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Studying Scientific Collaboration Networks Using Social Network Analysis And Structural Equation Modeling

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Abstract
The main objective of this study was to define a conceptual model to identify latent issues that involve the scientific collaboration in a R&D environment. We have used two complementary approaches to study scientific collaboration. At first, structural equation modeling with partial least squares was used to evaluate and test a conceptual model based on personal, behavioral, cultural and circumstantial factors to identify which of these factors best explain the propensity of authors of technical and scientific publications to establish collaboration links with each other. The first part produced a second order latent variable named "propensity to collaborate". In the second part, we evaluate if and how this propensity to collaborate is reflected in the structural position of these authors in the R&D coauthorship network of our case study, . The findings showed that the proposed factors moderately explain the authors' collaboration propensity in a R&D environment. Although the model has not been satisfactory to explain the authors' structural position in the coauthorship network, however, it was a starting point to study scientific collaboration using structural equation modeling and social network analysis.
Keywords: *scientific collaboration - conceptual model - collaboration propensity - R&D coauthorship network - structural equation modeling - social network analysis.*

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I. Introduction

The scientific collaboration is an issue that has aroused great interest in the scientific comunity (Luukkonen et al. 1992; Melin and Persson 1996; Katz and Martin 1997; Hara et al. 2003; Lee and Bozeman 2005; Sonnenwald 2007; Birnholtz 2007; Hou et al. 2008; Pike 2010; Kastelle and Steen 2010). In particular, contextualization of collaboration in the formation of social networks and how this binomial can present itself as a synonym of competitive advantage for people and organizations.

There are several studies showing the importance of scientific collaboration as a process of generation, preservation and dissemination of knowledge and therefore as a way to boost the researchers productivity (see Lee and Bozeman 2005; Parreiras et al. 2006; Oliveira and Grácio 2008; Hampton and Parker 2011; Wang et al. 2015).

Characterized as a complex social phenomenon, scientific collaboration has been systematically studied since the 60's (Glänzel and Schubert 2004). This socio-technical process of interaction among researchers enables the sharing of expertise and other resources making it a prerequisite for modern science (Melin and Persson 1996). How scientific research is dominated by complex problems that require of the researchers a broad multidisciplinary knowledge and as no researcher has all the knowledge and skills required (Hara et al. 2003), scientific collaboration becomes an important phenomenon to solve these problems.

There is no clear definition of the scientific collaboration term (Birnholtz 2007; Bukvova 2010), but there is a consensus that it is a process of interaction between two or more people to achieve a common goal. For example, for Sonnewald (2007) collaboration is the interaction process that occurs within a social context among two or more researchers to achieve a mutually shared goal. Katz and Martin (1997) define collaboration as the joint efforts of researchers to achieve a common goal of producing new knowledge. Vanz and Stumpf (2010) point out that collaboration is a social process and human interaction that can occur in various ways and reasons. Therefore, scientific collaboration is a process that combines experiences, skills and knowledge of different researchers, possibly with different perspectives and purposes, to achieve a common goal.

There are several approaches that can be examined to characterize and understand this complex phenomenon involving the nature of human interactions (Katz and Martin 1997):

- The question of how to measure scientific collaboration, in which the most widely used procedure is based on co-authorship;
- The factors that stimulate the formation of scientific collaboration networks;
- The role of communication and the effects of physical and social proximity in the propensity for collaboration;
- The collaboration effects on the productivity.

Studies have revealed a variety of factors which apparently contribute to understand and identify the collaboration activities. However, there are few specific reasons that have been clearly established to explain how and why this phenomenon occurs (Katz and Martin 1997). People can be motivated to collaborate, simply because they like to participate in social interactions or because the research problem under study requires complementary knowledges or skills they do not possess (Rijnsoever and Hessels, 2001). Anyway, in the Table 1 can be seen several reasons why researchers collaborate in the development of an R&D project.

Table 1 The reasons why the researchers collaborate.

a) Acess to expertise; b) To have access to equipments, resources and funding for research projects; c) To obtain prestige and visibility to advance professionally and progress more rapidly;
d) To enhance productivity;
e) To expand the networking;
f) To learn new skills or techniques;
g) To satisfy the curiosity or intellectual interests;
h) To share the excitement of an area with other people;
i) To reduce errors;
j) To reduce isolation, recharging energy and the excitement;
k) To promote academic support for students;
l) To enhance knowledge and learning.

Adapted from Beaver (2001).

The purpose of this work is to understand what factors, related to personal, behavioral, cultural and circumstantial characteristics, best explain the propensity of a researcher to establish collaboration links in research and development (R&D) environments, and to what degree this collaboration propensity explains, even partially, the structural position that these researchers occupied in the scientific collaboration network of a research institution in Brazil. To examine these characteristics we used two approaches based on structural equation modeling with partial least squares (PLS-SEM) and social network analysis metrics (SNA). Thus, it provides a theoretical and empirical contribution to the studies related to the scientific collaboration theme.

This paper is organized as follows. In the "Studies on scientific collaboration" is a summary of work-related scientific collaboration. In "Definition of the conceptual model and hypothesis" we described the theoretical concepts covered in this study. In the "Data and Methods" it is shown the data collection process and described the methods used for the analysis of the proposed conceptual model. The results achieved and the criteria of validity of the proposed model are discussed in "Results and discussion". And, finally, the "Conclusions" are disclosed.

Research collaboration background

The wealth of works available in the literature seeks to investigate how personal, social and organizational characteristics influence the creation of collaboration relationships that are established between people in different social contexts.

Mollenhorst et al. (2008), citing several authors point out that in many activities the choice of partners is influenced by the social context in what people are inside, such as family, neighborhood, workplace or voluntary associations, and too by the opportunities and preferences. Klein et al. (2004) examined whether the demographic characteristics, values and personality traits (extracted from Goldberg's Big Five) of a person influence his/her degree of centrality in a social network. They realized that people with low levels of neuroticism and values similarity between its members acquire leading positions in friendship and information networks. More recently, Kalish and Robins (2006) conducted a survey with 127 students from the first year of psychology course from one university to examine how individual psychological differences can influence a person to structure their social environment. Burt et al. (1998) examined the behavior of a person in a social structure. They concluded, for example, that the behavior of certain people positioned in rich networks in "structural holes" is oriented to changes and by the possibility of enjoying power. Already, Lee and Bozeman (2005) conducted a survey with 443 academic scientists to examine the impacts that scientific collaboration causes in the researchers productivity in relation to production of publications. Hara et al. (2003) developed a preliminary conceptual model to help clarify the social and human dimensions of collaboration and the properties that characterize their formation. Other studies seek to relate the degree of socio-demographic similarity as a variable that can influence the social structure. Therefore, many authors believe that many people prefer to interact with other people in similar age, educational level, lifestyle, etc. (Mollenhorst et al. 2008).

Other studies characterize scientific collaboration adopting an international collaboration based approach. Wang et al. (2015) found a significant increase on international cooperation in sports science area and hence an impact on the citations number of publications with international co-authorship. Schmoch and Schubert (2008) analyzed and showed that one indicator based in international co-publications was not proven to be a suitable alternative method to assess the quality of the scientific researches. Guan et al. (2015) used modeling structural equations techniques based on partial least square to examine how collaborative characteristics influence the scientific collaboration networks and, consequently, affect the scientific output.

In Brazil, Parreiras et al. (2006) applied to SNA methodology to descriptively analyze the co-authorship network in the area of information science. Maia and Caregnato (2008) conducted a study using co-authorship as an indicator of scientific collaboration networks. This study revealed, among other findings, that there was a correlation between the number of employees and the productivity, since the number of published articles increased, whereas the number of employees remained constant during the study period. Glänzel et al (2006) analized the evolution of publication activity and citation impact in Brazil, to find statistical evidences of the relation between international co-authorship and both research profile and citation impact in the Latin American region. Finally, Barroso et al. (2009 and 2010) studied a preservation mechanism of knowledge at IPEN. The study revealed a spontaneous collaboration network in research projects, based on real data, involving retired and active researchers. Using advanced analysis techniques of social networking various indicators were extracted and examined to describe the features, configuration and evolution of collaborative network along longitudinal stages.

However, when the focus of the research is to analyze the perspective of SEM the propensity of a researcher to establish collaboration links with other researchers, we found few studies that used SEM to measure this abstract concept of the propensity for collaboration.

Totterdell et al. (2008) examined individual differences that influence the propensity of people to connect with others in different contexts - academic and organizational environment. This propensity incorporates three unobservable factors directly: *make friends*, *make acquaintances* and *join others*. The authors concluded, for example, that certain personality traits and a person's job in an organization may define the states of their relationships. In our view about social network, we intuit that the proposed factors may have explanatory capacity, respectively, for the formation of strong, weak and intermediate links. Birnholtz (2007), based on an exploratory study with researchers from three different academic areas, examined the collaboration propensity of these researchers considering two perspectives: the social, characterized by an individualistic or collective orientation, resulting from a scientific competition environment for results or discovery and the nature of work in which researchers are involved. The results suggest that the nature of work of the researchers better explains the collaboration propensity. However, according to the author, these differences did not stay evident.

Definition of the conceptual model and of the hypothesis

Trying to promote a synthesized understanding of the aforementioned researches, we concluded that the propensity of a person to collaborate with each other or form a partnership is something that can be related to the following factors:

a) The personal traits that can act as a stimulant or inhibition factor to the interaction process;
b) The environmental or the social structure in which the person is inserted;
c) The factors related to opportunities for personal and professional growth.

The behavioral characteristics of a person can promote or hinder the collaboration process. To assess how an author ranks behaviorally and how this aspect of the personality affects the collaboration propensity, to the proposed model was incorporated into the "*propensity to connect with others - PCO*" model developed by Totterdell et al. (2008), which examined the individual differences that influence the propensity for people to connect with others in different contexts - academic and organizational. As mentioned, PCO is evaluated using three factors: *make friends*, *make acquaintances* and *join others*.

The other constructs (cognitive, emotional, cultural and circumstantial) incorporated into the proposed model, seek to understand conceptually what makes people more attractive as collaborators in research.

In this chain of arguments, Borges and Baranauskas (2004) and Olivera and Straus (2004) already argued that the cognitive and social skills are important factors influencing the collaboration environment. In a general context there is a significant presence of cognitive, social and technical aspects as incentive factors in the formation of collaborative relationships (Melin, 2000). Sonnenwald (2007), describes that cultural heritage is an aspect which influences the social and personal relationships.

Based on these definitions and in the collected data, we proposed a conceptual model, Fig. 1, which shows that the collaboration propensity is determined by the characteristics perceived in the predictors constructs.

From the definition and consolidation of the model that seeks to assess the propensity of an author to establish collaboration links with another author, sets up an association with the structural position that author occupied in the R&D coauthorship network of IPEN*, to check how much the collaboration propensity model explains, even partially, this structural position.

The structural position of an author in the network is related to the centrality concept which is an important structural property of social networks (Freeman 1978). Thus, authors who are more central play a more prominent role, and theoretically, are located in strategic positions within the network (Wasserman and Faust 1994).

This structural position in the network, defined as an endogenous construct, was measured by the following SNA indicators: degree centrality, closeness centrality, betweenness centrality, eigenvector centrality and cliques. These indicators are designed to understand the network features on a micro level that captures the individual characteristics of each author in the network (Yan et al. 2010).

The first three indicators were formalized by Freeman (1978). *Degree centrality (DegreeC)* refers to the number of links an author has to other author in the network. *Closeness centrality (CloseC)* corresponds to the inverse of the sum of the shortest distance from a specific author to all authors in the network. The final, *betweeness centrality (BetweC)* is based on the authors who are positioned along the shortest path connecting two other authors, acting as a broker.

The *eigenvector centrality (EigenC)* (Bonacich 1972 and 2007) considers that the connections of an author should be differentiated according to the centrality rank of adjacent authors. The fundamental idea is that an author will have a high eigenvector centrality if connected directly to other central authors in the network. The *clique* indicator is equivalent to a complete subgraph with a minimum of three or more authors that are all adjacent to each other, and there is no other author that meets this adjacency condition for all members of the clique (Wasserman and Faust 1994; Scott 2000).

The indicators that measure the constructs defined in the model were set as reflexive, as in social and behavioral sciences are more common models with reflexive indicators because they fit better with constructs related to personality and behavioral characteristics (Hair Jr. et al. 2010). In reflexive models we assume that the causal relationship is expressed by the construct.

It is recommended that the constructs are conceptualized based on a constitutive and operational definition (Pasquali 1998). The constitutive definition is typically based on statements expressed in dictionaries or encyclopedias, delimiting the theoretical foundations which the construct is inserted, whereas, the transition from the theoretical foundations for an instrument, i.e., of the abstract for concrete it is characterized by operational definition (Pasquali 1998). A constitutive definition of the constructs shown in Fig. 1 is submitted in the sequence. The questionnaire items introduce the context that fits the operational definition and are shown in Table 5 (Appendix).

It is common for the definition of hypotheses to provide an answer to the problem under study. In the sequence, are displayed the definitions related to the constructs and the hypotheses.

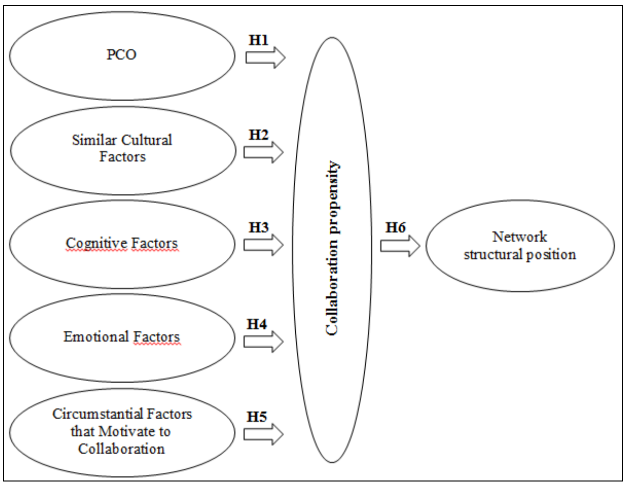

Fig. 1 Conceptual model proposed to evaluate the collaboration propensity and its influence on the structural position of an author on the network.

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The *PCO construct* has been adapted to the portuguese language from the work of Totterdell et al. (2008). This construct aims to evaluate how individual differences that guide people's behavior, based on specific personality aspects, influence on their propensity to connect with others. These individual differences are supported on three aspects: *make friends*, *make acquaintances* and *join others*, which may favor or expand relationships within a social structure and thus cause these people to be more likely to collaborate. With this, our first hypothesis was that:

H1: The PCO positively influences the authors' propensity to collaborate.

The culture concept as it is currently used was originated by Edward B. Tylor in 1871. For Tylor (1920, p. 1) culture is:

"*A complex which includes knowledge, belief, morality, art, laws, customs or any other capabilities and habits acquired by man as a member of society*" (Edward B. Tylor).

For Levi-Strauss (1969, p. 3), the man is a biological and social being and their responses to internal and external stimuli are dependent upon his nature or the social environment in which they live.

For the purposes of this paper, we define *cultural factors* as the set of attributes related to the values and basic assumptions of those who in some way influence their attitudes and behaviors. For example, for some collaborate with people who have similar philosophical ideals can be more attractive than others who have differing beliefs on these issues. We, therefore, propose the following hypothesis:

H2: Similar cultural traits stimulate the authors' propensity to collaborate.

The *cognitive factors* have been defined as the most important attributes and attitudes when one considers a purely rational choice. A rational choice is based on reason and facts that guide us in decisions. For example, it is very likely that we have a great interest in having as our partner a researcher with a broad knowledge on the subject of the work in question.

The studies that address the cognitive factors focus on understanding how people process the information, evaluate and interpret the situations, and what procedures are adopted for troubleshooting (Bossche et al. 2006). These cognitive skills have a strong relationship with the performance or the operation of a group (Lepine and Van Dyne 2001; DeChurch and Mesmer-Magnus 2010). Therefore, we are supposing that the cognitive aspects are motivating factors for the formation of partnerships in R&D projects and, therefore, we defined the following hypothesis:

H3: The cognitive factors influence the authors' propensity to establish collaboration links.

Evidences suggest that people, generally, direct their decisions based on some emotional characteristic (Pham et al. 2001). These characteristics or emotional factors may be important variables in the partners' selection process for developing an R&D work.

In this work, the *emotional factors* were classified as attributes or characteristics that make us feel good at working in team or collaborate with someone. For example, it is more pleasant to work with whom you have friendship. Hence, we hypothesized that:

H4: The emotional factors that represent positive characteristics influence the authors' propensity to establish collaborative links.

According to the definitions in some dictionaries of Portuguese and English language, the word circumstance denotes a particularity, situation, state or condition of things that accompanies a fact or event at given time and that causes a certain action or behavior. So the *circumstantial factors* were defined as the attributes and characteristics existing at any given time, situation or circumstance that may favor or facilitate the collaboration. The circumstantial factors may be related to opportunity factors. For example, the opportunity to develop a job with a researcher who is recognized worldwide. Hence, we propose the following hypothesis:

H5: The circumstantial factors contribute to the likely of authors to establish more collaborative links.

Finally, the last hypothesis was defined in order to assess how much the propensity of authors to collaborate explains the *structural position* that they holds in the R&D coauthorship network of IPEN. As previously defined, the network structural position was measured based on centrality and cliques indicators. Then, we propose the last hypothesis:

H6: The structural position that authors held in the network can be explained by the conceptual model set to assess the collaboration propensity.

II. Data And Methods

Data collect

Data collection was conducted through a survey research. According to Hair Jr. et al. (2005) the survey is a method to collect data from people, in which the data collected can reflect their behavioral characteristics and their experiences.

Data collection methods for the surveys are characterized by the administration of questionnaires or interviews. The interview is a procedure widely used in research whose purpose is to obtain qualitative data, while the questionnaire predominates in research where the purpose is to collect quantitative data (Hair Jr. et al. 2005). For data collection was used a questionnaire with closed questions administered by the interviewer (see questionnaire items in Table 5 in Appendix).

The target population of this study covers all employees of a research institution in Brazil who participated in the authorship or co-authorship of a technical and scientific publication within a period of 10 years. This team of collaborators includes researchers, technicians, analysts and assistants. In order to adjust the questionnaire, a pretest was performed using a survey research to a sample of 25 authors distributed among the various IPEN's research areas and selected according to the number of publications. These authors are part of the target sample.

Except for the items of the "Propensity to connect" construct which was adapted from model of Totterdell et al (2008), the items related to other constructs are new and were developed *a priori* to the goals and needs of this research.

The definition of the new items was based on a literature review of the work of Katz & Martin (1997), Beaver (2001), Hara et al. (2003), Borges & Baranauskas (2004), Olivera & Straus (2004), Bossche et al. (2006), Birnholtz (2007) and Sonnewald (2007). These works from the assumption that scientific collaboration involves various features and attributes related to personal, social, cultural and circumstantial aspects that can expand or limit the possibilities of collaboration.

The conduct of research in the pretest was established as follows: face to face structured interviews with 10 authors. First, using a questionnaire with open questions, in order to, assess the degree of conformity between the spontaneous answers of the authors and the proposed model. Later, a questionnaire with closed questions, model initial draft, was distributed to them to see if the answers provided, contextualized in the purposes of this research, were included in the model. These authors also evaluate whether the items were grouped appropriately to previously defined factors. Cleared the nonconformities and inconsistencies, the survey was expanded to other authors selected for the pretest. Finally, after adjusting all non-conformities and inconsistencies in the questionnaire formulation, it was distributed to all authors and co-authors selected to compose the sample.

For purposes of this article, the final questionnaire consists of 42 items divided into two parts:

i. First it contains 13 items to assess how an author classifies himself in terms of attributes or socio-behavioral characteristics;
ii. Then 29 items purposed at understand what makes people more attractive as research collaborators;

We used a Likert scale to the 42 items of the questionnaire. This Likert scale ranged from 1 to 5 points, indicating the degree of agreement or relevance to each item of questionnaire. The criteria used for selecting the sample for this research was based on collaboration, i.e., the IPEN's authors who developed a research paper with at least two other IPEN's authors. This criterion elected a total of 308 authors to compose the survey, of which 187 authors responded to the questionnaire, corresponding to a rate of return of approximately 60%.

However, from the 187 authors who responded to the questionnaire, four were discarded for presenting missing data. Thus, refined and suitable final sample for analysis from the standpoint of PLS-SEM method is comprised of 183 cases.

On studies that use PLS, despite some disagreement, a common rule is adopted to set the minimum size of the sample as equal to ten times the number of regression relationship for the greater complexity construct the structural model (Lee et al. 2011). In this work, the collaboration propensity construct is more complex with five regression relationships, therefore, based on the mentioned rule the minimum sample size required would be 50 cases. Another rule is presented in Hair Jr. et al. (2014), wherein to achieve a statistical power of 80%, significance level of 5% and detecting an R^2 value (determination coefficient) of 0.10, for a construct with five regression relationships, are needed a minimum sample of 147 cases. In this work, both rules minimum sample size were contemplated, resulting from a sample of 183 cases that were used in the analysis.

Measurement model assessment

The evaluation of the proposed conceptual model used a *Partial Least Square* based approach that is a variation of *Structural Equation Modeling* (PLS-SEM).

PLS-SEM is a causal modeling technique which purpose is to maximize the explained variance of latent variables or dependent constructs, which is widely used in various areas of research (Hair et al. 2011; Henseler et al. 2009). This technique was adopted to fulfill two basic questions of this research: simultaneous evaluation of a set of manifests variables (indicators) and latent variables (constructs) and does not require a large sample size (Henseler et al. 2009). The calculation of the results was performed using the program *SmartPLS* (Ringle et al. 2005).

The construct validity comprise to measure the proportion that a set of items or indicators is related to the construct it intends to measure, showing that the measured values obtained in the sample reflect with the values of the population (Hair Jr. et al. 2010). The reliability of this causal relationship between indicator and the construct is assessed by the measurement model.

The *face validity* is a subjective assessment of the questionnaire items and their correspondence with the construct. It is conducted through expert analysis, pre-testing, or other means (Hair Jr. et al. 2010). This analysis was supported by reviews and comments recommended by the 25 authors selected for the pretest phase. It was asked to these authors to assess the wording, consistency and finally the grouping of the statements was consistent with the structure proposed constructs: cognitive, emotional, cultural and circumstantial.

The *convergent validity* evaluates how much the indicators of a specific construct converge or share a common variance proportion (Hair Jr. et al. 2010). To indicate convergent validity is recommended values of *extracted variance average* (AVE) above 0.5 and factor loadings should be above 0.7. However, in exploratory studies wherein typically represent new scales factor loadings above 0.5 are acceptable (Hulland 1999; Hair Jr. et al. 2010). The AVE indicates that the construct explains at least half of the variance of the indicators (Hair et al. 2011). Therefore, convergent validity is also a way of checking the unidimensionality of the scale (Hair Jr. et al. 2010).

A complement to convergent validity is the *discriminant validity*, which provides evidence that measures a construct differ from measures of other constructs in the model (Hulland 1999). This implies that a construct is unique, representing phenomena that are not represented in the model by other constructs (Hair Jr. et al. 2014).

There are two criteria which are normally used to evaluate the discriminant validity. The first criterion uses an approach suggested by Fornell and Larcker (1981), wherein the result of the square root of the AVE values for each construct must not be lower than the values of the correlations between the constructs in the model. The idea is that a construct should share more variance with its associated indicators than any other construct (Hair Jr. et al. 2014). The second criterion is the cross-loadings, in which the factor loadings of the indicators associated with a specific construct must be greater than the factor loadings in other constructs (Hair et al. 2012; Hair et al. 2011). The occurrence of cross-loadings indicates a problem of discriminant validity (Hair Jr. et al. 2014; Hair Jr. et al. 2010).

The *composite reliability* and *Cronbach's alpha* (Cronbach, 1951) are reliability measures that evaluate if a set of indicators is consistent with the construct to be measured and are not recommended, for both measures, values less than 0.7 (Hair Jr. et al. 2014; Silva et al. 2008; Tenenhaus et al. 2005). However, in analyzes employing PLS-SEM many authors (Bagozzi and Yi 1988; Silva et al. 2008; Hair et al. 2011) recommend using the composite reliability (*CoC*) as a measure of reliability because the Cronbach's alpha tends to underestimate the internal consistency of latent variables in models based on PLS-SEM (Henseler et al. 2009). Reliability can be considered a convergent validity measure (Hair Jr. et al. 2010).

Structural model assessment

The structural model is characterized by the relationship between the constructs in a conceptual model, enabling to examine whether the hypothetical relationships made at the theoretical level are empirically acceptable (Pavlou and Chai 2002).

The evaluation of the structural model was based on indications suggested by Hair et al. (2011), Henseler et al. (2009), Hair Jr. et al. (2014) and Ringle et al. (2014). According to these authors the evaluation of the structural model should pay attention to the following criteria:

a) The explanation power of model by the coefficient of determination (R^2);
b) The magnitude and statistical significance of the path coefficients;
c) The quality of model fit.

The capacity of the conceptual model to explain the variance of the collaboration propensity construct was measured by the coefficient of determination (R^2). R^2 is a measure of the proportion of the variance of the dependent variable or endogenous construct (e.g. collaboration propensity) around its average which is explained by the independent or predictive variables (Hair Jr. et al. 2010). In the case of PLS-SEM, represents the variance proportion of the endogenous construct that is explained by all the constructs that have a regression relationship pointing to it. The R^2 values ranging from 0 to 1, and the higher the value of R^2 the greater the power of the variance explained to the endogenous construct. In the areas of social and behavioral sciences, values of *0.02*, *0.13* and *0.26*, for R^2, are classified as low, moderate, substantial, respectively (Cohen 1992; Henseler et al. 2009). However, Hair Jr. et al. (2014) indicate that the values for R^2 greater than 0.20 are considered high in disciplines that study consumer behavior.

The analysis of statistical significance of the regression coefficients (β) is performed by bootstrapping technique. This is a random resampling technique with replacement, which is reproduced from the original sample. Generally, 5,000 subsamples are previously defined for all the resampling process (Henseler et al. 2009; Hair et al. 2011; Wong 2013; Hair Jr. et al. 2014). The *bootstrapping* technique provides the *student t* values to evaluate the statistical significance values of measurement and structural model. Generally, social science accepted a statistical significance level - *Sig.* ≤ 5%, which corresponds to a $t \geq 1.96$ and can be expanded to *Sig. ≤ 10%*, which represents a t value ≥ 1.65, in situations where the nature of the study was exploratory. These *t student* values assess too whether the hypotheses defined for the model are statistically supported, that is, if the null hypothesis should be rejected or not.

The quality of model adjustment was evaluated based on two indices: relevance or predictive validity and effect size. The *predictive validity* of the model was evaluated using the Stone-Geisser's test (Q^2) (Stone 1974; Geisser 1974). This test assesses the model ability to adequately predict the indicators of endogenous construct (Henseler et al. 2009). Q^2 was calculated using the blindfolding procedure that applies only to endogenous constructs that has a reflective measurement model (Hair et al. 2011). The *blindfolding* procedure, which is available in *SmartPLS* program, provides two results: redundancy cross-validated (*CV red*) and cross-validate communality. Hair et al. (2011) and Henseler et al. (2009) suggest to use the *CV red*, since, evaluates the data prediction for the measurement and structural models. Q^2 values greater than zero suggest that the predictors constructs of a specific endogenous construct denote relevance or predictive validity (Hair et al. 2011).

Finally, the *effect size* (f^2) or indicator Cohen (Ringle et al. 2014) evaluates how a specific exogenous construct contributes to the R^2 values of the endogenous construct in the model (Wong 2013). Values 0.02, 0.15 and 0.35 are considered small, medium and large, respectively (Cohen 1992).

Refine the conceptual model originally proposed

As this is an exploratory study, the establishment of the conceptual model originally proposed did not meet some basic fundamental criteria of construct validity and reliability. So, it was necessary to make several adjustments to achieve a consistent model to the validity and reliability criteria. These adjustments comprised the removal of some model indicators (COG02, COG05, EMO13, EMO14, CUL19, and CIR23), and the remodeling of the model originally proposed as the inclusion of a common hierarchical construct for emotional and cognitive constructs, since these constructs deal with characteristics inherent to the personal traits and showed a correlation with an intensity moderate, $r=0.54$. Another adjustment was the remodeling of circumstantial construct that was subdivided in three new constructs which contribute directly to explain the collaboration propensity construct. The conceptual model remodeled is shown in Fig. 2.

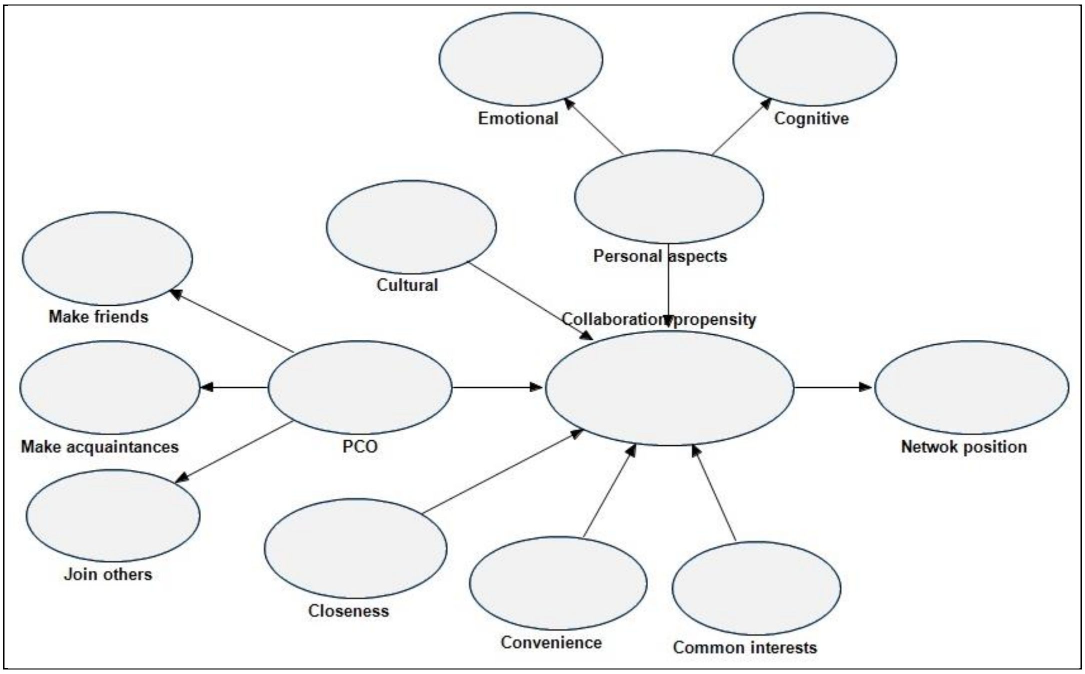

Fig. 2 Remodeled conceptual model.

With this new configuration of model was necessary to redefine the concepts that were stipulated to circumstantial construct, and consequently the hypothesis that considered it as a unique predictor of the collaboration propensity construct. The new constructs were formed from a segmentation circumstantial construct, and were conceptually defined as:

*Closeness: c*ircumstances that bring together authors;

*Convenience: c*ircumstances that make it convenient to collaboration, providing advantages that can stimulate the propensity of an author to collaborate;
*Common interests: c*ircumstances that provide a state or characteristic which are compliant and which can facilitate the collaboration propensity.

The configuration of a hierarchical construct for emotional and cognitive constructs demanded a redefinition of hypothesis H3 and H4. Hence, we propose the following hypothesis:
H3:4: The personal aspects linked to cognitive and emotional factors influence the authors' propensity to establish collaborative links.
Also, for this new configuration of model, it was necessary to define the hypotheses for new constructs. The new hypotheses were defined as follows:
H5a: The circumstances related to proximity aspects contribute to the authors will feel propensity to establish collaboration links.
H5b: The circumstances related to convenience aspects contribute to the authors will feel propensity to establish collaboration links.
H5c: The circumstances related to the common interests contribute to the authors will feel propensity to establish collaboration links.

Validity and reliability model
Analyzing the results shown in Table 2 we conclude that:
a) The values determined for the factor loadings are above or close to the recommended minimum of *0.5*;
b) The computed values for AVE are above the recommended minimum of *0.5*, except for the cognitive construct with a value of *0.49*;
c) The calculated values for composite reliability are above the recommended minimum of *0.7*;
d) These results together with the values determined for the factor loadings allow to assure that the remodeled conceptual model presents convergent validity and reliability, although some *Cronbach's alpha* values have not reached the recommended minimum of *0.7*, since it is recommended to adopt the composite reliability as a rule of reliability to models based on PLS-SEM for the reasons already mentioned;
e) Based on the criteria suggested by Fornell and Larcker (1981) to assess the discriminant validity, it turns out that the values of the square root of the AVE, exposed diagonal of Table 3 are higher than the values of the correlations between the constructs, which shows the remodeled conceptual model presents discriminant validity.

Table 2 Values obtained to evaluate the construct validity and reliability.

Constructs	*Indicator**	*Loadings*	*t-value*	*AVE*	*Composite reliability*	*Cronbach's Alpha*
Make friends	FPE01	0.918	58.585[a]	0.75	0.90	0.83
	FPE02	0.880	47.093[a]			
	FPE03	0.795	20.939[a]			
Make acquaintances	FPE04	0.691	12.162[a]	0.55	0.78	0.6
	FPE05	0.716	12.479[a]			
	FPE06	0.812	27.750[a]			
Join others	FPE07	0.744	15.780[a]	0.66	0.85	0.74
	FPE08	0.861	38.691[a]			
	FPE09	0.824	26.522[a]			
Cultural	CUL15	0.673	3.281[b]	0.63	0.87	0.8
	CUL16	0.813	3.684[a]			
	CUL17	0.815	4.291[a]			
	CUL18	0.854	4.266[a]			
Cognitive	COG01	0.620	6.830[a]	0.49	0.83	0.74
	COG03	0.692	12.291[a]			
	COG04	0.598	8.465[a]			
	COG06	0.809	26.310[a]			
	COG07	0.754	20.697[a]			
Emotional	EMO08	0.519	6.035[a]	0.5	0.83	0.74
	EMO09	0.655	10.529[a]			
	EMO10	0.733	11.346[a]			
	EMO11	0.873	43.914[a]			
	EMO12	0.719	17.409[a]			
Common interest	CIR20	0.681	7.947[a]	0.51	0.75	0.59

	CIR21	0.881	20.024[a]			
	CIR22	0.546	4.034[a]			
Closeness	CIR24	0.946	5.532[a]	0.50	0.74	0.64
	CIR28	0.611	2.582[c]			
	CIR29	0.492	1.659[d]			
Convenience	CIR25	0.639	1.917[d]	0.54	0.77	0.58
	CIR26	0.739	2.256[c]			
	CIR27	0.809	2.255[c]			
Collaboration propensity	FPE10	0.824	33.649[a]	0.59	0.85	0.77
	FPE11	0.798	22.545[a]			
	FPE12	0.718	13.234[a]			
	FPE13	0.735	13.125[a]			
Network position	BetweC	0.842	12.128[a]	0.78	0.95	0.93
	Clique	0.883	10.357[a]			
	CloseC	0.868	13.49[a]			
	DegreeC	0.964	14.363[a]			
	EigenC	0.861	10.306[a]			

Note: [a] p<0.001; [b] p<0.01; [c] p<0.05; [d] p<0.10.
** The indicators description is exposed in Table 5 in Appendix.*

Table 3 Correlations and AVE square root values to assess the discriminant validity.

	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11
1. Netwok position	**0,88**										
2. Cognitive	0,01	**0,70**									
3. Cultural	-0,10	-0,03	**0,79**								
4. Emotional	-0,01	0,46	0,16	**0,71**							
5. Closeness	-0,08	0,04	0,41	0,22	**0,71**						
6. Common interests	0,02	0,38	0,11	0,28	0,06	**0,72**					
7. Join others	0,20	0,16	-0,09	0,18	-0,08	0,15	**0,81**				
8. Make friends	0,17	0,17	0,05	0,21	-0,06	0,20	0,38	**0,87**			
9. Make acquaintances	0,12	0,18	-0,05	0,25	-0,04	0,13	0,46	0,59	**0,74**		
10. Convenience	0,08	0,09	0,21	0,22	0,42	0,38	0,00	0,02	-0,12	**0,73**	
11. Collaboration propensity	0,19	0,34	-0,15	0,26	-0,23	0,40	0,41	0,40	0,36	0,07	**0,77**

Note: AVE square root values for each construct are exposed on the diagonal, in bold.

Evaluation and discussion of the results of the remodeled model, and hypotheses testing

The remodeled conceptual model explains about *41%* of the variance of the collaboration propensity endogenous construct. The magnitude of R^2 depends on the complexity of the model and the research area. As mentioned above, R^2 values of *0.20* can be considered significant in researches related to human behavior.

In Table 4 we can see that:

a) The influence, characterized by path coefficients (β), and the percentage that each construct represents in the power of explanation (R^2) relative to *Collaboration propensity* construct;
b) The f^2 and Q^2 values to assess the overall fit of the model;
c) And finally, if the hypotheses are supported statistically, i.e., if the results attained meet the statistical significance criteria.

We can see that the *PCO* construct, which showed a very expressive statistical significance ($p<0.001$) is the one with the greatest influence ($\beta=0.362$) and the greatest explanatory power ($R^2=17.4\%$) in relation to the *Collaboration propensity* construct, suggesting that people who have relationship easiness and, consequently, like to have and cultivate friendships become more prone to establish collaboration links.

We also observed that the researches covering themes and projects common nature, and the affinity established in previous works are circumstances that can broaden perspectives of the authors to establish collaboration links. Thus, the *Common interests* construct with $\beta=0.245$, indicates that there is a positive influence on the propensity of an author to collaborate under such circumstances.

Table 4 Influence of each predictor construct in relation to collaboration propensity construct and evaluation of each hypothesis.

		Collaboration propensity					
	Constructs	*β*	*r**	*R^2*	*f^2*	*t-value*	*Hypothesis?*
H1	*PCO*	0.362	0.481	17.4%	0.189	6.020	*Supported*
H2	*Cultural*	-0.092	-0.146	1.3%	0.010	1.281	*Not Supported*
H3:4	*Personal aspects*	0.185	0.354	6.6%	0.044	2.737	*Supported*
H5a	*Closeness*	-0.246	-0.233	5.7%	0.068	2.793	*Not Supported*
H5b	*Convenience*	0.084	0.074	0.6%	0.007	0.983	*Not Supported*
H5c	*Common interests*	0.245	0.399	9.8%	0.072	3.408	*Supported*
	R^2	41.4%					
	Q^2	0.242					
		Netwok position					
H6	*Collaboration propensity*	0.188	0.189	3.6%		2.939	*Supported*
	Q^2	0.023					

** Pearson coefficient*

The hypothesis related to *Closeness* construct was not supported due to its direction, despite having been supported statistically.

The inverse relationship between the *Closeness* and *Collaboration propensity* constructs were strongly influenced by *CIR24* indicator that represents the assertive hierarchical level in the questionnaire. Removing the *CIR24* indicator of the model the *β* value is *-0.049*, while the *CIR24* indicator when correlated with the *CIR28* or *CIR29* indicators the minimum value attained for the *β* was *-0.239*. This aspect, taken based on the perception of the answers of the IPEN's authors indicates that there is small resistance these authors to establish collaboration links with authors who have a hierarchical level within the institution. Although the hierarchical level represents a barrier, the results also show that the IPEN's authors linked to the same department or center or who had an academic link in undergraduate or graduate courses, they also showed some resistance. The scientific competition reported in Birnholtz (2007), in which researchers compete intensely for reputation can be one of the reasons for these resistances.

The *Cultural* and *Convenience* constructs did not meet the criteria recommended for statistical significance, and they also displayed values quite innocuous for the *β* of *-0.092* and *0.084*, and for R^2 of *1.3%* and *0.6%*, respectively. Therefore, it is advisable to remove these two constructs from the model, obtaining thereby a more parsimonious model.

The *Personal aspects* construct, that comprises cognitive and emotional factors, explains *6.6%* of the collaboration propensity. Based on the results obtained for the *β* and statistical significance, we can conclude that the personal aspects have a modest positive influence on the propensity of an author to establish collaboration links.

Finally, the model proposed to evaluate the propensity of an IPEN's author in establishing collaboration links explained *3.6%* of the structural position that an author held in the R&D coauthorship network of IPEN. As mentioned earlier, the structural position has been based on centrality and cliques indicators of a dichotomized network that comprises the period 2001 to 2010. This value of *3.6%* can be considered negligible in the classification proposed by Hair et al. (2011). However, as a first study that combines social network analysis and structural equation modeling, it was found that there is a small influence of the collaboration propensity on the structural position that an author held in the network, and therefore, we suggest that new studies, following this same research line, to be conducted so that we can expand the understanding of this latent aspect involving scientific collaboration.

Based on the classification proposed by Cohen (1992), the values for the effect size of the predictors constructs on the *Collaboration propensity* construct, shown in Table 3, we concluded that:

a) The *Cultural* and *Convenience* constructs with effect size values of *0.01* and *0.007*, respectively, disclosed a very negligible impact;
b) The *Personal aspects*, *Closeness* and *Common interest* constructs have an effect size in the range between *0.04* and *0.07* approximately, which can be considered low;
c) The *Propensity connect* construct, as was to be expected because of the magnitude of R^2, showed a moderate impact on the *Collaboration propensity* construct.

We can notice also that the Q^2 values, for both constructs *Collaboration propensity* and *Network position*, point out that the model has predictive validity, because they have values greater than zero as previously described.

III. Conclusion

The main objective of this study was to understand, even partially, the propensity of an author to establish collaborative links with other authors of a research institution focusing on nuclear area in Brazil. For this, it proposed a conceptual model that consists of a set of observed variables arranged in various latent constructs related to personal, behavioral, cultural and circumstantial factors that we believe are important in influencing the decisions of authors to work within a collaboration context.

The results achieved with the conceptual model remodeled, calculated from respondents' answers, suggest that the authors who adopt behaviors and attitudes that lead to the practice of inclusion and social integration are those with a greater propensity to establish collaborative links. On the other hand, the similarities in certain cultural patterns theoretically not represent factors that stimulate or inhibit the propensity of the authors to collaborate. Despite the hypothetical direction, this result was not unexpected, because the research is limited to a group of people who are part of a society that, generally, not bases its cultural heritage based on the judgment of the differences.

Overall, each construct that represents the latent dimensions that summarize the set of observed variables defined in this study, explained very little collaboration propensity of the IPEN's authors, reaching values below 10%, except for the PCO construct that evaluates how people classify themselves in terms of socio-behavioral characteristics it reached a value greather than *17%*. However, the sum of the explanation power concerning all the constructs explained approximately *41%* of the collaboration propensity, which can be classified as a very significant value when we are evaluating aspects related to social and behavioral sciences.

Finally, the proposed conceptual model is not adequate to explain the structural position that an author held in R&D coauthorship network of IPEN, since the explanatory power was less than *4%*. However, the results obtained with the conceptual model serves as an empirical reference to direct future studies that combine the structural equation modeling techniques with social network analysis techniques.

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