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Examining the articulation of innovativeness in co-creative firms: a neural network approach

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ABSTRACT

Value co-creation is an emerging marketing and innovation paradigm describing a broader opening of the firm to its customers by providing them with the opportunity to become active participants in the design and development of personalized products, services and experiences. The aim of the present contribution is to provide preliminary results from a research project focusing on the relationship between value co-creation and the perception of innovation in technology-driven firms. The data was collected in a previous study using web search techniques and factor analysis to identify the key co-creation components and the frequency of firms’ online comments about their new products, processes and services. The present work focuses on using an Artificial Neural Network (ANN) approach to understand if the extent of value co-creation activities can be thought of as an indicator of the perception of innovation. The preliminary simulation results indicate the existence of such relationship. The ANN approach does not suggest a specific model but the relationship that was found out between the forecasted values of the perception of innovation and its actual values clearly points in this direction.

Value co-creation, innovation capacity, principal component analysis, artificial neural network approach, linear regression analysis

INTRODUCTION

The value co-creation paradigm

Value co-creation is an emerging business, marketing and innovation paradigm describing how customers and end users could be involved as active participants in the design and development of personalized products, services and experiences (Prahalad & Ramaswamy, 2004; Etgar, 2008; Payne, Storbacka, & Frow, 2008). It is based on the design and development of customer participation platforms providing firms with the technological and human resources, tools and mechanisms to benefit from the engagement experiences of individuals and communities as a new basis of value creation. The active participation of customers and end users is enabled through multiple interaction channels, very often by means of specifically designed technological platforms through the Internet (Sawhney, Gianmario & Prandelli, 2005; Nambisan & Nambisan, 2008; Nambisan & Baron, 2009). Indeed, it is the advances in Information and Communications Technologies (ICT) that has enabled customers to be much more active, knowledgeable, globally aware and willing to use interactive virtual environments to personalize the existing and shape new products and services. The ability of value co-creation platforms to enable the personalization of new products services challenges the operational presuppositions of traditional marketing segmentation techniques by promoting a new service-dominant logic (Vargo & Lusch, 2004; von Hippel, 2006a). The new dominant marketing logic enables firms to address broader heterogeneous markets aiming at a better fit between what a customer needs and what the firm does and offers. It entails a new vision of the topology and the dynamics of the entire value creation system including i) a shift from thinking about consumers to thinking about co-creators of value, ii) a shift from thinking about value chains to thinking about value networks, iii) a shift from thinking about product value to thinking about network value, iv) a shift from thinking about simple co-operation or competition to thinking about complex co-opetition, and v) a shift from thinking about individual firm strategy to thinking about strategy in relation to the entire value ecosystem (Hearn & Pace, 2006). Such vision promotes a new understanding of the customer centricity of the traditional value network concept which is now considered dynamically, as a people-driven web of potential value configurations that could be actualized on the basis of specific customer demands (Norman & Ramirez, 1993; Flint & Mentzer, 2006; Prahalad & Krishnan, 2008).
The adoption of value creation practices leads to the need of “changing the very nature of engagement and relationship between the institution of management and its employees, and between them and co-creators of value – customers, stakeholders, partners or other employees” (Ramaswamy, 2009). This ongoing change challenges the management of innovations by promoting a new vision of the nature of innovation itself (Prahalad & Krishnan, 2008; Kristensson, Matthing & Johansson, 2008; Tanev, Knudsen & Gerstberger, 2009). The new co-creative vision of innovation builds on two key distinctive features. The first one is the truly user-driven aspect of the value co-creation activities between firms and customers. In this sense, value co-creation platforms represent a natural extension of some of the key aspects of the user-driven innovation paradigm (von Hippel, 2006) by focusing on the development of participation platforms to literally, multiply the effect of user-driven innovation methods such as the design of innovation toolkits (von Hippel, 2001; Nambisan & Nambisan, 2008; Nambisan & Baron, 2009) and searching for lead users (von Hippel, 2006b; Bilgram, Brem & Voigt, 2008; Droge, C., Stanko, M. & Pollitte, W., 2009). Another distinctive feature is the focus on the co-opetitive (from co-opetition) nature of the interactions between the different stakeholders, including the customers and end users, participating in the value co-creation process. Before competing and negotiating to capture value, the different players in a value co-creation network need to compete and negotiate in order to be able to participate and to contribute value (Tanev, Knudsen & Gerstberger, 2009). The co-opetitive dimension of value co-creation platforms leads to a more dynamic type of economic mechanisms as underlying driver of the innovation processes. These mechanisms operate on the basis of multiple transactions between customers, partners and suppliers at multiple access points across the value network. They enable customers and end users to control the relationship between price and user experience (Prahalad & Ramaswamy, 2004; Etgar, 2006) by providing them with the opportunity to actualize (i.e., create) specific value chain configurations that would fit their proper need, context and preferences. It is in this context that we could talk about customer value co-creation. Although focusing on the proactive role of the customer, such understanding is generically holistic in nature; it embraces all the actors involved in the value creation process providing an opportunity for firms to broaden the boundaries of their open innovation processes.

A more systematic search in existing research literature identified several emerging streams in value co-creation research. One of these streams is focusing on issues related to new product development and innovation (Prahalad & Ramaswamy, 2003; Sawhney et al., 2005; Roberts, Bake, & Walker, 2005; Prahalad et al., 2008; Franke & Schreier, 2008; Kristensen et al., 2008; Michel, Brown, Gallan, 2008; Midgley, 2009; Romero & Molina, 2009; Tanev et al., 2009; Nambisan, 2009; Bowonder, Dambal, Kumar & Shirodkar, 2010; O’Her & Rindfleisch, 2010). This research stream emerges by means of a terminology that oscillates between the semantics of two other paradigms – user-driven innovation (von Hippel, 2005; Bogers, Aftuah & Bastian, 2010) and open innovation (Chesbrough, 2003). User-driven innovation distinguishes itself by promoting a single firm-driven, product-centric, non-transactional and participatory approach to user involvement in the design of new products and services. However, its focus on innovation toolkits (von Hippel, 2001) and innovation communities brings it close to the value co-creation paradigm with its focus on customer participation platforms, personalization of market offers, multiple stakeholder interactions and access to global resources (Prahalad et al., 2008), customer-driven business models, and virtual customer experience environments. On the other hand, the open innovation paradigm promotes a more generic and broader vision of the innovation landscape. It articulates the key mechanisms for inbound and outbound business and innovation processes, intellectual property, knowledge and resource flows used by firms to engage into a more proactive pursuit of new markets and innovations (Chesbrough, 2003).

Value co-creation and innovation

The participatory platform nature of value co-creation practices enables a broader and more systematic positioning of customers and end users across the entire innovation lifecycle leading to a significant enhancement of the user-driven innovation potential. As a result, the development of value co-creation platforms is increasingly recognized a promising innovation strategy associated with an ongoing change of the nature of innovation itself (Prahalad et al., 2003; Nambisan, 2009; Romero et al., 2009; Midgley, 2009; Bowonder et al., 2010). The co-creation paradigm positions the source of value within the co-creation experience which is actualized through the company-customer interaction events. By co-creating with the network, the customer becomes an active stakeholder in defining both the interaction and the context of the event including their specific personal meaning (Prahalad et al., 2003). The personal nature of the interactive experiences enables new dimensions of value which are based on the quality and the personal relevance of the interaction events as well as on the opportunity for customers to co-create their own unique end products, services and experiences (Franke et al., 2008). These dimensions are critical for the emergence of experience innovation networks.
RESEARCH OBJECTIVE AND METHODOLOGY

Research objective and hypothesis
The objective of this article is to apply an artificial neural network approach in examining the relationship between the degree of firms’ value co-creation activities and the perception of their innovativeness. The underlying hypothesis of this research was developed on the basis of the insights discussed in the brief summary of the literature on value co-creation: firms with a higher degree of involvement in co-creation activities are in a better position to articulate the innovative aspects of their new products, processes and services. The testing of this hypothesis is particularly relevant within the context of an increasingly global competitive environment where firms are struggling with the limits of their innovation capacity through investments in greater product variety and in traditional marketing techniques that do not necessarily lead to a better competitive positioning or differentiation (Prahalad et al., 2004, 2008).

Research methodology
Hicks et al. (2006) and Ferrier (2001) pioneered the concept that an analysis of the frequency of use of specific keywords on public websites and corporate news releases can be an adequate representation of the degree of importance the firms place on the concepts those keywords were chosen to represent. Allen et al. (2009ab) and Tanev et al. (2010ab) provided preliminary results demonstrating that this concept could be applied to classify value co-creation practices and articulated the key steps of the data gathering and analysis workflow. These research studies show that factor analysis of the frequencies of a specifically designed set of keywords can be used to extract the key components of value co-creation in a large sample of firms.

The research methodology employed in this work added an additional step focusing on the application of an ANN approach to test the initial hypothesis about the existence of a positive association between the degree of firms’ involvement in value co-creation activities and the degree of articulation of their innovativeness.

The artificial neural network approach
ANNs are computing methods (algorithms) whose behaviour mimics the behaviour of the human brain (Hykin, 1999; Angelini et al. 2008). ANNs are composed of basic elementary units (neurons) which, when taken as single units, are able to execute just basic operations, but when connected to create a network, they can perform complicated tasks and solve complex problems, especially when the particular problem model is unknown in advance and when the relationships amongst the different components are non-linear.
The main advantage of ANN approaches consists in their generalization capabilities, i.e. in their ability to operate over data that have never been seen before, and for this reason they are used in tasks such as pattern recognition, forecasting and classification. In addition, the application of the ANN approach has another significant advantage in not relying on, or assuming, any specific preliminary model. Since they do not impose a solution and try to “explain” the obtained results, they are often referred to as a “black box” approach. This feature makes them undesirable when an explanatory model is needed, but perfectly adequate when there is no clear information about the variables at hand. Furthermore they are robust with respect to noisy and missing data, which do not hinder the network operations (but of course trigger some degree of tolerable performance degradation). All those requirements make their use appropriate for the problem at hand, in which a model is still far from being developed.

In the most common ANN model, each neuron is connected to each neuron belonging to an adjacent layer, while there are no connections between neurons of the same layer. Input neurons have no ingoing connections, whereas their activations are used as input data of the problem under study. A specific function transfers these activations (without any computation) to neurons belonging to the first hidden layer, which compute their activation and transfer it either to the next hidden layer, or to the output layer. The information flow is called “feed-forward,” as neurons receive information from the previous layer and transfer their activation only to the next layer. Because of this feature, nets implemented using this hierarchy are referred to as feed-forward networks.

ANN “learning” can be defined as the network’s skill to modify its behaviour so as to provide the right outputs when facing given inputs. Supervised learning is characterised by a training set of correct examples used to train the network. The “training set” is composed of pairs of inputs and corresponding desired outputs. Then, the error produced by the network is used to change the weights. Generally, the error is evaluated on a latter set, the “test set”, and the algorithm stops when the error produced on this latter set falls below a given threshold. This kind of learning is applied in cases where the network has to generalise the given examples. In unsupervised learning algorithms, the network is only provided with a set of inputs: no desired output is given. The algorithm guides the network to self-organise and adapt its weights. This kind of learning is used for tasks such as data mining and clustering, where regularities in a large amount of data have to be found.

Finally, reinforcement learning trains the network by introducing prizes and penalties as a function of the network response. Prizes and penalties are then used to modify the weights. Reinforcement learning algorithms are applied, for instance, to train adaptive systems which perform a task composed of a sequence of actions. The final outcome is the result of this sequence, thus the contribution of each action has to be evaluated in the context of the action chain produced. In such a mechanism, it may happen that some operations performed at the beginning of training are dramatically influencing by the global behaviour. To overcome this problem, another system component could be defined, the so called “learning machine”, whose goal is to discover those operations: the learning machine has to be able to assign prizes and penalties to each action in the sequence, whilst the reinforcement signal is only used to give a global evaluation. In the ANN approach adopted here, we will use “supervised training”, thus we will refer just to this learning paradigm. It is of particular importance to point out the main advantages and limitations of ANN systems. It has been shown that a feed-forward network is able to approximate any function, and this “universal approximator” capability has always attracted scholarly interest. The main ANN advantage is the capability to work over unknown (and never seen before) data, provided they have the same features as the training data: this feature (referred to as “generalization”) is particularly important when dealing with forecasting problems, and it is really useful when dealing with noisy and incomplete data. Furthermore, no hypothesis is required about the underlying data distribution (necessary when using model-driven approaches), since ANNs are able to grasp relationships amongst data just by experience. This feature is useful when there is not a great deal of “a priori” knowledge about the problem at hand. To this extent, ANNs are thought to be well-performing to grasp non-linear relationships amongst large amounts of variables. Apart from that, the main ANN shortcoming stays in the fact that they are not able to explain the results obtained during learning, nor the relationships among data. This stems directly from the sub-symbolic knowledge representation where knowledge is spread all over the system: this qualifies as a big trouble for those who aim to know the reason underneath the choice who leads to the final results. There are studies that indicate the possibility to extract rules from ANN’s behaviour, but no unique results have been reported so far. Another shortcoming is identified with the term “over-fitting”, with whom we identify the situation in which a neural network correctly operates over the training set, but is not able to generalize and operate over unknown data. This may happen when too many hidden neurons are used, when the training set is too large or when the time is too long.
RESEARCH RESULTS

The research sample consisted of all the firms that were used in the previous study by Tanev et al. (2010) including firms used as cases in value co-creation research publications and firms involved in open source projects (Table 1).

<table>
<thead>
<tr>
<th>Type of firms</th>
<th>Frequency</th>
<th>Percent</th>
<th>Cumulative Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 GEN</td>
<td>65</td>
<td>23.8</td>
<td>23.8</td>
</tr>
<tr>
<td>2 ECL</td>
<td>133</td>
<td>48.7</td>
<td>72.5</td>
</tr>
<tr>
<td>3 OSS</td>
<td>75</td>
<td>27.5</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>273</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Firms included in the research sample organizations: GEN – general type firms, ECL – members of the Eclipse Foundation, OSS – non-Eclipse open source software firms.

Value co-creation components

Table 2 shows the specific composition of the extracted principal value co-creation components that was used to construct three value co-creation component variables for each of the firms in the sample (Tanev et al, 2010). Based on these results, the first co-creation component was interpreted as “Resources, processes, tools and mechanisms enabling customer and user involvement in production, assembly, manufacturing and self-service aiming at design and process flexibility based on product modularity and sharing of internal expertise, resources and IP.”

<table>
<thead>
<tr>
<th>Component # 1</th>
<th>Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>customer+OR+user+produce+OR+assemble+OR+manufacture</td>
<td>.727</td>
</tr>
<tr>
<td>product+OR+process+modularity+OR+modular+OR+module</td>
<td>.705</td>
</tr>
<tr>
<td>customer+OR+user+IP+OR+“intellectual+property”</td>
<td>.669</td>
</tr>
<tr>
<td>design+OR+process+flexibility+OR+flexible+OR+adaptable</td>
<td>.599</td>
</tr>
<tr>
<td>internal+expertise+OR+resource</td>
<td>.554</td>
</tr>
<tr>
<td>lease+OR+rent+OR+license+OR+“self+serve”+OR+“self+service”</td>
<td>.550</td>
</tr>
<tr>
<td>product+OR+process+OR+service+evolution+OR+evolve</td>
<td>.521</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component # 2</th>
<th>Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>customer+partnerships+OR+interaction+OR+relationship+OR+participate+OR+participation+OR+activity+OR+action</td>
<td>.778</td>
</tr>
<tr>
<td>customer+OR+user+risk+manage+OR+management+OR+control+OR+assess+OR+reduce+OR+reduction+OR+potential+OR+Exposure</td>
<td>.698</td>
</tr>
<tr>
<td>customer+OR+user+cooperate+OR+cooperation+OR+collaboration+OR+partnership</td>
<td>.691</td>
</tr>
<tr>
<td>cost+reduce+OR+reduction+OR+saving</td>
<td>.685</td>
</tr>
<tr>
<td>trust+OR+honesty+OR+integrity+OR+transparency</td>
<td>.647</td>
</tr>
<tr>
<td>customer+OR+user+experience</td>
<td>.627</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component # 3</th>
<th>Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>customer+OR+user+learn+OR+learning</td>
<td>.752</td>
</tr>
<tr>
<td>customer+OR+user+suggest+OR+suggestion+OR+input+OR+request+OR+demand</td>
<td>.737</td>
</tr>
<tr>
<td>customer+OR+user+OR+forum+OR+connect+OR+network+OR+networking</td>
<td>.716</td>
</tr>
<tr>
<td>customer+OR+user+options+OR+choice+OR+choose</td>
<td>.524</td>
</tr>
<tr>
<td>customer+OR+user+test+OR+trial+OR+beta</td>
<td>.512</td>
</tr>
</tbody>
</table>

Table 2. Composition of the three principal value co-creation components
The second co-creation component was interpreted as “Customer relationships enabled through partnerships and cooperation aiming at cost reduction, design and process flexibility, and leading to better customer and end user experiences based on risk management, transparency and trust.” The third co-creation component was interpreted as “Mutual learning mechanisms based on the existence of user networking forums enabling customer suggestions, input, demands and requests, and leading to multiple options for users through involvement in test and beta trials.” Table 3 shows the descriptive statistics of the three co-creation variables that were constructed by adding up the ratings of each of the keywords weighted by their loadings.

<table>
<thead>
<tr>
<th>Component</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Component_1**(1/3)</td>
<td>2.290</td>
<td>.821</td>
<td>.087</td>
<td>-.105</td>
</tr>
<tr>
<td>Component_2**(1/4)</td>
<td>1.857</td>
<td>.556</td>
<td>.028</td>
<td>.251</td>
</tr>
<tr>
<td>Component_3**(1/2)</td>
<td>5.984</td>
<td>2.457</td>
<td>.264</td>
<td>-.126</td>
</tr>
<tr>
<td>Component_All**(1/3)</td>
<td>3.973</td>
<td>1.105</td>
<td>-.078</td>
<td>-.238</td>
</tr>
</tbody>
</table>

Table 3. Descriptive statistics of the three principal component variables

Innovation-related metrics
Table 4 shows the descriptive statistics of the perception of innovativeness metric that was used by Tanev et al. (2010). It was measured by the frequency of firms’ online comments about new products, services and processes and collected by means of the composite keyword: new AND product OR service OR process OR application OR solution OR feature OR release OR version OR launch OR introduction OR introduce OR “new product” OR “new service” OR “new process” OR “new solution” OR “product launch.”

<table>
<thead>
<tr>
<th>Innovation metric</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perception**(1/2)</td>
<td>4.745</td>
<td>1.760</td>
<td>-.126</td>
<td>-.286</td>
</tr>
</tbody>
</table>

Table 4. Descriptive statistics of the innovation-related metrics

Results from the ANN approach
The ANN approach can be summarized as follows. The three value co-creation components were considered as the “input” variables; the perception of innovation was considered as the “output” variable. To test for the existence of the relationship between the input and the output variables, we made experiments with a feed-forward network (3 input neurons, 5 hidden neurons, 1 output neuron). The learning paradigm that was used was supervised learning, meaning that for each firm we have fed the net with the three input indices and the desired output. The data was partitioned in two sets – a “training set” (180 firms) and a “test set” (the remaining 93 firms). The goal of this experimental phase was to see if the network is able to correctly generalize the innovation-related output variable over non-seen-before data. The neural network was trained by means of BackPropagation Momentum (with parameters ni=0.2 and beta=0.5). Fig. 1 shows two graphs with x-axis, the expected output value for the test examples, and on the y-axis the actual network value for the very same dataset. In order to avoid over-fitting, we have performed this procedure over 50 different partitions of data to see if the results were general enough. Here we show just two representative plots amongst the 50 plots we have drawn. The results clearly indicate that there is a relationship between the actual and desired outputs, and this assertion is of the utmost importance, since it is observed over the test set. It suggests that, since the network has been trained using the co-creation component values, the variation of the co-creation components is able to explain firms’ perception of innovation.
CONCLUSIONS

To the best of our knowledge this research study provides the first empirically-driven results from a ANN approach based on a large sample of firms suggesting the existence of a positive association between the degree of value co-creation activities and firms’ perception of innovativeness. Although, it is impossible to claim the existence of a causal relationship, the results provide a first quantitative indication about some of the innovation-related outcomes of value co-creation practices. One of the specifics of the research methodology was the use of web search tools and online data on firms’ websites. The research insights presented here should be of potential interest to both academic researchers and business executives. We hope that the validation of the methodology will contribute to the future development of business intelligence tools for the benefit of both research scholars and practitioners.

REFERENCES


Figure 1. The two graphs represent the relationship between desired and actual output over two different partitions of the training and the test set. The x-axis corresponds to the expected output value; the y-axis corresponds to the actual network value of the very same dataset.


