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The Front-End of Product Development as Systems Thinking and Predictive Learning

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Abstract

Designing a new product, to be attractive to customers several years from its inception, is a major business challenge. The front-end of product development (the set of exploratory activities prior to project approval) is usually vague, unstructured and based on heuristics. Most supporting tools and methods interpolate data and are anchored in the present and the past. However, new product decisions are made for the future: predictive knowledge should be extrapolated from current information. This paper proposes the front-end should be akin to a scientific inquiry, with systems thinking and predictive learning as mainstays to create customer value and reduce its "fuzziness".

Keywords: fuzzy front-end, predevelopment, concept design, systems thinking, prediction, statistical learning, machine learning, strategic decision making, set-based concurrent engineering, lean product development.

1. Introduction

The front-end of product development (FEPD) comprises the activities preceding official approval and funding of a project - opportunity identification, idea generation and concept development [1]. It is often qualified as "fuzzy" because, in contrast to product development per se (clear, specific, systematic and deterministic), the front-end is vague, ambiguous, unstructured and probabilistic [2]. They are also called *predevelopment* activities and are often neglected, even if the fate of new products may be decided at this early stage [3].

Concept design is a key challenge in the FEPD. Product concept is a description of the technology, performance, features, and form of a product, or how it will satisfy customer needs [4]. It is an exclusive set of features (instances) - collectively, they

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do not belong to other sets (concepts) [5]. It is difficult to map variables (concept features) and to make sense of them into coherent and integrated concepts. Product strategy is usually performed based on heuristics and businesses struggle to keep track of knowledge and to use it effectively. Relying on heuristics can sometimes bring reasonable judgment but may also produce systematic errors [6]. There is variability in the staff's individual knowledge, skills, and experience. Often, a firm's knowledge may not be available, be inaccessible or even be forgotten and lost [7].

It is not uncommon for a recently launched product to be matched or surpassed by a new competitor, raising the bar and leaving the former behind in customer value, sales and profitability. There may be a contradiction in the product strategy process. Most supporting tools are rooted in the present and the past – competitor benchmarking, QFD (Quality Function Deployment), conventional market research, brainstorming and others. They are analytical techniques to interpolate data. But new product development needs to create value for the future: it should be predictive and extrapolate from data [8].

Although there is an extensive literature on the FEPD, there are few studies on how knowledge is created in the process [9]. Most articles tend to focus on organizational aspects, tools, process models and competencies [10] [11]. Knowledge creation is usually assumed to be implicit in the formal process. This paper investigates the FEPD as a set of activities to create knowledge to understand and to predict customer needs and aspirations, using systems thinking and data-based simulation.

2. Method

This study is grounded in literature review, theoretical model construction and simulation. With the question "knowledge creation in the front-end of product development" in mind, a literature review on *fuzzy front-end*, *front-end, predevelopment, front-end of innovation* and variations was performed. A Scopus query yielded 920 documents and Web-of-Science, 362. Initial screening, based on title and abstract content, reduced the set to 308 items. Additional review on *systems engineering, decision theory, knowledge creation, theory construction, set-based concurrent engineering, lean product development* and *statistical learning* added 134 potentially relevant works. Detailed content analysis, according to rigor, relevance and alignment to the research topic, lead to the documents on which this work is based.

Once literature was scrutinized, key concepts related to the front-end knowledge creation and decision-making were identified and defined. Definitions were compiled for theoretical fit, rigor and conciseness. A central proposition was made and a theoretical model showing both conventional and systemic approaches were built. The usefulness of a theory is subsumed by its capacity to predict a behavior. A computer experiment using an artificial neural network was conducted to simulate predictive learning in an automobile development case. As previously stated, the aim was to understand the role of systematic predictive learning in the front-end of product development and to explain why and how it can lead to customer value creation.

3. Theoretical background

The expression *fuzzy front end* (FFE) was coined by Reinertsen in 1985 [12]. FFE is the phase from the emergence of a new product need to the decision to commit resources in the development [13]. Its purpose – in economic terms – is to maximize the expected value (EV) of betting in the project [12], which is determined by its probability of success p, the upside of success U and the downside of failure D: $EV = p * U - (1 - p) * D$. The FFE can increase EV by increasing the probability of success, increasing the upside and reducing the downside. The latter can be accomplished by reducing uncertainty, getting better information about possible outcomes from existing information. Upside is increased by augmenting customer value. Woodroof [14] defines customer value as the evaluation of product features and performance, leading to the satisfaction of customer needs. Customer learning is the process of reducing the gap between what the company knows about customers and what they really value. The scholar remarks new learning tools are needed for predicting customer value. Tools such as QFD and conjoint-analysis are too narrowly focused on current design decisions and are lacking in predictive power. Cooper and Edgett [15] also identified compelling customer value as the most important reason for new product development success, others being "front loading" (anticipating problems early), spiral development (learning loops), holistic approach, continuous learning, portfolio management and an evolved stage-gate system.

Geyer, Lehnen and Herstatt [16] conducted a survey to determine the most used FEPD support methods and why companies prefer or avoid certain methods. The selection criteria were more related to familiarity and ease of use than to pure efficiency. Companies tend to stick to traditional methods, such as internal data (e.g. sales reports), external reports (from consulting, technical associations etc.) and customer observation, whereas they should consider different methodologies to seek optimal results. Khurana and Rosenthal [17] cautioned product concept is a hard-to-reach moving target: a prediction challenge. Most companies do not have a clear understanding of customer needs. However, success in the marketplace depends on how well the product concept matches customer value. Kim and Wilemon [18] remark well-defined concepts are essential to understand project requirements and risks, as well as to avoid ill-informed decisions. Since FFE conditions are vague and ambiguous, it is better to consider a comprehensive set of alternative solutions and to build a good information system on customers, competitors, technology and market conditions. Murphy and Kumar [19] point out the dynamic and unstructured nature of the front end as a challenge to generalize research findings. A project investment decision is still largely guided by "gut feel", suggesting firms are not fully aware of the evaluation methods available.

Jetter [8] also remarked companies relied on guessing instead of structured methods for handling the fuzzy front-end. The author accentuates a product concept will affect future customer experience not only at a still coming launch time but till the end of its disposal (a time span of about twenty years for some products, like automobiles). There is also uncertainty about future competitor moves. Tools such as QFD and market surveys are insufficient because they rely on historic knowledge and experience. She cites scenario building, knowledge mapping and system thinking as alternatives. In a subsequent article, Schroeder and Jetter [20] continued to elaborate on FFE supporting tools. Among requirements for effective tools: capacity to handle uncertain, imprecise and changing information; to process diverse information, turning tacit into explicit knowledge; to enhance information processing, avoiding oversimplification and decision bias. They emphasize a holistic systems-view as fundamental to provide critical understanding of dynamic relations and to encourage systemic learning and knowledge transfer among projects. The authors remark it is almost impossible to attribute an observed result (such as sales) to a certain decision (like a concept choice). Also impossible is to learn from decisions not chosen. Hence the role of simulation techniques, which support systemic learning by evaluating different decisions and their parameters. They encourage early information collection and problem solving through a wide range of hypotheses testing. They proposed systemic and holistic tools, capable of mapping fuzzy dynamic relations and extrapolating then into information about the future.

Eling and Herstatt [21] conducted a comprehensive literature review on the FFE state-of-art and concluded it still lacks a well-established conceptual framework and vocabulary, despite over three decades of existence. They identified the need for "a more holistic view on the topic of formalization".

4. Conceptual definitions

System: a set of elements, such as products, people, information, knowledge and other assets, combined to meet a need (adapted from NASA – National Aeronautics and Space Administration [22]). Elements within a system have mutual relations among them and with the environment [23]. Complex systems exhibit properties not present in a mere sum of their parts, the *emergent phenomena* [23];
Theory: system of concepts integrated into propositions, within a defined domain [24]. The goal of theory is to reduce the complexity of the world (i.e. reduce uncertainty), based on explanation and prediction [25];
Systems theory: a level of theoretical model-building that lies between pure mathematical constructions and theories in specialized disciplines. It allows moving back and forth from both worlds of Platonic theory and fuzzy practice and facilitates interdisciplinary communication [26];
Systems engineering: a logical way of thinking to design, operate, manage and dispose a system (adapted from [22]);
Concept: formally defined idea, capturing the essence of its meaning [25]. A unique mapping of arguments into values of a function (adapted from [5]);
Proposition: causal relationship explaining how and why concepts are related [25];
Domain: context of application (when and where) of a concept [25];
Data: raw facts and numbers [7];
Information: interpreted data [7];
Knowledge: information assimilated by a person [7];
Uncertainty: gap between information needed to perform a task and information that is available. It is a function of number of outputs, number of inputs and the level of performance necessary for the task [27];
Judgment: process of determining payoffs of decisions in particular situations. Without prediction, the decision maker is forced to a blind decision (*heuristic*). In the absence of prediction, the value of judgment decreases. As the cost of predictions decreases with the development of statistical learning algorithms, demand for decision making will increase and so will the value of human judgment [28];

Prediction: rigorous extrapolation of new information from existing information [28]. Good predictions require sound theoretical understanding and reliable data on initial conditions. The objective of prediction is "not to forecast but to construct alternative scenarios for the future and to analyze their sensitivity to error in both theory and data" [5];
Simulation: technique for understanding and predicting the behaviour of a system. Simulations are only as good as their assumptions [5];
Decision: choice derived from a judgment [28];
Learning: reduction in the gap between needed and available knowledge [14];
Statistical learning: techniques for inferring, modeling and predicting from complex data sets [29] [30]. It covers the disciplines of statistics, data mining, and predictive analytics [31] [32];
Supervised statistical learning: building statistical models for prediction, based on examples (data labels) [30];
Data mining: divided into two phases: exploratory, where data is used to create knowledge, to improve decision-making and to provide customer value; and testing, to confirm relationships discovered in the previous step [32];
Predictive analytics: uses relations confirmed from data mining to predict future customer behavior, an event involving many variables [32];
Value: capability to satisfy a stakeholder's need, created by the interaction of system elements in addition to their individual contributions (adapted from [22]). Better understanding of data leads to higher decision-making accuracy and to superior customer satisfaction [32];
Product development: process of transforming market and technology data into information that reduces uncertainty about customer needs, competition and technology, raising the likelihood of success [33].

5. Proposition and model

Scientific management is a systematic way or a set of methods for understanding and solving business problems [34]. It is the application of analytic techniques to processes, analysis of activities, splitting the problem into smaller blocks, elimination of unnecessary ones, grouping and sequencing those activities. In the axiomatic modality, research is driven by an idealized model. Assumptions, variables, derived solutions and insights are delimited within the scope of a model. Axiomatic research is usually *normative*, aiming at creating strategies, policies and actions, or to optimize a newly defined problem [34].

Fig.1. Conventional FEPD.

Managers usually interpret information and rely on "gut feel" to make product decisions [17] [19] (fig.1). They certainly strive to extract meaning from data and information on customers, competitors and technology, but the process is usually vague, subjective and heuristic. On the other hand, a systems approach can discipline the FEPD [8] [20] [35]. More than a single problem-solving event, it turns into theory-building, a knowledge creation activity [35] not unlike the work of a scientist in the laboratory [36]. Learning is an iterative process that produces knowledge that can be abstracted and transferred into future projects [37] [36]. A judgment without prediction is mere "guessing" [28]. Simulation and prediction (extrapolation of new information using simulation) increase the value of decision-making [28]. Fig. 2 shows the model integrating both theory and prediction in product strategy decision-making.

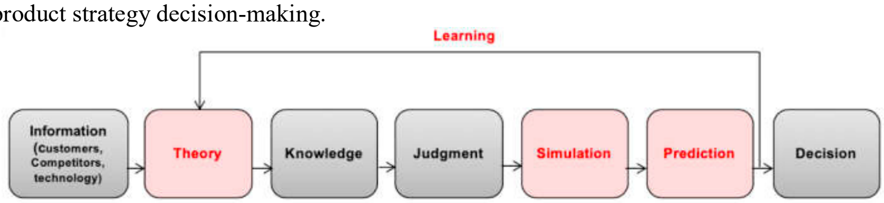

Fig.2. Systemic FEPD.

Proposition: *systems-thinking and predictive learning can reduce the uncertainty of the front-end and drive customer value creation in product development.*

6. Simulation

Vapnik and Izmailov [38] proposed using the intelligence of a "teacher" to accelerate statistical learning. Human learning requires far fewer examples than machine learning, due to the use of "intelligence" (in this case, teacher's intelligence) - in contraposition to brute force. A teacher provides *privileged information* - explanations, comments and metaphors. The authors claim privileged information is ubiquitous and can be found in almost any problem. They propose using both data and *statistical invariants* to drive learning [39]. The idea of invariants finds an analogy in the role of a good instructor or expert to guide the learning process. Many potential variables or features of a problem are irrelevant for the task at hand. An expert (teacher) helps to construct statistical invariants latent in the problem. Based on their knowledge and experience, experts offer "shortcuts", called *predicates*. Instead of initializing from a blank sheet of paper, the procedure starts by building on the expert's wisdom. Vapnik and Izmailov [39] exemplify (jocosely) with the "duck test": if it looks like a duck, swims like a duck and quacks like a duck, it probably is a duck (three predicates to qualify a duck, instead of many variables). The difference between invariants and features is that increasing invariants leads to more accurate predictions while the opposite is true for an increase in features, in this case requiring more training data.

For the experiment, a Brazilian automobile market segment was chosen: small SUVs (sport utility vehicles). Customer data collection started with semi-structured interviews and "storytelling". Six SUV owners were surveyed (three interviews, three storytelling). The interviews followed a predesigned script but were relatively flexible and lasted for about an hour each. In storytelling, users were asked to freely write an essay on their impressions and experiences. Interpretation of insights from those techniques yielded thirteen key value attributes, or independent variables (concept features): style, "ruggedness", space, trunk, comfort, "nimbleness", versatility, finish, features, connectivity, performance, economy and safety. Although not explicitly mentioned, three features - novelty, brand and price perception – were added. The selection of features, according to a researcher's domain knowledge and experience plays the role of the expert's invariant selection. Usually, additional data implies better learning, provided enough processing power and adequate algorithms are available. But data hunger is a problem in many real-life applications. The volume of data required is roughly proportional to the complexity of the model (number of independent variables). Sometimes, enough samples may not be available to model the problem. Hence, handling data should start with strategy and intelligence, using invariants and predicates. First, identifying the problem; then, judiciously selecting the model features and determining which data is needed. Human judgment partially substitutes for data scarcity, by carefully selecting the features most likely to be relevant.

Market share was chosen as the product competitiveness indicator (dependent variable). Sales data (vehicle registrations) were collected from the FENABRAVE - National Federation of Brazilian Vehicle Distributors - website (www3.fenabrave.org.br). The seventeen most representative products were selected for monthly sales figures from January 2013 to December 2018. Market share is the ratio between product sales and total market size. Using market share instead of straight sales purges (or at least reduces) effects of market seasonality and economic fluctuations, when comparing data from different points in time. Market share is the target value *y*, to be compared to estimated value *y-prime* for calculating errors (residuals) in the functions.

To synthesize the sample vectors, each product was evaluated according to the sixteen attributes (independent variables). Most sample vectors are recursive since their feature values are constant over time. However, some vectors may differ for the same product in different moments of time. For instance, "novelty" will decrease as time passes by. A product may be upgraded or customer perception may change over its life cycle. In a large company (e.g. an automobile manufacturer), such evaluation would rely on several resources: expert knowledge, proprietary research, static and dynamic testing, "tear down" etc. For this small-scale experiment, reviews from a specialized automobile magazine (https://quatrorodas.abril.com.br) were used as a proxy for part of the "expert knowledge and judgment". A scale from one to five was used to evaluate attributes. Small SUV market share (target variable *y*) between 2013 and 2018 has ranged from about 0.002 to 0.029. For normalization, they were scaled by a factor of 200 to bring them close to the independent variable *x* range.

The configuration of vector $\boldsymbol{x}$, with features x_i is the product concept proposition from the "expert". They represent a selected a priori finite set of predicates, which replace a potentially infinite set of functions (all possible product features, attributes and combinations). Selected predicates are also invariants in the creation of customer value: they are not individually affected in importance for the customers (which is not the same as the technical compromises among product attributes that sometimes occur in practice). Every concept feature must be clearly defined (e.g. "economy" means fuel autonomy in kilometers per liter, split between 70% of urban and 30% of road use; "trunk" stands for volumetric luggage capacity and easy loading access, etc.). A concept is given by $f(x, x^*, \alpha)$, where *x* is the feature variable, x^* is the expert's privileged information and α, variable parameter weight (calculated by the algorithm). As far as experts study customers, analyze relations among predicates, understand how they meet customers' needs and aspirations and make those propositions clear and explicit, they are constructing a theory of customer value, to be tested in simulations, to predict the market acceptance (measured by market share) of a hypothetical product.

In the process, 765 vector samples with sixteen independent feature variables (concept attributes) and target dependent values were synthesized. They were split in a 80:10:10 proportion among training, test and validation sets (they yielded slightly better performance than the default 70:15:15). Due to the relatively small sample size, a "shallow" neural network with one hidden layer was used. There is no consensus in the literature concerning the number of units in a hidden layer. A common bounding heuristic is between the ratio of input and output layer sizes and less than twice the input layer size (p). In the experiment, architectures ranging from p/2 to 2p nodes (8, 10, 12, 16, 20, 30) were tried, yielding correlations between 0.89 and 0.95 - the best result was achieved with ten units. The hidden layer was activated by a hyperbolic tangent function *g(z) = tanh(z)*. Target values are activated by the ReLU (rectified linear unit) function *f = max (0, x)*. As most nonlinear optimization techniques, the Levenberg-Marquardt method iterates to find the minimum of a multivariate function. It seeks to minimize the sum of squared errors in the nonlinear function and acts as a combination of a Taylor series approximation (Newton) and the steepest descent methods [40]. The experiment was run on MATLAB™ R2018a, in a MacBook™ with 1.2 GHz Intel™ Core M processor.

7. Results

The quality of result in a computer simulation is determined by its optimality – the extent a result achieved is the best possible [34]. The experiment yielded overall correlation coefficient R = 0.9485, after 15 epochs of 1,500 iterations. The correlation R for testing was 0.9612 and for validation, 0.9579. It was a small-scale experiment, with sixteen independent variables, 765 samples and a relatively coarse evaluation scale with discreet values. Nevertheless, it shows a customer-centered approach using expert knowledge and product concept simulation can produce significant results.

The combination of qualitative market research, evaluations from a specialized magazine and the researcher's judgment and experience were used to generate features (x, x^*), which played the role of predicates and invariants ("privileged information" [39]) supplied by an expert. Features x_i were combined into a vector design $\boldsymbol{x}$. The functions $y = f(x, x^*)$ are the set of hypotheses or the customer value theory in the project. The learning algorithm provided simulation and prediction based on that theory and yielded statistical validity. The acquired knowledge from the specific case can be abstracted to application in other settings (projects).

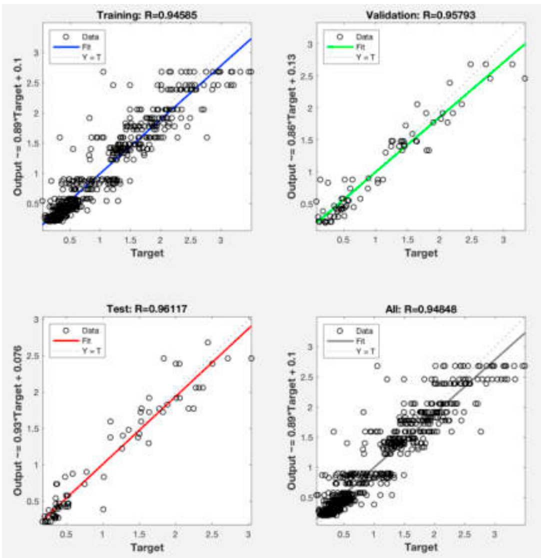

Fig 3. Correlation fits (MATLAB™).

8. Conclusion

Current product predevelopment practice may not be adequate. There is too much variability and loss of experience and knowledge. There is also lack of systems-view and integration. This article tackles a shortfall in the FEPD and suggests a systems approach supported by predictive learning. It integrates methodological rigor, human judgment, statistical learning and customer-centered view. The human expert is an active participant in the learning process, neither a mere "guesser" nor just a data provider. A stable set of functions (the artificial neural network) becomes a knowledge repository and a tool for market simulation: customer value, product attributes, technical features and specs, sales, prices, competitive data, market history, technology evolution are contemplated.

Machine learning extracts relationships that are difficult to map mentally or heuristically, but usually needs large amounts of training data. Data hunger is the Achilles' heel of supervised learning [41]. Manufacturing turned-digital companies usually do not have access to the huge volume of data native digital companies do. This study suggests a way to partially reduce the substantial need for data, by substituting human judgment. By feeding qualitative information and expert domain knowledge, it is possible to preclude the need for massive amounts of data, which would be required in the case of blind data feeding. The objective was to pre-select key customer values and use statistical learning to weigh and to refine the relations among concept attributes. Narrowing the range of potential research features - which would otherwise be extensive and demand a proportionally larger amount of training data - leads to increased efficiency and speed. In a certain way, data quality was traded for quantity.

The proposed model is an extension of substantive existing literature. It contributes by offering a holistic problem-solving framework, integrating both systems thinking and statistical learning, to explain and to predict in the FEPD. The learning process produces knowledge that can abstracted and transferred to other projects. However, the simulation was based on a single industry (automobile manufacturing) – a limitation. An artificial neural network was chosen as the simulation algorithm. However, that does not mean other tools - such as SVMs (support vector machines) - could not be equally or more effective. Future studies comparing the efficiency of alternative methods could be useful contributions. Overall, there is a need for more research on the FEPD as a knowledge creation process, more systemic and less fuzzy: a customer value creation laboratory.

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