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www.emeraldinsight.com/0025-1747.htm

Received 16 March 2017
Revised 2 October 2017
Accepted 26 November 2017

Strategic mapping: relationships that count

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Abstract

Purpose – The purpose of this paper is to study how the design of a strategy map can be supported by measures expressing the customers' perceptions about strategic factors and their related determinants. In particular, managers are provided with a fact-based test useful to revise prior knowledge and beliefs.

Design/methodology/approach – A case study is used to describe the adoption of the partial least squares path modelling (PLS-PM) approach to structural equation modelling in order to compare competing strategy maps and select the one that best fits customer perceptions. A focus group was organised to design the strategy maps, which were tested through a survey of 600 randomly selected resellers.

Findings – The empirical-based validation of a causal map by using PLS-PM may effectively stimulate a revision of managers' collective perceptions about a phenomenon characterised by implicit knowledge, as in the case of customer needs.

Research limitations/implications – The case-study company operates in a business-to-business environment, and thus only the needs of direct customers have been included in the analysis. Final users' needs should also be considered, even if different solutions are required for data collection.

Practical implications – The proposed approach provides a set of indicators which allow managers to identify strategic priorities, thus facilitating decision making and strategic planning.

Originality/value – In the strategic management literature, few attempts have been made to operationalise the complex and multidimensional latent constructs of a strategy map combining managers' implicit knowledge and empirical validation in a "holistic" manner. The adoption of PLS-PM is relatively new in testing the accuracy of causal maps.

Keywords Strategy maps, Business analytics, Knowledge discovery, Partial least squares path modelling

Paper type Research paper

1. Introduction

Strategy maps (or strategic causal maps) provide a visual representation of a company's objectives involving critical success factors (the strategic plan) and the fundamental causal relationships among them (Kaplan and Norton, 2000). The maps allow the summarising of the company's strategy in a clear and comprehensive manner, which should facilitate communication and learning throughout the organisation and focus the managers' attention on the fundamental objectives and initiatives through which they can be achieved.

The designing of a strategic plan, whether or not a map represents it, is always inspired by customers, who represent the fundamental source of sustainable value creation (Kaplan and Norton, 2004). Considering that knowledge about customers is generally implicit, information and intelligence becomes crucial to providing managers with empirical evidence (Teece, 2010) useful for supporting decisions about the critical factors and initiatives valuable to improving satisfaction for both new and existing customers, in turn influencing company performance.

Information technology can support managers by rationalising implicit knowledge about customers, helping them to articulate fully innovative and successful value proposals.

The authors thank two reviewers of the journal for their insightful and valuable comments that have substantially improved the paper. The authors are responsible for all the remaining errors.

0025-1747
DOI 10.1108/MD-03-2017-0224

Generally, in this context, IT tools are used to discover hidden customer needs or emerging trends by sorting through massive databases. However, highly skilled managers may be more inclined to articulate a value proposition by relying exclusively on their prior experience. In these cases, IT can provide an empirical benchmark that is useful in testing the reliability of managers' preconceptions. Within this last perspective, the aim of the present paper is to describe how the adoption of structural equation modelling (SEM) can support strategic management when managers' collective perceptions about customer needs and their antecedents and consequents are exploited through a strategy map.

Particularly, the knowledge and experience held by managers can be incorporated into an SEM algorithm in order to test the reliability of alternative strategic causal models that differ in terms of included variables and causal relationships. The results allow managers both to revise their prior beliefs and obtain empirical suggestions about strategic priorities, thus increasing the likelihood of a successful value proposition.

SEM is suitable for the testing of complex causal models using a holistic approach, simultaneously handling variables that are difficult to observe directly (unobservable constructs). As an additional benefit, SEM supports comparisons between alternative causal models, and is particularly helpful in identifying the set of paths that best describes the causal relationships among the variables (Roos *et al.*, 1997). This creates a positive interaction with the design of strategy maps because the employment of SEM can improve managerial ability to focus on the most significant opportunities and threats, which require attention if a manager is to create a durable competitive advantage.

Among the many estimation procedures used in SEM, partial least squares path modelling (PLS-PM) is particularly suitable and versatile for the purposes of this study, since strong assumptions about the sample size or shape of the variables' distribution are not required for its adoption. Furthermore, PLS-PM enables an explicit measurement of all the variables (both observable and unobservable) considered in a strategy map, including measures representing the relevance of the causal relations that can be particularly useful for the identification of strategic priorities.

Thus, the results of PLS-PM provide a fact-based test of a company's strategic plan, facilitating consensus among managers based on common ground. The same methodology can be replicated whenever managers need a fact-based validation of their perceptions about external as well as internal players included in a strategic plan.

Under a scientific perspective, this paper intends to contribute to the literature by discussing how quantitative measures may support strategic mapping under a confirmative approach.

The remainder of the paper is structured as follows: a review of the literature about causal mapping and strategic planning is summarised in the next section. Then, a description of the PLS-PM methodology is provided with the purpose of demonstrating how its adoption in the strategic management field may create positive implications for both academics and practitioners. Next, the steps taken to implement PLS-PM are described through a case study, after which the main findings are discussed. Final considerations, limitations and further research directions comprise the conclusion of the paper.

2. Causal mapping and strategic management

Managers often base strategic planning on their preconceptions about what is truly important for customers. Generally, they believe that the determinants of company performance are "self-evident". Therefore, their exploitation is considered unnecessary (Ittner and Larcker, 2003).

One way to reduce uncertainty is to stimulate explicit organisational learning and thus capture essential changes in the environment. The adoption of causal maps, in this context, can be particularly fruitful because they allow managers to articulate the expected outcomes in terms of value creation and value capture as well as their expected determinants, which are considered as a mix of organisational resources, competencies and initiatives.

Causal maps represent a peculiar form of cognitive maps. Cognitive maps provide a graphical representation of the knowledge and cognitions held by an individual (or a group of individuals) about a given subject, while causal maps are used to represent beliefs that can be modelled as a network, where every concept (element) is a node and directional connections between the nodes express cause-and-effect relations (Langfield-Smith, 1992). When causal maps are used in support of strategic management to provide a graphic representation of a strategy, they are often defined as strategy maps (Kaplan and Norton, 2000). Coherent with the purpose of this paper, the terms "strategy map" and "causal map" are hereby used synonymously.

The adoption of causal mapping in strategic management has been proposed in the literature for many years. Causal maps should help managers to understand how decisions are made (Axelrod, 1976). Jenkins and Johnson (1997) found that managers' cognitions, as represented through causal maps, are associated with business performance. Othman (2006) showed that the absence of a causal model can create difficulties in developing a strategic action plan and attaining the needed consensus and involvement on the part of lower organisational levels. Causal maps foster the alignment of individual mental models (Gonzalez *et al.*, 2012).

Vera-Muñoz *et al.* (2007) provided evidence that when strategy maps are exploited, managers are guided towards investing resources in those programmes that are expected to produce the greatest future benefits. Bresciani *et al.* (2014) provided evidence that strategy visualisation improves positive manager attitudes towards the content, as compared to a textual representation. Nevertheless, the designing of an effective strategy map requires a great deal of implicit knowledge about customer needs and value perceptions. Accordingly, a discovery approach based on real-world data may be appropriate (Teece, 2010).

Information technology can effectively support the generation of knowledge, allowing managers to produce useful information from the massive amount of data available in companies' information systems and on the internet. The adoption of information-based knowledge-management tools may improve managers' strategic capabilities – that is, the speed with which they react to environmental changes and make appropriate strategic decisions (Heinrichs and Lim, 2003). Furthermore, managers are supported in developing a fact-based consensus, driving decisions without exclusively relying on personal perceptions and past experiences.

The employment of information technology in strategy mapping can be helpful both as an exploratory method and a confirmatory method, and a wide range of methodologies have been experimented with in the literature. Exploratory methodologies are generally used to extract tacit knowledge by managers and articulate it into a causal map which could be the base to develop a performance measurement system (see, e.g. Abernethy *et al.*, 2005; Carley and Palmquist, 1993; Chaib-draa, 2002; Chen and Lee, 2003; Wolstenholme, 1983). As a confirmatory method, such techniques support managers in selecting the most accurate descriptive model from a range of competing representations (Homburg, 1991; Wang, 1996).

In other cases, scholars propose measures representing the strength of causal connections, which provide a powerful inference for use in the evaluation of alternatives (Montibeller and Belton, 2006). Nadkarni and Shenoy (2004) employed Bayesian networks to explicate managers' expectations about the existence of the relationships represented in a strategy map. Langfield-Smith (1992) proposed content measures with which to compare alternative strategy maps. The measures represent managers' individual assessments about: the factors to be included in the causal map; how they are causally connected; and the sign and strength of the connections. This approach is interesting since the content measures are proposed as a means to enhance (and not to replace) a qualitative assessment of causal maps, which may be particularly suitable for strategic management. In particular, the measures can evidence differences and similarities in managers' beliefs, or they can be employed to analyse how the managerial perceptions about a strategic concept change over time.

In all the previously cited studies, the causal measures summarise the points of view of the same managers involved in the design of the causal maps. In contrast, an approach is followed through which a set of causal measures that represent the customers' perceptions about the strength and directions of the relationship among the variables included in the strategic constructs designed by managers are calculated. The measures provide managers with an alternative perspective, which may be helpful in multiple ways. First, they allow managers to revise their individual and collective beliefs on an external fact basis. Furthermore, the causal values facilitate the identification of strategic priorities, i.e., the factors that customers perceive as company weaknesses, which may significantly affect customer satisfaction.

Concerning the design of a strategic causal map, in the literature, a wide range of methodologies have been proposed (Eden, 1992). Although the purpose of this paper is testing, rather than designing, a causal map, in this study, collective maps are referred to in particular (Langfield-Smith, 1996), which are assumed to be especially suitable for strategic mapping. Group model-building (or collective model-building) is effective in solving complex problems in a company or in a public administration (Larsen and Bloniarz, 2000). According to Shaw *et al.* (2003), a strategy map is a representation of a group of managers' shared strategic thinking; therefore, it is possible to define them as "group maps", whereas a cognitive map is referred to as an individual's belief about a phenomenon (Eden, 1992).

The design of a group map may be more challenging considering that individuals may be willing to defend their own opinions, and this can create conflicts. On the other hand, a group discussion may favour not only a shared vision but also the generation of new insights about the problem under discussion (Montibeller and Belton, 2006). The holistic comprehension of a complex organisational problem requires managers to integrate technical, organisational and personal perspectives (Mitroff and Linstone, 1995). Accordingly, in the proposed approach, collective strategic mapping involves managers at both the organisational and personal levels, which refer to collective and individual beliefs about a problem, respectively; whereas the quantitative methodology (PLS-PM) provides support for the technical perspective, i.e., the representation of the problem through data modelling and analytic tools.

In the following section, the basic concepts of PLS-PM are discussed in order to better understand the strengths and weaknesses of this technique.

3. PLS-PM and strategic mapping: methodological characteristics

In statistical terms, a strategy map, like all other kinds of causal maps, may be described through a SEM, wherein the factors are represented by variables linked to one another in a cause-and-effect relation expressed by the mean of a regression equation. The causal linkages (or paths) are described in the causal map as arrows whose directions express the expected relation between an antecedent and a consequent.

In strategic mapping, the system of equations provides a simplified but accurate representation of a company's strategic framework, summarizing in a comprehensive framework the most relevant causal antecedents, consequents and linkages that may be assumed to exist among these factors. This may be particularly relevant for strategic management because the visual representation of a strategy may require complex relations whereby a casual variable is expected to produce effects on multiple consequents, and, vice versa, an effect-variable may be influenced by multiple antecedents.

When translating a strategy map into an SEM, two aspects are worth considering: the measurement of the variables included in the map and the direction of the relation between the variables. Concerning the first issue, the variables included in an SEM may be manifest or latent, where the latter refers to factors that cannot be observed directly. As an example, customer satisfaction is one of the most common latent variables in management studies.

Concerning the direction of the relation between two variables, a formative or reflective relation may occur. In particular, a formative relation exists when a latent variable is dependent (or caused) by a number of manifest variables; conversely, a reflective relation is hypothesised when one or more manifest variables are assumed to be influenced by a latent construct (see Figure 1).

The estimation procedure employed in an SEM must be coherent with the need to model formative rather than reflective relations. As a consequence, a clear statement about the objectives of the application and the conceptualization underlying the model is needed. Generally, a reflective relation is suitable in strategic mapping, as the factors included in the map are more likely to be represented as latent constructs (customer satisfaction) which impact on a manifest variable (revenues).

An SEM is composed of two distinct parts – namely, the measurement (or outer) model and the structural (or inner) model (Chin, 1998; Lohmöller, 1989; Tenenhaus *et al.*, 2005). The measurement model specifies the relations between the manifest variables and their causal-related latent constructs, while the structural model specifies the causal relations between the latent variables (Cool *et al.*, 1989; Vinzi *et al.*, 2010).

The estimation methods employed in an SEM can be used to approximate both the causal linkages (path coefficients) and the latent variables (factor scores). Considering the complexity of the causal relationships and the number of the latent variables usually involved when modelling a strategy map, two techniques are generally adopted – PLS-PM and linear structural relations (LISREL) – while traditional statistical techniques (such as correlations, regressions, ANOVA, etc.) show a limited modelling capability when used under such conditions.

Also, PLS-PM and LISREL are based on different algorithms which tend to be suitable for different purposes. Without going into detail, the solution provided by LISREL represents the maximum likelihood that the estimated values in a causal model are an accurate approximation of the observed data, where accuracy is assessed through the structure of residuals between estimated and observed data. As a difference, a solution provided by PLS-PM corresponds to the maximisation of the variance explained by the latent constructs, which, in other words, is the minimum estimation error.

The different approaches produce significant implications when used in support of designing and testing a causal map. In particular, LISREL may often produce factor indeterminacy (Fornell and Bookstein, 1982; Gefen *et al.*, 2000), which means that multiple alternative solutions may fit the observed data with similar statistical significance.

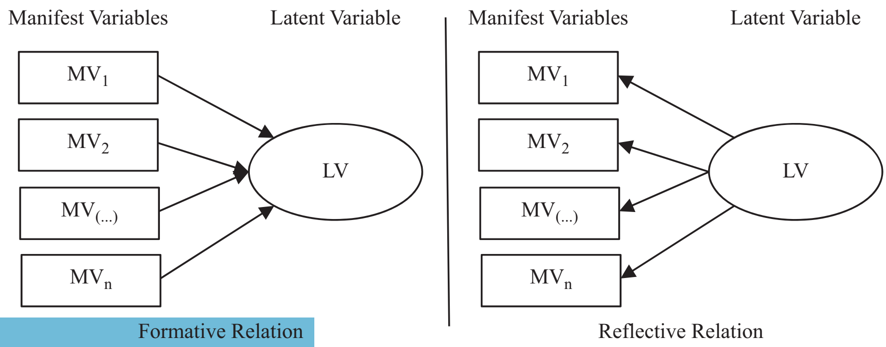

Figure 1.
Formative and reflective constructs

Therefore, LISREL is suitable when arguments based on a well-established theory can overrule competing solutions (Fornell and Bookstein, 1982).

Because of factor indeterminacy, the latent variables cannot be estimated, and this may represent a substantial limitation in strategic mapping since indications about the strategic priorities and insights for more effective initiatives are derived from a combination of the latent variable scores with the path coefficients. If the factor scores are indeterminate, such an analysis is not possible. Conversely, in PLS-PM, factor indeterminacy is by definition not possible because the method is explicitly aimed at producing a factor's estimation (Lowry and Gaskin, 2014). Consequently, factor scores are always available for further analysis.

As an additional consequence of factor indeterminacy, LISREL may produce improper solutions, i.e., values that are out of the admissible range parameters, and thus meaningless and unacceptable. PLS-PM, not being affected by factor indeterminacy, always produces an estimation, both meaningful and interpretable (Fornell and Bookstein, 1982).

PLS-PM also avoids many of the restrictive assumptions about data distributions and sample sizes required by maximum likelihood techniques, such as LISREL. This is particularly significant in the strategic management field, where it is difficult to completely satisfy such conditions (Vinzi *et al.*, 2010). In particular, in PLS-PM, estimates are obtained by dividing the set of model parameters into subsets and using ordinary multiple regressions for each subset. This allows the technique to provide robust solutions, especially when small samples and complex models are adopted (Lohmoller, 1989).

Concluding, PLS-PM is suitable for estimating parameters in a complex SEM characterised by multi-level relations and multiple latent variables, both formative and reflective, linked to one another in terms of causes and effects (Lowry and Gaskin, 2014).

As a main limitation, PLS-PM lacks an overall measure of goodness-of-fit (GoF) since it is not based on a global optimisation process, as in LISREL. The adequacy of the measurement model is mainly assessed by examining the convergent validity (or internal consistency) of the manifest variables associated with each construct. Convergent validity allows appraisal if a group of manifest variables refers to a unique construct. The possibility to represent latent concepts by uni- or multi-dimensional measures is a critical issue in the development of causal models (Hulland, 1999). Indeed, if a construct is assumed to be multidimensional, causal models should include separate groups of manifest variables, each representing a unique dimension.

Several composite reliability measures (Vinzi *et al.*, 2010) are suitable to check the dimensionality of constructs, such as Cronbach's α and Dillon-Goldstein's ρ. As a general rule of thumb, mono-dimensionality is accomplished when these indices are higher than 0.7.

In addition, the communality index can be used to assess the "quality" of the hypothesised relationships between measures and constructs. The index measures to what extent the manifest variability of the factors included in the causal model are explained by their corresponding latent variable scores (Vinzi *et al.*, 2010). Once the validity of the measurement model has been checked, the predictive power of each structural equation is assessed by the R^2 values, while the quality of the "whole" structural model can be tested through the redundancy index, which links the performance of the structural model to that of the measurement model.

The communality and redundancy indices can be combined to obtain a third measure, namely the GoF index (Tenenhaus *et al.*, 2004), which summarises the performance of the measurement and structural models and allows an assessment of the model's overall predictive performance (Vinzi *et al.*, 2010). As consequence, the GoF is useful to compare alternative causal models.

The statistical significance of GoF values can be checked using a cross-validation method, like bootstrapping. Bootstrapping is performed by creating a large number of control samples, extracted with replacement from the original data set. Each bootstrap sample has the same size as the data set. PLS-PM is used to estimate the causal model, and the GoF value is then calculated. As a result, the bootstrap provides a distribution of the GoF estimates calculated for all the control samples, which allows the determination of the confidence intervals and standard error estimates. When the standard error is relatively small, the original estimate of the GoF is relevant in statistical terms and can be used for alternative causal model comparisons.

Summarising, the adoption of PLS-PM in causal mapping may produce multiple advantages. In particular, the method is effective for modelling complex phenomena, including manifest and latent variables and both reflective and formative relationships. In addition, meaningful results can be obtained even when small samples are used and assumptions about the normality of data distribution are not met. Finally, the GoF index allows a comparison among alternative causal constructions.

4. Testing strategy maps in a manufacturing company

In this section, the employment of PLS-PM in support of strategic mapping for Lube Industries, an Italian manufacturer and leader in the kitchen furniture industry, is illustrated. In the case study, two strategy maps focussed on customer satisfaction are tested. The first map reproduces the European Customer Satisfaction Index (ECSI), which is based on widely accepted customer behaviour theories. According to the ECSI, customer satisfaction is affected by the following: image, customer expectations (CE), perceived quality (PQ) and perceived value. Customer satisfaction, in turn, impacts loyalty and complaints (Figure 1).

During a focus group including the project coordinator and the managers appointed to articulate the drivers of customer satisfaction and profitability, the ECSI model was employed as a starting point for discussion. The following managers were involved: sales, marketing, production, finance and R&D. Additionally, five strategic customers were invited to participate (Figure 2).

Because the company operates in a B2B environment, the managers referred to the company's direct customers, which are independent resellers – that is, multi-brand licensees who get in touch with final users in their own stores.

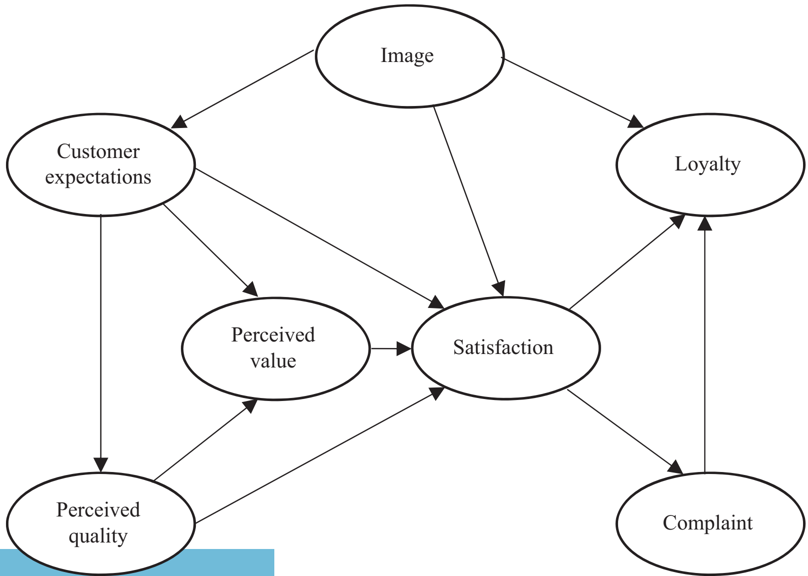

Figure 2.
The ECSI model

The focus group participants discussed how useful the ECSI model was in describing the resellers' satisfaction and its antecedents and consequents. As a result of this discussion, the collective strategy map shown in Figure 3 was designed (the elements in common with the ECSI model are in bold).

In the Lube map, both CE and PQ are influenced by three LVs which summarise the operations via which the company supports its resellers: technical/functional features, sell-out support and operating relations. The technical/functional features include accuracy and on-time delivery, rapidity in replacing defective or non-conforming products, and ease of use of the configurator software employed by the customer to customise the kitchen according to the requests of the final user. Sell-out support includes all of the following variables: richness and level of detail of catalogues, product promotions, advertising and training initiatives. Operating relations concern the individual interactions between the staff of Lube and their direct customers, and include courtesy, promptness in providing answers and solutions to specific requests and problems, technical assistance, and so forth. The antecedents in relation with CE are latent variables that express a customer's assessment of how important these attributes are for their satisfaction, while the antecedents of PQ express a customer's judgement about the quality provided by Lube with respect to that item. The perceived value refers to a reseller's assessment of the value of Lube's products and services. Finally, managers expect that improvements in customer satisfaction will produce an increase in profitability.

In total, the Lube strategy map included 33 manifest variables. A detailed list of all the manifest variables included in the map and their relations with LVs is shown in Table AI. PLS-PM was used to compare the ECSI and the Lube maps in order to select the most accurate model of customer satisfaction. Data processing was supported by XLSTAT software (details about the software settings may be provided by the authors upon request).

5. Discussion of results and managerial implications

The two maps described in the previous section were estimated using data collected via questionnaires sent to a statistically significant sample of resellers. The respondents were

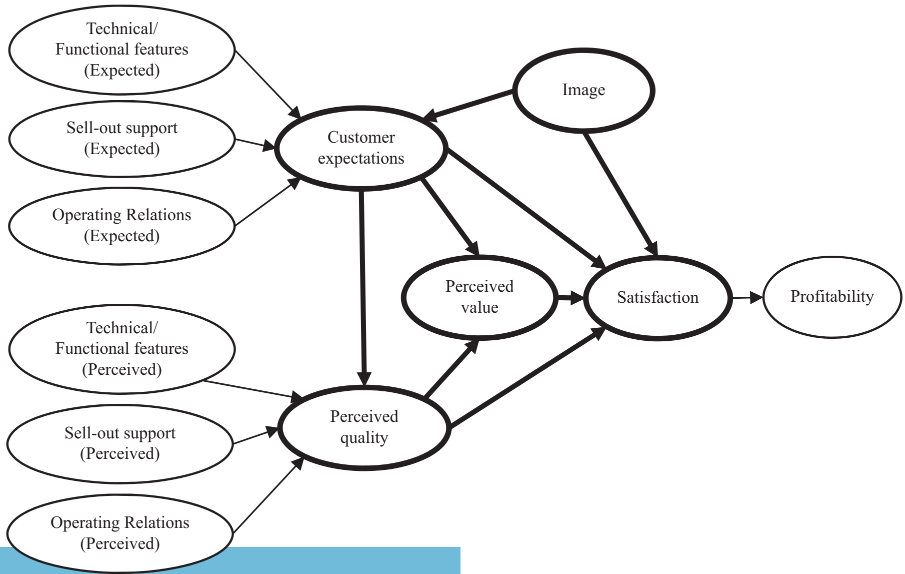

Figure 3.
The Lube causal map

asked to express their levels of satisfaction with every MV on a 10-level scale. The sample was composed of 600 resellers who were randomly selected and stratified by turnover and geographic area. In Table I, the GoF indices for the two strategy maps are summarised, showing their GoF.

The higher value of GoF for the Lube causal map provides evidence that such a causal model describes the network of variables affecting customer satisfaction better than the ECSI model does. As explained in Section 3, the robustness of GoF by means of a bootstrap estimation was checked. The standard errors were relatively low and provided statistical significance for the similarities of GoF and its bootstrap estimates, showing that it can be employed with acceptable confidence in the comparison of the two causal maps, while the upper and lower bounds show the ranges for the confidence intervals.

In addition, all the blocks of MVs related to an LV must be checked for homogeneity and unidimensionality; and towards this end, Dillion-Goldstein's ρ was calculated. In all cases, the results were higher than 0.82, which is remarkably higher than the minimum threshold of 0.70. In managerial terms, the results support the managers' collective assumptions about the direction of the relationships.

The factor loadings represent the correlations between each MV and its own LV, and allow managers to understand the impact produced by the former on the latter. In Table II, a summary of the results is shown (the entire list is shown in Table AI).

As an example, looking at the MVs in relation to technical/functional features (perceived), the delivery accuracy produces the greatest impact on PQ, whereas the lowest relevance is attributed to the ease of use of the configurator software provided by the company, which allows the resellers to process the final users' sales orders.

The results associated with the structural model, i.e., the path coefficients and the R^2 values of the various regressions, are shown in Figure 5. Notwithstanding the complexity of the Lube map, the R^2 associated with customer satisfaction shows that it is well predicted by its antecedents ($R^2 = 0.773$). The R^2 value of profitability is not very high (0.365), meaning that the relationship with customer satisfaction could be non-linear or that additional variables should be included in the model.

In Figure 4, CE represent an external variable which summarises the customers' personal beliefs about the relation with Lube. CE are influenced in particular by technical/functional features, which scores the higher path coefficient (0.406), while the factor loadings in Table II shows that customers are particularly demanding with respect to all the MVs related to technical/functional features except for the configurator software ease of use. When expectations are remarkably high, customers may easily become unsatisfied, and this may explain the negative relation with satisfaction. Being an exogenous variable, customer expectation is not easily influenced by managerial initiatives.

Table I.
GoF Indices

	GoF	GoF (bootstrap)	SE	Upper bound (95%)	Lower bound (95%)
ECSI model	0.483	0.489	0.036	0.409	0.561
LUBE causal map	0.681	0.680	0.033	0.602	0.750

Table II.
Factor loadings of MVs associated to perceived quality (LV)

Latent variables		Manifest variables	Factor loadings
Perceived Quality	Technical/functional Features (perceived)	On-time delivery	0.78
		Delivery accuracy	0.826
		Promptness in replacing products	0.792
		Configurator software ease of use	0.542

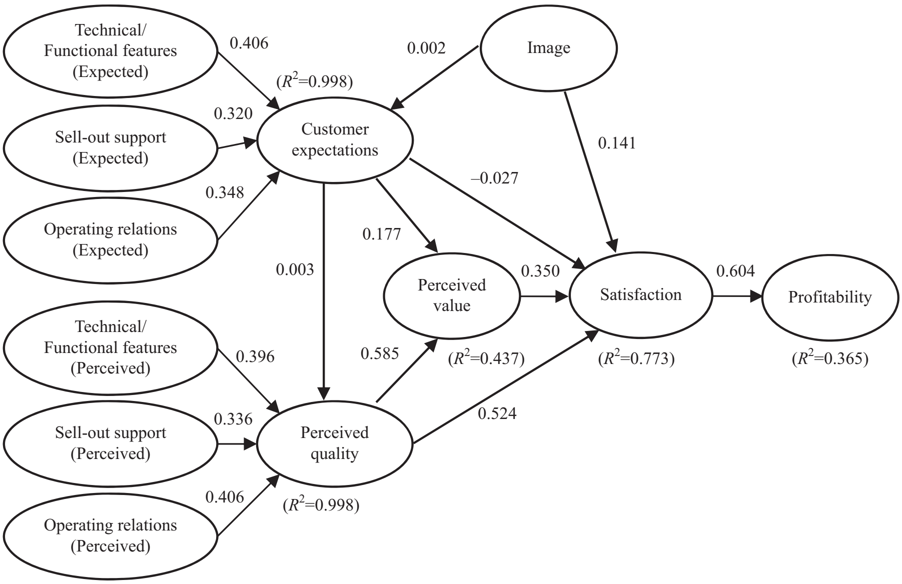

Figure 4.
Path coefficients and R^2 values of the structural model

PQ has the greatest impact on customer satisfaction, and operating relations produce the strongest impact on PQ and therefore represent a key factor. PQ also produces indirect effects on satisfaction, by improving the customers' perceptions about the monetary value of the company proposition, i.e. the perceived value. Perceived value in turn influence satisfaction to some extent and the factor loadings for its MVs are really high, in particular for Value compared to competitors (see Table AI for details). This means that an increase in this key factors would result in a significant improvement in perceived value.

In general, the identification of the key drivers impacting satisfaction is fundamental to developing strategies aimed at improving long-term relationships with resellers. PLS-PM allows the combination of managers' beliefs and data analysis (Tenenhaus *et al.*, 2005), revealing new knowledge or confirming pre-existing perceptions about customers. To enhance the visualisation of the strategic priorities, i.e., the factors that produce significant impacts on customer satisfaction and therefore require managerial initiatives, the variables in the map can be displayed in a matrix derived by Martilla and James (1977) (see Figure 5).

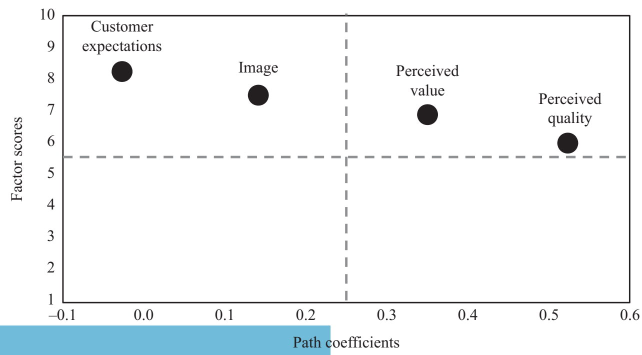

Figure 5.
Important/performance Matrix for customer satisfaction

The *x*-axes in the matrix represent the path coefficients, i.e., the impact that a variable may produce on customer satisfaction, whereas the *y*-axes represent the average importance/performance scores expressed by customers.

The company strengths, i.e., the variables that produce large impacts on satisfaction and show high quality perceptions (factor scores), are located in the upper-right corner of the matrix. These variables require actions aimed at protecting or improving even more customer satisfaction. The variables with high impact and low performance are located in the lower-right quadrant and represent weaknesses, via which the company may be particularly exposed to competition risks. The variables in the upper-left quadrant represent drivers of satisfaction, which are perceived as basic but necessary, while the variables in the lower-left quadrant represent non-strategic items, which can be ignored.

In Figure 5, image, perceived value and PQ represent customer perceptions, which may be influenced to some extent through specific managerial initiatives. Similar to some of the comments for Figure 4, PQ is the strategic priority which is expected to produce the highest impact on satisfaction, but something may be done to improve the scores attributed by customers.

In a subsequent step of analysis, the MVs in relation to PQ could be displayed in a new matrix in order to allow the managers to examine and select the strategic priorities in more detail.

6. Conclusions

The present paper shows how PLS-PM can support managers in validating a strategy map and identifying strategic priorities. Strategy maps allow the explicit representation of managers' collective cognitions about the factors relevant to the fulfilment of customer needs, as well as the development of a suitable value proposition. PLS-PM supports this process by providing an empirical validation based on customers' perceptions. This can be particularly suitable when alternative strategy maps are evaluated by managers. Additionally, when a model is selected, PLS-PM allows managers to calculate the magnitude of the impacts produced by a factor on its consequents, and these measures indicate the variables that require immediate improvement.

The proposed methodology extends the literature on strategic management and its positive interactions with data-mining applications, showing that within a confirmative approach, information may stimulate an empirical-based revision of managers' beliefs about a phenomenon characterised by implicit knowledge, as in the case of customer needs.

The paper also provides several managerial implications. Knowing the magnitude of the impact that a variable is expected to produce allows managers to test the robustness of their collective perceptions and provides a model that facilitates decision making and strategic planning.

Finally, the IPM matrix employed to visualise the obtained results can also be considered a vehicle with which to create a common level of comprehension throughout the organisation regarding the strategic potential of each variable and the kinds of intervention needed to improve or protect value creation.

This paper has certain limitations. The proposed methodology was adopted in a company operating in a B2B environment, and the analysis is limited to the needs of direct customers. The final users should also be considered, even if different solutions are needed to collect the relevant data. Similar difficulties may arise when the strategy is directed towards new customers who are substantially different from the actual ones. In those cases, data collection of a representative sample of the targeted customers is needed in order to obtain relevant indicators, but the applicability of the methodology should never be compromised.

As additional issue is that managers may have different inclinations towards revising their knowledge in light of the information produced by PLS-PM. Further research could focus on the factors impacting the various perceptions of managers regarding the usefulness of the information produced by a data-mining application. Despite the abovementioned limitations, the proposed methodology is suitable whenever individual or collective perceptions about a phenomenon require empirical validation in support of decision-making.

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Appendix

Latent variables	Code	Manifest variables Description	Factor loadings
Image	IMG1	Brand notoriety	0.723
	IMG2	Image coherence	0.875
	IMG3	Breadth of products range	0.852
	IMG4	Innovation capacity	0.84
Perceived quality			
Technical functional features	PQ1	On-time delivery (perceived)	0.78
	PQ2	Delivery accuracy (perceived)	0.826
	PQ3	Promptness in replacing products (perceived)	0.792
	PQ4	Configurator software ease of use (perceived)	0.542
Sell-out support	PQ5	Catalogue usefulness (perceived)	0.634
	PQ6	Advertising (perceived)	0.745
	PQ10	In-store support (perceived)	0.814
	PQ11	Training initiatives (perceived)	0.709
Operating relations	PQ7	Ease of contacting Lube (perceived)	0.912
	PQ8	Staff courtesy (perceived)	0.893
	PQ9	Technical support (perceived)	0.874
Customer expectations			
Technical functional features	CE1	On-time delivery (expected)	0.894
	CE2	Accuracy in delivery (expected)	0.858
	CE3	Promptness in replacing products (expected)	0.888
	CE4	Software ease of use (expected)	0.797
Sell-out support	CE5	Catalogue usefulness (expected)	0.815
	CE6	Advertising (expected)	0.842
	CE10	In-store support (expected)	0.872
	CE11	Training initiatives (expected)	0.758
Operating relations	CE7	Ease of contacting Lube (expected)	0.918
	CE8	Staff courtesy (expected)	0.938
	CE9	Technical support (expected)	0.915
Perceived value	PV1	Quality/price ratio	0.855
	PV2	Value compared to competitors	0.924
Customer satisfaction	CS1	Overall satisfaction	0.934
	CS2	Satisfaction compared to an ideal benchmark	0.96
	CS3	Fulfilment of expectations	0.96
Profitability	PROF1	Customer return on sales	0.926
	PROF2	Customer operating profit/total operating profit	0.903

Table AI. Outer weights and correlations between MV and LV

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