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Estatística

Using factorial analysis for validating a maturity measurement instrument in open innovation

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Abstract:

Open innovation (OI) has taken its place as a mainstream innovation process. Although the growing interest in OI since then, there are still many unanswered questions. One of the most persistent for researchers alike relates to how OI can be measured: what framework could companies adopt to measure OI? What are the most important constructs to be considered in the definition of a framework for OI? We identify constructs to be considered in a framework for the maturity measurement in medium and large companies in Brazil, considering strategic, organizational and operational aspects. The purpose of this paper is to develop an OI measurement instrument that has sound psychometric properties and recognize a key feature on the field. The results suggest that the constructs have good empirical support. In the manner in which the instrument is presented, it is possible to separately measure construct related to each of the approaches.

Keywords: Brazil, open innovation, performance measures, factorial analysis, cluster analysis.

Introduction

Since Chesbrough (2003), different researchers have conducted a number of theoretical and empirical studies in order to clarify the concept of open innovation (OI), whose definition has also undergone a series of improvements and adjustments in order to adapt to the latest findings on the topic. Recently, Chesbrough and Bogers (2014) define OI as a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization’s business model. Although the growing interest in OI since then, there are still many unanswered questions. One of the most persistent for researchers and practitioners alike relates to how OI can be measured.

Despite the growing interest in OI since 2003, there are still many unanswered questions. Two of the most persistent for researchers and practitioners alike relates to how OI can be implemented and measured. The literature concerning this first issue is growing fast. Mortara and Minshall (2011) tried to answer this question reviewing a sample of 43 cross-sector firms for their OI implementation approaches.

The study analyzed how firms moved from practicing closed to open innovation, classifying the adoption path according to the impetus for the adoption of the OI paradigm and the coordination of the OI implementation. More recently, Ades et al. (2013) analyzed three cases firms whose innovation management processes have been consolidated. These referred to its terms of alignment with existing corporate strategy, its requirements such as culture, skill and motivation, the strategy and the implementation process, the results achieved and the present barriers and enablers. But, for the second issue, there is still a gap in the literature in this area of knowledge.

Measurement instruments that have sound psychometric properties can make an important contribution toward this end. These instruments would provide confidence to the user that the information they obtain are reliable and valid (Singh & Smith, 2006). Further, if these instruments get universally accepted, then this will prevent the continual reinvention of the wheel, facilitate congruence in research and eventually, impact positively upon the intellectual development of the field.

Thus, the aim of this work is to identify the constructs to be considered in a maturity model for OI system measurement, considering strategic, organizational and operational aspects. Maturity models offer organizations a simple but effective possibility to measure the quality of their processes (Wendler, 2012). Firms can use maturity as an indication of the measurement of organizational capability. In this paper, an empirically validated OI measurement instrument is presented in order to ensure that the instrument reflects the state of art in the field, a thorough analysis of the knowledge base was undertaken to identify the recent and foremost publications on OI about its measurement approach, its constructs and their main practices. This analysis of the literature identified nine constructs, divided into strategic, organizational and operational aspects.

In addition, a scientific process that comprehensively tests the psychometric properties of the instrument is used. The outcome is an OI measurement instrument that has sound reliability and validity that researchers and practitioners can use for benchmarking within and across organizations.

Instrument development and validation process

The psychometric method (Nunnaly, 1978) was employed for the purpose of developing and validating the measurement instrument. One part of the field is concerned with the objective measurement of skills and knowledge, abilities, attitudes, personality traits, and educational achievement. As a result of these focuses, psychometric research involves two major tasks: (i) the construction of instruments; and (ii) the development of procedures for measurement. Practitioners are described as psychometricians.

Literature review

A Systematic Literature Review (SLR) was the procedure used to identify the constructs for OI in the knowledge base on this topic. Galvão and Pereira (2014) state that the SLR is suitable for all empirical evidence that used predefined eligibility criteria to answer a specific research question. SLR uses explicit systematic methods that are selected having the objective of minimizing deviations, thus providing results, conclusions and decisions with greater confidence.

Constructs of OI

This section deals with defining constructs for Open Innovation measurement. Constructs are latent variables, meaning that they cannot be measured directly. From the Systematic Literature Review, nine OI constructs were synthesized. These constructs are presented in Table 1 that presents the questionnaire that was applied in the companies for data collection.

Measurement scale

The Likert scale was used to measure all the items. This scale is able to deal with the conceptual nature of the subject area, a large number of items and difficulties with eliciting specific information from respondents. The Likert Scale measures attitudes and behaviors using response options ranging from one extreme to another (for example, anything likely to extremely likely). Unlike a simple answer question yes or no, a Likert scale allows to discover levels of opinion (Dawes, 2008).

For OI constructs, respondents were requested to indicate their level of agreement with the items that most closely reflected the situation at their work site. For the business conditions construct, managers' perceptions of how their organizations were affected by business environmental factors were evaluated. As for the organizational performance items, managers' perceptions of the degree of satisfaction their organizations had with their performance levels were assessed (Singh & Smith, 2006).

Pretesting

Independent third-party advice to fix possible tautological problems and improve the clarity of the statements was obtained. Two experts (one in OI and linguistics, and one in statistics) were asked to examine the draft questionnaire and suggest possible improvements. Many useful suggestions were made and these were incorporated into the instrument.

TABLE 1.
Items assigned to the nine constructs identified.

Construct	Itens	Totaly Desagree/7 – Totaly Agree 1 … 7
OI Dimensions 1.1 Outside-in 1.2 Inside-out 1.3 Coupled	1- For the outside-in process to be effective, it is necessary to open channels of communication with clients and suppliers, investing in a global knowledge creation base 2- The outside-in model combines externally and internally developed technologies to produce an offer that will be marketed 3- The main stages of the outside-in process include the search for external innovations, selection and acquisition of appropriate innovations, integration of them into the R&D effort 4- The inside-out process means that the company makes profits by licensing intellectual property or multiply the transfer of technology to other organization 5- IP licensing entails risks of loss of competitive advantage 6- The inside-out process has the strategy of marketing a technology with technological partners that help establish a market standard 7- Companies that decide to opt for the coupling process, combine the process from the outside to the inside (to acquire external knowledge) with the process from the inside out (to bring ideas to the market) 8- External partners for coupled processes may also include non-profit organizations (such as universities or laboratories) or individuals; These potential partners differ in how to produce and market innovation	
Pecuniary Practices of OI Outsourcing R & D Inward licensing Outward Licensing	9- Outsourcing R&D is a less costly alternative than mergers or acquisitions because it reduces the uncertainty and risk of the development 10- Outsourcing R&D accelerates the time for the development of an innovation 11- The acquisition of licenses (capture of external ideas) is not a substitute for internal R&D 12- It is possible to innovate at a higher speed and at a comparatively lower cost if the company has the ability to access and incorporate the external know-how by acquiring the license 13- It is necessary to evaluate the cost involved in purchasing licenses in order to benefit from this practice 14- Companies must free market their ideas in order to profit from unused ideas 15- The practice of selling IP is justified by the fact that protecting certain ideas can be very expensive or not expensive 16- The advantage of marketing IP is in achieving varied collaborations of the external environment	
Non-pecuniary Practices of OI 2.1 External Relationship 2.2 Networks 2.3 Co-development 2.4 Co-creation 2.5 Ideation	17- Working with internal and external teams in external relationship networks can generate conflict in the project 18- The company benefits from external relationship networks for project development 19- Joint development reduces project costs 20- Joint development increases the degree of innovation of the company 21- Co-creation adds value to the customer 22- The creativity and innovation of employees is important for the company to be innovative 23- The ideation or suggestion system is an effective tool to promote creativity and innovation in the company	
Implementation Process 3.1 Un-Freezing 3.2 Moving 3.3 Institutionalizng	24- To implement OI processes you need a leader 25- Documenting the procedures used to establish open innovation in the company facilitates learning 26- OI has changed the nature of the organizational structure 27- AI has built new multifunctional interfaces in the company 28- OI changes the interaction of employees with work, making them more dynamic and proactive 29- OI has improved the effectiveness of the company's operations 30- The use of OI helps the company achieve its established strategic objectives 31- OI has made it possible to decentralize the decision-making process	
Results: Company image	32- OI has brought a differentiated corporate image to the company's stakeholders 33- Working with OI makes the company create and communicate a positive image for its customers, shareholders, employees and suppliers 34- OI has increased the reputation and trust of the company	
Results: Economic Performance	35- The company's economic performance improved with OI 36- Companies that invest in innovation tend to improve their economic performance 37- Innovation plays a central role in increasing the company's competitive advantage and promoting economic development	
Results: Product Innovation	38- OI is able of generating competitive advantage in the medium and long term 39- Innovation has the capacity to generate value to the products and services of a company 40- OI provides more effective ways of taking the product to market	

Pilot testing

The instrument, presented in Table 1, was sent to professionals working in areas of innovation of 10 companies in Brazil in order to obtain feedback on the questionnaire. Useable responses were received from all the organizations. A range of statistical tests for reliability and validity was performed. This research decided to use the Cronbach alpha coefficient that was presented by Lee J. Cronbach in 1951 as a way of estimating the reliability of a questionnaire applied in a survey. In the same study, according to Cortina (1993), the alpha coefficient is certainly one of the statistics tools that are more important and widespread in research involving the construction of tests and their application. It is an index used to measure the reliability of the internal consistency of a scale, that is, to evaluate the magnitude in which the items of an instrument are correlated. Cronbach's alpha is the average of the correlations between the items that are part of an instrument (Streiner, 2003).

Data collection

The empirical data presented were obtained from innovative Brazilian companies. A total of 120 companies (24% of the population) were selected from the 500 largest and best companies in Brazil, which are selected annually by Exame magazine. This list is a part of more than 3000 companies that have published financial statements in the Official Gazette of the states until May 2016. In addition, we considered companies of significant size and well-known in the market, which did not disclose their results, but had their revenues estimated by our analysts. About 60 organizations responded. After accounting for non-deliverable questionnaires, a final response rate of 50 percent was achieved. The level of analysis for this study was limited to the administrative level. Managers and professionals in charge of innovation-related activities were specifically asked to complete the questionnaires because it was considered that they were best qualified to answer the questions.

Statistical tests

A range of statistical tests was performed on data obtained from the survey to assess the reliability and validity of the instrument. In this work, we have chosen to use as a reference the work of Singh and Smith (2006), because it had the same goal, but a different object of study. The set of statistical tests for validity and reliability is shown below. It was inspired in Singh and Smith (2006).

The methodology that was followed is composed of 7 questions and 7 steps: Are all items assigned to construct unique? Apply Step 1 - Test for multicollinearity. Are all items assigned to one dimensional constructs? Apply Step 2 - Test for unidimensionality. Are all items assigned to reliable constructs? Apply Step 3 - Test for reliability. Is the assignment of items to constructs proper? Apply Step 4 - Item assignment test. Do items (representing alternative measures), measure the same construct? Apply Step 5 - Test for convergent construct validity. Do the constituent items estimate only one construct? Apply Step 6 - Test for discriminant construct validity. How well do the items relate to independent measures of the concept? Step 7 - Test for predictive validity.

It is important to emphasize that they will be the basis for the validation of the proposed instrument. In the case of this research, the central objective is to validate the instrument for measurement of maturity in open innovation. The initial application of this instrument will be used to carry out the statistical tests to validate the instrument, that is, the capacity it has to measure the maturity in OI related to the constructs that were identified and not the initial presentation of the maturity level in levels detailed.

The first test to be performed is the multicollinearity test that in regression is a condition that occurs when some predictive variables in the model are correlated to other predictor variables. Strong multicollinearity is problematic because it can increase the variance of the regression coefficients, making them unstable (Kotz & Nadarajah, 1988).

Having established that the items did not present multicollinearity, it is then necessary to verify that all items are one-dimensional, that is, all items collectively estimate a single construct (Ahire, Golhar, & Waller, 1996). To check for unidimensionality of the items, this research used a Principal Component Analysis. PCA is a mathematical technique of multivariate analysis, which enables investigations with a large number of data available. It also enables the identification of the measures responsible for the greatest variations among the results, without significant loss of information. In addition, it transforms an original set of variables into another set: the principal components (PC) of equivalent dimensions. Currently, one of the main uses of PCA occurs when the variables originate from processes in which several characteristics must be observed at the same time. This technique has been studied by authors such as Johnson and Wichern (2007).

Once unidimensionality of the items is established, it is the necessary to assess the reliability of the constructs (Flynn, Schroeder, & Sakakibara, 1994). The most common method for measuring reliability of self-administered survey questionnaires involves estimating internal consistency. According to Cortina (1993), the alpha coefficient is certainly one of the most important and widespread statistical tools in research involving the construction of tests and their application. It is an index used to measure the reliability of the internal consistency of a scale, that is, to evaluate the magnitude in which the items of an instrument are correlated (Cortina, 1993). Cronbach's alpha is the average of the correlations between the items that are part of an instrument (Streiner, 2003). This coefficient can also be conceptualized as the measure by which some construct, concept or factor measured is present in each item. Generally, a group of items that explores a common factor shows a high alpha value of Cronbach.

The next step in validation process involves evaluating whether the items have been properly assigned to constructs. Factor analysis was used for this test. The essential goal of factor analysis is to describe, if possible, covariance relationships among the several variables in terms of a reduced number of underlying but unobservable random quantities, called factors. The factorial analysis can be seen as an extension of the analysis of the principal components since both can be considered as approximations to the covariance matrix. However, the approach made by the factorial analysis model is more elaborate and focuses on the analysis of data consistency with a predefined structure (Kim & Mueller, 1978). Factors can be termed as a construct, which can be a variable not observed, scales, items, or a measure of any kind. At analysis, factors explain the variance of observed variables, as by the correlations between the variables being analyzed. Both principal component analysis and factorial analysis are techniques of multivariate analysis, which are applied to a set of variables, to find out which of these are most relevant in the composition of each factor, these being independent of each other.

Construct validity, also called concept validity, is the type of validation that gives meaning to test scores, as it points to obtaining evidence that the observable behaviors that were chosen as indicators of the construct actually represent it (Yin, 2005). The construct validity determines whether the items that are operationalized, that is, the questions of the questionnaire, measure the concept intended for analysis. On construct validity emphasize the existence of two types of complementary strategies to prove the hypotheses established regarding the construct studied: convergent validity and divergent validity.

Thus, in the validation process, it is necessary to specify the predicted hypotheses among the variables involved indicating: 1. The expected meaning of the relationship, whether positive, negative, or lack of relationship and; 2. The expected relative magnitude of the relationship, where one can prove the existence of larger and clearer relationships.

Assessing the validity of constructs involves two questions: Do items truly measure what you intend to measure, and do they measure just that? This requires the evaluation of convergent and discriminant validations (Pannirselvam, Siferd, & Ruch, 1998). The first refers to the extent to which varied approaches to measuring constructs produce the same results. In the case of the self-administered questionnaire, each item is treated as a different approach to measure the same construct. In terms of discriminant validity, a construct exhibits this validity if the items assigned estimate only one construct. If an item of one construct strongly reflects on another construct, then the correlation between these constructs would be high (Ahire et al., 1996).

In presenting validity manipulation as one of the steps of the validation protocol, Kim (2009) defines it as a test performed to determine causal relations between dependent and independent variables, and this validation step may be associated with the predictive validity process. This type of validity is distinguished from two perspectives, according to the temporality of the criterion: simple predictive validity and concurrent validity.

The design of a validation study referred to the criterion follows the steps (Yin, 2005): 1. Define a relevant criterion and establish a method for its measurement; 2. Select a sample of subjects representative of the population in which the test will be used later; 3. Apply the test and get a score for each subject; 4. Obtain a measure of each subject at the same time of the test application, which characterizes the concurrent validity, or at a later time, which characterizes the predictive validity; 5. Determine the degree or the relationship between the scores obtained by the subjects in the test and the criterion measure.

Discussion and remarks

This study proposed the creation of an instrument for measuring the OI level of maturity in Brazilian medium and large companies. This tool was based on maturity models since they provide organizations with a simple but effective possibility to measure the quality of their processes and also because companies can use maturity as an indication of the measure of organizational capacity. This comes to emphasize the importance that the open innovation approach has to modernize the business environment. It is known that the long-term collaborative relationship among groups gains more advantages than horizontal alliance of enterprises in the aspect of collaborative product innovation, which is effective because it improves the product innovation revenue (Wu, Gu, Wu, & Zhou, 2016). First of all, the general contractor, as the core enterprise, should try to create a cooperative and innovative environment for node enterprises and develop a motivational mechanism based on knowledge sharing and innovation. Second, the general contractor should build a trust mechanism among node enterprises to promote their knowledge communication and cooperation, which helps lower the knowledge sharing cost and raise the knowledge concealing cost (Wu & Tang, 2015). These are important aspects to be considered in the approach of open innovation.

To meet this purpose, the research method used was the descriptive survey. The research descriptive survey aims to understand the relevance of a phenomenon and describe its distribution in a population (Forza, 2002). It is important to emphasize that this research did not aim to test the causal relationship between the constructs, which, according to Hair Jr., Babin, Money, and Samouel (2005), would mean testing hypotheses that state that one event leads to another by means of a temporal sequence. The data collected in this work refer only to the period from August to December 2016. Information was collected from 60 companies. However, after processing the data, it was found that only 41 companies replied to the questionnaire completely so that the data could be used. To guide the research on the measurement of the level of maturity in open innovation, the first guiding question was formulated: What are the most important constructs to be considered in the definition of an instrument to measure the level of maturity in open innovation? According to the literature review, this research identified nine constructs that should be considered, namely: 1- Top management leadership, 2- Organizational Culture; 3- Business Model; 4- Organizational Structure; 5- Knowledge management; 6- R&D Team Organization; 7- OI Dimensions; 8- OI Practices; 9- Implementation Process.

Having defined the constructs, which was the first objective of this research, a framework was proposed to define the relationship between the identified constructs. Figure 1 shows the relationship of the characteristics between the OI constructs and their respective bibliographic references.

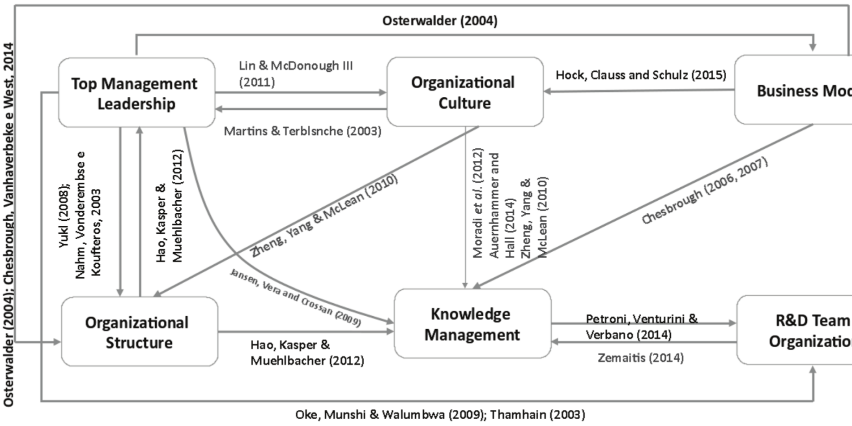

FIGURE 1.
Relationship Between OI Constructs and Bibliographic References.

Top management leadership is related to culture and organizational structure because it is the responsibility of leaders to influence the change from closed to open innovation approach. Likewise, the business model will impact on the KC and organizational structure. Finally, the R & D team will need the leadership to be able to evolve from an innovation approach. Thus, Figure 1 synthesizes the relationship that the constructs, which were grouped, have.

In order to validate the instrument that was developed, statistical tests were performed to demonstrate reliability. These tests were multicollinearity, unidimensionality, reliability, item assignment test, item classification, construction validity and predictive validity. Following the logic proposed by Singh and Smith (2006).

Step 1 was the Multicollinearity Test, because before performing the factorial analysis it is necessary to check the existence of acceptable levels of correlation between the variables for the success of the analysis result. Analyzing the correlation matrix generated by the Minitab software that revealed many values with high correlation, one can observe the presence of significant correlations at the level of 0.05.

Step 2 was the Principal Component Analysis. The PCA is a factorial method whose main characteristic is the reduction of the number of the characters. The calculation of the principal components was effective in reducing the variables to be considered, since of the 40 initial variables there was a reduction of 27 variables. For data analysis, with only 13 variables it will be possible to understand 83.3% of all the information. With this you gain time without losing relevant information.

Step 3 was the Cronbach Alpha Reliability Test. In order to verify to which degree the items of a questionnaire are interrelated, the Cronbach alpha estimate is used. As shown in the research, all variables showed Cronbach's alpha score greater than 0.7 demonstrating relevant internal confidence. And the total Cronbach's alpha value was 0.8953.

Step 4 was Factorial Analysis. The factorial analysis identifies and groups sets of interrelated variables, and to justify their use, it is desired a degree of multicollinearity (one variable can be explained by another variable) between the variables, and the data matrix must present acceptable correlations.

The first step was the Bartlett sphericity test, which is one of the means to check the appropriateness of the application of the factorial analysis (Mingoti, 2005). Barlett`s sphericity test is a construct based on the multivariate normality of rand vector. The normality of the data is desirable, but it is not required when using the PCA, which is the case of this research. With the PCA, we were able to observe the existence of a correlation in the data. This has shown that the data set has a significant correlation structure which is required for using multivariate analysis (Johnson & Wichern, 2007). This is why we use the Kaiser-Meyer-Olkin (KMO) criterion because it is another way to identify if the factorial analysis model in use is adequately fitted to the data, this is done by testing the overall consistency of the data. Although the KMO value was below 0.5, the Bartlett sphericity test value was very small, close to zero, which allowed the adoption of the Factorial Analysis (AF) method for data treatment.

In choosing the number of factors, the Kaiser standardization criterion was chosen, that is, retained factors should have eigenvalues greater than 1. This criterion was chosen since this work consists of an exploratory research without a priori delimitation of the number of factors to be obtained. According to Hair Jr. et al. (2005), this criterion is the most used and suitable for research instruments that have between 20 and 50 variables, as is the case of this work, which has 40 variables. Thus, by performing the factor analysis, we found 13 factors that explain about 83.26% of the total data variance. To confirm, the Scree test, as presented in Figure 2, was used. The red line shows where the selection of the selected factors was made.

The Scree test is performed by constructing the graph of latent roots in relation to the number of factors. It can be observed that it presents a slow decrease of the curve after the thirteenth factor, suggesting that only the first thirteen factors are considered as the object of the study. Then, we started with the analysis of commonalities, which corresponds to the proportion of variance of each variable explained by the main components retained, and which, by practical rule, should be greater than 0.70 for each variable. The commonalities exhibit the initial value equal to 1 and, after extraction of the desired number of factors, the commonalities vary between 0 and 1, with 0 when the common factors explain no variance of the variable and 1 when they explain all their variance. For all variables, the extraction value was higher than 0.7. Once the eigenvalues are known, the eigenvectors can be determined, which in turn constitute the basis for obtaining the eigenvectors. Through them it is possible to write a linear combination of the set of original variables, giving rise to factorial loads.

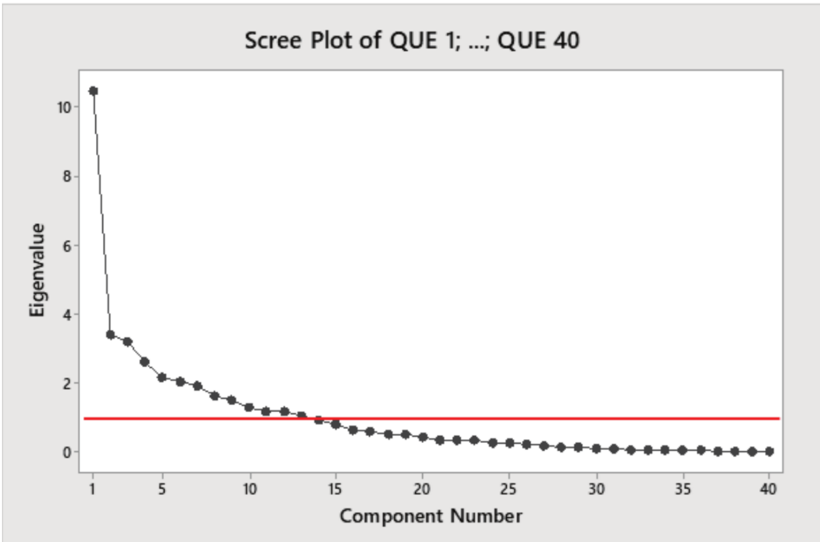

FIGURE 2.
Scree Plot Graphic.

The results of the commonalities of each variable show that all variables have a strong relation with the retained factors because they have high commonalities, and therefore there is no need to withdraw any of the variables.

Continuing the analyses, the next step was the rotation of factors, that is, it is a rotation process capable of transforming the complex structure of correlation of variables into a simpler structure for interpreting the factors. Specifically, the Varimax rotation method was applied, because this method provides a clear separation between the factors, preserving the original orientation of the same. For a sample size of up to 50 entries, only factorial loads equal to or greater than 0.75 may be considered significant. In this way, the option was to use the cut at 0.70. It was verified the presence of values above 0.7.

As seen, as practical rules, we have that the minimum significant factor load is 0.30. Loads at 0.40 are considered most important and above 0.50 are considered significant. However, in a sample size of 50 entries, only factorial loads equal to or greater than 0.75 can be considered significant. In this way, the option was to use the cut at 0.70. The variables with higher weights are those most correlated with the factor.

This was followed by an individualized study of the factors, their most representative variables and their contributions to explain the context of the study. The representative variables in each factor are highlighted by circles to facilitate visualization. It shows the factor loads in relation to the extracted components. To avoid the problem of indetermination of the relationship between variable and factors, the same variable cannot contribute to the construction of different factors. Factor 1: Questions 35,36,37,34,30, 33,38,3,32,40,29,27,39; Factor 2: Questions 24,26,25,12; Factor 3: Questions 2, 4, 16 Factor 4: Questions 22,23,7; Factor 5: Questions 8, 21, 18; Factor 6: Questions 17,14,1,19; Factor 7: Questions 20, 28; Factor 8: Question 13; Factor 9: Questions 10 , 9; Factor 10: Question 6; Factor 11: Question 31; Factor 12: Question 11 and Factor 13: Question 5.

Step 5 was the Cluster Analysis. This analysis is a technique used to classify objects or cases into relatively homogeneous groups called clusters. Cluster analysis is widely used in the various areas of knowledge, since it is a continuous measure that allows the individual interpretation of each group and the relationship that this group has with the others. For this work the hierarchical criterion of agglomeration adopted was the Complete Linkage method. This method was chosen because it is a procedure based on the maximum distance, that is, it finds two objects separated by the longest distance and places them in the first group. Considering the formation of 13 clusters, due to the number of generated factors, the dendrogram displays the information in the amalgam table in the form of a tree diagram as shown in Figure 3. The dendrogram is a tree-shaped graph where we can observe changes in the levels of similarity for the successive stages of the clustering. Then, the vertical axis shows the level of similarity; the horizontal axis, the individuals. The vertical lines starting from the grouped individuals have height corresponding to the level that the individuals are considered similar.

In this case, questions 1, 11 constitute the first grouping; Questions 2,4, 19, 20 is the second; the questions 3, 29, 30, 32, 33, 34, 35, 36, 39, 40 constitute the third; the question 5 the fourth, the 6, 9, 10 questions the fifth, the questions 7, 22, 23 the sixth, the questions 8, 21 the seventh, questions 12, 13 the eighth, questions 14, 17 the ninth cluster, questions 15, 16 the tenth cluster, questions 18, 37, 38 eleventh, questions the twelfth 24, 25, 26 and questions 27, 28, 31, the thirteenth respectively. This stage of cluster analysis was developed aiming to make the formation of the factors through clusters more visual since it complements the factorial analysis.

Because the data collected are highly correlated, the use of the factorial analysis for validation of the instrument is indicated, as presented above. We can affirm that the instrument that was developed in this work is capable of analyzing the level of open innovation maturity in companies to which it is proposed. This is due to the fact that, through the factorial analysis we could have a great reduction of variables, as shown in the PCA, implying a simpler and faster analysis without loss of information. In addition, the factorial analysis and the cluster analysis demonstrated by clustering the grouping of homogeneous issues that can be analyzed together facilitating the interpretation of the information.

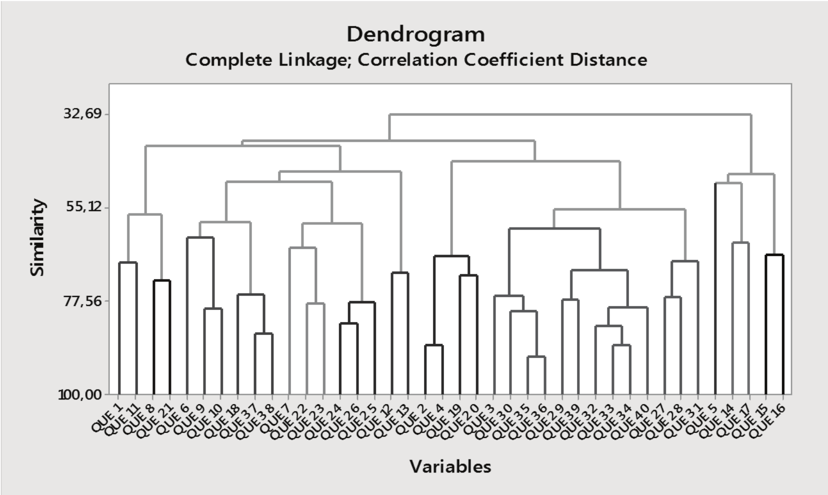

FIGURE 3.
Cluster analysis of variables.

Conclusion

The present work aimed to contribute to fill a gap identified in the literature in research on open innovation. The gap was the lack of a framework for analyzing the maturity of open innovation in medium and large companies in Brazil. We consider operational aspects the dimensions of open innovation, its practices and its implementation process, which are the subject of most studies published in the knowledge base on this topic.

Few studies in the literature, aiming to contribute to a framework or describe how different segments of companies have implemented the approach of open innovation have bothered to consider what we call strategic and organizational aspects.

The results provide tentative evidence that the instrument presented here is reliable and valid. Reliability was demonstrated with Cronbach’s alpha values, whose constructs measured exceeded the minimum criterion. This is quite good for an instrument which is composed entirely of new scales. However, successive studies should continue to refine the instrument and increase its alpha values.

Content validity was demonstrated throughout the paper. The framework summarizes the literature review by separating the domain of open innovation into nine constructs: 1. Top management leadership, 2. Organizational Culture, 3. Business Model, 4. Organizational Structure, 5. Knowledge management, 6. R&D Team Organization, 7. OI Dimensions, 8. OI Practices and 9. Implementation Process. Construct validity was very strong for the scales. All the scales had high eigenvalues and loadings of individual items on constructs, demonstrating that the scales measure single, independent constructs.

In this paper, an OI maturity measurement instrument validated using multivariate techniques was presented. Throughout the instrument development and validation process, a clear attempt was made to ensure that the contemporary reality in terms of how it is practiced was reflected. The instrument enables users to easily identify the construct and associated items for each of the approaches. In this way, users can tailor the instrument to their requirements.

This work offers as main contribution an instrument created from the literature review to measure the degree of OI maturity in Brazilian medium and large companies. For the proposed instrument in this paper to contribute in this respect, considerable additional work remains. These include further validation of the instrument in a longitudinal sense over several time intervals, testing the instrument in several other geographical domains, using it in other industry settings and triangulating the instrument with other research methods. All of these will generate greater consensus on its acceptance as a universally applicable OI instrument.

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