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MEASURING THE ORGANIZATIONAL ANALYTICAL COMPETENCE: DEVELOPMENT OF A SCALE

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Research paper

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Abstract

The massive growth in the amount of data that companies, organizations, and society have been compelled to deal with, reinforces the need for studies on subjects such as business intelligence, business intelligence and analytics, and big data. Although certain aspects of these themes are already established in research, there is still a lack of understanding and consensus on how to combine variables to encourage better use of data. In this study, we propose a comprehensive conceptualization of a new construct -- analytical competence (ACOMP) -- comprised of three dimensions grounded in the business intelligence and analytics literature and absorptive capacity theory. To properly develop the ACOMP scale, we followed a six-step procedure and collected data from 82 organizations. We validated a nomological model where the ACOMP scale was tested as an antecedent of organizational performance regarding making decisions and learning. The results of this study provide support for ACOMP as a valid and reliable scale that is useful for both academic and managerial purposes.

Keywords: *Business Intelligence, Business Intelligence and Analytics, Analytical Competence, Big data*.

1 Introduction

As a society, we are creating more data today than ever before in our history. As a result, data is everywhere, and people are able to search and use the data to be informed about almost everything. This evolution has resulted in a society that is more data-oriented, where most of our actions are based on data or transformed into data, and the main patron is the technology itself. Although we are living in a big data era, organizations still lack the expertise to exploit all this data. Researchers have already pointed out that there are organizational skills needed to work with the large volume of data (Watson, 2009; Watson, Wixom and Ariyachandra, 2013) and developing analytics as an organizational competence has become an essential capability for an organization interested in making good decisions and achieving better levels of competitiveness (Davenport, 2006).

Organizational analytical competence can be defined as a set of knowledge and skills required for effective business intelligence analytics (BIA) (Chiang, Goes and Stohr, 2012). Organizational competence is related to the ability required to exploit the available data and transform it into value for the business. In other words, it is the capacity to generate insights and actions, which is a de-facto contribution to the firm's performance. Analytical competence requires developing knowledge and capabilities not only in the domain of disciplines such as statistics, computer science, and information technology but also in business, communication, and problem-solving (Chiang et al., 2012). Some studies have made the connection between performance via the proper use of data and efficient information management (Davenport, 2006; Mithas, Ramasubbu and Sambamurthy, 2011; Torres, Sidorova and Jones, 2018), reinforcing data analytics as a differentiator of competitiveness. Top-performing organizations became 'smarter' by using analytics, while lower performers do not engage much in analytics, thus leading us to believe that developing analytical competence has become an essential skill to generate value (Lavalle et al., 2011).

Although the theme "analytics" and the requirement to become analytical have been heavily explored in the managerial literature (Schelegel, 2011; Hostmann, 2012; Rozwell et al., 2012), there is still a lack of theoretical foundation to define the phenomenon of analytical competence of the organization, as well as its dimensions. More recently, Gupta and George (2016) and Ghasemaghaei, Ebrahimi, and Hassanein (2018) used RBV to study how managing resources can lead to superior firm performance in BIA initiatives. In the same vein, Torres et al. (2018) employed the dynamic capabilities theory to conclude that organizations may improve decision quality. Although these studies have contributed to the understanding on how BIA can leverage superior organizational performance, they focus on a broad range of resources, rather than on the skills necessary to perform analytics. Additionally, they operationalize their measurement models as formative or majorly formative, although in some cases most of the latent variables present substantive intercorrelations. Proposing a model as formative means that the researcher is confident about the model containing both the necessary and sufficient dimensions, and that they are dissimilar enough to the point to show reduced intercorrelations. As consequence, more research is still needed to identify what are the underpinnings of analytical and how to measure this construct.

Given the importance of analytical competence for both the academic and managerial community, this research has two primary objectives. First, we properly define the analytical competence (ACOMP) as a set of organizational skills combined and second, we propose an approach to measure it as a multidimensional, reflective construct leveraged by the absorptive capacity theory. This paper covers the theoretical background, followed by the scale development, validation, discussion and conclusion.

2 Absorptive Capacity

Since the original work from Cohen and Levinthal (1990), absorptive capacity (ACAP) has been widely used in information systems, as a lens to understand theoretical perspectives and phenomena such as IT governance, IT innovation, knowledge management, IT business value and others (Iyengar, Sweeney and Montealegre, 2015). ACAP is defined as the ability to recognize new external knowledge, assimilate it, and apply it to business ends (Cohen & Levinthal, 1990). At the core of the definition is competence in the form of knowledge and communication, as well as the notion of complementary resources. For instance, absorptive capacity (ACAP) has been used to generate organizational learning in diverse situations, such as facilitating the information flow and learning to the top management and operational level (Elbashir, Collier and Sutton, 2011; Elbashir et al., 2013), and also as an enabler of market knowledge creation (Malhotra, Gosain and Sawy, 2005).

Cohen and Levinthal (1990) describe the concerns related to ACAP, but unfortunately, they did not present a formal means to measure it. This may partially explain why ACAP has been conceptualized and measured in many different ways, engendering a lack of consensus on how to properly measure it. Several researchers have proposed scales for ACAP (Szulanski, 1996; Lane and Lubatkin, 1998; Jansen, Van den Bosch and Volberda, 2005; Malhotra et al., 2005), suggesting distinct scales differing based on the organizational and inter-organizational level of analysis, first-order and second-order reflective, and multi and unidimensional. A few have kept their scales faithful to Cohen and Levinthal's original conceptualization. The majority changed its primary idea or followed the re-conceptualization proposed by Zahra and George (2002). Zahra and George presented a re-conceptualization of the ACAP construct, including one additional dimension and reconfiguring the conceptualization of the other three dimensions, resulting in two ideations called PACAP (Potential Absorptive Capacity) and RACAP (Realized Absorptive Capacity). The duality resulting from this approach has been well accepted, but neither the authors nor their followers have presented a scale to measure the construct cleft in two parts.

Back to Cohen and Levinthal's approach, Pavlou and El Sawy (2006) applied ACAP to study the development of new products in a turbulent environment. They proposed a new scale with 10 items, reflective, unidimensional, and applicable to group level of analysis. Due to the versatility of this scale, it became one of the most adopted and popular scales to measure ACAP in the IS field, and it has been since used by other authors such as Liu et al. (2013), Iyengar et al. (2015), and Roberts (2015). Although some authors have used similar constructs, it is noted that so far ACAP has never been operationalized based on a complete scale development procedure.

3 Analytical Competence (ACOMP)

As stated above, at the core of ACAP is competence. According to Woodruffe (1993), competence is a comprehensive term that includes almost everything that directly or indirectly can be converted into performance. In the IS research field, organizational competence has frequently been related to the idea of the alignment between IT and business areas, with the emphasis on IT transitioning from an operational role to a more strategic focus (Roepke, Agarwal and Ferratt, 2000). For example, Prahalad and Hamel (1990) defined competency as collective learning in the organization that is created from the coordination, integration, and harmonization of diverse skills and knowledge of their employees. Similarly, as analytical competence is likely to influence corporate performance, we assume analytical competence as an organizational competence to support organizational performance (Bassellier, Reich and Benbasat, 2001).

In recent years, data has become a source of competitiveness and the term analytics has gained popularity as commonly linked with the use of emergent technologies to handle huge volume of data with the potential to positively impact business areas such as healthcare, government, market intelligence, security, public safety and others (Chen et al., 2012). There are many managerial prescriptions about how to build a good organizational analytical environment (Schelegel, 2011; Chandler, 2014), while on the academic side studies have proposed the concept of Business Intelligence Analytics (BIA) success (Popovič, Hackney, Coelho and Jaklič, 2012; Seddon, Constantinidis and Dod, 2012; Işik, Jones and Sidorova, 2013). More recently, studies examined more closely how organizational resources can be combined to analythics initiatives to suceed (Gupta and George, 2016); Ghasemaghaei, Ebrahimi, and Hassanein, 2018, and Torres et al. 2018). However, addressing and measuring such analytical competence as an organizational combination of skills does not appear to exist. Some researchers have argued the importance of information technology competence for business managers (Bassellier et al., 2001), while others have focused on the necessity of information technology professionals to develop business competence (Genevieve and Benbasat, 2004). In both cases, there are no references on how to assess the resulting combined organizational analytical competence as the interrelatedness skills combined throughout the organization. Furthermore, researchers have pointed out the shortage of professionals prepared to manage advanced analytics required to support the five Vs (volume, velocity, variety, veracity and a value) of big data and the urgent necessity of developing professionals with new knowledge and skills to deal with analytics (Chiang et al., 2012; Watson, 2012).

Due to the demanding and challenging scenario regarding analytical competence faced by organizations, there is an understanding about the necessity of developing new skills inside the organization (Henry and Hiltbrand, 2012) but, again, there is a lack of knowledge that could guide researchers and practitioners on how to measure them. Therefore, to address this gap, this study proposes a new construct, named analytical competence (ACOMP), defined as the organizational competence to combine multiple skills to comprehensively process data to support performance.

Based on an extensive literature review, we identified three sets of skills relevant to ACOMP: Analytical Skills, IT & Data Skills and Problem-Solving Skills. We thus propose ACOMP to be a multi-dimensional, reflective second-order construct. Multidimensional constructs have been used in the organizational behavior research for a long time, as an efficient representation of complex phenomena (Edwards, 2001). Therefore, due to the conceptual complexity of ACOMP, we defined it as a superordinate multidimensional construct, represented by a set of skills that are manifestations of the general construct ACOMP. In this way, we expect that a strategic change in the focal construct ACOMP produces a change in its sub-dimensions, since the dimensions are interrelated to produce the competence, the level of maturity in one type of skill should be balanced and impacts the other skills. For instance, we expected that as organizations become more competent, increases of the level of analytical skills would demand improvements in the IT & data skills to acomplish the necessary levels of analythical compentence. This interrelatedness between the dimensions is key for achieving new levels of analythical competence. In the same logic, an advanced problem-solving skill will push the development of the other skills dimensions.

3.1 Analytical Skills

Analytical Skills is the first dimension of analytical competence and can be defined as the ability of using statistics and computer science techniques such as machine learning, geospatial and temporal analysis, text mining and computational linguistics, statistical analyses, among others advanced analyses (Chiang et al., 2012) to provide a better understanding of the business. Some authors argue that the use of analytical tools allow the organization to identify the value of customer-based market opportunities (Roberts and Grover, 2012), allowing the organization to carry out a number of strategic moves to appropriate the economic margins available. The academic community has already pointed out the necessity of an organization to count on analytical skills to be able to reach higher levels of maturity in BIA (Lukman et al., 2011; Chen et al., 2012; Raber, Winter and Wortmann, 2012; Raber, Wortmann and Winter, 2013; Watson and Marjanovic, 2013). Those researchers have also argued that to take advantage of big data's features, organizations will require new and advanced analytical abilities to exploit the data and technology available. Therefore, since the academic and managerial communities agree that in times of big data, the challenges regarding analytical skill has become more a matter of competitiveness, this skill was included as one of the dimensions of analytical competence.

3.2 IT & Data Skills

IT & Data Skills is the second dimension of analytical competence and defined as the ability to get data from multiples sources. It is related to topics such as relational database, data warehouse, ETL (extract, transform and load) procedures, semi-structured and unstructured data management. IT & Data Skill are directly related to data treatment, but indirectly connected to information technology, once the infrastructure of the data requires IT skills as well (Chiang et al., 2012). In other words, to access structured or unstructured data in different types of database, or data repository or any other source of data, it will indeed require a specific set of skill which is covered by this dimension. For instance, to manipulating structure data requires a minimum knowledge of relational database and SQL (Structured Query Language). Despite recent research expressing that emerging big data technologies are still an under-explored field in organizations, there are already some cases showing how IT & Data Skills are important for providing a better understanding of consumer behavior on social media, or even exploring the vast number of possibilities of mobile analytics (Chau and Xu, 2012; O'Leary, 2013). Therefore, considering the evidence on how IT & Data Skills plays an important role on analytical competence, this dimension was included in the construct.

3.3 Problem-solving Skills

Problem-solving Skills is the last dimension of analytical competence and refers to the ability to deal with and find new solutions to complex problems. In other words, it represents the level of proactivity toward new initiatives and creativity to solve problems. A very complex problem is called wicked, and it crosses a number of knowledge domains and requires new ways of thinking (Henry and Hiltbrand, 2012). Cohen and Levinthal argue that problem-solving is a type of learning capability, following the logic that as an organization learns, the more knowledge the organization obtains. This cumulative and progressive cycle facilitates the assimilation of new knowledge (Cohen & Levinthal, 1990). For that reason, to guarantee competitiveness in a more global and complex scenario, it is important for organizations to develop a problem-solving skill, so, it is included as a dimension of analytical competence.

According to Prahalad and Hamel (1990), competences grow as they are applied and shared, so, using this logic we can assume that ACOMP will grow by the integration and harmonization of those three skill dimensions. For instance, if the organization has both analytical and IT & data skills well integrated, its analytical competence is higher than other organizations that are only focused on IT & data skill without an analytical approach or vice versa. As more an organization is capable of sharing their abilities, more competent, it will be.

4 Scale development process

The instrument development was carried out in six steps, which were based on the scale development procedures proposed by Mackenzie et al. (2011), and the card sorting technique described by Moore & Benbasat (1991). In order to clarify the process, we used the activities and outcomes of each step are described in Figure 1.

4.1 Step 1 - Conceptualization

The conceptualization stage consisted of a wide literature review developed in two stages procedure inspired and adapted from Jourdan *et al*. (2008). The review took place between May and June of 2016, and in the 1st stage of the literature review we focused on seeking the largest possible number of articles that was published after 2000, which containing the following keywords: BI (Business Intelligence), BA (Business Analytics), BIA (Business Intelligence analytics), Analytics and Big data. We chose these key-words because the concept of analytical competence is related to the capacity of using the data to generate intelligence to business. At this stage, the effort concentrated on those articles that treat the subject of various forms, without necessarily applying specific content filters. Therefore, in the second stage, the objective was to select from a list of pre-selected articles, only the ones that presented characteristics that describe BI, BA, and BIA as a process, a model, or at levels that provide a maturity connotation.

The search was made in the main journals of the Information System area, using the EBSCO Discovery database. At the end of this process, 23 papers were manually selected to compose the theoretical bases to address the conceptualization of the ACOMP dimensions.

Conceptualization & Development of Measures		**Scale Evaluation and Refinement**		**Construct Conceptualization**	**Scale Assessment and Validation**
Step 1: Structure Literature Review	**Step 2: Item Pool creation**	**Step 3: Card Sorting**	**Step 4: Qualitative Interviews**	**Step 5: Model Specification**	**Step 6: Scale Validation**
Activities					
Two-stages review focused on papers related to analytical and competence subjects. 31 papers manually selected and classified according to their focus.	The dimensions of ACOMP emerged from the literature review made in step 1 and a consistent item pool was created.	Each judge participated in one round and took, on average, 30 minutes to finish it. They all made card piles and named it in accordance with their understating of the subject.	Final qualitative step consisted of asking five questions about ACOMP to 10 seniors professionals (Managers, Directors and CIOs) from different organizations.	A formal model of Analytical competence was defined as a multidimensional and reflective construct.	334 questionnaires sent to a list of organizations associated with the American Chamber of Commerce (AMCHAM), 110 questionnaires were collected, and 82 were completed and valid.
Manual select 17 papers that use ACAP as the theory to support the theme analytics.	Four Ph.D. students (judge) performed the card sorting.	Four rounds were done. The card sorting process ended with very few differences among the way experts.	Refinement of wording and small adjustments.	We check the convergent and discriminant validity.	The scale was tested using STATA (SEM) to verify the validity and reliability.
Outcomes					
Analytics is a drive to achieve organizational success; Analytics framework; Levels of maturity in Analytics.	Standard cards with the dimension and items.	ACOMP construct was defined by 3 dimensions and 15 items.	The answers confirmed the completeness of the dimensions of the scale.	ACOMP was conceptualized as a multidimensional and reflective construct.	Reliability and validity of ACOMP scale established

Figure 1 – Activities and Outcomes of Six-Step Scale Development Process

The goal was to identify the gap regarding organizational analytical competence constructs (ACOMP), to correctly specify the nature of the construct by identifying the property, dimensions, stability and also setting a valid and precise definition for them (Mackenzie et al., 2011). As a result of this stage, we emerged with the intrinsic characteristics of the ACOMP construct and its three dimensions: Analytical Skill (AS), IT & Data Skill (ITD) and Problem-Solving Skill (PSS) that were inspired by the theoretical field of business intelligence and analytics and anchored on original ACAP statements developed by Cohen and Levinthal (1990). Table 1 presents the reference source used to compose each dimension of analytical competence.

#	Reference Source	Analytical Skill	IT & Data Skill	Problem Solving Skill
1	Bassellier and Benbasat 2001			x
2	Chau and Xu 2012	x	x	x
3	Chen et al. 2012	x	x	
4	Chiang et al. 2012	x	x	x
5	Chuah and Wong 2014	x	x	x
6	Cohen and Levinthal 1990	x	x	x
7	Finneran and Russell 2011	x		
8	Gonzales and Eckerson 2015; Gonzales 2011	x		
9	Halper and Krishnan 2014	x		
10	Henry and Hiltbrand 2012			x
11	Hostmann 2012	x		
12	Işik et al. 2013	x	x	
13	Lu and Ramamurthy 2011		x	x
14	Lukman et al. 2011	x	x	
15	Malladi and Krishnan 2013	x	x	
16	Merchant et al. 2014	x	x	x
17	O'Leary 2013		x	x
18	Popovič et al. 2012	x	x	
19	Raber et al. 2012; Raber et al. 2013	x		
20	Sacu and Spruit 2010	x	x	
21	Tamm at al. 2013	x	x	
22	Watson and Marjanovic 2013	x	x	
23	Wixom et al. 2011	x	x	x

Table 1 – Reference sources used to compose the dimensions of ACOMP

4.2 Step 2 - Item Pool creation

The goal of this stage was to ensure content validity of the construct, so a list of items was created for each dimension and several refined reviews were made to eliminate redundancy. The items related to the dimensions of ACOMP emerged from the literature review made in step 1, and the goal of this step is to compose a consistent item pool to be evaluated in the next stage. At the end of this process, each dimension has gotten to at least six items. The typical item was a statement where the respondent would evaluate the level of skill of each area using a 7-point Likert scale, where 1 means very low and 7 very high. Each item statement was written in a 3 X 5-inch index card in order to compose a card set with the items for the dimensions of the analytical competence construct. After that, these cards were shuffled and presented to a group of four Ph.D. students, who were invited to perform the card sorting due to their knowledge in this technique and in the IS area. The activity was performed in four rounds, and these Ph.D. students were nominated "the judges" and received the instructions of how they should perform. After the procedure explanation, the judges were asked if everything was entirely clear, and they could pose questions about it before starting.

4.3 Step 3 - Card Sorting

The card sorting is a process for selecting which are the items that are important for the construct, meaning that the item has face validity to be a measure of the construct or dimension it should measure. The judges should create a number of piles they found necessary and name it with the label they believe best identifies the items. Each judge participated in one round and took, on average, 30 minutes to finish it. They all made card piles and named it following their understating of the subject.

This process was repeated four times, and the goal was to check the face validity of the construct and the content validity, as well. In other words, check if the items look like they measure the construct and if the items are also fully measuring the domain of the construct. The card sorting process ended with very few differences among the way experts have grouped and named the items of each construct. Therefore, the Analytical Competence construct was defined by three reflective dimensions: Analytical skills, IT & Data skills and Problem-solving skills, which was composed of five reflective items for each dimension. According to Edwards (2001), a multidimensional construct is used when it is necessary to provide holistic representations of complex phenomena, allowing researchers to combine predictors with broad outcomes to increase explained variance (Edwards, 2001). Moreover, since analytical competence is a multidimensional and reflective construct, it is important to check the convergent and discriminant validity. Although, before that, we double checked the results found here with a qualitative step which is detailed in step 4.

4.4 Step 4 – Qualitative Interviews

In order to verify if something was missing in the ACOMP definition, we made a final qualitative step that consisted of asking five questions about Analytical Competence in the context of BIA to 10 seniors professionals from different organizations. The questions were sent by email, and there was also a possibility to schedule a meeting session with the respondent. Most of the respondents answered it by email and just one preferred a meeting. After collecting all the answers, we rechecked the model, the dimensions and the items, just to guarantee the constructs covered everything they have mentioned. The results confirmed that the dimensions were adequate and understandable, so we kept the same dimensions and items, but we made few adjustments regarding rephrasing few words in the items to make it clearer and easier to understand.

4.5 Step 5 – Model Specification

The model specifications were made in line with previous studies that posit that organizations that are more competent in exploring data and technologies are smarter than their competitors, once they are more prepared to propose, elaborate and implement solutions. There are authors who described this phenomenon by setting levels of maturity in BIA (Lukman et al., 2011; Chen et al., 2012; Raber et al., 2012, 2013; Watson and Marjanovic, 2013), while others provide frameworks to be used to rapidly achieve BIA success (Popovič et al., 2012; Seddon et al., 2012; Işik et al., 2013). According to Mackenzie *et al*. (2011), it is important to provide a clear and concise definition of the construct, and also determine the type of property the construct represents, as well as, the entity to which it applies the dimensionality, and the stability. Thus, considering the proposed theoretical background and also the guidelines for conceptualizing multi-dimensional construct in IS field (Polites, Roberts and Thatcher, 2012), the Analytical Competence (ACOMP) construct was designed as an organizational phenomenon that represents the ability of the organization to explore the data to generate intelligence to the business. It was modeled as a multidimensional construct, reflective first-order and reflective second-order (type I in Jarvis et al. 2003, p. 205), composed by three reflective dimensions: Analytical skills, IT & Data skills and Problem-solving skills, and formed by fifteen reflective items. According to Polites *et al.* (2012), multidimensional constructs have been used more frequently in top IS journals in recent years, since it enables the capture of complex concepts and due to their potential to advance a theory (Edwards, 2001). Thus, due to the complexity of the phenomenon of Analytical Competence, we proposed three dimensions and a set of items for ACOMP construct, as showed in Table 2.

4.6 Step 6: Scale Validation

In order to pre-test the scale, an online questionnaire was created on the Qualtrics platform and sent to several professionals of private and public organizations from various sectors and sizes that are associated with the American Chamber of Commerce (AMCHAM). As the survey was carried out in Brazil, it was necessary to translate the questionnaire into Portuguese. Also, we conducted a back translation to ensure the meaning of the items did not change. The translations were done by two different individuals fluent in both languages.

Dimension	Items	***The people in my organization who engage in Business Intelligence and Analytics activities....***
Analytical Skill	AS1	...have skills to do statistical analysis
	AS2	...have skills to use advance datamining tools
	AS3	...have skills to use text mining
	AS4	...know how to do geospatial and temporal analysis
	AS5	...have skills to perform optimization and simulation
IT & Data Skill	ITS1	...have IT skills to manage data
	ITS2	...have IT skills to extract data from different data sources
	ITS3	...have IT skills for manipulating structured data
	ITS4	...have IT skills for manipulating unstructured data ***(dropped)***
	ITS5	...have IT skills to explore social media data
Problem-Solving Skill	PS1	...have problem-solving abilities
	PS2	...know how to solve complex problems
	PS3	...have creativity to solve problems
	PS4	...have initiative to find new solutions
	PS5	...have proactive attitude to find new solutions

Table 2 – Dimensions and Items of Analytical Competence (ACOMP)

We use G*Power software version 3.1.9.2 to estimate the sample size with a power of 0.95, considering a small effect size of 0.15 and three predictors, which resulted in a sample size of 74 respondents (Faul, Erdfelder, Lang and Buchner, 2007). During January and February of 2017, we sent 334 questionnaires to a list of organizations associated with the American Chamber of Commerce (AMCHAM) in Brazil, and 110 questionnaires were collected. Among those answered questionnaires, there were 82 completed and valid, while the others 28 were incomplete and discarded from the sample. Based on the data collection results, we had a response rate of 25%, and the sample size was considered acceptable, once it was greater than 74.

Table 3 shows the sample characteristics such as organization size, FTE (Full Time Employee) and the respondent title. Regarding the hierarchic position of the respondents, the sample is mostly composed of decision-makers, such as CEO, CIO, and directors that represented 32% of the sample, followed by 46% of managers, and 10% of supervisors. The other 12% were analyst and people engaged in some activity of BIA, such as preparing data and analyses.

Organization Size		**Full-Time Employee**
13%	Small businesses	< 50
42%	Medium Companies	50 - 500
45%	Large enterprises	> 500

Respondent Title			
4%	CEO	46%	Managers
5%	CIO	10%	Supervisors
23%	Directors	12%	Analyst & Others

Table 3 - Sample General Characteristics

Figure 2 shows the estimation of the basic measurement model of ACOMP, which is composed of three dimensions with five indicators each. The measurement model was estimated with the covariance-based structural equation modeling (CB-SEM), a popular technique in IS research to build and test theories with quantitative data (Evermann and Tate, 2011). Although some literature associate CB-SEM to a large-sample methodology (Gefen and Rigdon, 2011), the most relevant restriction is related to sample distribution. To guarantee robustness, given signs of the presence of non-multivariate normality, we estimated the model using the Satorra-Bentley (SB) method, which is considered a robust method to be used in combination with CB-SEM models under the threat of non-normality. We first tested the measurement model of ACOMP for multivariate normality, and the results showed the Doornik-Hansen (DU) of 89.74 and a p-value<0.000, what means non-normal multivariate distribution, which is considered a frequent outcome in surveys with Likert scales.

Afterward, the model was estimated using maximum likelihood, which presumes conditional multivariate normality among the observed variables. We also included in the estimation process the Satorra-Bentley (SB) method to test the standard error type of robustness of the model. The correlation among errors was estimated using modification index, so, as noticed in figure 2, there is an error correlation between AS1 and AS2 indicators that can be explained by the interpretation of the content of items. Although the content of AS1 asked about the level of skills to do statistical analysis and AS2 refers to the level of skills to use advanced data mining tools, the scope of both items can be understood as similar skills, what can explain the correlation between AS1 and AS2 error. Therefore, we also tested the model regarding internal validity and reliability, and one indicator (ITS4) of the dimension IT & Data Skill was dropped. In reflective models, dropping an indicator should not affect the conceptual domain of the construct, (Jarvis, MacKenzie and Podsakoff, 2003), so, since the loading of indicator ITS4 was 0.58, what is below of the recommendations, it was dropped. According to Hair et al. (2011), the reflective models should present internal validity and reliability greater than 0.7, except in exploratory research, where 0.6 is acceptable. Otherwise, any value under 0.7 is considered inadequate.

4.6.1 Evaluating the Goodness of Fit of the Measurement Model

To evaluate the goodness of Fit of the measurement model, we employed STATA (version 15.1) and CFA (Confirmatory Factor Analyses) to analyze the data and assessed the estimation of the model to verify whether it was properly defined. We chose using CBSEM because it is the primary confirmatory methodology and provides better protection from measurement error, although it requires that the covariance among the observed variables conform to a network of overlapping proportionality constraints (Gefen and Rigdon, 2011).

The estimations results can be found in Table 4 and indicate a good model fit, with a chi-square of 75.666 and 61.136 with Satorra-Bentley estimation. In both cases, the values are consistent with the recommendations on the evaluation of CBSEM (Gefen and Rigdon, 2011; Mackenzie et al., 2011). Also, regarding the fit of the model, the SRMR (standardized root means square residual) stayed in 0.043, what according to Mackenzie et al. (2011) indicates good fit. We calculated the RMSEA (root mean square error of approximation) with and without the Satorra-Bentley (SB) method, and in both cases, the results stayed below 0.05 what also indicates the good fit of the model. Therefore, we also assessed the model fit regarding the CFI (comparative fit index) and the TLI (Tucker Lewis index), both cases with and without the Satorra-Bentley (SB) method. The results again corroborated to the good fit of the model, since all values were above 0.95 (Gefen and Rigdon, 2011; Mackenzie et al., 2011)

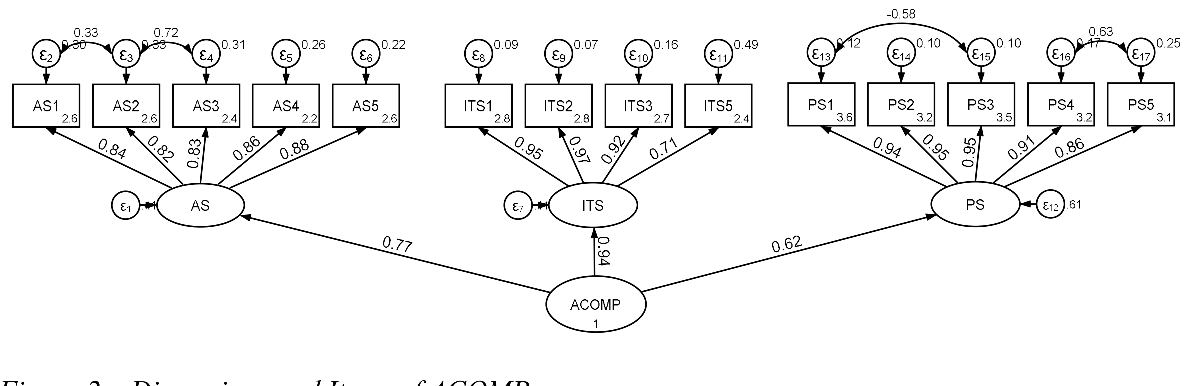

Figure 2 – Dimensions and Items of ACOMP

Model	chi2 (70)	chi2 SB (70)	RMSEA	RMSEA SB	CFI	CFI SB	TLI	TLI SB	SRMR	CD
Basic Model	75.666	61.136	0.031	0.000	0.996	1.000	0.995	1.010	0.043	0.910

Table 4 – Fit Statistics for the ACOMP Measurement Model

4.6.2 Assessing the Validity and Reliability of the set of indicators at the construct level

To assess discriminant validity, the indicators of one construct should load more strongly with itself than on another construct in the model (Chin, 1998). As it is showed in table 5, the discriminant validity cross loading of ACOMP dimensions is adequate, since all indicators are highly loaded on their constructs (Chin, 1998).

	IT&Data Skill	Analytical Skill	Problem Solving Skill
ITS1	**0.952**	0.679	0.532
ITS2	**0.967**	0.690	0.540
ITS3	**0.919**	0.656	0.513
ITS5	**0.713**	0.509	0.399
AS1	0.600	**0.840**	0.458
AS2	0.584	**0.818**	0.446
AS3	0.594	**0.832**	0.454
AS4	0.614	**0.860**	0.469
AS5	0.630	**0.883**	0.481
PS1	0.523	0.511	**0.937**
PS2	0.530	0.517	**0.949**
PS3	0.529	0.516	**0.947**
PS4	0.510	0.498	**0.913**
PS5	0.483	0.471	**0.865**

Table 5 – Discriminant Validity Cross loading table of ACOMP dimension items

According to Mackenzie et al. (2011), the internal consistency of first-order constructs with reflective indicators has been often estimated by Cronbach's Alpha. We evaluated the construct reliabilities, and the majority of measures exceeded 0.70 (see Table 6), suggesting reasonable reliability. Following Fornell & Larcker (1981) criterion, the convergent validity of the dimensions was also assessed by calculating the average variance extracted (AVE) of the latent variables, which values exceeded 0.5, indicating adequate convergent validity. The AVEs values of each latent variable are demonstrated in the diagonal of Table 6.

		CONBRACH'S ALPHA	RELIABILITY (ρ)	1	2	3
IT&Data Skill (ITS)	1	0.935	0.802	**0.798**		
Analytical Skill (AS)	2	0.938	0.727	0.525	**0.718**	
Problem Solving Skill (PS)	3	0.967	0.929	0.346	0.230	**0.851**

Table 6: Squared correlations among latent variables

4.6.3 Assessing the Nomological Validity of ACOMP scale

To assess the nomological validity of ACOMP scale, we add a nomological consequence construct denominated Support to Learning & Decision (LEARN & DECISION) (Figure 3), which is composed by six reflective indicators (Table 8) that measure how ACOMP supports the learning and decision process in the organization. The relationship between ACOMP and LEARN & DECISION is in line with Cohen and Levinthal (1990) seminal paper, which states that ACAP implies a cumulative and progressive improvement in the performance of learning, with the goal of generating value to the business. The ACAP theory is in the foundations of ACOMP, so, we expected that ACOMP positively support the learning and decision-making process. We estimate the Fit Statistics for the Nomological Measurement Model with Satorra-Bentley, and it indicated a good model fit, with a chi-square with Satorra-Bentley estimation of 153.132. The other indexes presented in Table 7 confirms the good fit of the nomological model and are also consistent with MacKenzie et al. (2011, p.321). Figure 3 shows that the focal construct ACOMP behave as we expected, and it positively impacts the organizational decision making and learning process, what also reinforces that ACOMP conceptualization is coherent with ACAP foundation. Hence, we can conclude that ACOMP scale is valid in its nomological network.

Model	chi2 (158)	chi2 SB (158)	RMSEA	RMSEA SB	CFI	CFI SB	TLI	TLI SB	SRMR	CD
Nomological Model	**180.965**	**153.132**	**0.042**	**0.000**	**0.998**	**1.000**	**0.986**	**1.003**	**0.065**	**0.859**

Table 7 – Fit Statistics for the Nomological Measurement Model

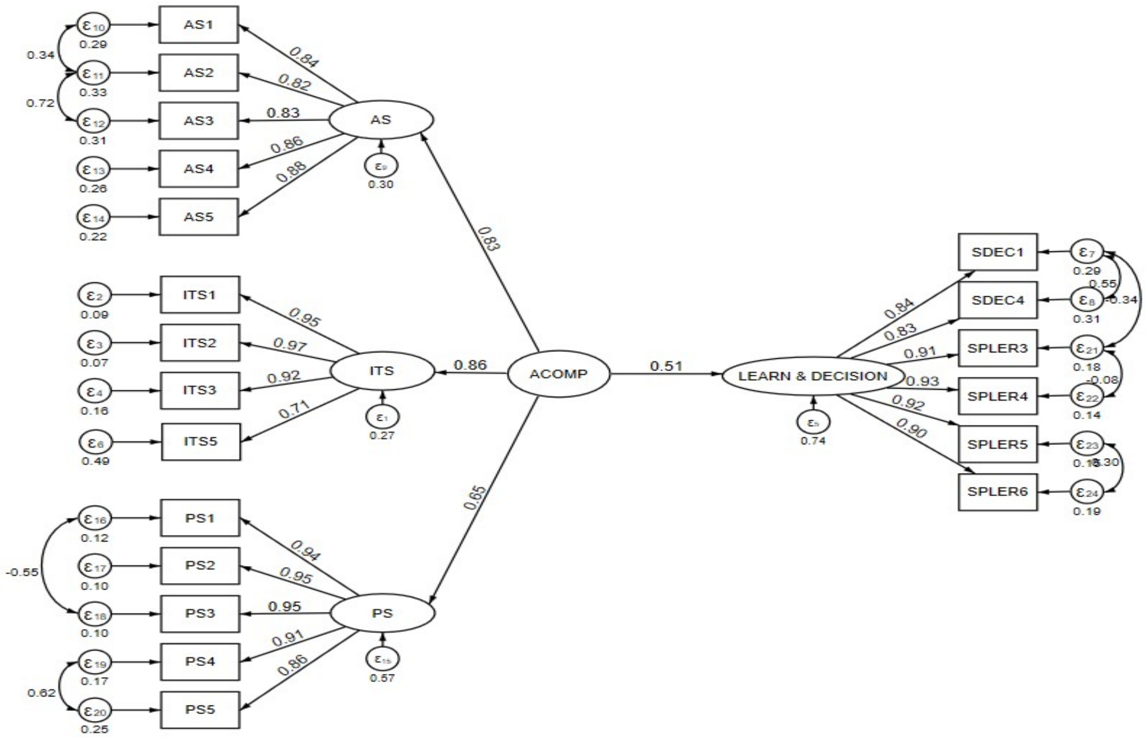

Figure 3 – Nomological Validity of ACOMP Scale

Construct	Items	***Our approach to Analytical Competence contributes to...***	References
Learn and Decision	SDEC1	...making assertive decisions	(Sharma et al.,2014)
	SDEC4	...efficiency in decision and actions orchestration	
	SPLER3	...effective management of corporative and strategic planning changes	(Popovič et al., 2012) (Trkman et al., 2010) (Bronzo et al., 2013)
	SPLER4	...improvement of the capability to act and react to market events	
	SPLER5	...improvement of business risk management	
	SPLER6	...adding value to products and services delivery to customers	

Table 8 – The items of Learn and Decision

5 Discussion

The goal of this study was to develop and validate a conceptualization of the construct Analytical Competence (ACOMP). We followed a strict method which involved a six-step procedure that resulted in a superordinate multidimensional construct, represented by a set of 3 interrelated dimensions and 14 items that are manifestations of the general construct ACOMP. This interrelatedness between the dimensions is key for achieving new levels of analytical competence. Following this logic, an advance in one skill will push the development of the other skills dimensions. The measurement model was tested using the covariance-based structural equation modeling (CB-SEM), and we also employed STATA (version 15.1) and CFA (Confirmatory Factor Analyses) to assess the data. The results supported ACOMP as a valid scale to measure the ability of an organization to use data to improve organizational learning and the decisions making process.

Regarding the theoretical and managerial context and considering the current demand for big data analyses faced by organizations, we believe that this paper makes a significant contribution by proposing the Analytical Competence construct. To the best of our knowledge, a scale to measure this ability did not previously exist. We followed a robust procedure to develop the scale by performing several steps and analyses, to conceptualize, develop, refine, measure, and test the scale. Developing analytical competence is a consistent drive to improve skills that will allow organizations to take advantage of the data available. In this way, we consider the analytical competence construct a contribution not only to the academic but also, to the managerial community as well.
This study also contributes to IS field, since it pointed out the alignment between ACAP and ACOMP, by addressing similarities between both concepts, such as the competence component, and also the learning ability which is implicit in both constructs. Our results have also reinforced the potential of ACAP theory to explain a complex phenomenon in IS field. The ACOMP scale is consistent with the original idea of Cohen and Levinthal (1990), who argue that learning capabilities increase the organizational capacity to recognize, assimilate and apply an idea to commercial ends.

The investigation also has managerial contributions, once these constructs can be used to measure the level of analytical competence of an organization and also suggest that analytical competence is a combination of multidisciplinary skill that organizations should develop to be able to exploit data in a better way. In this way, organizations could use it to drive their investments in Business Intelligence and Analytics and clearly identify areas in which to invest in order to improve their ACOMP.

Regarding limitations, this study is not free of it, and we recognize the extension of the research scope to other countries should be considered in future studies to achieve a broad generalization. A larger sample, composed of organizations from other countries, could enrich the research since it can clarify if cultural issues impact the results.

6 Conclusion

Given the importance of analytical competence for both the academic and managerial community, with this research, we provided a measurement instrument that can benefit organizations to become smarter and better prepared to take advantage of big data's features. On the theoretical side, our findings contribute to the theory by offering a model to measure the outcomes of analytical competence, which is a new construct that has not been previously defined and tested in IS field. On the other side, the investigation also has managerial contributions, once the instrument can be used to measure the level of analytical competence of an organization, and even suggesting that ACOMP is a combination of multidisciplinary skill that organizations should develop to be able to exploit data better. Although our findings are coherent with ACAP theory foundations and BIA literature, this study contributes by adding a new construct ACOMP to IS field. Therefore, these results have important implications for both researchers and practitioners, once ACOMP model can be used as a reference to measure how analytical competence contributes to the business. Based on that, organizations can improve their decision-making process, drive actions and investments in analytical competence or BIA initiatives.

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