DECISION SCIENCES INSTITUTE

The Role of Business Analytics on Organizational Resilience

Larissa Alves Sincorá
Universidade Federal do Espírito Santo
Email: sincora.larissa@gmail.com

Marcos Paulo Valadares de Oliveira
Universidade Federal do Espírito Santo
Email: marcos.p.oliveira@ufes.br

Hélio Zanquetto Filho
Universidade Federal do Espírito Santo
Email: zanquetto@gmail.com

Teresa Cristina Janes Carneiro
Universidade Federal do Espírito Santo
Email: carneiro.teresa@gmail.com

Marcelo Bronzo Ladeira
Universidade Federal de Minas Gerais
Email: marcelobronzo@face.ufmg.br

ABSTRACT

Aiming to investigate the role of Analytical Capabilities on Organizational Resilience this paper reports the results of a survey developed in companies located in the state of Espirito Santo/Brazil. Data analysis used structural equation modeling. The results show that the analytical capabilities positively influence organizational resilience.

KEYWORDS: Business Analytics, Analytical Capabilities, Resilience, Performance.

INTRODUCTION

Over the last three decades, the business environment has undergone radical changes driven by a series of breakthroughs and innovations that have also brought a variety of strategic and operational challenges to modern organizations in both public and private sectors (Doumpos & Zopounidis, 2016). One of the most fundamental challenges involves the design of resilient processes and the improvement of procedures for the planning and decision, which can provide a superior competitive advantage by improving operational efficiency, promote innovation and create added value for all parties. In this context, business analytics emerges as a powerful alternative to intelligibly reprogram organizational strategies and support the decision-making process based on facts and data (Doumpos & Zopounidis, 2016; Seddon, Constantinidis, Tamm, & Dod, 2016; Vidgen, Shaw, & Grant, 2017), especially in situations related to ruptures and vulnerabilities in the supply chain.

With the proliferation of Internet of Things (IoT) and IT systems like Enterprise Resource Planning (ERP), more and more data is generated, captured and stored. In this context, the survival and growth of many organizations nowadays are linked to their capabilities to effectively utilize large amount of data from different sources to drive their strategic and operational decisions. Thus, data analysis is becoming a critical factor of success (Barbosa, Vicente, Ladeira, & Oliveira, 2017).

Benefits of business analytics adoption are increasingly evident and robust. Business Analytics (BA) is a comprehensive term that comes from the industry. BA refers to the application of a wide range of data-driven analytical techniques and methods in different business domains (Chae, Yang, Olson, & Sheu, 2014). It is a relatively new term whose focus is on improving organizations' performance through a decision-making process based on fact and data (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017; Bayrak, 2015; Bronzo et al., 2013; Cosic, Shanks, & Maynard, 2015; T. H. Davenport & Harris, 2007b; Holsapple, Lee-Post, & Pakath, 2014; Mortenson, Doherty, & Robinson, 2015; Seddon et al., 2016; Vidgen et al., 2017).

Organizations such as the Boston Red Sox, Netflix, Amazon.com, CEMEX, Capital One, Harrah's Entertainment, Procter & Gamble, Best Buy, amongst others, use business analytics to build their competitive strategies, guide their decision-making, and beat the competition. By applying their analytical capabilities to the data, these organizations identify the most profitable customers, accelerate product innovation, optimize supply chains, and manage to work with more competitive prices (Davenport & Harris, 2007).

This work explores the organizational analytical capabilities, identified as one of the five formative dimensions of BA (analytical capabilities, information quality, analytical technology, leadership commitment and analytical strategy) (T. Davenport, Cohen, & Jacobson, 2005). Such choice is justified by the fact that organizations continually need to make high quality decisions, quickly and clearly due to the dynamics involved in their operations. It is observed that it becomes easier for those who develop a set of capabilities to collect, aggregate, synthesize and analyze large volumes of data to support the decision-making process (Strategy & Leadership, 2009). Moreover, it is understood that analytical capabilities, once present in the organizational structure, can impact and interact with different resources and capabilities (J. B. Barney & Clark, 2007) and, consequently, influence organizational performance.

Thus, considering the interaction of such capabilities with the different resources and variables, it becomes relevant to analyze how organizational analytical capabilities relates to performance results in terms of resilience. The organizational resilience (Fiksel, Polyviou, Croxton, & Pettit, 2015; Pettit, Croxton, & Fiksel, 2013; Pettit, Fiksel, & Croxton, 2010) has currently received attention and emphasis from companies due to the continuous increase of vulnerabilities of its supply chains (Ambulkar, Blackhurst, & Grawe, 2015). In addition, the World Economic Forum indicated that more than 80% of the companies are now concerned with the development of supply chain resilience (Bhatia, Lane, & Wain, 2013) due to their harmful effects on operations. Therefore, considering that organizational analytical capabilities are in a position to positively influence performance results, it is understood that they are hypothetically related to organizational resilience. It is based on such argument that this research effort will be directed to answer the following research question: *What is the impact of organizational analytical capabilities on organizational resilience?*

The article is structured in five main sections. After this introduction, it is presented in section two the definition and the theoretical relations between constructs, the research hypothesis and the proposed conceptual model. In section three, the methodological path is presented. In the fourth section the results are pointed out and the discussion developed in light of the researched theory. And in the fifth and last section, it summarizes the findings and final considerations of the study along with the research limitations, proposing questions that may guide future research endeavors.

THEORETICAL BASIS, CONCEPTUAL MODEL AND RESEARCH HYPOTHESIS

Organizational Analytical Capabilities

Davenport, Cohen and Jacobson (2005) emphasize that analytical capabilities is one of the formative dimensions of BA in the organizational context, pointing out that although analytical software becomes increasingly popular and easy to use, companies that are beginning to become analytical oriented or are already competing on analytics still require substantial analytical capabilities from its members.

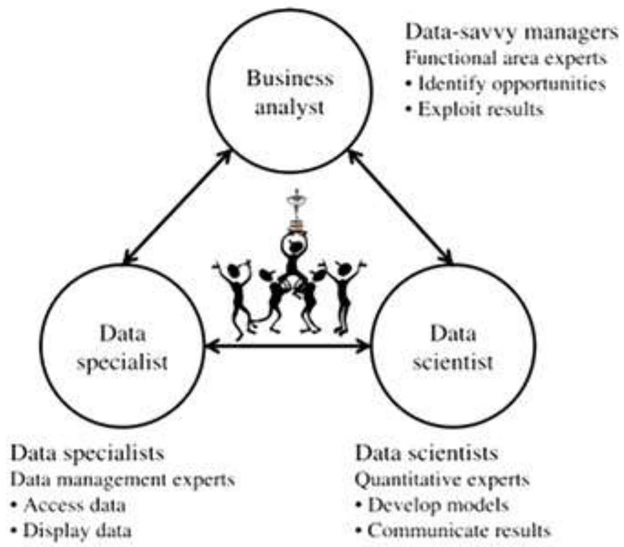
Analytical capabilities, according to Acito and Khatri (2014), refers to the use of a portfolio of analytical methods and tools, including those that support traditional ad hoc queries, inferential statistics, predictive analysis, simulation and optimization, aiming to support inquisitive, descriptive, predictive and prescriptive analysis at the managerial level, supporting the decision-making process (Acito & Khatri, 2014).

Delen and Demirkan (2013) brought another connotation for the respective dimension by considering the abilities to understand the needs of the business, to deal with large data – big data – usually complex and unstructured, and provide meaning to support the decision-making process.

Corroborating with the ideas of Delen and Demirkan (2013) and Acito and Khatri (2014), Holsapple, Lee-Post and Pakath (2014) argue that the key set of analytical capabilities is based on the combination of skills to manage evidence (facts/data) through models and logical and systemic reasoning. In this portfolio of competences lies the respective abilities: the use of quantitative and qualitative techniques and their combinations; the use of statistical techniques; systematic use of reasoning; management models of descriptive, explanatory, and predictive nature; and effective work based on evidence (eg, reports, databases, click- streams, documents, sensors, maps, etc.) (Holsapple et al., 2014).

Therefore, based on explained above and the definitions and a set of works on the subject (Acito & Khatri, 2014; Bayrak, 2015; Bronzo et al., 2013; Delen & Demirkan, 2013; Doumpos & Zopounidis, 2016; Gorman & Klimberg, 2014; Holsapple et al., 2014; Mortenson et al., 2015; Oliveira, McCormack, & Trkman, 2012; Sincorá, Carneiro, & Oliveira, 2015; Trkman, McCormack, Oliveira, & Ladeira, 2010; Troilo, Bouchet, Urban, & Sutton, 2015; Wagner, Brandt, & Neumann, 2016; Wilder & Ozgur, 2015), the conceptual and operational domain of the Organizational Analytical Capabilities construct is based on the synergistic inter-relationship amongst: i) Statistical Capabilities (referring to the ability to develop logical, critical and analytical reasoning about organizational reality from quantitative data); ii) Business Capabilities (inherent in the ability to identify problems, formulate and implement solutions, conduct decision making from facts and data, develop expression and communication compatible with the business environment); and iii) Capabilities in Information Technology (related to the competence to operate machines, information systems, and work with computational modeling), as represented in Figure 1.

Figure 1: Synergistic flow between the skills of the multidisciplinary teams of an organization oriented by data analysis



Source: Adapted from Wilder and Ozgur (2015).

Organizational Resilience

In today's turbulent and uncertain environment, every organization in a supply chain is susceptible to disruption (Ambulkar et al., 2015; Ponomarov & Holcomb, 2009). The global reach of supply chains, products with shorter life cycles, and increasing customer requirements have made organizations aware that disruptions can cause undesirable operational and financial impact. In this way, disruptions such as the loss of a critical supplier, a major factory fire, or even an act of terrorism, have the potential to negatively affect revenue and cost. However, even if researchers and practitioners fully agree about its importance, what it is observed is that a vast majority of the companies still give limited attention to manage potential risks and do not have the capabilities to deal with them (Trkman, Oliveira, & McCormack, 2016), acting predominantly more reactive than proactive (Bhatia et al., 2013).

Based on this scenario, companies are now focusing on performance improvement and on the capacity to respond to the contingencies and risks, developing resilience in order to mitigate the effects of ruptures in their operations as they may result in negative consequences for the organization and for the whole supply chain (Ambulkar et al., 2015). Several researchers point out that resilient firms are less vulnerable to risk situations and are more able to deal with supply chain disruptions when they occur in more resilient processes (Blackhurst, Dunn, & Craighead, 2011; Fiksel et al., 2015; Pettit et al., 2013; Ponomarov & Holcomb, 2009; Rice & Caniato, 2003; Sheffi, 2005; Sutcliffe & Vogus, 2003; Weick, Sutcliffe, & Obstfeld, 1999; Wieland & Wallenburg, 2013; Wildavsky, 1988; Zsidisin & Wagner, 2010).

Although the theory about resilience is still in full development and discussion (Ponomarov & Holcomb, 2009; Wieland & Wallenburg, 2013), it was adopted an operational definition for the theme, as well as a set of key elements capable of characterize it in order to enable its measurement. Thus, based on Pettit, Croxton and Fiksel (2013, 2010), the conceptual domain built to delimit the Organizational Resilience construct consisted in the ability to survive, adapt and grow in the face of turbulent change. In other words, operationally, it refers to the abilities to discern and prepare for unexpected events (Anticipation), to respond to disturbances by modifying processes and operations (Adaptability), and to recover from them, returning to the normal operating state (Recovery), maintaining control over the structure and functions and the continuity of operational processes at the desired level. This is, therefore, the essence of resilience, whether it is analyzed from the perspective of the supply chain or the organizational scope.

Theoretical Relationship Between Organizational Analytic Capabilities And Organizational Resilience

The company's resource-based view (RBV) provides an important basis for understanding how competitive advantage is created and sustained over time, given that firms gain competitive advantage through the accumulation of internal resources and capabilities that are rare, valuable, and difficult to imitate (Barney, 1991). These capabilities consist of attributes, skills, organizational processes, knowledge, and capabilities that enable an organization to achieve superior performance and sustainable competitive advantage over its competitors (Teece, Pisano, & Shuen, 1997).

In formulating the perspective of dynamic capabilities, Teece et al. (1997) argue that the capabilities of an organization can be renewed and developed to achieve congruence with the changing environment, making it possible to adapt, integrate, and reconfigure resources, organizational capacities, and functional competencies to respond to the challenges of the external environment. These dynamic capabilities, when approached in contexts of reaction to unforeseen situations, become important bases for the achievement of good Organizational Resilience performance results since they enable organizations to respond to the challenges imposed by the environment through the reconfiguration of their organizational resources. Thus, when considering that the data and information generated by the organization also constitute resources (Chae et al., 2014; Cosic et al., 2015), it is assumed that when they are reconfigured based on the application of analytical capabilities, particularly to help the organization to cope with turbulence and uncertainty, such resources become rare, valuable, and difficult to imitate. Thus, the cross-referencing of data and information enabled by Organizational Analytical Capabilities allows the production of knowledge and insights to aid decision-making, envision future scenarios, capture opportunities, and identify problems and other possibilities that help the organization perform satisfactory resource reconfigurations to better respond to environmental challenges and therefore collaborate for better resilience outcomes.

Some of the crucial aspects of resilience are anticipation, adaptability, and recovery (Pettit et al., 2013, 2010), and it is interesting that these dimensions go together. According to Wieland and Wallenburg (2013), resilience can be improved by investing in the routine of sharing knowledge about relevant changes in the environment, in advance or when they occur. In this manner, to anticipate, it is necessary to acquire knowledge about possible changes that may occur in the future (Zsidisin & Wagner, 2010). To adapt to changes, which may or may not be predicted, it is necessary to reconfigure organizational resources, and to enable such reconfiguration, it is pertinent to control and evaluate the results of the implemented actions.

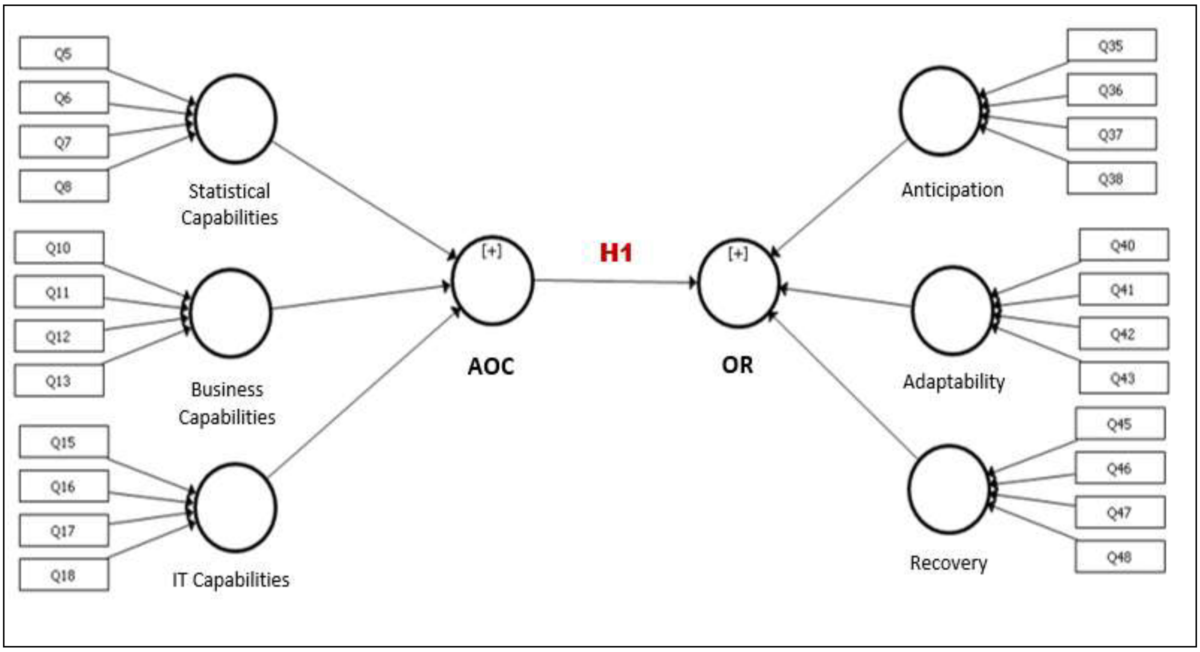
Therefore, the development of skills in anticipation, adaptability, and recovery can be positively supported in organizations that maintain an approach to use and share their data and information among different working groups that can be further used in the most diverse applications and business needs.

Finally, following these considerations, it is assumed that when Organizational Analytical Capabilities (composed of statistical capabilities, business capabilities, and information technology capabilities) act in an integrated and coordinated manner, they can have a significant impact on Organizational Resilience. It is therefore argued that the better the integration between Organizational Analytical Capabilities, the greater the possibility of positively influence Organizational Resilience. This assumption results in the central hypothesis of the study: **H1:** Organizational Analytical Capabilities positively impacts Organizational Resilience.

Presentation of the Conceptual Model

The hypothetical model of this study contemplates constructs related to the conceptual domains of Organizational Analytical Capabilities (OAC) and Organizational Resilience (OR). As shown in Figure 2, the conceptual model of this study presents OAC as predictor of OR (the operationalization of each of the constructs of the model is presented in detailed fashion at the Appendix).

Figure 2 - Conceptual Model and related questions



Source: Authors (2018).

METHODOLOGY

Design of the Survey, Source and Data Collection

This research was conducted based on a survey questionnaire. The questions were based on the literature, which served as a theoretical basis for the formulation of 34 measures - 4 related to the profile of the respondent/company and 30 related to the constructs studied -, the questionnaire used the Likert scale from 1 (one) to 5 (five) points.

In order to operationalize the OAC scales, we undertook a bibliometric study in seven databases of the area of Social Sciences (Ebsco, Emerald, Jstor, Sage, Scielo, Science Direct and Web of Science) to identify a set of manifest variables - with a higher incidence in the literature - that could measure the construct studied. The articles were collected searching for the term "business analytics" in the title, abstract and keywords that were published between 2004- 2015. For the measurement of the OR construct, it was adapted from the scale developed by Pettit et al. (2013), titled Supply Chain Resilience Assessment and Management (SCRAM), validated with data from seven global organizations from the industry and services sector.

After structuring the questionnaire, the 34 questions were validated by a group of experts (PhDs and managers) experienced in the conduction and application of surveys. These professionals contributed to the objectivity, clarity and coherence of the instrument, eliminating redundancies, ambiguities and content overlaps.

The data used in the survey was collected from online questionnaires applied to managers of companies associated to FINDES (Federation of Industries of the State of Espírito Santo) and CRA-ES (Regional Council of Administration of the State of Espírito Santo). The managers selected to participate in the survey were those who held positions related to production, logistics, marketing, sales, quality, purchasing and product development. It is worth mentioning that in order to guarantee the participation of key informants, contacts were made via telephone before sending of survey link to the email address informed by the respondent.

Espírito Santo is one of the states located in the Southeast region of Brazil. The state's economy is essentially based on traditional activities such as construction, extraction and processing of marble and granite, coffee agriculture, the garment industry, and tourism. In addition, the state has a solid position in the steel, furniture, mining, pulp, and fruit growing sectors, also emerging in new economic sectors such as oil and gas production and agro-tourism (Ferrari & Arthmar, 2011).

However, with the worsening of the current economic crisis in the country, the state has been forced to rethink alternatives for the readjustment of its development model. The changes imposed by the current political and economic situation generated turbulence and marked the trajectory of the sectors of industry, commerce, and service of Espírito Santo, compelling these sectors to incorporate into their operations and strategies technological and managerial innovations that are able to cope with the modifications that have been occurring in the internal and external markets.

This context provides the study with information about how the use of data and information by companies in Espírito Santo has been impacted their performances, based on the evaluation of their OAC and their supposed impact on the organizational resilience. Therefore, through the data collected in this scenario, it becomes possible to identify viable paths to generate a competitive advantage sustained through informational resources and the application of analytical capabilities.

Having that said, the criteria used to calculate the sample were recommended by Hair, Hult, Ringle and Sarstedt (2017) for the use of Structural Equation Modeling (SEM), based on the partial least squares (PLS) algorithm, which consisted of the following conditions:

a) The value of the sample should be 10 times ≥ the number of indicators of the construct that has the highest number of formative indicators of the measurement model; or

b) The sample value should be 10 times ≥ the number of the greatest number of paths directed to a particular construct of the structural model.

Therefore, based on the respective criteria, a minimum sample size of 50 respondents was identified. However, 83 questionnaires answered were collected from FINDES respondents, and the remaining 211 respondents were collected from CRA-ES. After performing a preliminary analysis to identify equivalence issues and avoid sample problems with the data collected, the final sample consisted of 288 valid cases.

Data Processing

According to Knoppern et al. (2015), interviewee data from heterogeneous groups should not be grouped and/or compared without first examining whether they are equivalent, since ignoring questions of equivalence can lead to ambiguous and erroneous conclusions.
In order to check the equivalence between those two groups (FINDES and CRA-ES), a multi-group analysis was performed (Ringle, Wende, & Becker, 2014). The equivalence test consisted of three steps: the tests of configural equivalence, metric and scalar. The configural equivalence was verified with all loads of the indicators demonstrating significant to the same factors between the groups. Similarly, the metric equivalence test showed no statistical difference between the factor loads of each group, with all p-values of the confidence interval between 0.025 to 0.975 (Sarstedt, Henseler, & Ringle, 2011). Finally, through the data obtained by the bootstrapping technique ran with 5,000 sub-samples (Hair, Sarstedt, Ringle, & Gudergan, 2018), the scalar equivalence test revealed that all p-values of the difference between groups are not significant at a 95% confidence level (Table 1). This result shows that there is no statistically significant difference between groups, thus indicating the possibility of grouping the data.

Table 1 – Scalar equivalence Test using PLS-MGA technique

PLS-MGA	**Path Coefficients-diff (GROUP (1.0) vs GROUP (2.0) |)**	***p*-Value (GROUP (1.0) vs GROUP (2.0))**
OAC → OR	0,002	0,503
Statistical Capabilities → OAC	0,024	0,550
Business Capabilities → OAC	0,231	0,220
IT Capabilities → AOC	0,242	0,787

Source: Authors (2018).

PRESENTATION AND DISCUSSION OF RESULTS

Results of Descriptive Statistics

The descriptive statistics for the profile of the respondent and companies that composed the sample was based basically on the frequency distribution and the graphical representation of these variables. Related to the “Position of the Respondent” in the company, half of the respondents belong to strategic positions (sum of the functions of president 4%, director 16% and manager 29%), followed by analyst 16%, assistant 13% and other positions 22%. This sample composition is beneficial for the study, since they denote greater knowledge about fundamental questions of the study and capture greater understanding of the organizational functioning due to the position they occupy, above all, positioned in areas related to operations. Regarding the variable “Business Sector”, it was possible to observe that 69% of the sample came from the service sector, followed by commercial companies (19%) and industrial (12%) respectively and more than 70% of the companies have more than 5 years age. Considering the “Size”, following the definition given by the National Bank for Economic and Social Development of Brazil (BNDES) based on annual revenues, 32% of the companies participating in the study are micro-sized, followed respectively by small companies (30%) and the minority, represented by 10%, refer to medium-large and large-sized companies.

Results of the Structural Equation Modeling

The structural equation modeling analysis technique was used to validate the proposed conceptual model, as well as verify the hypothesized relationship. Initially, based on Smart software PLS-SEM 3.0 (Ringle et al., 2014), it was possible to carry out the validation tests of the measurement model (convergent validity test, collinearity test, and significance and relevance test). Thus, after removing the indicator q6 - referring to the Statistical Capabilities -, since it presented high collinearity within the set of indicators in which it belonged, the results showed that all relations between indicators and constructs were considered valid within the quality criteria.

With the measurement models validated, we proceeded to validate the structural model of the research (the direct and indirect relations between the constructs of the model). Initially, when carrying out the multicollinearity test, which evaluates whether the constructs are highly intercorrelated, it was identified that there are no problems of this nature, which indicates a good quality measure for the general adjustment of the theoretical model, since they were adequately defined, having a robust conceptual coverage and without shadowing with other theoretical concepts.

The Significance and Relevance *t* test, with 287 degrees of freedom and 5% significance level, using data from Bootstrapping, demonstrated that the hypothesis **H1**: Organizational Analytic Capabilities positively impacts Organizational Resilience was accepted since it is statistically significant, as can be seen in Table 2.

Table 2 - Total effects

Direction of the Path of Coefficient			Path Coefficients Values	*p-value**
Statistics Capabilities	→	OAC	0,071	0,477
Business Capabilities	→	OAC	0,520	0,000
IT Capabilities	→	OAC	0,466	0,000
OAC	→	OR	0,785	0,000

* The path coefficients significance of the 1st and 2nd order constructs, at the p-value level <0.05, when submitted to the t-test with the Bootstrapping technique.

Source: Prepared by the authors based on the research data.

Also, through the t test, it is possible to emphasize that only the paths coefficient of Business Capabilities (0.520) and Capabilities in Information Technology (0.466) have been shown to maintain statistical significance in relation to OACs, thus revealing that first-order constructs are the ones that contribute the most to indirectly impact OR behavior.

This conclusion reinforces the assumptions of Wieland and Wallenburg (2013) and Zsidisin and Wagner (2010) that organizational resilience can be improved by investing in the routine of sharing knowledge about relevant changes in the business environment, in advance or when change happens. Corroborating this discussion, experts from different regions and sectors of the economy, invited by the World Economic Forum (Bhatia et al., 2013) to discuss measures to build resilience, recognized that priority number one was to improve the sharing of information among the different actors in the chain. Such line of thought stresses that the expansion of the use of data sharing platforms to identify and respond to risks can enable the visibility of information, providing early warning of problems and allowing decentralized solutions.

It is also reflected in the Information Technology Capabilities that companies are increasingly targeting constant investments in technology platforms, ERP systems and corporate management solutions. It turns out an incipient paradigm shift, that is, the technological infrastructure has not only served to store data without the effective contribution to the managerial process, but has effectively contributed to the business needs, since it has been identified among the companies researched the organizational competence to operate machines, information systems and work with computer modeling.

The results of the test also point to the importance of Business Capabilities, since their presence in the business structure indicates that the organization is able to understand its business needs, interpret the analyzes performed in large databases and provide meaning supporting the decision making and revealing opportunities that emerge in the business routine, with the potential to communicate and share them whenever they are needed (Acito & Khatri, 2014; Bayrak, 2015; Cosic et al., 2015; Cybulski, Keller, Nguyen, & Saundage, 2013; Delen & Demirkan, 2013; Gorman & Klimberg, 2014; Informs, 2014; Mcclure & Sircar, 2008; Mortenson et al., 2015; Ranyard, Fildes, & Hu, 2015; Rasmussen & Ulrich, 2015; Troilo et al., 2015; Wilder & Ozgur, 2015).

However, the explanation that the Statistical Capabilities did not show a significant antecedent to OR may be in the reality of the organizations researched. Because it does not have all the analytical capabilities that have been developed to fuel the decision-making process, most decisions are based on subjective knowledge of the business rather than on quantitative and numerical data. Possibly, the companies that composed the study are not familiar with the extraction and use of data of quantitative nature due to the lack of skills to work with descriptive, predictive and prescriptive analyzes, thus revealing the need for investments to foster the development of logical reasoning based on critical and analytical information about organization.

Despite of this results, it is important to highlight that Fahimnia et al. (2015) found that quantitative risk analysis is rapidly expanding across studies and research related to the subject, quantitative and analytical models - inherent in statistical skills - (i.e. mathematical models, optimization, simulation, analysis decision-makers and others) are being used to manage both organizational and supply chain risks, thus strengthening the capabilities of anticipating organizations to identify potential risks and barriers.

Nevertheless, from the Variance Coefficient (R^2) evaluation, it was verified that 61.6% of the variation that occurs in the behavior of the endogenous OR construct can be explained by the variation that occurs in the OAC. Thus, it was concluded that if a manager wants to develop the analytical capabilities of her company, she should make efforts to improve its capabilities, especially in business (inherent in the ability to identify problems, formulate and implement solutions, data and facts, developing expression and communication compatible with the business environment) and in information technology (related to the ability to explore dataset, sanitize data, integrate dataset and build big data environments). In this way, OACs can act as medium- and long-term performance driver, helping companies to design and develop new capabilities, especially in terms of resilience, improving with time, skills and competitiveness standards.

In a managerial decision, for example, the relevance of this data is that the company can choose to invest on the promotion of analytical skills since it will benefit the company's performance, especially regarding its capacity to respond to its stakeholders in situations of turbulence, challenges and uncertainties, thus contributing to deliver satisfactory results to both its clients and shareholders.

It is understood that the advantages obtained by the organization from the continuous use of its data and information, which are successively generated and circulated in the organizational environment, support business operations and decision-making processes and help to leverage resilience levels achieving satisfactory and meaningful performance results.

Therefore, organizations that understand the value of analytical orientation through the development of their analytical capabilities, will better manage their business problems specially when they experience turbulence and disruptions in their operations. In this way, they will be in a better position to build and strengthen their capabilities in resilience and, therefore, to achieve superior performance results (Sheffi, 2005).

The findings are also reinforced by experts who claim that optimization requires discipline, the use of business analytics and the involvement of a broad range of business, technology, and executive work both within and outside the organization (Bhatia et al., 2013). Therefore, to mitigate the risks, vulnerabilities and ruptures, it is necessary to encourage organizations to follow agile and adaptive strategies to improve resilience (Bhatia et al., 2013; Fiksel et al., 2015). This opportunity is verified through the application of analytical practices in the business routine and in the day-to-day chain, given that the analytical approach itself allows actions to intelligibly reprogram organizational strategies and operations, facilitating the development of capabilities to compensate or mitigate vulnerabilities.

CONCLUSIONS

The research results present relevant findings, both from the practical and academic point of view, by presenting that organizational analytical capabilities act as a critical and predictive element to determine organizational resilience.

Thus, the results of the research contributed to clarify the Organizational Analytical Capabilities construct, which has emerged since the last decade as a relevant topic for the scientific community in studies related to Business Analytics. Regarding the managerial context, the effort of this research made it possible for managers to understand what analytical skills are critical to be developed and articulated by the work teams. Moreover, it demonstrated the importance of valuing and developing capabilities under statistical analysis, given that empirical research has revealed that such capabilities allows leveraging and influencing the behavior of resilience.

In seeking answers to the central problems of the study about the impact of organizational analytical capabilities on organizational resilience, the answer obtained was that the impact for this relationship is positive, therefore, companies that have an orientation focused on the analysis of their data, will be better able to go through situations vulnerabilities. Faced with these findings, we can depict that the analytical approach, besides being able to act as a resource for other organizational variables, it is also an important strategy for the development of resilience, since it allows intelligently reprogramming business activities when potential risks, ruptures or vulnerabilities are detected.

In addition, the study also showed the need to invest not only in software and hardware, but also in the development and recruitment of qualified professionals to undertake the analysis of the vast amount of information that organizations and society today deal with. Thus, without such properly prepared individuals, of course, many economic sectors will be missing the opportunity to improve their performance and take competition in their markets based on data analysis.

Another implication of the research lies in the understanding that business analytics can generate business value from structured and highly analytical decision-making processes (Seddon et al., 2016; Sharma, Mithas, & Kankanhalli, 2014) and not only limited to the treatment and analysis of data and information (Emblemsvåg, 2005). The refinement and use of resilience capabilities can also generate benefits at the organizational and network level, especially when attention and resources are directed to the generation of value over time and not only to protect themselves from risk (Trkman et al., 2016).

In addition, research findings also have clear implications for both academics and practitioners. Over the last few years, disruptive events have significantly increased the internal and external risks of organizations (Hohenstein, Feisel, Hartmann, & Giunipero, 2015). Thus, the proposed conceptual model for measuring analytical capabilities and organizational resilience provides an excellent managerial orientation to build analytical practices and resilience in various business areas. The component elements of the constructs can be used to evaluate the level of use of the data and information by the organization, as well as to measure resilience results in order to implement actions to strengthen its own resilience and to identify the priority areas in which the should be prioritized.

Thus, measuring resilience, whether in organizations or in supply chains, reveals itself a relevant managerial need, since this attitude supports the knowledge and understanding of managing unexpected risk events, as well as helps companies to assess their ability to respond to disruptions. Therefore, measuring the resilience level of business operations influences decision makers in prioritizing the development of resilience capabilities needed (Hohenstein et al., 2015).

An example of a company that is already working on this dynamic response to possible disruptions using different mitigation tactics is Procter & Gamble, which by applying monitoring tools has increased its resilience capabilities, bringing together, updating, and using data and information regarding critical points in its supply chain (Sáenz & Revilla, 2014).

Likewise, at the supply chain level, associations are created around the world to protect themselves against possible vulnerabilities in which they are sensitive. An example is C-TPAT (Customs-Trade Partnership against Terrorism) which is a voluntary initiative that creates joint security protocols for member companies to strengthen and improve US supply chains. TradeXchange, on the other hand, is an association of Singapore that engages business partners to collaborate in logistics activities, allowing flexibility and quick collective response to the anomalies that emerge from the supply chain. Also, associations such as the Kyohokai were formed aiming at mutual learning at Toyota Motor Company (Bhatia et al., 2013).

Regarding the limitations, because it is an essentially quantitative research, the study presented restrictions on a qualitative analysis of the queried questions. If such an analysis had been possible, more explanatory and detailed results would possibly be obtained. Although this is a recognized restriction, the proposal to carry out a quantitative research was met within the statistical criteria, as well as validation of the proposed conceptual model and verification of the hypothesized relationship.

Despite this set of restrictions, the study of CA (analytical capabilities) represents expressive contours for the field of research, especially in Decision Making. Since only a few years ago the topic was effectively discussed in organizational studies and in management science. Taking root as a new teaching and research arena, publications are increasingly growing and popularizing, contributing for the evolution of the analytic movement. Therefore, the analytical approach that first emerged within the context of consulting and evolved over a short period of time within the applied social sciences has received increasing attention from the scientific community interested in understanding its phenomenon and its impacts and configurations within organizations, thus justifying in part, the validity of the study performed here.

It is necessary to suggest future work on the subject. Thus, it is possible to evaluate the extent that the Process Management construct, for example, may prove significant to positively impact both organizational and supply chain resilience. As well as analyze how its relationship with the analytical capacities improves the development and the reinforcement of the resilience. This investigation is valid, given the suspicion that the analytical capabilities can leverage the influence they exert on the performance of the organization when being undertaken in the business routine, especially supporting the management of business processes and obtaining relevant information about the processes itself (Bronzo et al., 2013; Galbraith, 1974; Muehlen & Shapiro, 2010).

In addition, it is recommended that new studies can be developed based on the validated model in this study by taking a qualitative approach. An alternative approach of qualitative nature can bring new and useful information regarding the relationships between the constructs investigated in the present research, considering, for example, interviews and participant or non-participant observations on decision-making practice in organizations.

APPENDIX

Figure 3 – Research constructs and indicators.

FORMATIVE CONSTRUCTS: SECOND-ORDER	FORMATIVE CONSTRUCTS: FIRST-ORDER	ITEMS/ FORMATIVE INDICATORS *
ORGANIZATIONAL ANALYTICAL CAPABILITIES (OAC)	Statistical Capabilities	▪ inquisitive analysis; ▪ descriptive analysis; ▪ predictive analysis; ▪ prescriptive analysis; ▪ Improving the decision-making process (reflexive indicator).
	Business Capabilities	▪ communication of problems; ▪ data translation; ▪ interpretation of analyses;

FORMATIVE CONSTRUCTS: SECOND-ORDER	FORMATIVE CONSTRUCTS: FIRST-ORDER	ITEMS/ FORMATIVE INDICATORS *
		▪ decision-making; ▪ Improving the decision-making process (reflexive indicator).
	Information Technology Capabilities	▪ data exploration; ▪ data hygiene; ▪ data integration; ▪ creation of environments; ▪ Improving the decision-making process (reflexive indicator).
ORGANIZATIONAL RESILIENCE (OR)	Anticipation	▪ identification of risks; ▪ monitoring deviations; ▪ early recognition of disruptions; ▪ recognition of opportunities; ▪ Good predictive capacity (reflexive indicator).
	Adaptability	▪ modification of processes; ▪ simulation of processes; ▪ development of technology; ▪ use of continuous improvement; ▪ Good capacity for adaptation (reflexive indicator).
	Recovery	▪ organization of response teams; ▪ communication of information; ▪ managing public relations; ▪ mitigation of effects of interruption; ▪ Good capacity for recovery (reflexive indicator).

Source: Prepared by authors based on research data.

*In the research instrument, there are 30 indicators used to measure the second-order constructs of OAC and OR. These indicators were derived from the items presented in this table. Thus, for each item present in the table, there is 1 (one) corresponding question in the research questionnaire.

REFERENCES

Acito, F., & Khatri, V. (2014). Business analytics: Why now and what next? *Business Horizons*, *57*(5), 565–570. https://doi.org/10.1016/j.bushor.2014.06.001

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, *33–34*, 111–122. https://doi.org/10.1016/j.jom.2014.11.002

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems*, *25*(March), 29–44. https://doi.org/10.1016/j.accinf.2017.03.003

Barbosa, M. W., Vicente, A. de la C., Ladeira, M. B., & Oliveira, M. P. V. de. (2017). Managing supply chain resources with Big Data Analytics: a systematic review. *International Journal of Logistics Research and Applications*, *21*(3), 177–200. https://doi.org/10.1080/13675567.2017.1369501

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120.

Barney, J. B., & Clark, D. N. (2007). *Resource-based theory: Creating and sustaining competitive advantage*. Oxford University Press Oxford.

Bayrak, T. (2015). A Review of Business Analytics: A Business Enabler or Another Passing Fad. *Procedia - Social and Behavioral Sciences*, *195*, 230–239. https://doi.org/10.1016/j.sbspro.2015.06.354

Bhatia, G., Lane, C., & Wain, A. (2013). *Building Resilience in Supply Chain*. *World Economic Forum*. Retrieved from http://www3.weforum.org/docs/WEF_RRN_MO_BuildingResilienceSupplyChains_ExecutiveSummary_2013.pdf

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. *Journal of Business Logistics*, *32*(4), 374–391. https://doi.org/10.1111/j.0000-0000.2011.01032.x

Bronzo, M., Resende, P. T. V. de, Oliveira, M. P. V. de, McCormack, K. P., de Sousa, P. R., & Ferreira, R. L. (2013). Improving performance aligning business analytics with process orientation. *International Journal of Information Management*, *33*(2), 300–307. https://doi.org/10.1016/j.ijinfomgt.2012.11.011

Chae, B. (Kevin), Yang, C., Olson, D., & Sheu, C. (2014). The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. *Decision Support Systems*, *59*, 119–126. https://doi.org/10.1016/j.dss.2013.10.012

Cosic, R., Shanks, G., & Maynard, S. (2015). A business analytics capability framework. *Australasian Journal of Information Systems*, *19*, S5–S19.

Cybulski, J. L., Keller, S., Nguyen, L., & Saundage, D. (2013). Creative problem solving in digital space using visual analytics. *Computers in Human Behavior*, *Article in*, 1–16. https://doi.org/10.1016/j.chb.2013.10.061

Davenport, T., Cohen, D., & Jacobson, A. (2005). *Competing on Analytics*. Retrieved from http://www.babsonknowledge.org/analytics.pdf

Davenport, T. H., & Harris, J. G. (2007a). *Competing on analytics: The new science of winning* (1st ed.). Boston, MA, EUA: Harvard Business Review Press. Retrieved from https://www.amazon.com/Competing-Analytics-New-Science-Winning/dp/1422103323

Davenport, T. H., & Harris, J. G. (2007b). *Competing on Analytics: The new science of winning*. Boston, MA, MA: Harvard Business School Press.

Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support*

Systems, *55*(1), 359–363. https://doi.org/10.1016/j.dss.2012.05.044

Doumpos, M., & Zopounidis, C. (2016). Editorial to the special issue “business analytics.” *Omega*, *59*(Parte A), 1–3. https://doi.org/10.1016/j.omega.2015.06.006

Emblemsvåg, J. (2005). Business analytics: getting behind the numbers. *International Journal of Productivity and Performance Management*, *54*(1), 47–58. https://doi.org/10.1108/17410400510571446

Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative Models for Managing Supply Chain Risks: A Review. *European Journal of Operational Research*, *247*(1), 1–15. https://doi.org/10.1016/j.ejor.2015.04.034

Ferrari, M. A. R., & Arthmar, R. (2011). *Novas leituras sobre a economia do Espírito Santo*. (J. C. Furlani, Ed.) (1st ed.). Vitória, ES: PPGEco / CORECON-ES. Retrieved from http://internet.sefaz.es.gov.br/informacoes/arquivos/publicacoes/novasleiturassobreaeconomiadoes(final).pdf

Fiksel, J., Polyviou, M., Croxton, K. L., & Pettit, T. J. (2015). From Risk to Resilience: Learning to Deal With Disruption. *MIT Sloan Management Review*, *56*(2), 79–86.

Galbraith, J. R. (1974). Organization Design: An Information Processing View. *Interfaces*, *4*(3), 28–36. https://doi.org/10.1287/inte.4.3.28

Gorman, M. F. ., & Klimberg, R. K. (2014). Benchmarking Academic Programs in Business Analytics. *Interfaces*, *44*(3), 329–341. https://doi.org/http://dx.doi.org/10.1287/inte.2014.0739.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. (T. Oaks, Ed.) (2ª). California: SAGE Publications, Inc.

Hair, J. F., Sarstedt, M., Ringle, C., & Gudergan, S. P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling* (1ª). Los Angeles: SAGE Publications, Inc.

Hohenstein, N.-O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). *Research on the phenomenon of supply chain resilience: A systematic review and paths for further investigation*. *International Journal of Physical Distribution & Logistics Management* (Vol. 45). https://doi.org/DOI 10.1108/IJPDLM-05-2013-0155

Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. *Decision Support Systems*, *64*, 130–141. https://doi.org/10.1016/j.dss.2014.05.013

Informs. (2014). *Certified Analytics Professional (CAP) - Examination Study Guide*. *Institute for Operations Research and the Management Sciences* (1ª). Catonsville: Institute for Operations Research and the Management Sciences.

Knoppern, D., Ateş, M. A., Brandon-Jones, A., Luzzini, D., Van Raaij, E., & Wynstra, F. (2015). A comprehensive assessment of measurement equivalence in operations management. *International Journal of Production Research*, *53*(1), 166–182. https://doi.org/doi.org/10.1080/00207543.2014.944

Mcclure, R., & Sircar, S. (2008). Quantitative Literacy for Undergraduate Business Students in the 21st Century. *Journal of Education for Business*, *83*(6), 369–374.

Mortenson, M. J., Doherty, N. F., & Robinson, S. (2015). Operational research from Taylorism to

Terabytes: A research agenda for the analytics age. *European Journal of Operational Research*, *241*(3), 583–595. https://doi.org/10.1016/j.ejor.2014.08.029

Muehlen, M. zur, & Shapiro, R. (2010). Business Process Analytics. In *Handbook on Business Process Management 2, International Handbooks on Information Systems* (Vol.2, Vol. 2, pp. 137–157). Berlin: Springer Verlag. https://doi.org/10.1007/978-3-642-01982-1_7

Oliveira, M. P. V. de, McCormack, K., & Trkman, P. (2012). Business analytics in supply chains – The contingent effect of business process maturity. *Expert Systems with Applications*, *39*(5), 5488–5498. https://doi.org/10.1016/j.eswa.2011.11.073

Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool. *Journal of Business Logistics*, *34*(1), 46–76.

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring Supply Chain Resilience: Development of a Conceptual Framework. *Journal of Business Logistics*, *31*(1), 1–21.

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873

Ranyard, J. C., Fildes, R., & Hu, T.-I. (2015). Reassessing the scope of OR practice: The Influences of Problem Structuring Methods and the Analytics Movement. *European Journal of Operational Research*, *245*(1), 1–13. https://doi.org/10.1016/j.ejor.2015.01.058

Rasmussen, T., & Ulrich, D. (2015). Learning from practice: how HR analytics avoids being a management fad. *Organizational Dynamics*, *44*(3), 236–242. https://doi.org/10.1016/j.orgdyn.2015.05.008

Rice, J. B., & Caniato, F. (2003). Building a Secure and Resilient Supply Network. *Suplly Chain Management Review*, *7*(5), 22–30. Retrieved from http://web.mit.edu/scresponse/repository/Rice_SCResp_Article_SCMR.pdf

Ringle, C. M., Wende, S., & Becker, J.-M. (2014). SmartPLS 3.0. Hamburg, Germany: SmartPLS. Retrieved from http://www.smartpls.com.

Sáenz, M. J., & Revilla, E. (2014). Creating More Resilient Supply Chains. *MIT Sloan Management Review*, *55*(4), 22–24. https://doi.org/10.1111/j.1447-0748.2005.00242.x

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup Analysis in Partial Least Squares (PLS) Path Modeling: Alternative Methods and Empirical Results, (September 2017), 195–218. https://doi.org/10.1108/S1474-7979(2011)0000022012

Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H. (2016). How does business analytics contribute tobusiness value? *Information Systems Journal*, (April), 1–33. https://doi.org/10.1111/isj.12101

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, *23*(4), 433–441. https://doi.org/http://dx.doi.org/10.1057/ejis.2014.17

Sheffi, Y. (2005). *The Resilient Enterprise: overcoming vulnerability for competitive advantage*. Cambridge, MA: MIT Press.

Sincorá, L. A., Carneiro, T. C. J., & Oliveira, M. P. V. de. (2015). Business Analytics: how's and whither will go? In *12th CONTECSI - International Conference on Information Systems and Technology Management* (pp. 1–23). São Paulo.

Strategy & Leadership. (2009). Roundtable: how decision analytics help leaders compete. *Strategy & Leadership*, *37*(3), 37–41. https://doi.org/10.1108/10878570910954637

Sutcliffe, K. M., & Vogus, T. J. (2003). Organizing for Resilience. In K. S. Cameron, J. E. Dutton, & R. E. Quinn (Eds.), *Positive Organizational Scholarship: Foundations of a New Discipline* (pp. 94–110). San Francisco: Berrett-Koehler.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Trkman, P., McCormack, K., Oliveira, M. P. V. de, & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, *49*(3), 318–327. https://doi.org/10.1016/j.dss.2010.03.007

Trkman, P., Oliveira, M. P. V. de, & McCormack, K. (2016). Value-oriented supply chain risk management: you get what you expect. *Industrial Management & Data Systems*, *116*(5), 1061–1083. https://doi.org/10.1108/IMDS-09-2015-0368

Troilo, M., Bouchet, A., Urban, T. L., & Sutton, W. A. (2015). Perception, reality, and the adoption of business analytics: Evidence from North American professional sport organizations. *Omega*, 1–12. https://doi.org/10.1016/j.omega.2015.05.011

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(February), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Wagner, S., Brandt, T., & Neumann, D. (2016). In free float: Developing Business Analytics support for carsharing providers. *Omega*, *59*(Part A), 4–14. https://doi.org/10.1016/j.omega.2015.02.011

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (1999). Organizing for High Reliability: Processes of Collective Mindfulness. *Research in Organizational Behavior*, *1*, 81–123.

Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International Journal of Physical Distribution & Logistics Management*, *43*(4), 300–320. https://doi.org/10.1108/IJPDLM-08-2012-0243

Wildavsky, A. (1988). *Searching for Safety*. New Brunswick, NJ: Transaction Publishers.

Wilder, C. R., & Ozgur, C. O. (2015). Business Analytics Curriculum for Undergraduate Majors. *INFORMS Transactions on Education*, *15*(2), 180–187. https://doi.org/http://dx.doi.org/10.1287/ited.2014.0134

Zsidisin, G. A., & Wagner, S. M. (2010). Do Perceptions Become Reality? The Moderation Role of Supply Chain Resiliency on Disruption Occurrence. *Journal of Business Logistics*, *31*(2), 1–20. https://doi.org/10.1002/j.2158-1592.2010.tb00140.x