

Data-Mining Tools for Business Model Design: The Impact of Organizational Heterogeneity

Nicola Castellano and Roberto Del Gobbo

Abstract Business models may be considered as “cognitive” devices since a deep level of knowledge about customers, suppliers, and competitors is needed for their development. Recent studies show that data-mining tools produce a positive interaction with business models, empowering the strategic performance capabilities that drive the achievement of competitive advantage.

The present paper aims to discuss whether the adoption in a real context of data mining in support of business modeling may be enabled or hindered by organizational heterogeneity.

The Structured Neural Network, adopted in the case study, is particularly suitable in support of strategic management, since it stimulates the convergence of personal knowledge and beliefs toward the exploitation of the key concepts and the cause-and-effect relations needed for the design of the business model. Furthermore, it provides a fact-based test for its robustness. The results provide both scientific and practical implications.

Keywords Business models • Data mining • Structured Neural Network • Decision-making support • Knowledge discovery

1 Introduction

Extant studies about business models do not express consensus about what a business model is, how it is composed, and what it is for, probably due to extreme difficulties in creating a general taxonomy which might be adaptable to every kind of environment. However, some concepts seem to be generalizable:

- Business models should explicit the value proposition that a company aims to address to its customers.

N. Castellano (✉) • R. Del Gobbo
Department of Economics and Law, University of Macerata, 62100, Via Crescimbeni 14,
Macerata, Italy
e-mail: nicola.castellano@unimc.it; roberto.delgobbo@unimc.it

- A learning and cognitive ability is needed during the exploitation of a business model in order to detect signals that reveal the opportunity to adapt the existing model to changing environments (for established companies) or to create a new model (for start-up companies).

The adoption of business models assumes that strategy is “discovery driven” rather than planning oriented. Earlier approaches to strategy assumed that managers should have been focusing on discovering the company core competencies and consequently in searching the most profitable market opportunities. Conversely the business model approach assumes that managers should be constantly monitoring the changes in customers’ need and values, in order to properly adapt the company value proposition [1].

The learning activity about customer needs and values can be intended as a knowledge discovery and, considering the massive amount of data often available, can be facilitated by the use of data-mining applications. Heinrichs and Lim [2] show that the adoption of data-mining tools creates a positive interaction with business models, improving the managers’ speed to focus on the most significant opportunities and threats that require actions to develop and sustain the competitive advantage.

The research of Heinrichs and Lim is based on an experimental study which implicitly assumes that all the respondents play the same role in a virtual company environment, holding similar skills and competencies.

The present paper aims to extend the research by investigating the adoption of a data-mining tool in support of a business model design in a real context, characterized by extreme organizational differences concerning the actors involved, that can enable or hinder the effective adoption of the information tool. In particular the data-mining application is limited to the initial stage of the business model design, when a common explicit knowledge about the customer needs is required to develop a suitable value proposition accordingly.

The results obtained provide slight evidence that Structured Neural Networks (the tool adopted) may provide effective support to decision-making, even when organizational heterogeneity occurs. The paper also provide evidence that the successful adoption is conditioned by the organizational attitude to learn and discuss the managers’ personal beliefs.

As practical implication, the paper also provides an example about how the information emerging from the data-mining tool may support the knowledge generation (for what concern the customer needs) and ease the design of a business model.

The remainder of the paper is structured as follows: in Sects. 2 and 3, a review of the literature about knowledge generation in support of the business models’ design and data mining is summarized. The case study research is described in Sect. 4, while in Sect. 5 the main findings are discussed. Final considerations and further research directions are described in the last section.

2 Knowledge Generation and Business Modeling

Business models adopt a holistic and systemic perspective, based on activities, intended to describe dynamics, components, and linkages through which value is created and captured.

In essence a business model describes how the company intends to meet specific customer needs, how the customers will be disposed to reward the value received, and how the company is expecting to generate an adequate level of profit [3].

Despite the definitions adopted, a common issue in literature is that the design of a business model requires creativity at first, as well as a good level of knowledge about customers, suppliers, and competitors. The business models may be considered as “cognitive” devices [4]. They promote an outside-in, rather than an inside-out, focus [1], meaning that the managers should be constantly engaged in discovering and adapting to the changing customer needs and values. Internal core competencies and key resources should be developed accordingly.

In particular for what concern the customers, the questions that need to be answered are the following [3]: What do customers really value? How will the company satisfy their needs? What might the customer pay for the value received?

Reasonably, non-accurate assumptions produce uncertainty and risky future outcomes. Managers make frequently false assumptions in those areas where they believe to hold a deeper understanding and knowledge, so they don't perceive the necessity to test their thinking [5]. The only possible way to reduce the uncertainty risk is to have a clear and explicit organizational learning, able to capture the essential changes in the environment. Furthermore, it is necessary that managers are inclined to learn, to discuss, and to revise their personal beliefs and knowledge about the company and its competitive environment.

If the customer needs are clearly exploited, the managers will have the possibility to formulate a suitable value proposition. Furthermore, the knowledge about what the customers are willing to pay for is essential in order to connect the sale prices with the items perceived by customers as more valuable, thus amplifying the managers' expectations about monetization.

Assuming that lot of knowledge about these players is implicit, the managers involved in the business model design may face difficulties to fully rationalize and articulate it, and then a discovery approach based on experimentation and learning may be needed [3].

The generation of knowledge can be effectively supported by information technology, through which useful information might be produced sourcing from the massive amount of data often available in the companies' information systems and on the Internet. The adoption of information-based knowledge management tools may produce the following advantages [2]:

- Improve the managers' strategic capability, intended as the speed needed to react to environmental changes and select appropriate strategic and tactical business models.

- Develop a fact-based consensus, driving decisions without exclusively relying on personal perceptions and past experience.

Generally, the knowledge creation is supported by the following information tools: data bases, cognitive maps, decision support systems, data mining, and intranets. In particular the adoption of data mining is ever increasing.

Data-mining tools are based on statistical and machine learning theories. Their first adoptions date back to the end of the 1980s in support of marketing and other operating tasks. In the present paper, a Structured Neural Network (SNN hereafter) is adopted, since it is particularly suitable for supporting the business models' design. In the following section, the main characteristics of SNN are described.

3 Structured Neural Networks and Business Modeling

Neural Networks are inspired by biological systems and can be defined as computational models composed by a system of units (neurons) and linking connections (weights).

Every neuron is stimulated by data received as input and produces a value as output. The inputs can be generated either by external stimuli or produced by preceding neurons.

In general, the adoption of a NN is suitable when the relationships between the variables are known to be nonlinear or, not known, a priori. Additionally, a NN may be preferred over traditional parametric statistical models, when the data do not meet the assumptions required by the parametric model or when significant outliers are included in the dataset.

Usually NN applications produce results without requiring any preliminary explicit assumption about the system or the process modeled; therefore, many users, especially those not holding developed informatics skills, may perceive NN as a "black box" and may feel skeptical about the significance and reliability of the information produced.

Particularly, when supporting strategic decisions, a preliminary shared knowledge about the variables included in the model and their expected cause-and-effect relations may improve the level of trust and acceptance among the managers involved. In this context the SNN technique can be considered a valid solution for predictive modeling.

SNN is based on cognitive models that summarize the managers' beliefs and experiences about a concept [6]. Their adoption requires a preliminary exploitation and sharing of personal knowledge, converted into an explicit cause-and-effect predictive model. The SNN allows managers to test the robustness of the predictive model and provide insights about the relevance of the expected relations between the variables in terms of magnitude of the impacts produced.

The adoption of a SNN requires a top-down approach, suitable for hypothesis testing, in order to confirm existing notions and opinions about a fact [7].

Generally, the adoption of a data mining requires the integration of managerial and technical (statistic and informatics) skills, which are usually held by different actors. Consequently managerial interaction is required to generate useful insights.

In the following section, we describe the adoption of a SNN in Lube, a company operating in the kitchen furniture industry. The SNN has been adopted to support the initial step of the business model design, during which the customers' perceptions are explored in order to discover the items considered as more valuable. The information obtained will drive managers in developing a suitable value proposition.

4 Mining Through Customers' Perceptions

The Lube company is actually ranked as one of the top Italian kitchen producers. In Italy the company gets in touch with its final users by means of a wide network composed by 1500 private resellers, which are usually multi-branded licensees.

The resellers can significantly influence the final users' purchasing decision, since they have room to promote the brands of the companies they feel more satisfied with. Their level of satisfaction, in turn, is affected by multiple factors which include, of course, the product, but also extend to the operating processes (promotional, commercial, logistic, administrative, and so forth) that the resellers need to manage in strict connection with Lube.

For the above mentioned reasons, when exploring the customer needs and value perceptions in order to design an effective business model, the managers of Lube need to consider a double-layer customer perspective, centered either on the final users and the direct customers (i.e. the resellers). The direct customer perspective must help the managers to discover the needs and value perceptions of the resellers, in order to develop suitable actions and resources and activate win-win relations that may trigger shared satisfaction and profitability and a durable competitive advantage.

The Lube company does represent an interesting case study at least for two reasons. To the best of our knowledge, this paper represents the first attempt to describe the adoption of a data mining in support of a business model design. Secondly, considering the critical role of the relations between Lube and its customers, the process employed to implement the data mining and the information produced may develop the recent growing literature about network business models [8, 9].

The case study can be considered *explanatory*, since it is employed to explain how a set of (qualitative) variables impact on a complex phenomenon. The case study methodology is well suited for many kinds of information systems and software engineering research, as the objects of study are contemporary phenomena hard to study in isolation [10]. Data are collected through direct observation, adopting an action research approach. In particular one of the authors directly

participated to the processes under investigation with the role of project coordinator.

The case study describes an attempt to adopt a Structured Neural Network, in support of the design of a business model. The project has been divided in three steps:

Business model design, through knowledge exploitation and sharing of personal beliefs

Data collection about customer perceptions through survey

Adoption of the data-mining technique to test the robustness of the business model

The case study may extend the extant literature on business models, by providing evidence about how the qualitative factors may enable or hinder the adoption of data mining in an organizational context characterized by heterogeneity. Summarizing, we formulate the following research questions:

RQ1: May the adoption of data-mining tools provide results perceived as useful by managers even in a context characterized by organizational heterogeneity?

RQ2: Are there any organizational factors enabling or hindering the perceived usefulness of results?

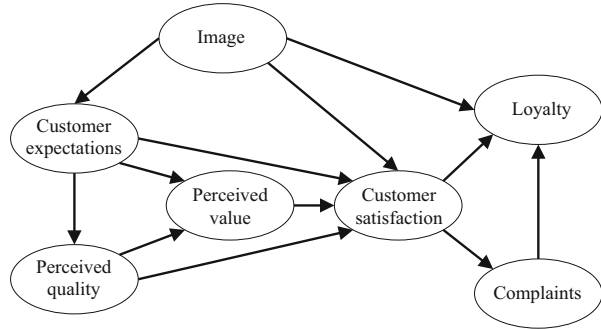
During the first step the managers of the company have been involved in creating a shared causal map in which the most significant cause-and-effect relations between customer needs, value perceptions, and level of satisfaction are represented.

According to Langfield-Smith [12], collective maps cannot be elicited by means of a structured protocol, since its determinants (the collective cognitions) are not durable and persist only during the collective encounter. Conversely, the products resulting from the collective cognitions can be investigated and so the processes needed to their development.

In particular, the collective cognitions are expressed during encounters where a group of individuals attempt to find some common ground in order to take a shared decision or agree to take some collective action. Consequently, the identity of these collective cognitions may be inferred only from the group's discussion and behavior. For that reason we decided to base our analysis only on what occurred during managers' meetings.

As an initial step, a focus group has been organized, participated by the project coordinator and by the following directors: sales, marketing, production, finance, and R&D. Furthermore, a panel of five significant customers, considered as strategic partners in terms of volume of sales and robustness of the relation with Lube, participated to the focus group in order to stimulate a discussion between managers' beliefs and customer expectations useful to elicit a more customer-oriented causal map.

To facilitate the discussion, the project coordinator asked the participants to comment the well-known ECSI framework (European Customer Satisfaction Index) and adjust it according to the peculiarities of the Lube environment (see Fig. 1).

Fig. 1 The ECSI model

The ECSI provides an economic assessment of customer satisfaction. It derives from an adaptation of the Swedish customer satisfaction barometer [13], and its wide theoretical ground lends it to be adaptable to several different industries.

Customer satisfaction cannot be directly measured since it is developed through mental constructions. Assuming that a set of determinants produces relevant impacts on customer satisfaction, the measures about those variables might then provide a valid proxy of customer satisfaction.

During the focus group, the managers articulated the variables expected to impact on customers satisfaction and loyalty.

As a result, the satisfaction framework shown in Fig. 2 has been developed. For matters of privacy only, a simplified version is shown.

The Lube framework includes the latent variables (LV), customer expectations (CE), perceived quality (PQ), image, perceived value, satisfaction, and profitability.

Either CE or PQ is connected to a group of 11 manifest variables (MV), representing the technical/functional features, sellout support, and operating relations.

The technical/functional features determine the efficiency of the operating processes, in which the company and the customers are involved, and include accuracy and on-time delivery to final users, rapidity in replacing defective or nonconforming products, and availability and ease of use of the configurator software employed by the customers to design the kitchen project on the base of the requests received by the final users and to submit the order to the headquarter.

Sellout support includes all the activities undertaken in order to increase the likelihood for the customers to successfully sell the kitchens produced by Lube. The following variables are considered: richness and detail of catalogs, merchandising initiatives organized by the headquarter (products promotions, advertising material, and so forth), and specific training initiatives directed toward the customers.

Operating relations represent the human side of the relation between Lube and its customers and include courtesy, promptness of the headquarter staff in providing answers and solutions to the customers' requests and problems, and technical assistance.

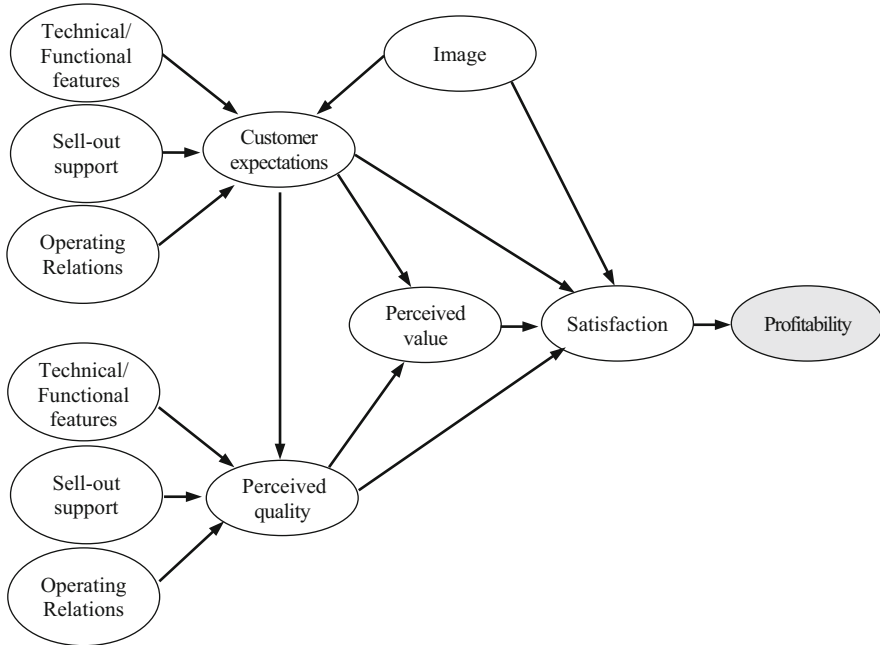


Fig. 2 The (direct) customer perspective of Lube business model

The CE expresses how customers consider relevant the three drivers, whereas PQ measures the perceptions of customers about how Lube produces quality and satisfaction when managing issues relating to the three drivers.

The perceived value is connected to the quality/price ratio and to a qualitative assessment about the value of products and services provided by Lube in comparison with those of the main competitors.

The architecture of the network defines how the nodes are interconnected. In total the developed framework considered 34 manifest variables. The construction of the SNN was conducted by following the structured process described by Coakley and Brown [11]. The software “STATISTICA Data Miner” (StatSoft) was employed to support the analysis.

In the following step, a sample of customers has been involved in a survey and has been asked to evaluate, through a questionnaire, the 34 manifest variables by means of a 10-level qualitative scale, where 1 expresses a “very negative” and 10 a “very positive” opinion about the item.

The sample was composed by 600 sales outlets randomly selected. The sample was stratified by level of sales and by geographical area. The survey consisted of items related to each LV shown in Fig. 2. As input variables for the model, 24 questions have been identified. All items were scaled from 1 to 10. The data collected allowed to develop a Structured Neural Network (SNN) to measure the

significance of the stimuli produced by the variables included in the framework (the arrows in Fig. 2).

As described above, SNN are particularly suitable in this context, since they allow to model nonlinear relations between variables in the absence of any a priori information about their shape and nature, as in the case of customer satisfaction and its determinants.

Moreover, since the customer perspective of Lube business model has been developed as a cognitive representation of the managers' knowledge, exploited and shared, the SNN may provide a test of robustness based on data sourced directly from customers and representing their needs and beliefs. The SNN provides, then, a fact-based support to the managers' assumptions and provide a focus on the variables which should be more sensitive in improving satisfaction and profitability.

The inclusion of profitability in the network allows to quantify the importance of a latent variable in creating monetary value and allows managers to evaluate whether the costs generated by the initiatives aimed to improve satisfaction might be covered by the expected revenue streams.

Figure 3 shows the results produced by the adoption of the SNN: the weights reflect the importance of the stimuli produced on the neurons. When a weight is negative, the connection produces an "inhibitory" effect. As an example, customer expectation produces an inhibitory effect on perceived value. This means in practical terms that the customers' expectations do not produce a direct impact on

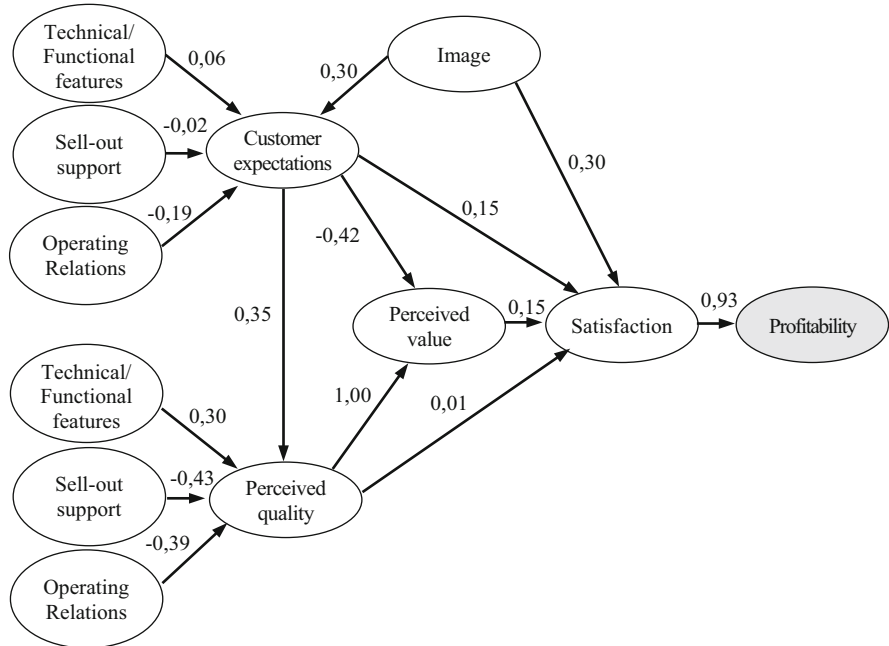


Fig. 3 Results produced by the Structured Neural Network

perceived value but produce a stimulus on perceived quality that, in turn, stimulates perceived value and satisfaction. Conversely, when the weights are positive, the highest the value, the highest the magnitude of the stimulus produced on the neuron.

5 Discussion of Results and Managerial Implications

The results produced by the SNN have been discussed during a meeting participated by the CEO, the project coordinator, and all the managers involved in the focus group. The managers hold extremely different profiles for what concern the past working experience and educational background (see Table 1).

The CEO did not attend university; he got a high school certificate in accounting and worked in the company since the early 1970s. He developed a really high experience in the industry and he is one of the elder managers.

The directors of marketing and finance are both graduated in economic disciplines and have been working in their actual role for more than 20 years. The directors of R&D and production also have been working in Lube for more than 30 years covering different positions that let them develop a high on-the-job experience and technical skills on production planning and product development.

The sales director developed past experiences in different companies of the same industry, and once in the company, he covered different roles in the sales department, such as the head of the sales orders processing office. None of the managers involved have developed competencies related to the management information systems.

The project coordinator is the youngest in the group; he is graduated in economic disciplines, got a PhD in management, and developed deep mathematic, statistic,

Table 1 Managers' profile: working experience and educational background

Managers	Level of instruction	Experience in the company	Previous working experiences	Information systems skills
CEO	High School Certificate	>40 years	No	Low
Sales	High School Certificate	> 25 years	Yes	Low
Marketing	Degree in Economics	> 20 years	Yes	Low
Production	High School Certificate	> 30 years	Yes	Low
Finance	Degree in Economics	> 20 years	No	Low
R&D	High School Certificate	> 30 years	No	Low
Project Coordinator	PhD in Management	< 15 years	No	High

and informatics skills. His experience in the company is relatively low (compared to that of other managers). He represents the company intelligence, since he is appointed to produce almost all the information needed in support of strategic and tactical decision-making.

Despite the differences between the managers, they all considered as reliable the results obtained and did not show any skepticism, neither when the results, unexpectedly, did not confirm their individual or collective expectations and prior beliefs.

The results obtained are in line with extant literature [2], but in addition our study provides an empiric slight evidence that the adoption of data-mining tools may provide an effective support to strategic planning and business model design, even when the operating managers do not hold similar competencies, past experiences, and educational background.

It's worth noting that the CEO played a key role in determining the tool effectiveness in terms of support to decision-making. During the meeting he never showed any doubt about the reliability of the results produced by the SNN and always considered them as accurate and reasonable. His mind-set positively influenced all the participants that aligned their mental attitudes with that of the CEO. We may then argue that the company attitude to learn, either if shared between managers or produced by a top-down persuasion, is necessary to determine the effectiveness of the information tool.

For what concern the managerial implications, the managers agreed that the image was the main driver of customer satisfaction since it showed the largest positive weight in connection to the satisfaction neuron. After the discussion the managers decided to align their decision to what revealed by the SSN: the corporate and product image needed to be strengthened, in order to positively impact on satisfaction and foster profitability. Surprisingly, before the meeting the image was generally perceived as one of the less significant drivers of customer satisfaction.

6 Conclusions

Summarizing, the present paper shows how a SNN may support the business model design and its managerial implications in terms of knowledge generated.

The paper extends literature on business models since it shows that data-mining tools, and Structured Neural Networks in particular, may improve the managers' strategic capability even when they do not hold similar competencies and educational background. The successful adoption of the SNN has been positively conditioned by the mental attitude of the CEO that played a key role in determining the general acceptance of the results by all other managers and the effectiveness of information produced in driving decision-making.

The paper also provides several managerial implications. It shows that the preliminary design of the network can be considered as a knowledge creation

step, where managers' experience and perceptions are converted into collective explicit knowledge through externalization.

The cognitive map developed, which represents the architecture of the SNN, can be considered an explicit vehicle of information that allow to transfer, share, and discuss company knowledge throughout the organization and foster a general consensus about company policies and strategies.

The quantitative results, expressed in terms of magnitude of the impact that a variable is expected to produce, allow to test the robustness of managers' perceptions and provide a model that facilitate decision-making and strategic planning.

Finally, it's worth noting that the considerations drawn in the case study are context specific and may not necessarily be generalizable to other companies. Further applications of data-mining tools both in similar and different organizational and competitive environments might provide further comparable evidences.

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