revolution in photography that GoPro sparked. Due to his involvement in the action sports community, which was a niche that the major players in the photography industry did not consider, Woodman promoted the GoPro in 2004 (Shannon, 2016). Through his comprehension of novel supply-side and demand-side situations, he not only enhanced the product but also successfully ushered in a novel technological paradigm.

He took advantage of newer information and technological advancements to enhance a crucial function, such as portability, and added a feature—impact resistance—that is essential for filming extreme sports up close. Regarding the first classification, the product's portability could be seen as a resource because it affects the amount of space needed for use and storage. On the other hand, the camera's impact resistance could be seen as a harmful function because it comes with a common downside.

Woodman offered clients the opportunity to simultaneously record and capture their passions (Berardinetti, 2016). GoPro adopted this strategy in conjunction with accessory manufacturers and by making GoPro almost universally installable. More specifically, mounting the camera anywhere was a novel feature that benefited end users and can be categorized as a helpful feature that was developed. The availability of accessories can also be considered a helpful function, but in this case, it was just an enhancement.

Based on the results of this evaluation, Table 7 summarizes the design decisions that make up the GoPro example. The model then calculated a 97% success probability.

Table 7: GoPro analysis

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

IV. CONCLUSION

A new technological paradigm necessitates not just design and technology-related decisions but also administrative activities and strategic evaluations.

This latter viewpoint is the main emphasis of the current investigation. According to the traditional criteria of innovation management literature, it does not investigate either of the conditions necessary to support the emergence of a new technological paradigm and radical innovation or the preferred strategic and managerial orientation; instead, it approaches the issue from a complementary perspective derived from engineering design. The emphasis on the design choices that support drastic changes is complimentary to the more conventional viewpoints rather than in opposition to them. This point of view seeks to unlock the mystery of technology and provide the opportunity for in-depth analyses of the phenomenon at the microscale.

In light of this, the current study suggests a model to predict how the market will value novel items in relation to their design choices. In actuality, designers create attributes that greatly define products and influence consumer perception; nevertheless, design choices also adhere to particular trends in the development of technology. Therefore, it is possible to assess the effectiveness of design decisions by investigating the relationship between each choice—whether successful or not—and recurring patterns in the evolution of products.

Nearly 90% of the subset used correctly is predicted by the suggested model. Studies on moderating factors have also been conducted, and it is still shown that design variables are important for the success of products. Aside from the conventional criteria that the management literature has traditionally studied, design decisions can have a significant impact on product success. In addition, the model performs better than earlier models for comparable uses.

This is most likely caused by the administrative viewpoint that supplemented the technical one in the functional analysis of the products, as well as the more rigorous methodological foundation upon which the model is built. The implications that follow are important. Initially, managers are given another instrument for decision support to use in situations where market demands are hardly discernible. By using this type of assistance, it is possible to identify the most promising initiatives and prevent the loss of funds, time, and resources that arises from working on undervalued projects.

Second, designers receive cues about how their particular decisions will affect the success of their products, even in the absence of feedback from users. As a result, engineers can utilize these cues to determine what features should be changed to improve the likelihood that a product will succeed. As a result, the model's conclusions are especially applicable in situations involving radical innovation and when it is difficult to identify market needs.

But it's clear that in order to get more trustworthy results and define the application period, the suggested model needs to be further tested by examining more case studies.

The model's broad applicability across industries is defined by examining the efficacy of design choices that may be connected to recurring patterns of product progression, although the model's industry-specific parameters need to be adjusted at the right time. In this regard, gathering an increasing number of cases would allow the development of industry-specific models capable of identifying the quirks unique to each area.

Ultimately, the time-lapse analysis of each new feature that described a new paradigm looked at how it actually affected the way the product was used. Indeed, a product's innovations may have an impact on it both during usage and in storage. In the first instance, an automobile can reduce noise while being driven, while in the second, a folding chair can conserve room when not in use. Therefore, in order to finish the study, we must expand our analysis to include examples where innovations were applied that had an impact on them even when they were not used.

REFERENCES

1. Sivadas E., & Dwyer F.R. (2000). An examination of organizational factors influencing new product success in internal and alliance-based processes. *Journal of Marketing*, *64*(1), 31-49.
2. Sahlo A., & Cuhls K. (2003). Technology foresight - Past and future. *Journal of Forecasting, 2*(2-3), 79-82.
3. Okoli C., & Pawlowski, S.D. (2004). The delphi method as a research tool: An example, design considerations and applications. *Information & Management*, *42*(1), 15-29.
4. Rothaermel F.T., Hitt M.A., & Jobe, L.A. (2006). Balancing vertical integration and strategic outsourcing: effects on product portfolio, product success, and firm performance. *Strategic Management*, *27*(11), 1033-1056.
5. Arboretti Giancristofaro, R. & Salmaso, L. (2007). Model performance analysis and model validation in logistic regression. *Statistica*, *63*(2), 375-396.
6. Pisano G.P., & Verganti, R. (2008). Which kind of collaboration is right for you?. *Harvard Business Review*, *86*, 78-86.
7. Troy L.C., Hirunyawipada T., & Paswan, A.K. (2008). Cross-functional integration and new product success: An empirical investigation of the findings. *Journal of Marketing*, *72*(6), 132-146.
8. Borgianni Y., Cascini G., Pucillo F., & Rotini F. (2013). Supporting product design by anticipating the success chances of new value profiles. *Computers in Industry, 64*(4).
9. Cantamessa, M. (2005). *Fundamentals of product portfolio management*.
10. Norman D.A., & Verganti R. (2014). Incremental and radical innovation: design research vs. technology and meaning change. *Design Issues, 30* (1), 78-96.