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ALAMIR COSTA LOURO

COMO O FIT ENTRE ANALYTICS ADAPTATIVO E CULTURA ORGÂNICA INFLUENCIA O DESEMPENHO ORGANIZACIONAL?

O Papel Interveniente Das Capabilidades De Marketing E Da Capacidade Absortiva.

VITÓRIA - ES

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Tese apresentado ao Programa de Pós–Graduação em Administração de Empresas do Centro de Ciências Jurídicas e Econômicas da Universidade Federal do Espírito Santo como requisito para obtenção do título de Doutor em Administração

Orientador: Marcelo Moll Brandão
Co-Orientador: Jurij Jaklič

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Alamir Costa Louro

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RESUMO

Na disciplina de marketing, há um interesse considerável em entender como o conhecimento do mercado é aprendido de forma a melhorar o desempenho organizacional e, recentemente, como o analytics está mudando esse processo de aprendizado. Uma bibliometria e uma revisão sistemática introduziram o link entre o analytics e as capabilidades de marketing, resultando em uma rede nomológica que apresenta algumas oportunidades para testar como o analytics aumenta o desempenho por meio de construtos intervenientes. Portanto, é pré-suposto que apenas o analytics não consegue melhorar o desempenho organizacional. O trabalho tem como objetivo diminuir a lacuna das capabilidades de marketing usando uma nova perspectiva para a cultura organizacional e para o analytics adaptativo com base nos conceitos de Day (2011) de forma a melhorar o processo de aprendizagem do conhecimento do mercado. O modelo apresenta dois construtos intervenientes após o desenvolvimento passo a passo de uma escala para o construto de fit. O constructo de fit abrange a estrutura condicional do analytics adaptativo e a cultura orgânica, explicando melhor como o fit aumenta o desempenho organizacional. O mecanismo engendra o construto fit, medido como covariação, capabilidades de marketing e a capacidade absortiva em um esforço multi-indústria na União Européia e no Brasil. A tese do fit entre cultura e analytics facilitado por uma mediação paralela expande o papel do analytics na teoria e interconecta, ainda mais, as literaturas de sistemas de informação e estratégias de marketing.

Keywords: Fit. Analytics. Cultura. Capabilidades Adaptativas. Capabilidades de Marketing. Capacidade Absortiva.

ABSTRACT

In marketing discipline, there is considerable interest in understanding how market knowledge is learned to improve organizational performance, and recently, how analytics is changing this learning process. A bibliometric and a systematic review introduced the link between analytics and marketing capabilities resulting in a nomological network that presents some opportunities to test how analytics boosts performance through intervening constructs. Thus it is conjectured that analytics alone cannot improve performance. The work aims to narrow the marketing capabilities gap using a new perspective for organizational culture and adaptive analytics based on Day (2011) adaptive concepts enhancing the market knowledge learning process. The model presents two intervening constructs after a step-by-step scale development for a fit construct. The fit construct embraces the conditional structure of adaptive analytics and the organic culture, explaining better how the fit boosts organizational performance. The mechanism engenders the fit construct, measured as covariation, marketing capabilities, and absorptive capacity on multi-industry effort in the European Union and Brazil. The thesis of fitted culture and analytics facilitated by a parallel mediation expands analytics role on theory and interconnects, even more, the information systems and marketing strategy literature.

Keywords: Fit. Analytics. Culture. Adaptive Capabilities. Marketing Capabilities. Absorptive Capacity.

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ACRONYMS LIST

ACAP - Absorptive Capacity

AIC3 - Modified AIC with Factor 3

B2B - Business to Business

B2C - Business to Customer

BI&A - Business Intelligence and Analytics

CAIC - Consistent Akaike information criterion

CRM - Customer Relationship Management

CTA-PLS - Confirmatory Tetrad Analysis PLS

CVF - Competing Values Framework

ED - Environmental Dynamism

EN - Normed entropy statistic

FIMIX-PLS - Finite Mixture PLS

FIT_AAOC - Adaptive Analytics & Organic Culture Fit

IoT - Internet of Things

IT - Information Technology

MCs - Marketing capabilities

MGA-PLS - Multi-Group Analysis PLS

NPD - New product development

OLS - Ordinary Least Square

OP - Organizational performance

PLS - Partial Least Square

PLS-POS - Predicted-oriented segmentation PLS

R&D - Research and Development

RBV - Resource-Based View

SEM-PLS - Structured Equation Modeling PLS

SRMR - Standardized root mean square residual

HOW CAN THE FIT BETWEEN ADAPTIVE ANALYTICS AND ORGANIC CULTURE INFLUENCE ORGANIZATIONAL PERFORMANCE?

The marketing capabilities and absorptive capacity intervening role.

1 INTRODUCTION

According to the literature review conducted by Barrales-Molina, Martínez-López, and Gázquez-Abad (2014), marketing discipline increases attention in emerging revolutionary technologies and in recent data-driven decision-making scenario, in particular, using the capabilities literature. Nowadays, to fully understand the market knowledge learning process, it is first necessary to uncover the role of culture and analytics and its underpinning mechanisms that allow the impact of new market opportunities on organizational performance.

Market information volume interactively conveyed by emerging revolutionary technologies like big data and internet of things (IoT), or related to mobile connectivity or e(m)-commerce are used as inputs to advanced analytical methods that transform internal or external data, structured or not, on market knowledge (Wedel & Kannan, 2016), i.e., they are new market opportunities for organizational learning. Emerging revolutionary technologies and analytics are recent, complex, and studied as a performance-driven phenomenon (Chuang & Lin, 2017; Wamba et al., 2017).

For Barrales-Molina et al. (2014) there is a “wide range of marketing resources, capabilities and, processes” (p.2) that hinder the 'connection and integration of these elements into a common framework. The plethora of capabilities, without clear construct content delimitation and scale validation, may have contributed to conflicting and misleading findings of the nature and contributions of analytics for marketing.

It is conjectured that analytics alone cannot improve organizational performance, then the most prominent contribution of the present thesis is to uncover the role of the intervening variables that help to explain, in the context of market knowledge learning, how analytics impacts on performance in a multi-industry survey in European Union and Brazil. To reach this goal, we developed a fit construct that mix analytics with adaptive approach concepts of Day (2011) and organic culture.

The research question presents two intervening variables: "**What are the role of marketing capabilities and absorptive capacity in the relationship between the adaptive analytics and organic culture fit and organizational performance?"**

2. THEORETICAL REFERENCE: FOUNDATIONS AND TRENDS IN ANALYTICS AND MARKETING RELATIONSHIP

Market dynamics, including its dialectic process of (de) regulation, (de) globalization, the last thirty-year information technology (IT) commoditization, the recent emergence of new revolutionary technology and national and international political uncertainties, beyond the cultural differences (Conti, Parente, & de Vasconcelos, 2015), alters the environmental dynamism and competitive advantage search.

The advanced analysis with a marketing emphasis, denominated in the present work as marketing analytics, helps to transform internal or external data, structured or not, in strategic information. It demands some in-depth marketing modeling techniques for the market's response prediction, optimization of marketing-mix, and personalization for the customers (Wedel & Kannan, 2016). Data mining in texts, voice, video, digital media, or websites is a technology that helps organizations, providing insights that are used to adjust the business rules and to create a relationship with their customers in a more relevant and connected way (Cooke & Zubcsek, 2017).

Analytics, as a field of study, has been gaining momentum in the last two decades, both in business and academic realms (Chen, Chiang & Storey, 2012). A search on Google Scholar in October 2019, with the keywords 'marketing' and 'analytics,' brought more than 470 thousand hits, with most of them consisting of recent publications.

Some updated literature already predicts, for some industries, that emergent technologies and analytics will be enablers of competitive advantage and the organizations need to understand their data and prepare it for a more efficient use (Côrte-real, Oliveira, & Ruivo, 2017; Wang & Hajli, 2017; Braganza, Brooks, Nepelski, Ali, & Moro, 2017).

The development of new products (Xu, Frankwick, & Ramirez, 2016), instant and recurrent feedback from transactions made by customers (Cooke & Zubcsek, 2017), and shared insights or co-creation innovation with customers (Khanagha, Volberda, & Oshri, 2017) are examples of activities supported by analytics technologies. There are also pricing and promotion, marketing mix, customer lifecycle value (Germann, Lilien, Fiedler, & Kraus, 2014), advertisement, sales force, branding, positioning, and market segmentation, all guided toward data (Wedel & Kannan, 2016).

The present section aims to answer how the capabilities literature can associate analytics and marketing with performance; then, it is presented some descriptive bibliometric results, after two cluster analysis for author coupling and keyword co-occurrence; then it is established a systematic review of recent quantitative papers from where, finally, it is proposed a nomological network that shows the pathways to improve quantitative research in marketing strategy using analytics. Those are necessary for both beginners, who do not know how to start studying, and for experienced researchers, as a shortcut to the primary constructs for future quantitative studies.

2.1 MARKETING AND ANALYTICS DUO: FOUNDATIONS

The present section provides a twenty-year summary of the analytics development as a research field while highlighting the major strengths of combining this area with marketing, especially from the perspective of the capabilities literature.

The broad term analytics is considered a young but increasingly important field of study, mainly characterized as the set of techniques, tools, and approaches aiming at accurate analysis of business data to improve decision-making. The evolution of this multidisciplinary field can be simplified into three major time periods, as proposed by Chen et al. (2012) framework: BI&A 1.0, BI&A 2.0, and BI&A 3.0.

The first period occurs in the 1990s, where the combination of statistical techniques and data mining practices lead to the development of better analytical tools, designed for the extraction and storage of data into robust databases (Chen et al., 2012). Therefore, the goal of marketing professionals was to optimize the collection, structuring, and later analysis of the data available in the market.

The second period begins with the popularization of the Internet on a global scale, which drastically transformed the way data is shared and expanding the volume of information that can be accessed. This scenario can be described as a big opportunity for marketers, since the shift towards digital communication impacts on the marketing mix formula (Germann et al., 2014; Wedel & Kannan, 2016), changing the main channels used to produce advertising and customer relationship management.

The third and most recent period is directly related to the so-called internet of things (IoT) and big data phenomena. This opens a new perspective on how new high-tech products can be used as a data source to provide useful and individualized information to enhance market knowledge, though it also brings uncertainty about the best techniques and approaches to collect, process, and analyze data (Chen et al., 2012).

The work of Chen et al. (2012) provides insightful information about how the area of BI&A evolved since its inception. Parallel to that, it is necessary to have business strategy discussions, primarily related to the resource-based view (Barney, 2014) and capabilities literature. In the marketing field, e-commerce and market intelligence subareas are the candidates to benefit the most from all sources of analytical tools (Chen et al., 2012). But, how can those analytical tools/methods/approaches be viewed as a proper capability, which is able to achieve performance?

2.2 BIBLIOMETRIC REVIEW

It was performed a bibliometric study in Scopus and Web of Science bases to analyze the state of the art that relates marketing and analytics. The sample criteria were created using "marketing AND analytics AND (capabilities OR resources)"as the search string in titles, abstracts, and keywords. English only, and with no period of time limit criteria. The keywords capabilities or resources were chosen for the theoretical delimitation of the present work, which used the resource-based view and its underlying literature about capabilities as cornerstones.

It was confirmed that the extracted articles are adherent to the research delimitation with a search based on the titles, abstracts, and keywords. Those were passed onto a spreadsheet, from where other theories were found with low occurrences, such as the configuration theory, game theory, innovations theory, while, with a bigger number of occurrences, it was perceived capabilities, Resource-Based Theory, or Resource-Based View (RBV).

According to Quevedo-Silva, Santos, Brandão, and Vils (2016), the bibliometric method brings a broader comprehension of themes or areas, allowing the identification of trends. According to the bibliographic review of those authors, this type of study performs three, mutually non-exclusive, approaches: (i) descriptive, that draws broad lines or the most studied topics in an area, identifying research groups, publication year, leading authors and methods used; (ii) about methodology, which ought to understand the methodological domain of the researched area by classifying and counting the research drawings and the test techniques mostly used, adjacently, it aims to find study opportunities and highlight a determined area research tradition; lastly the approach of (iii) descriptive analysis, which deepens the knowledge using cluster analysis of authors, theories, and keywords from the sample metadata.

The descriptive step was used to introduce the present bibliometric study, but the second step was not performed with a bibliometric approach, due to the research delimitation. Regarding the methodological domain, it was not carried out on all 705 articles, because it was chosen to perform this analysis in a much more detailed manner, beginning with a shorter list presented in the applied research section. Finally, the last step, cluster analysis, is shown as research trends.

2.2.1 Descriptive step

The tables from 1 to 8 represent (i) a descriptive approach. And, the analytical approach (iii) was primarily achieved with the usage of clusters about co-citations, co-occurrence, and coupling information from authors and keywords. Besides that, it was from these clusters analysis that one started to associate marketing and analytics using capabilities literature.

Table 1 describes the basic information from this sample since 1972; detailed information by year is presented in Table 2. It is highlighted that there were only included journal articles excluding revisions and conference papers, workshops, editorials, and tutorials. From a total of 898, counting the two bases of extraction, and after the exclusion of repetitions, it resulted in 778 articles. The exclusion of articles was executed by "mergeDbSources" function of the "bibliometrix" package (Aria & Cuccurullo, 2017).

Table 1–Bibliometric results - general description

Main Information about data			
Articles	898	Authors of single-authored articles	138
Sources (Journals)	412	Authors of multi-authored articles	1479
Journal Keywords	1980	Articles per Author index	0.547
Author's Keywords	2014	Authors per Article index	1.82
Average citations per article	9.321	Co-Authors per Articles index	2.71
First Authors	1641	Collaboration Index	2.36
Author Appearances	1999	Period	1972 – 2019
Scopus articles	499	Web of Science articles	399

Source: Prepared by the author (2019) using the R software

Table 1 also describes the number of articles in Scopus and Web of Science, the number of sources, keywords used by authors and journals, authors, and some indexes that relate this information with each other.

Table 2–Number of articles annual evolution

Annual Scientific Production										
Year	1972-2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Articles	72	26	27	22	42	50	74	101	152	128	161
Annual Percentage Growth Rate 3.93											

Source: Prepared by the author (2019) using the R software

In fact, from 1972 until the year 2008, only 72 articles were found in the sample, so, the last decade grouped around 92% of the articles in the sample. The year 2019 was excluded from the table, but it presented49 published articles. The bibliometrix package (Aria & Cuccurullo, 2017) used by the software R (R Core Team, 2019) calculated that there is positive annual growth, demonstrating an increasing interest in the topic. Appendix A presents all the source codes used in the present thesis.

From a total of 1999 authors and co-authors, there were five top authors shown in Table 3 as the most productive ones. The last column depicts the results according to the fractional authorship articles, dividing the article by number of authors, for authors and co-authors, generating a new author's ranking. It is interesting to notice the prominence of authors that do not relate to marketing, for example, Huang´s papers are related to operational research, while Denpeld, Wu, Chang BR, and Chang V all have papers belonging to the computational and information management.

Table 3– Most productive authors – Whom Beginners need to read

	AUTHORS	ARTICLES	AUTHORS	FRACTIONAL AUTHORSHIP ARTICLES
1	HUANG,T	6	SMALES,LA	3.33
2	VAN,DENPOELD	6	DYBVIG,A	3.00
3	WU,J	6	PANIAN,Z	3.00
4	CHANG,BR	5	PLAZA,B	2.67
5	CHANG,V	5	VAN,DENPOELD	2.42

Source: Prepared by the author (2019) using the R software

From the 778 articles in the sample, five were highlighted as the most cited (see Table 4). MacRoberts and MacRoberts (2010) say that, despite the criticism, the citation measurement is the most common in science, notwithstanding all sorts of known errors.

Table 4–Most cited articles (belonging to the sample) – Third step for beginners

	PAPER	Total	Total Year
1	Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information Communication and Society*, 15(5), 662–679.	937	187.40
2	Andreoni, J., & Levinson, A. (2001). The simple analytics of the environmental Kuznets curve. *Journal of Public Economics*, 80(2), 269–286.	204	12.75
3	Weng, L., Menczer, F., & Ahn, Y.-Y. (2013). Virality Prediction and Community Structure in Social Networks. *Nature SCIENTIFIC REPORTS*, 3, 1–6.	147	36.75
4	Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. *Journal of Big Data*, 2(1), 1.	92	46.00
5	Capizzi, M. T., & Ferguson, R. (2005). Loyalty trends for the twenty-first century. *Journal of Consumer Marketing*, 22(2), 72–80.	77	6.42

Source: Prepared by the author (2019) using the R software

In Table 4, it is highlighted the article of Boyd and Crawford (2012), which is a theoretical essay about cultural, technological, and educational implications from big data. It brings a contribution for the present discussion by considering possible mistakes related to the accuracy, objectivity or even context loss with the quantitative analysis in the big data era, an area of knowledge that demands teams with specific expertise(Wedel & Kannan, 2016;Wamba et al., 2017). It is interesting to notice that marketing journals are not the most cited.

The information in Table 5 demonstrates that Brazil is not one of the central countries in the productions and citations of this area. Extending the search, Brazil was found in the 18th position of the ranking.

Table5–Most productive countries

	Total Papers per Country			Total Citations per Country		
	COUNTRY	ARTICLES	FREQ	COUNTRY	CITATIONS	AVG
1	USA	285	0.4241	USA	4358	15.291
2	England	35	0.0521	England	332	9.486
3	China	30	0.0446	United Kingdom	194	8.435
4	India	25	0.0372	Australia	157	6.542
5	Australia	24	0.0357	Germany	150	8.333

Source: Prepared by the author (2019) using the R software

Table 6 shows that for the extracted sample from Web of Science and Scopus bases: five journals are connected to the information systems literature, one is related to operational research, and two are from marketing, confirming Table 4 information. The h5-index is also presented in this table, which is an h-index for articles published within the last five complete years. According to Hirsch (2005), the h-index is an excellent example of citation metrics that evaluates the productivity and the impact of published works of an academic or a journal.

Table 6–Most relevant sources – Fourth step for beginners (where to search)

	SOURCES	ARTICLES	h5-index	JCR(2018)
1	Expert Systems With Applications	17	92	3.768
2	Decision Support Systems	14	70	3.565
3	European Journal Of Operational Research	13	82	3.428
4	IBM Journal Of Research And Development	10	25	0.962
5	Computer Standards & Interfaces	10	26	1.465
6	International Journal Of Information Management	10	53	4.516
7	Journal Of Direct Data And Digital Marketing Practice	10	8	no longer published
8	Marketing Science	10	40	2.794

Source: Prepared by the author (2019) using the R software

Table 7 demonstrates the keywords associated with the authors (DE) and provided by Scopus and Web of Science (ID). A more in-depth analysis is performed in Table 10 and Figure 2.

Table 7–Most relevant keywords – Second step for beginners (what to search)

	AUTHOR KEYWORDS (DE)	ARTICLES	KEYWORDS-PLUS (ID)	ARTICLES
1	Analytics	72	Marketing	49
2	Big Data	64	Management	39
3	Social Media	48	Model	37
4	Big Data Analytics	30	Performance	35
5	Predictive Analytics	27	Analytics	34
6	Marketing	25	Market	28
7	Business Analytics	22	Commerce	25
8	Data Analytics	22	Impact	25
9	Data Mining	21	Big Data	23
10	Social Media Analytics	19	Social Media	23

Source: Prepared by the author (2019) using the R software

Bibliometrix created Table 8 from a total of 12,941 references found in the extracted sample. Therefore, they are the most referenced articles by authors. Although all these papers were evaluated and perceived as potentially significant in the existing literature that tries to associate marketing and analytics, the work of Chen et al. (2012) should be highlighted. Their bibliometric review and the nomological network not only show the importance of BI&A but also demonstrate the connections with different lines of research, including marketing.

Table 8–Most referred articles– First step for beginners

Most Referenced Papers	Total
Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics : From Big Data To Big Impact. *MIS Quarterly*, *36*(4), 1165–1188.	38
Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007	12
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). Big data: The next frontier for innovation, competition, and productivity. *McKinsey Global Institute*, (June), 156. https://doi.org/10.1080/01443610903114527	11
McAfee, A., & Brynjolfsson, E. (2012). Big Data. The management revolution. *Harvard Business Review*, *90*(10), 61–68. https://doi.org/10.1007/s12599-013-0249-5	11
Antweiler, W., & Frank, Z. M. (2004). Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *Journal of Finance*, *59*(3), 1259–1294. https://doi.org/10.1017/CBO9781107415324.004	10

Source: Prepared by the author (2019) using the R software

Thus, the articles presented in Table 8 are the primary source of knowledge for those less familiar with the subject.

2.2.2 Analytical step

A Bibliometric work enables the combination of an enormous amount of bibliographic data through statistical analyses (Vogel & Guttel, 2013). It was initiated a descriptive-analytical step with author co-citation description after author coupling, and keywords co-occurrence were also described graphically.

As an aesthetics option, it was decided not to show all cluster analyses in graphics. Author co-citation has a size (number of vertices) of 5945, and Chen H. is the top overall author, centrality index (0.320), and betweenness index (0.064). These indexes highlighted the author, therefore adopting it as the cornerstone work. Co-citation is reasonable to interpret the foundations; however, to find trends, it is necessary a coupling analysis (Vogel & Güttel, 2013).

Coupling analysis is a bibliometric technique that measures the frequency in which two documents of a sample have at least one reference in common. Then it considers the overlap of their bibliographies (Kessler, 1963; Zupic & Cater, 2015). The bibliographic coupling shifts attention from traditional works to trends in scientific literature, enhancing bibliometric applications (Vogel & Guttel, 2013). Figure 1 presents the bibliographic coupling for the present sample.

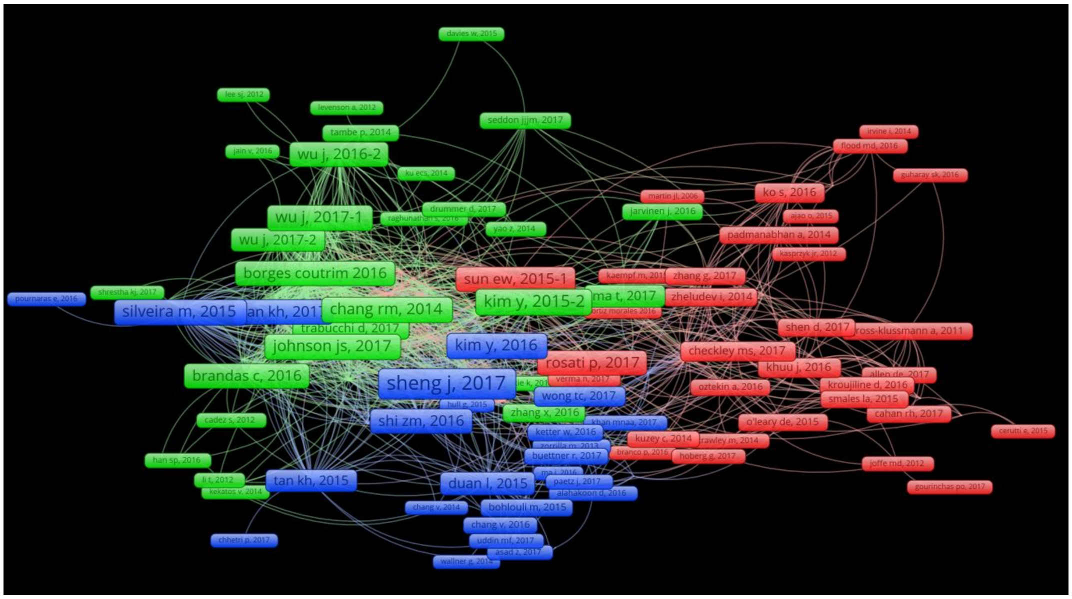

*Figure 1.*Author Coupling

Source: Prepared by the author (2019) using the R and VOSViewer software

There are several centrality indexes used to measure the ways in which authors may be connected to one another. For a detailed comparison and its use in marketing, see Chandler and Wieland (2010). Briefly, the betweenness centrality was created by Freeman (1978), and it is the “least number of connections that pass through actor k and connect actor i and actor j together” (Chandler & Wieland, 2010, p. 205), i.e., it is a measure of flow, meaning that the greater the index, the greater is the importance of the actor (an author, university or keyword) to the literature. For example, authors with higher index become connectors, and other authors may become dependent on them as bridges to other papers, not directly connected.

Table 9 presents a fractional counting of author coupling. When fractional counting is used, it reduces the influence of documents with many authors (Perianes-Rodriguez, Waltman, & van Eck, 2016).

Table 9–Top betweenness centrality articles per cluster

Article	Cluster	Betweenness Centrality
Sheng, J., Amankwah-amoah, J., & Wang, X. (2017). A multidisciplinary perspective of big data in management research. *International Journal of Production Economics*, 191(November 2016), 97–112. https://doi.org/10.1016/j.ijpe.2017.06.006	Blue	386,98
Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing*, 80(1), 7–25. https://doi.org/10.1509/jm.14.0249	Green	266,07
Grover, P. (2017). Big Data Analytics : A Review on Theoretical Contributions and Tools Used in Literature. *Global Journal of Flexible Systems Management*, 18(3), 203–229. https://doi.org/10.1007/s40171-017-0159-3	Green	222,14
Johnson, J. S., Friend, S. B., & Lee, H. S. (2017). Big Data Facilitation, Utilization, and Monetization: Exploring the 3Vs in a New Product Development Process. *Journal of Product Innovation Management*, 34(5), 640–658. https://doi.org/10.1111/jpim.12397	Green	217,52
Tan, K. H., Zhan, Y. Z., Ji, G., Ye, F., & Chang, C. (2015). Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics*, 165(July 2015), 223–233. https://doi.org/10.1016/j.ijpe.2014.12.034	Blue	216,23
Tan, K. H., & Zhan, Y. (2017). Improving new product development using big data: a case study of an electronics company. *R and D Management*, 47(4), 570–582. https://doi.org/10.1111/radm.12242	Blue	215,19
Rosati, P., Cummins, M., Deeney, P., Gogolin, F., van der Werff, L., & Lynn, T. (2017). The effect of data breach announcements beyond the stock price: Empirical evidence on market activity. *International Review of Financial Analysis*, 49, 146–154. https://doi.org/10.1016/j.irfa.2017.01.001	Red	159,57
Chou, C., Chang, C. J., & Peng, J. (2016). Integrating XBRL data with textual information in Chinese : A semantic web approach. *International Journal of Accounting Information Systems*, 21, 32–46. https://doi.org/10.1016/j.accinf.2016.04.002	Red	75,88
Huang, T., Fildes, R., & Soopramanien, D. (2014). The value of competitive information in forecasting FMCG retail product sales and the variable selection problem. *European Journal of Operational Research*, 237(2), 738–748. https://doi.org/10.1016/j.ejor.2014.02.022	Red	70,09

Source: Prepared by the author (2019) using the R software

As can be seen in Table 9, the red cluster has smaller centrality indexes. Additionally, Figure 1 represents it as a separate, detached, literature from cluster blue and green. Indeed, the red cluster presents more technical papers, applications on marketing (Huang, Fildes, & Soopramanien, 2014), finance (Rosati et al., 2017), or accounting (Chou, Chang, & Peng, 2016). For example, Huang, Fildes, and Soopramanien (2014) discuss sales forecasting, but the focus is on the best algorithm choice, comparing time series and "autoregressive distributed lag." For their part, Chou, Chang, and Peng (2016) discuss semantic web technologies to integrate textual accounting disclosures.

On the other hand, with a more theoretical approach, the blue cluster discusses the application of big data in supporting supply chain operations (Tan, Zhan, Ji, Ye, & Chang, 2015) and attempts to explain how organizations gain new product development ideas or optimize their manufacturing processes using big data. For their turn, Sheng, Amankwah-amoah, and Wang (2017) created a big data bibliography review and generated a framework for value achievement and management practice. Finally, Tan and Zhan (2017) also discuss new product development on three electronics companies as successful case studies.

The green cluster is focused on marketing, and most of the papers are related to its issues, especially customer orientation. For example, Johnson, Friend, and Lee (2017) focus on new product development using big data by contrasting exploration and exploitation of different market turbulences. Kumar et al. (2016) empirically tested customer performance using social media as a channel for marketing communication through inbound marketing. In addition, Grover (2017) also discusses competitive advantage and organizational performance. His focus is on the evolution of big data on social media analytics, text mining, and machine learning applications on marketing and supply chain management disciplines, considering a multi-industry overview of platforms and tools.

We also analyzed the conceptual structure of the field with another network analysis, evaluating the clusters of keywords co-occurrence. This method uses the actual content of the documents to build a similarity measure (Callon, Courtial, Turner, & Bauin, 1983). It is a square matrix initially created with a 1,909 dimension of the keywords, also called similarity matrix, which results in the proximity rates that are plotted in a map using the free software

VOSViewer (van Eck & Waltman, 2010). Figure 2 shows almost all vertices or keywords available.

In both Figures 1 and 2,it was adopted probabilistic similarity measures for normalization purposes. The probabilistic method name in VosViewer is "Association strength," understood as the best normalization for scientometric research (Eck & Waltman, 2009).

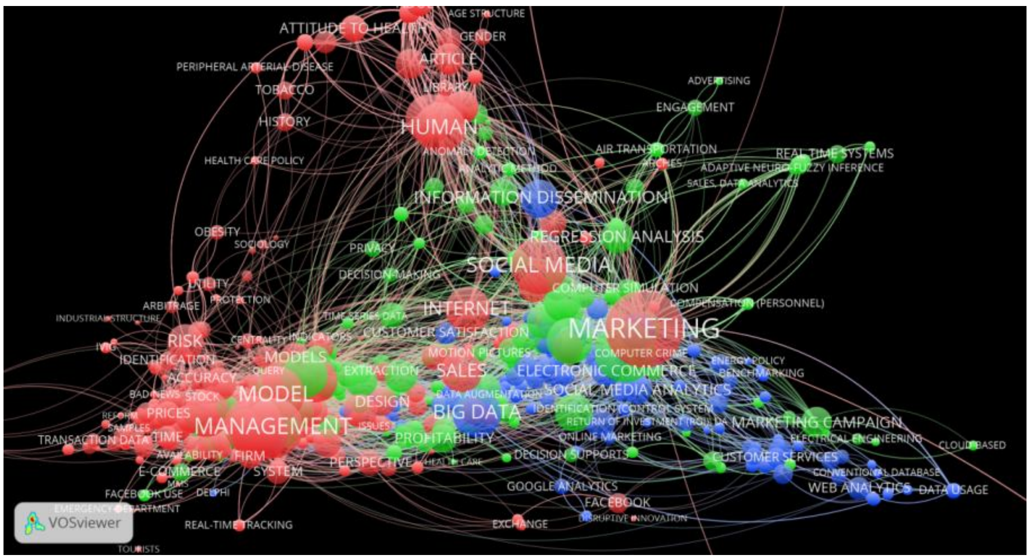

*Figure 2.*Keywords Co-occurrence
Source: Prepared by the author (2019) using the R and VOSViewer software

The red cluster was categorized as “Performance Management,” with a total of 911 keywords, which are mostly related to management/strategy literature. Then the blue cluster was categorized as “Technology and Learning.” It has 405 keywords, and more technical or information systems literature related. Lastly, the green cluster was categorized as “Customer Orientation,” with 653 keywords, and it is more related to marketing. The most important keywords are referenced by the clusters in Table 10.

Table 10– Top betweenness centrality keywords per cluster

Keyword	Cluster	Betweenness Centrality
Marketing	Red	248,17
Sales	Red	84,86
Management	Red	56,40
Social media	Blue	51,41
Data mining	Blue	34,50
Learning systems	Blue	14,87
Big data	Blue	14,12
Decision making	Green	12,68
Artificial intelligence	Blue	10,84
Forecasting	Red	9,55
Model	Red	9,47
Profitability	Green	7,62
Algorithms	Blue	7,22
Internet	Red	6,77
Electronic commerce	Green	6,72
Information dissemination	Blue	5,39

Source: Prepared by the author (2019) using the R software

We used the bibliometric analytical step as a start to understanding the primary constructs related to the present thesis; an additional step to deepen the literature review was necessary to analyze the papers belonging to capabilities in marketing, information systems, and strategy journals. The result of this revision focused on quantitative works pointed out as applied research.

2.3 APPLIED RESEARCH REVIEW:TRENDS

For this bibliographical revision, following Hong, Chan, Thong, Chasalow, and Dhillon (2013) guidelines, about contextual constructs, i.e., similar constructs with different names depending on context, the present work considered terms like big data analytics, social media analytics, marketing analytics, and customer analytics as constructs related to specific contexts from the general construct business analytics, following the Chen et al. (2012) approach. It was necessary to analyze quantitative works using all these terms.

Table11– Applied studies summary

Reference	Constructs	Main Results
(Chang et al., 2010)	1.1Customer-centric organizational culture 1.2Customer-centric management system 2.CRM technology use 3.*Marketing capabilities* 4.Organizational performance	Marketing Capability is the mediator between the CRM use and Organizational performance.
(Trainor et al., 2014)	1.1Customer-Centric Management System 1.2-Social Media Technology Use 2-Social CRM capabilities 3-Customer Relationship performance Covariate(Cov)1-Training Cov2-Management Support Cov3-Organizational Size	The usage of social media technology does not by itself have a direct result on the development of relationship performance.
(Wamba et al., 2017)	1.1-BDA(big data analytics) infrastructure capability 1.2-BDA management capability 1.3- BDA personnel capability 2- BDA capability 3-process-oriented dynamic capabilities 4-Performance	Direct impact from the Big Data Analytics Capability in performance, just as the mediating effects of "Process Orientation Capability" over this relationship.
(Côrte-Real et al., 2017)	1.1-endogenous knowledge management 1.2-exogenous knowledge management 1.3-knowledge sharing with partners 2-Agility 3-Process-level performance 4-competitive advantages cov1-"time since adoption of BDA"; cov2- industry; cov3-country; cov4-technological turbulence; cov5 - Leadership in product/process innovation; cov6-Impact of new technology on operations.	To create agility, external knowledge from Big Data Analytics applications can be more effective than internal knowledge.
(Chuang & Lin, 2017)	1.1- e-service capability 1.2 - service innovation orientation 2- information-value offering 3- Customer relationship performance 4-Organizational performance cov- market turbulence	The positive effects of the information value in customer relationship performance and Organizational performance became evident in highly turbulent markets.
(Popovič, Hackney, Coelho, & Jaklič, 2014)	1-Information sharing values (ISV) 2.1-BI system quality (BISQ) 2.2 -Information quality (IQ) 3-Information use (IU)	The information-sharing value is a mediator between the dimensions of information systems.
(Chuang & Lin, 2013)	1-Technology resource 2-Human resource 3-Business resource 4-Customer orientation 5-Customer information quality 6-Customer relationship performance 7-Overall firm performance	The customer relationship performance has a mediating role in the relation between the quality of the customer's information and the global performance of the organization.

Source: Prepared by the author (2019)

It was also performed a bibliographical revision (Table 11) in international journals with significant JCR indexes, deliberated as more than one, and available in periodicos.capes.gov.br. The searched constructs were related to “Performance Management,” “Technology and Learning,” or “Customer Orientation.”

By delimitation, it was included only the papers that exhibited the structural model and their respective measurements. Other works, not initially selected, were included by ramification, like a snowball(similar to convenience sampling) from the articles initially chosen. The result is presented in Table 11, which is the summary of this applied bibliographic review with pertinent and explicit quantitative models only. It shows the constructs and a brief description of the general idea of each work.

Table 11 reveals a list of selected applied research with explicit quantitative models since the year 2010,from where future studies can be operationalized using the nomological network constructs options (see Figure 4).

Marketing analytics can be studied from the capabilities literature point of view (Germann et al., 2014; Wamba et al., 2017), but a literature mapping shows different levels of abstractions and some challenging issues (see Figure 3).Figure 3 helps to explain the present work's theoretical background/choices.

Figure 3 shows, on the left side, the levels of abstractions found in marketing and strategy literature about capabilities. It means that it is possible to talk about capabilities general level and 3 levels of marketing capabilities, according to Day (2011, 2014). And the right side interconnects the three literature the present work uses.

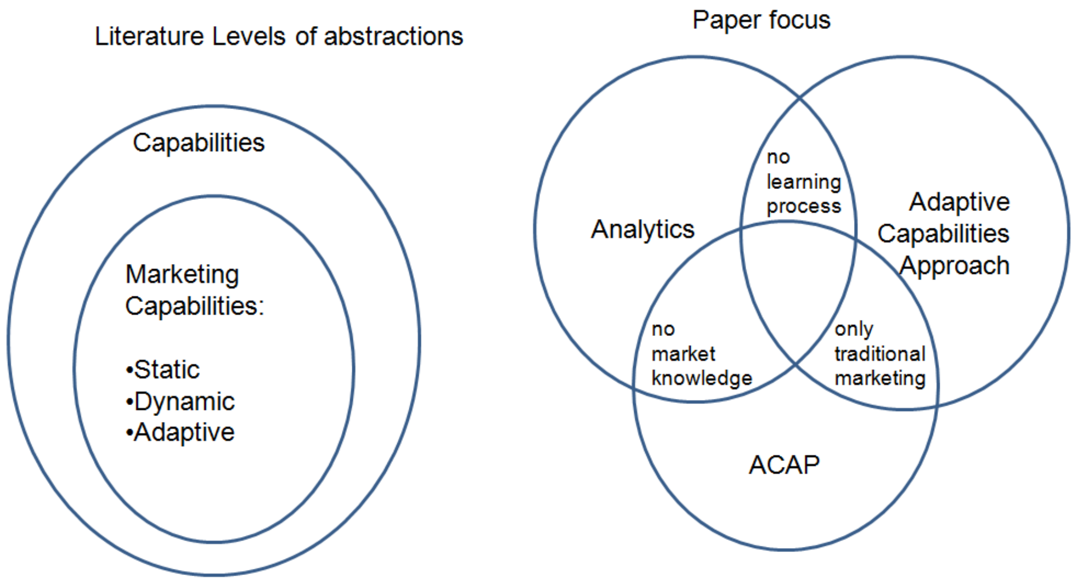

*Figure 3.*Literaturelevels of abstractions
Source: Prepared by the authors (2019)

On the right side, the issues represent research opportunities or gaps. Issue 1 (no market knowledge) of Figure 3 is related to how information systems literature uses capabilities to explain the learning process, but these approaches don´t focus on the market knowledge learning (Popovič, Hackney, Coelho, & Jaklič, 2012; Teo, Nishant, & Koh, 2016; Wang & Byrd, 2017), and market knowledge is vital for changing organizational strategies (Barrales-Molina et al., 2014).

Issue 2 (only traditional marketing) of Figure 3 is related to how marketing and strategy literature uses the absorptive capacity (ACAP) concept of the learning process. It uses exploitative and explorative processes or responsive and proactive market orientation (Barrales-Molina et al., 2014; Ozdemir, Kandemir, & Eng, 2017).This literature is prominent, but it lacks discussing analytics; thus, it stays in traditional marketing methods (Wedel & Kannan, 2016); it doesn´t narrow the marketing capabilities gap.

Disciplines of marketing (Germann et al., 2014; Wang & Hajli, 2017) and information systems (Pavlou & Sawy, 2010; Teo et al., 2016) are interested in the market knowledge exploitative and explorative learning process. However, Day (2011) proposed anticipatory and experimental dimensions to close the marketing gap, and the Issue 3 (no learning process) of Figure 3 gives this opportunity of explaining the Day approach using analytics, but still last one question about the learning process that has its response in the intersection of the three literature.

2.4 NOMOLOGICAL NETWORK: TRENDS

It was developed the full crossing of Figure 3, but before it is necessary to understand the difference between absorptive capacity (ACAP) and adaptive analytics capabilities. Both are outside-in (Day, 1994), but the adaptive capabilities proposed by Day (2011) can´t be confused with ACAP.

ACAP is about how market information becomes valuable, but not as proactive as the adaptive approach. Adaptive analytics is the market openness for vigilant deep market insights and continuous experimental behavior (Day, 2011; 2014). This kind of capability is an approach to what to do with market knowledge. Adaptive analytics conceptualization, from one point of view, is intrinsically linked to the marketing approach for BI&A trending paths (Chen et al., 2012), and the ACAP approach is connected with traditional linked marketing methods.

A recurrent and vital step to develop a model is the construct choice process (MacKenzie, Podsakoff, & Podsakoff, 2011), and a nomological network can help with this (see Figure 4). This step is especially crucial for marketing latent constructs (Jarvis, MacKenzie, & Podsakoff, 2004).

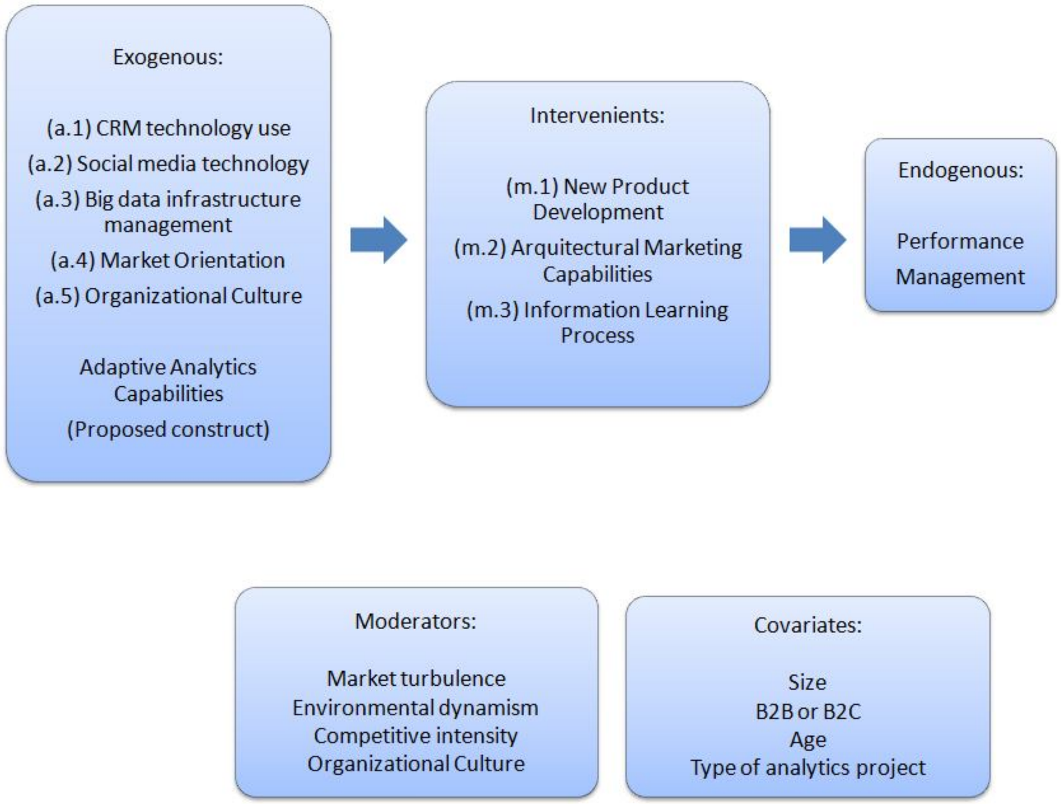

*Figure 4.*Adaptive analytics capabilities nomological network

Source: Prepared by the author (2019)

Figure 4 shows suggested exogenous, covariates, moderators, intervenients, and endogenous from the systematic review. Some possible reference papers for exogenous constructs are (a.1) (Chang et al., 2010), (a.2): (Trainor et al., 2014), (a.3) (Wamba et al., 2017), (a.4) (Rapp et al., 2010) and (a.5)(Chang et al., 2010; Trainor et al., 2014). The covariates, moderators, and performance are from recurrent sources of the literature (Jayachandran, Sharma, Kaufman, & Raman, 2005; Rapp el al., 2010). Finally, the intervenients/mediation reference works are (m.1) (Xu et al., 2016), (m.2) (Morgan, Zou, Vorhies, & Katsikeas, 2003), and (m.3) (Cohen & Levinthal, 1990).

2.5 DISCUSSIONS

After reading the papers separated by using author coupling analysis, it is possible to infer that green and blue clusters are mostly related to business, management, and marketing papers. The green cluster can be connected with “Customer Orientation,” blue with “Performance Management,” and the red cluster can be linked to “Technology and Learning,” representing a more computational or technological group of papers.

After analyzing the clusters in Figures 1 and 2 and Tables 9 and 10, firstly, it was seen that the "Consumer Orientation" cluster seems to be a central topic in the intersection between marketing and analytics. This cluster mostly involves analyzing structured data or text, social media, mobile data, etc., for marketing and operation purposes. Consumer feelings and behavior are hard to grasp due to market/customer turbulence (Johnson, Friend, & Lee, 2017), but it is on the focus of social analysts, especially in marketing.

Secondly, in the "Performance Management" cluster, big data is hyped(Grover, 2017; Tan, Zhan, Ji, Ye, & Chang, 2015). New approaches in marketing analytics attempt to improve organizational performance(Kim, Jo, & Shin, 2016). Many papers predict big data's impact on performance, and its changes in management and strategy are also discussed(Sheng, Amankwah-amoah, & Wang, 2017).

Thirdly, "Technology and Learning" cluster papers usually deals with analytics/data science techniques and technological issues. These technologies improve information collection and market data processing to predict, for example, customer behavior/feelings (Kumar et al., 2016). The main objective of some of these cluster papers is to enhance operational efficiency using analytics and capabilities(Popovič, Hackney, Tassabehji, & Castelli, 2016; Chen & Nath, 2018).

After the systematic review of quantitative papers, Figure 4 proposed an initial nomological network. Before that, Figure 3 presented the issues/gaps in the literature and offered adaptive analytics capabilities as an answer that covers these issues. Adaptive analytics capabilities can represent a learning process that is concerned with the market knowledge and overcomes traditional marketing methods using analytics. The nomological network is helpful in developing future models, aiming to embrace adaptive analytics capabilities, its relationship with organizational performance, and also presents the most critical candidate variables in the context.

2.6 RESEARCH DIRECTIONS

The present work serves as a guide for the study of the emerging area of analytics in marketing using capabilities literature. Similar to Chen et al. (2012), a bibliometric study was carried out to raise the state of the art on academic discussions surrounding BI&A, and, then, to combine it with RBV/capabilities related publications. It works as the basis for a better comprehension of the phenomenon by beginners (as seen in Tables 4 and 8) and a shortcut for advanced researchers (see information in Table 11 and Figure 4).

In addition to this systematic examination, an applied review was conducted to generate a nomological network after reading all sample abstracts and all papers content of Tables 4, 8, 9, and 11. As well as to report the operationalized, most used, and theory consistent variables related to the phenomenon, together with possible covariates and other intervening variables. Thus, the major contribution of the present work is to provide theoretical model options using past research to ease future quantitative studies about the intersection between marketing and analytics.

"Consumer Orientation," Technology and Learning," and "Performance Management" looks like to be the trending areas. Additionally, the review shows that the technologies which mediate direct interactions between organizations and customers can boost products and services offers and development. Therefore, consumer orientation is hyped by using analytics as a new core element for marketing strategy. In this context, big data is even more hyped(Johnson, Friend, & Lee, 2017). The literature also presents solutions such as more specialized market segmentation/personalization, advancing the brand, and advertising research (Kumar et al., 2016). These trends make the research agenda.

An opportunity comes from testing some of the possible relationships of the nomological network (see Figure 4). Future studies could focus on the impacts of the adaptive mechanisms upheld by analytics. All exogenous constructs from the nomological network can be seen as path-dependence elements, and, then, can be studied using a longitudinal approach to understand the building process of these paths with any other moderator, mediator, or covariate presented. Industry idiosyncrasies can tell the story of capabilities path-dependence elements.

New quantitative work can follow the idea of some current studies that provided empirical evidence confirming the role developed by organizational capabilities to generate dynamism from their innovation/technology team (Barrales-Molina et al., 2014). The quantitative work can study sustained/durable or temporary/transient (Day, 2014) competitive advantages. In any of these scenarios, it is proposed that future studies include constructs related to technology, such as team capability, technology use, technology infrastructure, technology management/leadership, and/or innovation orientation.

This thesis suggests performance as a primary endogenous construct. Admittedly, it is possible to deal with customer relationships, marketing, financial, or other types of performance, with subjective or objective approaches. On the other hand, there are many endogenous possibilities, and we suggest a few in the nomological network.

The covariates showed in Figure 4 encourage research about performance and its antecedents, and also, moderation and/or mediation and/or covariates typical of common constructs, like training, management support, size, industry, country, and/or more exciting constructs, such as environmental dynamism, leadership in innovation, culture, the impact of new technology, market or technological turbulence. For sure, this is not the whole list, but it presents thousands of possibilities to explain performance in different contexts.

From this myriad of modeling possibilities, there is one exciting issue discussed in the present thesis and shown in the nomological network (see Figure 4): How organizational culture is inserted in the model? As an exogenous construct, as a moderator or as part of an adaptive analytics construct, as proposed in the next section?

3. ADAPTATIVE ANALYTICS & ORGANIC CULTURE FIT SCALE DEVELOPMENT AND VALIDATION

3.1 INTRODUCTION

Revolutionary technologies improved analytics power giving life to adaptive analytics capabilities that can explore and exploit the market knowledge (Louro, Brandão, Jaklič, and Sarcinelli (2019). However, there is a literature gap in measuring a construct that represents the fit between organizational culture and the adaptive capabilities related to analytics. The new construct explains why some organizations have different marketing capabilities gap (Day, 2011). Then, a scale for adaptive analytics & organic cultural fit (FIT_AAOC) is proposed, and its correlation was tested with absorptive capacity(ACAP), marketing capabilities(MC), and organizational performance(OP).

Different management disciplines hold that organizational culture is a kind of social system within an organization that helps to explain strategic choices to obtain better performance (Schein, 1990). In updated marketing and management literature, there is interest in organizational culture as the antecedent of organizational performance(Lu, Plewa, and Ho, 2016; Wu, 2016; Mandal, 2017).

Louro et al. (2019) tested how market orientation and customer analytics capabilities, an adaptive approach, impacts on organizational performance. Both market orientation and organic organizational culture have a positive effect on performance (Deshpandé & Farley, 2004; Wei, Samiee, & Lee, 2014). The present work changed Louro et al. (2019) scale to test the fit between adaptive analytics capabilities and organic culture, understood as a spectrum of organizational culture "relatively open, externally oriented" (Deshpandé & Farley, 2004, p.10).

The present thesis uses fit as covariation, one of the three different approaches to conceptualize and operationalize fit (Vorhies & Morgan, 2003; Yarbrough, Morgan, & Vorhies, 2011), others are as gestalts and as profile deviation. The covariation approach suggests that "the degree of internal consistency in resource allocations has a significant effect on performance" (Venkatraman, 1989, p. 439). The covariation approach option increased model parsimony. The fit measurement was operationalized using confirmatory factor analysis, as indicated by Venkatraman (1989).

Fit is classified into six different perspectives: moderation, mediation, matching, covariation, gestalts, and profile deviation (Venkatraman, 1989;Venkatraman & Prescott, 1990). The present thesis followed the covariation perspective like the prominent marketing literature (Vorhies & Morgan, 2003; Yarbrough, Morgan, & Vorhies, 2011), but it is essential to justify why this is the most suitable fit perspective for the present case.

The matching perspective is when two first-order constructs are consistently low, medium, or high with each other, and it is operationalized as a difference between items (Venkatraman, 1989). However, this is not the present case because both adaptive analytics and organic culture are conjecture to have higher scores to impact performance. Fit as Gestalts perspective is defined in terms of the degree of internal coherence among a set of theoretical attributes, involving many variables, which is not the present case with only adaptive analytics and organic culture as first-order of the fit second-order construct.

Fit as Mediation is a significant intervening mechanism that exists between an antecedent variable and the consequent variable, it is assumed that this perspective could not improve the model parsimony, and there is no theoretical reasoning in literature. Fit as a profile deviation enables us to understand if an ideal strategic profile is specified as positively related to the performance. However, our aim is not to assess misalignment from the ideal profile because we assumed that there is no perfect profile for our general sample executed in the EU and Brazil for different industries.

Finally, Fit as moderation is the impact that an independent variable has on a dependent variable to which it is related to the level of a third variable, the moderator. This perspective is operationalized as an interaction (Venkatraman, 1989) of the two first-order constructs as contingency theorists do. It is another valid perspective for the present thesis, but we preferred Fit as Covariation, as it is a pattern of variation or internal consistency among a set of underlying theoretically related variables.

The covariation approach suggests that "the degree of internal consistency in resource allocations has a significant effect on performance" (Venkatraman, 1989, p. 439). Resources or capabilities allocation makes more sense to the present thesis context. The fit measurement was operationalized using confirmatory factor analysis, as indicated by Venkatraman (1989), and reproduced by Loi, Lam, Ngo, and Cheong (2015), Felipe, Roldán, & Leal-Rodríguez (2016) and Yang, Sun, Zhang, and Wang(2017)using PLS-SEM. A more in-deep discussion about fit measure multidimensionality is introduced by Polites, Roberts, and Thatcher (2012).

The most prominent contribution of the present thesis chapter is the step-by-step scale development of FIT_AAOC. In the following sections, we discuss some concepts and assumptions, and after we propose the FIT_AAOC scale. Synthetically, the present article presents the constructs for a correlation test after the development of a new construct that is the fit, as covariation, between a type of adaptive capability and a variety of organizational culture. It is conjectured that analytics can improve preexisting marketing capabilities and exploitative processes.

3.2 THEORETICAL DEVELOPMENT

3.2.1 Basic concepts

A building block in marketing capabilities literature, from the very beginning, i.e., in RBV (Resource-Based View), is the conception of organizations as a bundle of resources (tangible or intangible assets) that with their heterogeneity make the organizations idiosyncratic, and bring competitive advantage. There is a need to acquire\reconfigure\transform these resources to cope with market complexity, and capabilities literature evolves from this point of view (Day, 2011; Morgan, 2012).

By its turn, dynamic capabilities, an unfolding of the RBV, is a set of specific and identifiable processes, like product development, strategic decision-making, and strategic alliances (Eisenhardt & Martin, 2000). Finally, marketing literature develops the term marketing capabilities using concepts of dynamic capabilities (Morgan, 2012; Kozlenkova et al., 2014). Based on RBV\capabilities literature, Wei et al. (2014) confirm the positive relationship between organic culture and market responsiveness, an adaptive approach.

Another different literature deals with the learning process using the absorptive capacity (ACAP) construct. ACAP is defined as “the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities.” (Cohen & Levinthal, 1990, p.128).

ACAP starts with the cognitive capacity of individuals, and its organizational development is history-or path-dependent. ACAP also is facilitated by organic organizational characteristics in circumstances of uncertainty (Cohen & Levinthal, 1990). Based on the management literature review, Strese, Adams, Flatten, and Brettel (2016) recently discussed the relationship between organic culture and absorptive capacity, pointing a positive relationship.

Day (2011, 2014) criticize the current RBV literature, and even the contemporary dynamic capabilities literature, as less dynamic theories than the market demands, suggesting the existence of the adaptive capabilities. The present work advocates that an organization with good Fit (FIT_AAOC) explores better market opportunities using analytics.

3.2.2 Marketing capabilities types

Marketing capabilities are an extension of dynamic capabilities that uses market knowledge via cross-functional marketing processes (Barrales-Molina et al., 2014). To Day (2011), there are three different marketing capabilities: static, dynamic, and adaptive.

Market complexity can be learned using market knowledge, and traditionally, resources and capabilities, static and dynamic, were conceptualized to reconfigure the organizational processes, and themselves, to respond to the market demands. According to Day (2011), dynamic capabilities looking for fitness and efficiency included systematic sensing and scanning that static did not have, but they remain with an inside-out focus, not using the opportunities properly from market knowledge.

To overcome the dynamic capabilities limitations, Day (2011) defines adaptive capabilities characteristics to respond to the increasing marketing capabilities gap:

> "(1) Vigilant market learning that enhances deep market insights with an advance warning system to anticipate market changes and unmet needs, (2) adaptive market experimentation that continuously learns from experiments, and (3) open marketing that forges relationships with those at the forefront of new media and social networking technologies and mobilizes the skills of current partners". (Day, 2011, p.183)

Thus the adaptive capabilities are outside-in focused via experimental learning, and they can anticipate behaviors with a faster reconfiguration. When an organization has a smaller marketing capabilities gap means that market knowledge impacts more organizational performance. Finally, adaptive capabilities are better to narrow the marketing capabilities gap than dynamic or static capabilities (Day ,2011).

3.2.3 Assumptions about capabilities, analytics and culture literature

From the previous concepts, the first assumption is that there is a marketing capabilities gap, and it is related to the evolution of market complexity (Day, 2011, 2014). Organizations that explore better the market opportunities have a smaller gap. Day pointed to the Internet and the shrinking cost of communication as causes for widening this gap, the market opportunities are increasing, but few organizations have the right capabilities to explore them. In this context, emerging revolutionary technologies need increasing attention in order to respond to new market inquiries or new data-driven learning opportunities.

Despite some literature that uses these emerging revolutionary technologies as cornerstones (Erevelles, Fukawa, & Swayne, 2016; Wamba et al., 2017), an assumption is that big data, IoT, social media, etc., are just sources, or kinds, of data that analytics can use, or not, to enable organizational performance, i.e., analytics here is a sophisticated data technology approach for decision-making (Davenport, 2006) that can be used with adaptive approach like in Louro et al. (2019).

The last assumption of the present work is about the organic culture as the focus for the fit construct. In the present thesis we used the organizational culture model by Cameron and Quinn (2006) due to its applicability in different organizations and its ubiquitous use in the national (Reis, Trullen, & Story, 2016) and foreign topic-related (Strese et al., 2016; Ogbeibu, Senadjki, & Gaskin, 2018) research. Figure 5 presents the Competing Values Framework (CVF) and shows its adaptation for the present thesis.

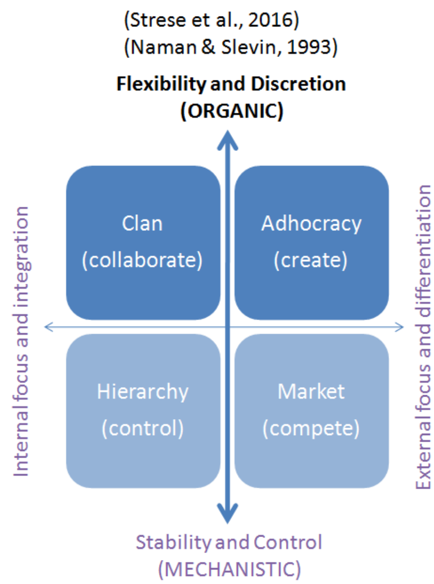

*Figure 5.*CVFadaptation and references

Source: Adapted from *Cameron and Quinn (2006)*

CVF has four types of cultures and two dimensions. One dimension is about the process, and the other is about organizational emphasis, contrasting internal maintenance and external positioning organizations. It is assumed that this last dimension is captured using the outside-in characteristic of adaptive capabilities (Day, 2011, 2014). Thus it is not focused here, and Figure 5 highlights only the process dimension, vertical arrow.

The other CVF´s dimension is about the process that is a continuum to contrast organizations focused more on flexibility and spontaneity (organic) or on control and stability(mechanistic). It is assumed that analytics can be improved by adopting organic organizational structures because only this type of culture promotes innovation (Naman & Slevin, 1993; Strese et al., 2016). Thus, it is measured the fit using only how the organization is organic, voiding problems with ipsative original scale (Cameron & Quinn, 2006). In other words, it is used only two out of four culture CVF´s types of organizational culture, Clan and Ad Hoc, using Likert-type scale (Sarros, Gray, Densten, & Cooper, 2005).

3.3 FIT_AAOCSTEP-BY-STEP SCALE DEVELOPMENT

Traditional marketing and strategy literature use the absorptive capability (ACAP) concept for the overall information learning process. It uses exploitative and explorative or responsive and proactive market orientation (Barrales-Molina et al., 2014; Ozdemir et al., 2017). This literature is prominent but lacks the opportunity to talk about analytics and stands in traditional marketing methods and approaches (Wedel & Kannan, 2016), which do not narrow the marketing capabilities gap(Day, 2011). Thus, FIT_AAOC is proposed as a solution.

Market knowledge is a fundamental point of connection between the present thesis constructs. The knowledge nature may be diverse, from CRM systems, social media, new revolutionary technologies like IoT and big data, etc. FIT_AAOC uses data-driven quantitative evidence (Davenport, 2006) and the adaptive approach when there is an organic organizational culture.

Information systems literature uses capabilities to explain the information learning process (Popovič et al., 2012; Teo et al., 2016; Wang & Byrd, 2017), but these approaches do not focus on the market knowledge, and its essential role for changing/reconfiguring organizational strategies (Barrales-Molina et al., 2014). The use of market knowledge through FIT_AAOC, i.e., the covariation of organic culture and adaptive analytics, makes the present work unique.

To solve the lack of a FIT_AAOC construct and test its correlation with important constructs from literature, the researcher developed a new scale using the MacKenzie et al. (2011) ten steps validity framework (see Figure 6).

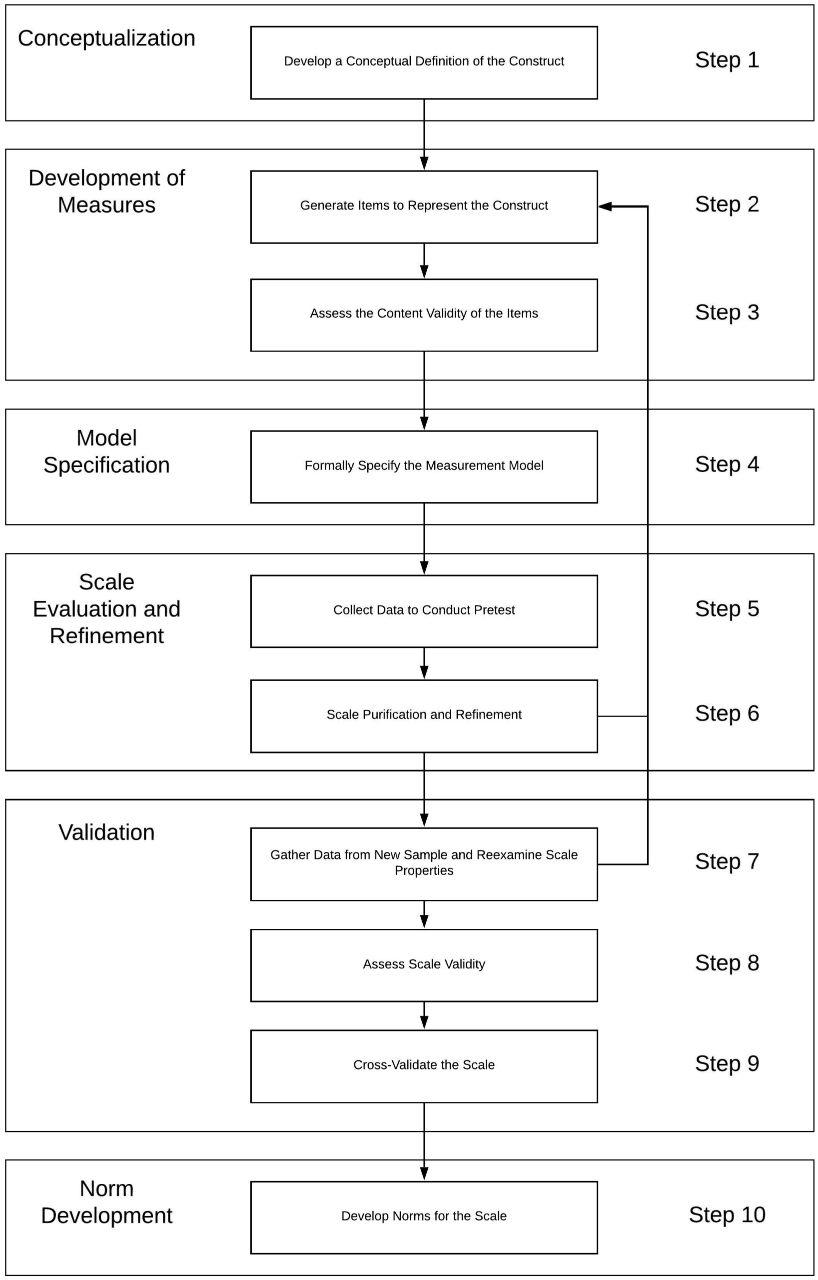

*Figure 6.*Construct validity framework

Source: Adapted from MacKenzie et al. (2011)

FIT_AAOC reflects the "organic culture" and "analytical information quality" exploited by "a team" with specific "expertise" (analytical, technological, and business). In summary, to develop a conceptual definition of the construct (validity framework – step 1), FIT_AAOC can be classified as a fit between "organic culture, "and "adaptive analytics" that by its turn has two dimensions: "analytical information quality," and "team expertise."Notwithstanding, FIT_AAOC definition is based on three others, adaptive capability, analytics, and organic culture defined in the present theoretical review.

Using MacKenzie et al. (2011) concepts (validity framework – step 1), organizations are the FIT_AAOC "entity" (p. 298). Additionally, the FIT_AAOC "general property" (p. 298)of these organic organizations is to use a sophisticated data technology approach to boost market openness in a continuously experimental behavior (Day, 2011). FIT_AAOC is "multidimensional" (p. 299), and its "stability" (p. 299) is across cases, where cases are, for example, projects of marketing, data science, R&D, or product/brand innovations.

About dimensionality, FIT_AAOC has three reflective first-order constructs. Information quality is a known construct (Gorla et al., 2010; Wieder & Ossimitz, 2015), but it is vital to understand that the revolutionary emerging technologies deal with data in new ways, that boost the "analytical information quality."Market data here is not only from information systems, inside databases, but are from the web, social media; different data smashed into data lakes or data warehouses or even independent datasets like texts, videos, and denormalized spreadsheets prepared before analytics. The data engineering and cleansing process gives life to another kind of data and then to another type of information quality (Provost & Fawcett, 2013), which we called "analytical information quality."

"Teams" with particular "expertise" perform analytics (Wamba et al., 2017). Studies provide evidence that confirms the decisive role developed by innovation teams in the learning process (Barrales-Molina et al., 2014;Sincorá, Oliveira, Zanquetto-Filho, & Ladeira, 2018). Another example is a quantitative work executed with Chinese senior executives that identified the exchange and integration of team knowledge improving the organizational financial performance through new product development (Tseng & Lee, 2014).

Analytics alone impacts absorptive capacity using market knowledge (Barrales-Molina et al., 2014). FIT_AAOC is a construct that responds to market accelerating velocity and complexity with a more outside-in data-driven and exploratory features to help the learning process when it is fitted with an organic culture. The two first-order constructs do not have a causal relationship with FIT_AAOC. Thus, they represent the second-order construct.

Another critical point for construct definition is about the reflective/formative issue, and it is essential to understand that any construct is not inherently reflective or formative (MacKenzie et al., 2011); it is a matter of definition. The three dimensions are manifestations of FIT_AAOC, for example, learning a new statistical method like cluster analysis increases the team expertise, and indeed, this new skill can make the analytical information quality better. Another example, the analytical information improvement or better organic culture can make, for example, business expertise better.

As part of validity framework step 1, the definition of the construct, it is essential to differentiate it from others (MacKenzie et al., 2011). To summarize the position of FIT_AAOC, Figure 7 shows the market knowledge used by adaptive analytics when there is a good fit with the organic culture, FIT_AAOC, during the reconfiguration process of ACAP and/or MC.

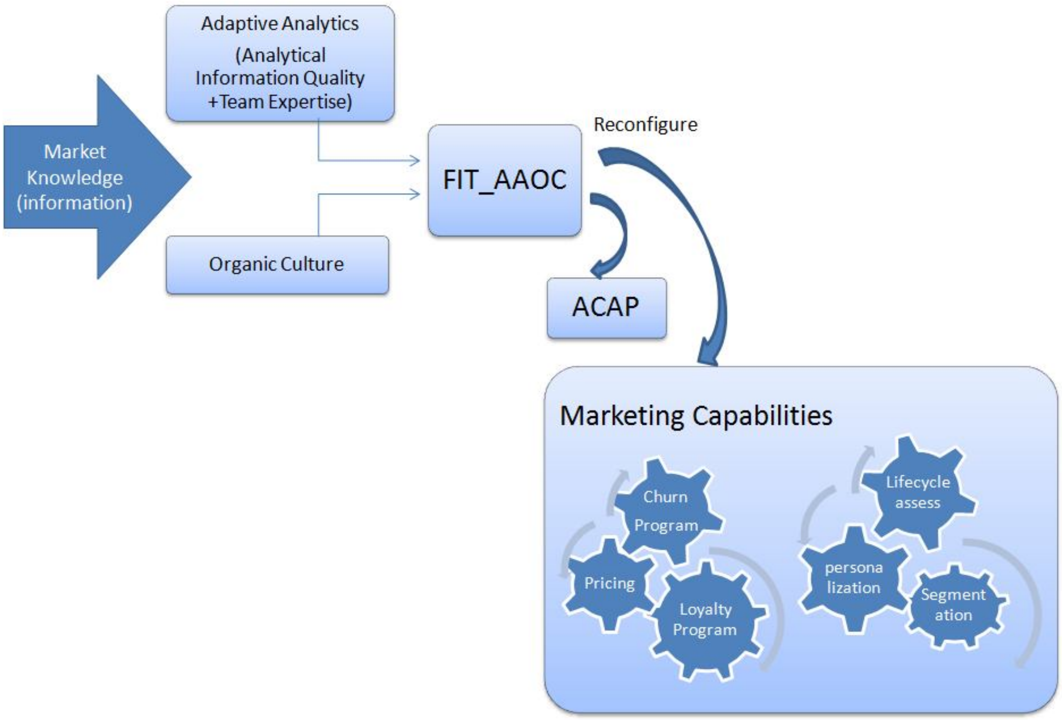

*Figure 7.*FIT_AAOC Framework
Source: Prepared by the author (2019)

Figure 7 shows the FIT_AAOC framework. It represents the use of market knowledge, information when the organization has good FIT_AAOC to reconfigure ACAP and or marketing capabilities (exemplified as gears). This reconfiguration process can be through, for example, marketing capabilities like customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, personalization. On the other hand, this reconfiguration process can be through ACAP, learning processes.

When the fit is good, the organization reconfigure marketing capabilities and exploitative processes using market knowledge. FIT_AAOC can also influence dynamic marketing capabilities like new product development or any other capability (not represented in figure 7), but the present work only tested FIT_AAOC correlation with marketing capabilities and absorptive capacity.

3.4 SCALE DEVELOPMENT METHOD

A survey was executed to collect data to conduct a pre-test (validity framework - step 5) with Brazilian and European Union users of Linkedin using a google docs form. It was sent after mining professionals employed (at least one year) and from the following profiles: Marketing Manager/ Analyst, Product/ Brand Manager/ Analyst, Marketing Research Manager/ Analyst, R&D Manager/ Analyst, Top Management, IT Manager/ Analyst, Innovation Manager/ Analyst, Data Analyst/ Scientist and Other Management Positions.

The survey was open between November 2018 and May 2019, and without additional treatments, it totaled (n =414) records, 202 from EU, and 212 from Brazil, named as the validation sample for scale validation and items purification (MacKenzie et al., 2011). From this large sample was separated the heuristic holdout randomly (n =300), and finally, the correlation and confirmatory factor analysis tests with a final subsample (n =356) without IT profile. It is in Appendix E a schematic description of the samples present in this paragraph.

Table 12 defines two first-order FIT_AAOC constructs, being Adaptive Analytics with two dimensions(Analytical Information Quality and Team Expertise) and Organic Culture with only one. It is presented how to operationalize the questionnaire (see Appendix B).The validity framework step 2 is concerned with generating items for FIT_AAOC. They are all new but adapted from the literature review, as referenced in Table 12. With no formative indicators, the formal specification of the measurement model (validity framework - step 4) is presented in Table 12.

Table 12 - FIT_AAOC - Defining the first-order constructs

Defining the Constructs	Source of the indicators
(i) Analytical Information Quality – refers to the quality of analytical information outputs Team Expertise– Represents the professional abilities of the project team that are fundamental to perform tasks. (ex: skills or knowledge) of two different sources of scale items.	(i) Adaptation from Chuang and Lin(2013) scale
(ii) Analytical Expertise- for Holsapple, Lee-Post, and Pakath (2014) is about to give high priority to the resolution and recognition of problems based on quantitative evidence. This expertise has other characteristics: data-driven learning and experimentation (Day, 2011).	(ii) Analytical Expertise–New scale inspired by Popovičet al. (2012) and Day (2011)
(iii.a) Technological Expertise - represents the professional abilities of the project team (ex: skills or knowledge) that are considered fundamental to perform tasks related to programming languages, data engineering, and cleansing, etc. to improve Analytical Information Quality and learn market Knowledge	(iii.a) Technological Expertise–New scale inspired by Kim et al. (2012) and Day (2011)
(iii.b) Business Expertise - represents the professional abilities of the project team (ex: skills or knowledge) to perform tasks related to internal and external business understanding, and related to the capacity to collaborate inter and intra-organizations, all task driven by market immersion and openness looking for industry foresight, customer insights or collaborative networks (Day, 2011).	(iii.b) Expertise in Business–New scale inspired by Kim et al. (2012) and Day (2011)
(iv) Organic Culture - refers to flexibility and spontaneity as a characteristic of the organization	(iv) Adaptation from Cameron and Quinn (2006)

Source: Prepared by the author (2019)

Table 12 adaptation (i) changed the original items that deal with data improvements by CRM implementation, so the new items address any type of data improvement. By its turn, the adaptation (ii) was necessary because the original scale did not encompass the Davenport (2006) concept of quantitative evidence in decision-making. This author explains this characteristic as a background for competing on analytics. Additionally, in the three questions of the original work of Chuang and Lin (2013) was given more emphasis on the use of quantitative sources of information.

Regarding the team expertise, no other questionnaire tested concepts of quantitative evidence, market immersion, and experimentation, critical parts of FIT_AAOC, and Day (2011) concepts. This idiosyncrasy came from the FIT_AAOC contextualization as a fit with adaptive capabilities discussed in the theoretical section.

The adaptations (iii.a) and (iii.b) were necessary because it is assumed that analytics projects can be done by *ad hoc* teams formed for this purpose, at a strategic level of top management or even as a specific management initiative like marketing research, or innovation, IT, R&D, or product/brand management. The original scale assumes IT only (Kim et al., 2012).

In a preliminary version, the FIT_AAOC construct had four first-order constructs; the original analytical culture construct was transformed into team analytical expertise. This suggestion came from the face/content validity process (validity framework – step 3). This process was performed through a google docs form sent and answered only by experts, in a total of four Ph.D.s. and four Ph.D. candidates. They associated each item from the FIT_AAOC scale, presented randomly, with the respective first-order construct dimension to validate if the item initially thought makes sense. This procedure resulted in the confirmation of all items versus the first-order construct, using the criteria of 7 out of 8 right responses.

For the other constructs, the references are all based on known marketing and information system disciplines papers. Marketing capabilities are about marketing competencies (Conant, Mokwa, & Varadarajan, 1990) and is a reproduction of Song et al. (2007) multi-industry scale. The absorptive capacity came from Pavlou and Sawy (2013), and finally, organizational performance is a reproduction of Law and Ngai (2007) scale, this last scale is different from Louro et al. (2019) scale to improve item robustness.

Startup or not, service or product, B2B or B2C, and respondents profile were used as categorical data for multi-group analyses based on the nonparametric equivalence analysis technique called Partial Least Square - Multi-Group Analysis (PLS-MGA), considered an original extension of Henseler, Ringle, and Sinkovics (2009) MGA method. Aside from previous variables, the work used only seven-point Likert scales, ranging from "totally disagree" (1) to "totally agree" (7).

Organizational size, age, and early and late respondents were tested, dividing equally the subsamples by the mean. Using PLS-MGA again, no significant differences were found. Another precaution was to assess common method bias using Harman’s single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), resulting in an exploratory factor analysis of FIT_AAOC with the unrotated factor solution showing three factors explaining 59,3% of the variance, and the first factor explaining only 25%.

The values of univariate skewness and kurtosis of 6 from 42 variables are out of interval from -1 to 1, available in the descriptive statistics in appendix D. The validation sample has no univariate normality, what was confirmed after executing the Shapiro-Wilks and Kolmogorov-Smirnov tests rejecting the hypothesis of normality for all 42 variables (Hair et al., 2009). But the residuals from the regressions have a reasonable approximation to normality. Thus it is close to multivariate normality. There is no missing data. The empirical measurement model tests were made using SmartPLS software (version 3.2.4), and the correlation tests were made using summed items on SPSS (version 23).

3.5 MEASUREMENT MODEL TEST

We tested constructs' validity and reliability, assuming a measurement model with organizational performance as the endogenous construct and the other FIT_AAOC, ACAP, and MC as exogenous. The present measurement model is an initial step for the future structural model test (see section 4.4).

The scale purification and refinement (validity framework - step 6) resulted in the exclusion of two questions (numbers 1 and 7), as seen in Appendix B, due to cross-loadings tests. We gathered data from a new sample (validity framework - step 7), a holdout with only

300 first registers, a heuristic subsample, and tested it again (MacKenzie et al., 2011) confirming the exclusions.

Multi-Group Analyses was performed using startup or not, service or product, B2B or B2C, organizational size, age, and early and late respondents (validity framework - step 9). The PLS-MGA and the Permutation algorithm with MICOM procedure were performed using the combination of these groups, resulting in p-values bigger than 0.05, i.e., rejecting the hypothesis of group differences. The same result was found for the European Union and Brazil samples.

However, for profiles assessment, the PLS-MGA shows differences from IT, 56 registers, and non-IT respondents, 356 registers, then only non-IT respondents were used as the validation subsample (MacKenzie et al., 2011) for correlation tests.

Using the validation subsample with the MICOM process (Henseler, Ringle, & Sarstedt, 2016), we confirmed the possibility of pooling the data of the other profiles, aside from IT. The step 1, configural invariance assessment, ensure that both setup and algorithm parameters of the measurement and the structural model are identical; we did no additional data treatment for each group, and algorithm settings are the same. For step 2 (compositional invariance) and 3 (composites' equality of mean values and variances across groups), we used the permutation algorithm with 5000 permutations confirming no significance, and thus, measurement invariance.

The sample size for model tests was accepted because the FIT_AAOC construct has the biggest number of variables, 17 after the deletion of 2 items. Therefore, preliminary would be 170 respondents using the rule of thumb of 10 times (Hair et al., 2017). Another conservative way, making a statistical power test in 95%, and assuming an R-square of 25%, the software GPower determines, for a significance of 1%, the size of the sample as 185 respondents. The GPower statistical test chosen is one that tries to maximize the multiple regressions R square, adding new predictors to the solution, f² (Faul et al., 2007).

All constructs are reflective according to the content definition, or *a priori* specification, and according to confirmatory tetrad analysis, CTA-PLS tests, using Gudergan, Ringle, Wende, and Will (2008) procedures. All latent variables tetrads have vanished (validity framework - step 6 - scale purification and refinement) confirming no formative construct.

The FIT_AAOC´s hierarchical components are treated using repeated indicators approach (Hair et al., 2017), and the results regarding the validity and reliability show Cronbach's alpha and composite reliability greater than 0.7 and AVE, greater than 0.5. They are measured for the first-order and second-order FIT_AAOC construct (MacKenzie et al., 2011). The external loads of convergent validity are greater than 0.7 (validity framework - step 6).

Table 13 - Fornell-Larcker Criterion

	ACAP	FIT_AAOC	OP	MC
Absorptive Capability (ACAP)	0.851			
Adaptive Analytics & Organic Culture (FIT_AAOC)	0.802	0.878		
Organizational performance(OP)	0.601	0.661	0.742	
Marketing capabilities(MC)	0.698	0.738	0.603	0.775

Source: Prepared by the author (2019) using SmartPLS

It was analyzed discriminant validity using the Fornell-Larcker criterion, according to which the square root of the AVE must be greater than the other constructs loads. After the exclusion of two items, the cross-loading test showed no problem, confirming the validity at construct level (validity framework - step 6). Both tests were executed for the multidimensional constructs of FIT_AAOC (validity framework - step 8).

3.6 CORRELATION TESTS

Literature assumes that analytics is correlated with marketing capabilities like customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization (Germann et al., 2014; Wedel & Kannan, 2016). Analytics is also correlated with performance (Wamba et al., 2017). Organic culture is positively related to ACAP (Strese et al., 2016). But FIT_AAOC is not only analytics and the , but FIT_AAOC is also the fit with adaptive capability that, by its turn, correlate with other marketing capabilities and performance (Erevelles et al., 2016).

Table14 - Correlation Tests

	FIT_AAOC	ACAP	MC	OP
Adaptive Analytics & Organic Culture (FIT_AAOC)	--			
Absorptive Capability (ACAP)	.788	--		
Marketing capabilities(MC)	.731	.764	--	
Organizational performance(OP)	.592	.622	.630	--

Source: Prepared by the author (2019) using SPSS

Table 14 presented high correlations that will receive attention in the next section.

3.7 DISCUSSION

These results raise the opportunity to develop a model to understand the role of FIT_AAOC in the management mechanism to improve Organizational performance. Marketing capabilities(MC) and absorptive capacity (ACAP) are a useful construct choice, but other capabilities like New Product Development still needs to be uncovered in the extensive process of discovering how can market knowledge impacts organizational performance.

The correlation between FIT_AAOC and marketing capabilities shows the importance of teams of technologists and scientists that lead to complex and sophisticated knowledge impacting marketing capabilities(Cohen & Levinthal, 1990). By its turn, the correlation between FIT_AAOC and absorptive capacity shows the importance of analytics to reveal new opportunities for transforming the decision-making process (Wang & Byrd, 2017). However, the literature tradition did no tested teams in an organic organization that has a good fit with analytical information quality to work well with analytics.

From the correlation of FIT_AAOC and MC/ACAP, we conjecture that if there are preexisting capabilities, then FIT_AAOC boosts performance. Extant literature argues that technology effectiveness is enabled by preexisting capabilities (Boulding et al., 2005). Thus, Marketing capabilities and absorptive capacity need to be tested as mediators between FIT_AAOC and performance.

From the relatively weaker correlation of FIT_AAOC and Organizational performance, we conjecture that FIT_AAOC depends on preexisting capabilities to improve performance. That is another reason to test the mediation mechanisms.

The research tests gave us the opportunity to develop norms for the FIT_AAOC scale (validity framework – step 10). One important norm is about the survey population profile, which excludes IT professionals, and possibly should include managers of other organizational areas that can benefit from market knowledge.

Finally, the present work gave a detailed scale development for a Fit construct permitting the tests of its correlation with performance; future studies can explore the mediation role for other capabilities (Boulding et al., 2005) as the mechanism to enable FIT_AAOC to impact performance. Nonetheless, the examination of FIT_AAOC as a fit construct of culture and adaptive analytics has become especially important due to the present context characterized by the exponential production/dissemination of data (Day, 2011).

3.8 SCALE VALIDATION CONCLUSIONS

The current section starts to explain organizations that fit their culture to the process of continually act upon analytics with the adaptive approach. The study shows the correlation between FIT_AAOC, absorptive capacity, marketing capabilities, and organizational performance. These correlations give us a clue that analytics can boost traditional marketing methods of customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, personalization, and additionally correlate with the information learning process; both will receive attention in the next section.

The results show findings both from an academic and practice point of view. The results of the research contributed to clarifying the construct development, and additionally, presents the correlation with constructs of the future model. Regarding the managerial context, this research effort enabled managers to understand what the FIT_AAOCs are and what they need to be developed and articulated by work teams involved in market knowledge learning. The expertise of these teams is used to recognize the value of new market knowledge, assimilating and applying them as analytical information when there is a good fit with an organic culture.

The four most significant limitations of the research translate into wide avenues for future research. The first is to understand why IT professionals have different behaviors about the topic. Another limitation is about the not tested delimitation of services *versus* products, B2B *versus* B2C, and industry type. Third, the organizational life cycle is not tested either, and indeed the learning process and analytical information quality both depend on time spent by teams. Moreover, finally, the sample came from Brazil, and then a broadened sample could respond to whether our scale holds in different contexts.

The results yet contribute to the scarce empirical literature on the adaptive capabilities and on fit, especially building a new construct, FIT_AAOC, with two first-order constructs in a hierarchical component model. Besides the scale development, the correlation tests suggest that adaptive capabilities like FIT_AAOC can help to narrow the marketing capabilities gap.

4 HOW CAN THE FIT BETWEEN ADAPTIVE ANALYTICS AND ORGANIC CULTURE IMPACT ORGANIZATIONAL PERFORMANCE

4.1 INTRODUCTION

A massive number of recent empirical studies in marketing and information systems have used a myriad of capabilities constructs related to analytics, including variations, such as business analytics, business intelligence & analytics (BI&A), CRM analytics, social media analytics, big data analytics (Chuang & Lin, 2017; Côrte-Real et al., 2017; Trainor et al., 2014; Wamba et al., 2017) and customer analytics capabilities (Louro et al., 2019).

It is essential to notice that ACAP was created (Cohen & Levinthal, 1990) and reorganized (Flatten, Engelen, Zahra, & Brettel, 2011) as a multidimensional construct (acquisition, assimilation, transformation, and exploitation), but sometimes it is measured as one of these unidimensional constructs. The present work used Pavlou and Sawy (2013) exploitation dimension of ACAP, precisely in the same way Wang and Byrd (2017) did for measuring how business analytics capabilities impact on ACAP. This approach gave ACAP an exploitation perspective.

One can notice some practical examples of adaptive analytics, first-order of FIT_AAOC. First, there are some digital marketing technologies, like A/B tests and recommendation systems, that facilitate large-scale field experiments, producing market knowledge and becoming powerful tools for eliciting the causal effects of marketing actions (Wedel & Kannan, 2016).

The A/B test history started with changes in website colors for improving sales. Nowadays, it is applied machine learning to test small details for fully automated super individualized market-mix. For their part, recommendation systems can interact directly with stock management or other marketing capabilities, such as loyalty programs and CRM, building super segmentation approaches.

Another example of how adaptive analytics can narrow the marketing capabilities gap is the IoT potential for a collaborative network business model. IoT can use customer experience management and feelings analysis with opinions and behaviors through voice or video analytics. Another less mainstream example is about new product development (NPD), in the case, for example, created by a startup using the loyalty forecast of latent customers through big data. There are many examples of adaptive analytics, but it is conjectured here that organizations with good FIT_AAOC can increase its impact on organizational performance.

The most prominent contribution of the present section is to test how FIT_AAOC narrows the marketing capabilities gap as an antecedent of organizational performance. Also, the role of two mediators and different covariates is discussed to explain the fit impact at various scenarios in a multi-industry study in two different locations. The whole model was tested using Structured Equation Modeling (SEM) with Partial Least Square (PLS) and Ordinary Least Square (OLS) with SPSS PROCESS macro to deep the mediation test. In short, the thesis presents a parallel mediation mechanism to show how some organizations have a shorter marketing capabilities gap than others.

4.2 THEORETICAL MODEL AND HYPOTHESES

The theoretical model is shown in Figure 8, and hypotheses are introduced afterward. The fit variable covariation approach increased the model parsimony when compared with

Louro et al. (2019).It is because this final model explains the mediation mechanism of only one exogenous variable (F_AAOC), while Louro et al. (2019) illustrated it with two. Therefore the present work explains better the mediation mechanism.

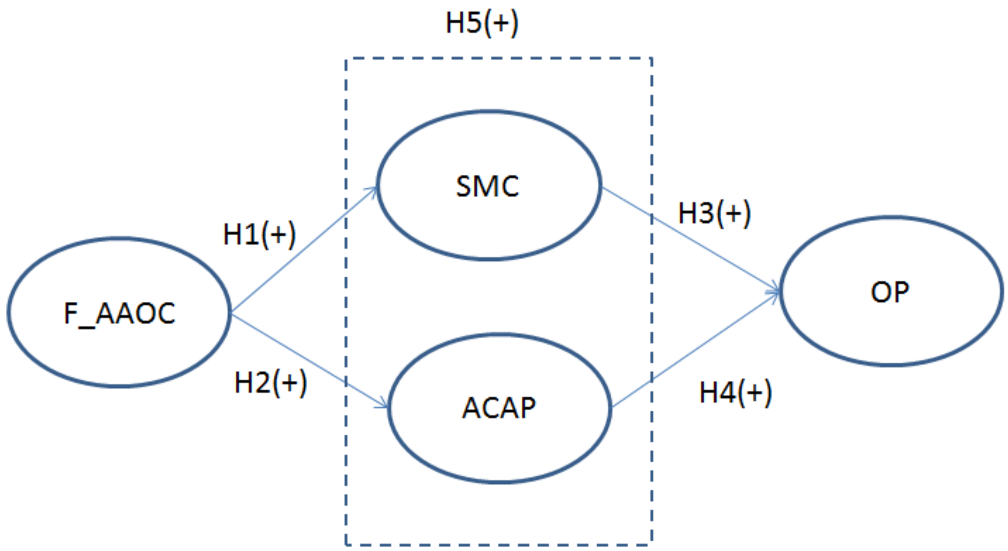

*Figure 8.*Theoretical Model

Source: Prepared by the authors (2019)

Information systems literature uses capabilities to explain the learning process (Popovič et al., 2012; Teo et al., 2016; Wang & Byrd, 2017), but these approaches do not focus on the market knowledge learning process, and market knowledge is essential for changing/reconfiguring organizational strategies (Barrales-Molina et al., 2014). Additionally, it is conjectured here that an excellent FIT_AAOC boosts market knowledge learning. Measuring how FIT_AAOC can better impact on organizational performance makes the present work unique.

Day (2011) claims the need for a culture of discovery, arguing that creative culture is vital for encouraging vigilance and adaptability. However, he does highlight: "Unfortunately, many cultures remain risk-averse, with limited flexibility to explore widely" (Day, 2011, p. 191).

Complementary capabilities should be integrated by teams of technologists and scientists that deal with complex and sophisticated technological knowledge, according to Cohen & Levinthal (1990). This seminal work about market information learning, before the analytics boom, already indicated that technologies support the market knowledge, impacting on other marketing capabilities. Therefore, analytics can improve marketing capabilities like customer lifecycle assessment, loyalty, and churn programs, pricing, segmentation, and personalization (Germann et al., 2014; Wedel & Kannan, 2016).

Taking the last assumptions and using a similar fit construct approach developed in Yarbrough et al. (2011) and created by Venkatraman (1989), the first hypothesis is raised.

H1. FIT_AAOC has a direct positive effect on marketing capabilities.

Cohen and Levinthal (1990) explain that distinctive business needs and organizational procedures/routines should be integrated by teams of technologists and scientists, dealing with complex and sophisticated technological knowledge.

Adaptive analytics positively impacts absorptive capacity using market knowledge (Barrales-Molina et al., 2014). Besides, organic organizational culture impacts absorptive capacity positively (Strese et al., 2016). Thus, the fit between adaptive analytics and organic culture creates the second hypothesis.

H2. FIT_AAOC has a direct positive effect on absorptive capacity.

The marketing literature is concerned with the relationship between marketing and performance constructs using capabilities (Morgan, 2012; Kozlenkova et al., 2014). It is assumed the importance of marketing capabilities for performance, and the following hypothesis is declared:

H3. Marketing capabilities have a direct positive effect on organizational performance.

As explained by Flatten et al. (2011): "ACAP consists of transformation capabilities, which enable firms to develop new processes or to add changes to existing processes, and exploitation capabilities, which are used to convert knowledge into new products that enhance performance and competitive advantage" (p. 100).

First-mover advantages and responsiveness to customers' needs are the reasons for superior performance (Flatten et al., 2011). We assume the ACAP literature (Barrales-Molina et al., 2014; Braganza et al., 2017; Wang & Byrd, 2017) to raise another hypothesis.

H4. Absorptive capacity has a direct positive effect on organizational performance.

Organizations with good FIT_AAOC can reconfigure capabilities and information learning processes; however, to do so, it is conjectured here that analytics can improve marketing capabilities and exploitative processes, if there are preexisting procedures/routines.

Extant literature argues that IT-related capabilities are enablers for marketing capabilities (Barrales-Molina et al., 2014; Wang, Hu, & Hu, 2013), which indicates the dependence of some capabilities on others. Additionally, there is evidence that technology effectiveness and IT-related capabilities outputs resulted in a positive effect on preexisting capabilities (Boulding et al., 2005).

Absorptive capacity has been tested as a positive mediator between IT-related capabilities and organizational performance (Liu, Ke, Wei, & Hua, 2013). Finally, some IT-related capabilities about analytics are assumed to have a direct effect on performance (Wamba et al., 2017), and organic culture also has some evidence of a direct effect on performance (Deshpandé & Farley, 2004; Wei et al., 2014).

Thus, we assume that FIT_AAOC translates organizational performance, just through marketing capabilities. From this discussion, and using the terminology defined by Zhao, Lynch, and Chen (2010) about mediation, it was formulated the fifth and central hypothesis.

H5. Marketing capabilities and absorptive capacity have a parallel mediating role between FIT_AAOC and organizational performance.

Briefly, FIT_AAOC, as a measure related to adaptive capabilities, depends on preexisting marketing capabilities to improve performance, and this is the reason to test the mediation and to expect a non-significant direct relationship to performance.

4.3 METHOD

Most of the present thesis method is described in sections3.4 and 3.5, where the measurement model test was presented after the construct development. The current section shows the structural model test, hypotheses results, and post-hoc analyses.

It was chosen PLS-SEM and OLS for several reasons. First, PLS-SEM is not a panacea (Henseler et al., 2014), but it is a modest and realistic technique to establish rigor in sophisticated modeling(Akter, Wamba, & Dewan, 2017), which is appropriate for testing early stages of theories (Hair et al. 2017), as in the present thesis. To date, there is no other work that examined the fit between culture and analytics. In addition, PROCESS was used to test the mediations deeply.

However, both approaches have limitations. In SmartPLS, the covariates are treated as control variables, using moderation or multi-group analysis (section 3.5 described the MGA and permutation results that give the possibility of pooling the data). In OLS of PROCESS macro, it is possible to include the covariates on the regressions execution. The OLS approach uses summed items, though, assuming equal weighting of indicators, therefore losing the measurement error analysis for latent variables (Hair et al., 2017).

The covariates included in the OLS regressions were an essential part of the analysis: (i) log of organization size; (ii) age; (iii) if the organization is a startup or not; (iv) if the most predominant approach is B2B or B2C; (v) if the most predominant focus is on product or service; (vi) how the organization is technology dependent (single item from 1 to 7); (vii) environmental dynamism; (viii) country. The log used for size (number of employees) was necessary to avoid non-linear behaviors.

4.4 STRUCTURAL MODEL TEST

According to Hair et al. (2017), the first step of the structural model is to evaluate collinearity with the VIF indicator, using as a parameter <5, and the highest result was 3.391. Second, path coefficients were estimated using the Bootstrapping procedure, with 5000 subsamples with the option "no sign changes." All coefficients were significant (p-value <0.05), including the not hypothesized direct effect of FIT_AAOC and Organizational performance, as can be seen in Figure 9.

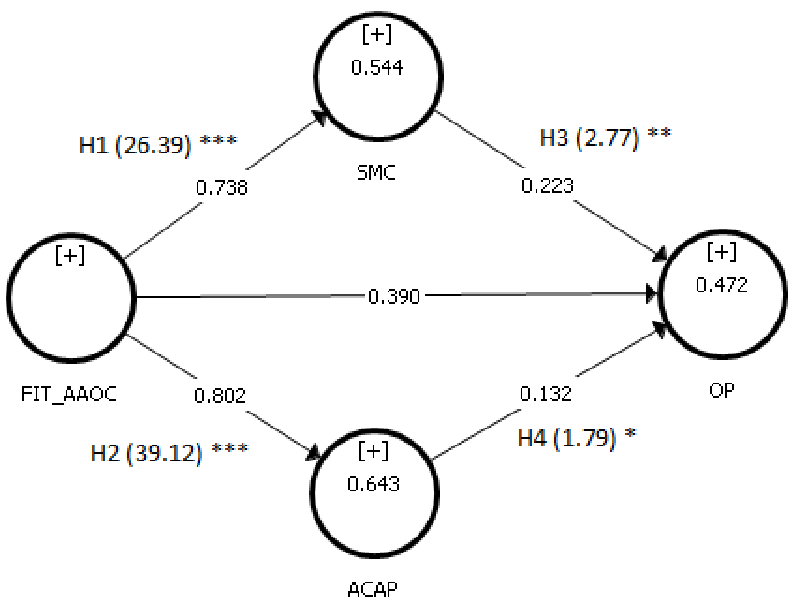

*Figure 9.*SmartPLS results

Source: Prepared by the authors (2019) using SmartPLS

The third step was to evaluate the determination coefficient that measures the model predictive accuracy. The results were presented in Figure 9 inside the circles, with adjusted R-square values of 0.642 for ACAP, 0.543 for MC, and 0.467 for OP, which is considered near to moderate by Hair et al. (2011), parameter 0.5.

In step four, one sought to measure the size of the effect f square (f^2), which evaluates if any omitted constructs generate a substantive impact on the endogenous constructs. The result of FIT_AAOC on ACAP and MC is great; the result of MC and ACAP on OP is medium (0.317).

In the fifth step, Table 15 shows the predictive relevance evaluated using the Blindfolding algorithm with the default configuration, omission distance equal to 7, cross-validated redundancy, resulting in a Q^2 that represents medium (> 0.15) and large (> 0.35) predictive relevance, parameters of Hair et al. (2017).

Table 15 - Blindfolding

	SSO	SSE	Q^2 (=1-SSE/SSO)	Predictive relevance
FIT_AAOC	1,077.000	1,077.000		
ACAP	1,077.000	576.752	0.464	Large
MC	1,436.000	975.528	0.321	Medium
OP	1,795.000	1,348.767	0.249	Medium

Source: Prepared by the authors (2019)

Figure 9 shows the PLS algorithm of SEM ran in SmartPLS with significance and t statistics. The estimated model goodness of fit presented standardized root mean square residual (SRMR) index equal to 0.074, representing good model fit in a conservative analysis, <0.08 parameter by Hair et al. (2017). Thus, the first four hypotheses were confirmed, which corroborated with the existing literature.

For a more in-depth analysis (see Table 16 and Figure 10), the macro PROCESS of SPSS confirmed the H5, parallel mediation effect, (a1b1), and (a2b2) <0.001, but (c´) was significant. The ordinary least squares (OLS) regression analysis with the summed scores were used with template 4.

It was used the procedures and parameters of Hayes (2013), and the results of the bootstrap with 10000 resample are summarized in Table 16 with results for R2, F statistics (degree of freedom 1 and 2), and p-values. It also includes unstandardized regression coefficients of direct paths (a1, a2, b1,b2, and c'), and the indirect paths a1b1 and a2b2 with significance level for bias-corrected 95% confidence intervals, and standard error (SE).

Table 16 - PROCESS OLS mediation results

Antecedent		M(Absorptive Capacity)				M(Marketing capabilities)				Y(Organizational performance)		
		Coeff.	SE	*p*		Coeff.	SE	*p*		Coeff.	SE	*p*
X(FIT_AAOC)	a1	.4326	.0274	<.001	a2	.3136	.0249	<.001	c'	.0965	.0344	.005
M(ACAP)		--	--	--		--	--	--	b1	.1908	.0556	<.001
M(MC)		--	--	--		--	--	--	b2	.2471	.0612	<.001
Constant	i1	-.2534	.02686	NS	i1	.9522	.2438	<.001	I2	1.3223	.2579	<.001
		R2 = .638 p<.001				R2 = .5783 p<.001				R2 = .5034 p<.001		
		F(11,347) = 55,6748				F(11,347) = 43,2595				F(13,345) = 26,8974		

Source: Prepared by the authors (2019)

The H5 hypothesis was confirmed (see Figure 10 and Table 16). The indirect effect (a1b1) + (a2b2) resulted in a value of .1600 and it was significant both for the normal theory test p-value [<.001] and for the bootstrap confidence interval [.1113,.2163] (Hayes, 2013).

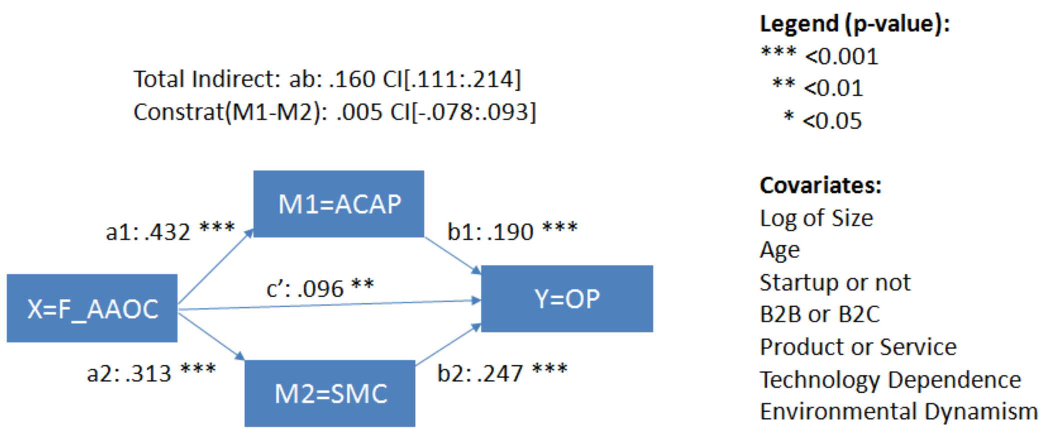

*Figure 10.*PROCESS SPSS outputs - Parallel Mediation
Source: Prepared by the authors (2019)

Therefore, H5 was confirmed, but there are some differences in effect and significance between PLS-SEM and OLS. PROCESS indicates less significant direct effect mediation between FIT_AAOC and organizational performance. This problem is addressed in the post-hoc analysis of moderators. The confirmed indirect effects agreed with part of the information systems, and marketing literature assumed as correct, which has a definite impact on practice and theory.

The indirect effect has to be analyzed together with the size of the effect f^2, which evaluates if any omitted constructs generate a substantive impact on the endogenous constructs. This caveat is necessary to avoid the epiphenomenal association, which means a mediator correlated with another omitted construct (Hayes, 2013). f^2 results present a robust association between exogenous and endogenous construct, as it will be seen.

The indirect effect has a value of .16, but it is a scale-bound metric, then it is dependent on the constructs metrics. The measurement metrics in the current model are not inherently meaningful because they are responses to rating scales aggregated over multiple questions (Hayes, 2013). The completely standardized indirect effect is .3383 with bootstrap confidence interval [.2345,.4411] can be compared with the completely standardized direct effect "c´_ps" value of .2040, which demonstrates the importance of the parallel mediation analysis, following the caveats about effect size indexes and instructions of Hayes (2013) in PROCESS version 3.3.

The confirmed parallel mediation effect is as important as it is higher the indirect effect value, in addition to the inexistence of direct effect (Zhao et al., 2010). Unfortunately, the direct effect was also confirmed, suggesting further study is necessary. Notwithstanding, the pairwise contrast between indirect effects (M2-M1) presents no significant difference between MC and ACAP effects, which means that one is not better than the other.

Table 17 - Research hypothesis

Hypothesis	Description	Results
H_1	FIT_AAOC has a direct positive effect on marketing capabilities.	Confirmed
H_2	FIT_AAOC has a direct positive effect on absorptive capacity.	Confirmed
H_3	Marketing capabilities have a direct positive effect on organizational performance.	Confirmed
H_4	Absorptive capacity has a direct positive effect on organizational performance.	Confirmed
H_5	Marketing capabilities and absorptive capacity have a parallel mediating role between the FIT_AAOC and organizational performance	Confirmed

Source: Prepared by the authors (2019)

In summary, all five hypotheses confirmations are shown in Table 17.

4.5 DISCUSSION

The hypothesis H1 and H2 confirmed that the fit between culture and analytics is related to information learning of teams of technologists and scientists that deal with complex and sophisticated knowledge (Cohen & Levinthal, 1990) impacting on marketing capabilities and on the exploitation dimension of ACAP, both with moderated R-square. For its part, the hypothesis H3 confirmed the marketing capabilities literature (Morgan, 2012; Kozlenkova et al., 2014) and raised the possibility of using the term "marketing capabilities." Additionally, H4 confirmed the information learning exploitative processes literature related to how responsiveness to customers' needs impacts performance.

The hypothesis H5 showed that organizations with good FIT_AAOC boost performance passing through marketing capabilities and absorptive capacity. This result gives organic culture an enabler behavior for IT-related capabilities (Barrales-Molina et al., 2014), and FIT_AAOC impact is as strong as there are preexisting marketing capabilities and information learning exploitative processes. These results expand the knowledge for both managers and academics, in particular for those who take for granted the importance of analytics and think about it naively.

The direct impact of FIT_AAOC can be explained by the first-order constructs' effects on performance, which has been already presumed by the literature related to organic culture (Deshpandé & Farley, 2004) and analytics capabilities (Wamba et al., 2017).

4.6 POST-HOC ANALYSES

Although the official analysis was executed in the last section, it is possible to analyze alternative models that are possible by theory and/or by the proposed nomological network. An alternative model, not hypothesized, with the same constructs was tested, and multiple serial mediations (FIT_AAOC>ACAP>MC>OP) did not present better results(see Table 18) than the parallel model.

Table 18 presents the comparison between serial and parallel models, and it also shows the results of single mediation for contrast.

Table18 - Alternative models comparison

Model options	Indirect effect FIT_AAOC on OP	Direct effect FIT_AAOC on OP	R2 (OP)
Only ACAP as mediator	.1255	.1310	.4311
Only MC as mediator	.1067	.1498	.4311
Parallel of ACAP and MC	.1600	.0965	.5035
Serial with ACAP before MC	.1600	.0965	.5035

Source: Prepared by the author (2019) using SPSS

Another alternative model, not hypothesized, is to replace the organic culture indicators by mechanistic culture indicators as first-order of the fit construct. This was also tested, presenting poor results. PLS algorithm presented problems in the measurement model with the AVE index (.438, parameter >.5) of the second-order construct, and Cronbach's Alpha (.677, parameter >.7) of the first-order culture construct. Besides, various outer loads presented problems, and the bootstrap algorithm showed no significance in path coefficient ACAP>OP with p_value equals to 0.075.

The third and last alternative of study is related to Louro et al. (2019) results for the environmental dynamism moderation effect. In section 3.5, it was executed the multi-group analysis for environmental dynamism - a latent variable - and location (Brazil versus European Union) - a dichotomous variable. The MGA cannot provide the most appropriate segmentation result because it does not deal with unobservable heterogeneity. Thus, it is possible to search for different levels of the dyad environmental dynamism vs. location without specifying, *a priori*, the subgroup like it is done in MGA and permutation algorithms.

Avoiding heterogeneity is a complex and still evolving topic (Sarstedt & Ringle, 2010; Sarstedt, Henseler, & Ringle, 2011; Becker & Rai, 2013; Henseler et al., 2014; Hult et al., 2018; Hair, Sarstedt, Ringle, & Gudergan, 2018), that needs more exploration in the present study, given its nature (multi-industry in two different locations). Initially, it was used FIMIX-PLS, which can provide metrics for unobserved heterogeneity (Hair et al., 2018). It is the first choice for clusterization tasks when PLS is used because it can segment data on the basis of heterogeneity of path model, not just items like common clustering algorithms.

The first step in any cluster analysis is to define the number of clusters (Provost & Fawcett, 2013). It was executed three different tasks to decide it. Firstly, it was performed FIMIX-PLS four times, using 2, 3,4, and 5 clusters as options; the indexes are presented in Table19. Following Sarstedt et al. (2011), the best indexes are heuristic consistent Akaike information criterion (CAIC) and $AIC_3$when they are convergent, then the result was a 3 clusters solution, as it can be seen in bold in Table 19.

Table 19 - FIMIX-PLS fit indexes

	2 clusters	3 clusters	4 clusters	5 clusters	Selection Criteria	Best index
AIC (Akaike Information Criterion)	2160.820	2049.068	2046.422	2046.282	Smallest	5
AIC_3 (Modified AIC with Factor 3)	2177.820	**2075.068**	2081.422	2090.282	Smallest	3
AIC_4 (Modified AIC with Factor 4)	2194.820	2101.068	2116.422	2134.282	Smallest	3
BIC (Bayesian Information Criteria)	2226.836	2150.035	2182.338	2217.148	Smallest	3
CAIC (Consistent AIC)	2243.836	**2176.035**	2217.338	2261.148	Smallest	3
HQ (Hannan Quinn Criterion)	2187.072	2089.219	2100.470	2114.229	Smallest	3
MDL_5 (Minimum Description Length with Factor 5)	2626.902	2761.900	3006.003	3252.613	Smallest	2
LnL (LogLikelihood)	-1063.410	-998.534	-988.211	-979.141	Smallest	2
EN (Entropy Statistic (Normed))	0.378	0.490	0.479	0.536	>0.5	5
NFI (Non-Fuzzy Index)	0.455	0.486	0.461	0.478	Biggest	3
NEC (Normalized Entropy Criterion)	223.363	183.179	187.154	166.593	Smallest	5

Source: Prepared by the author (2019) using SmartPLS

Table 19 presents all indexes provided by SmartPLS. Aside from the Sarstedt et al. (2011) index choice, "AIC 4 and BIC do not provide an indication of how well-separated the segments are” (Hair et al., 2018). One option to solve this limitation is the normed entropy statistics (EN) index, where “values above 0.50 permit a clear-cut classification” (p. 169). However, in this study, the result for 3 clusters was EN 0.49, not passing the EN threshold; so, the other two tasks were performed.

The second task, a personal heuristic, was to create the column "best index" to compare each fit index, resulting in 6 best indexes for the 3 clusters solution. Finally, the third task was to execute the traditional cluster analysis using the package "nbclust" (Charrad, Ghazzali, Boiteau, & Niknafs, 2015) in R with the parameter number of clusters ranging from 2 to 7.It was executed with different methods, Kmeans and centroid (with Euclidean, Manhattan, and Maximum distance), and all of them resulted in 2 clusters solutions as the best option. Appendix A presents the R source codes for "nbclust" and "ClustPlot" used for visual comparison of the two solutions; figures are in Appendix C. After the three tasks, the 3 clusters solution was the choice to proceed.

The second step was to assign the three clusters identification to the original dataset and test media difference using the summed items in R. The "Mann-Whitney" non-parametric test was executed, resulting in significant differences by Cluster when tested adaptive analytics & organic culture fit(FIT_AAOC) and age. In fact, Cluster 1 represented61.4%, Cluster 2 with 24.5%, and Cluster 3with 14.1%of the sample. The complete analysis can be seen in Table 20.

Table 20 - Fimix clusters compared

	Cluster 1 (N=268)	**Cluster 2 (N=52)**	**Cluster 3 (N=39)**	**p-value**
Location:				0.113
EU	137 (51.1%)	20 (38.5%)	15 (38.5%)	
BR	131 (48.9%)	32 (61.5%)	24 (61.5%)	
Log of size	1.81 (1.18)	2.01 (1.16)	1.58 (1.18)	0.229
Age	23.6 (29.4)	37.3 (54.8)	20.5 (23.3)	0.018
Startup				0.617
No	189 (70.5%)	40 (76.9%)	27 (69.2%)	
Yes	79 (29.5%)	12 (23.1%)	12 (30.8%)	
B2B OR B2C				0.767
B2B	173 (64.6%)	31 (59.6%)	24 (61.5%)	
B2C	95 (35.4%)	21 (40.4%)	15 (38.5%)	
Focus				0.754
Service	185 (69.0%)	34 (65.4%)	25 (64.1%)	
Product	83 (31.0%)	18 (34.6%)	14 (35.9%)	
High-tech	4.99 (1.84)	5.08 (1.98)	4.41 (2.06)	0.171
Organizational Performance (OP)	5.27 (1.01)	5.05 (0.98)	4.92 (1.02)	0.059
Environmental Dynamism (ED)	5.35 (1.07)	5.23 (0.94)	4.98 (1.32)	0.127
FIT_AAOC	0.10 (0.94)	-0.25 (1.03)	-0.36 (1.25)	0.004

Source: Prepared by the author (2019) using R

Table 20 was created using the "compareGroups" package (Subirana, Sanz, & Vila, 2015). FIT_AAOC is standardized because it is a second-order construct. The results showed that, from the covariates, only age and FIT_AAOC have a significant difference using as a criterion the 3 clusters provided by FIMIX-PLS. The number of cases in clusters 2 and 3 makes the solution not viable, so the suggested next step (Hair et al., 2018), predicted-oriented segmentation (PLS-POS), was not executed.

The dyad environmental dynamism vs. location did not generate unobserved heterogeneity, at least using the finite mixture approach. Thus, environmental dynamism moderation presented by Louro et al. (2019) was not replicated in the present work, and it requires more attention in future studies.

4.7 CONCLUSIONS

The current work helps to explain how analytics uses market knowledge to improve organizational performance. It is conjectured that analytics alone cannot improve performance, and pre-existing capabilities and a fit with organizational culture are needed.

The bibliometric and systematic review contributed to the nomological network that presented some opportunities to test how analytics boosts performance using intervening constructs. It also introduced concepts to build an analytics construct based on Day’s (2011) studies. The new construct tries to explain organizations that continually act upon emerging technological trends using market knowledge with an adaptive approach and organic culture, or, in other words, that narrows the marketing capabilities gap.

The model test uses additional covariates, and it presented a path to academic and practical findings. One academic contribution is how to adopt the emerging revolutionary technologies in traditional disciplines, departing from terms like "big data," and assuming that the essential concept is related to how to use information, or in the present case, how to use market knowledge. For management practices, these results suggest that headhunters should take precautions because both tests showed that analytics require pre-existing capabilities to improve its impact.

The results showed that adaptive analytics fitted with organic culture boost traditional marketing capabilities, such as customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization, measured as marketing capabilities. Additionally, it improves previous information learning exploitative processes, measured as absorptive capacity. In summary, the thesis demonstrated that to boost organizational performance, using analytics, it is necessary to have a good fit between organic culture and adaptive analytics. Moreover, to enhance the studied impact, both pre-existing marketing capabilities and absorptive capacity are essential.

The post hoc tests about unobserved heterogeneity showed that organizations in different environmental dynamics and locations (European Union versus Brazil) do not generate unobserved heterogeneity, at least not when using the finite mixed approach. Future studies can conduct industry-specific analyses to verify these results. On the other hand, FIT_AAOC and age seem to generate unobserved heterogeneity. So, future studies could improve the sample and test the antecedents of the fit between organic culture and adaptive analytics.

The present thesis highlights are: (i) the new analytical information quality that is different from the widespread information quality construct; (ii) the applied step-by-step scale development; (iii) the rich covariate list; (iv) the link of two different literature traditions, marketing, and information learning; and (v) the preliminary perception of no difference of location and environmental dynamism on the relationships tested.

Future studies may research how traditional marketing capabilities can launch adaptive business models, such as experimental spin-offs, startups for industry foresight, promotion for joint ventures or other organizations networks, and/or collaborative strategies. It may focus on how these adaptive business models can benefit from analytics and how environmental dynamism can influence this process.

Other future studies may discuss market entry strategies, such as licensing, franchising, joint ventures, product diversification/development, market development, or decisions (market share versus market growth positioning, for example). All these strategic choices can benefit from analytics, and they can also be analyzed from the FIT_AAOC perspective, by expanding the fit construct to include a first-order construct related to marketing strategy.

The present work's limitations are several: (i) cross-sectional data, (ii) possible unobserved heterogeneity, (iii) possible omitted variables because the mediations are not indirect-only (Zhao et al., 2010), (iv) possible omitted selection because of the unexplained behavior of IT professionals, (v) more covariables are possible, such as team age, type of innovation, leadership, etc. A notable highlight is a need for a broader sample. Although the initial sample seemed large enough, after deleting the IT professionals, it was not possible to continue the unobserved heterogeneity, because the segments were too small.

This work provides a useful tool to assess organizations regarding FIT_AAOC, which makes it possible to compare with competitors and predict the investments the organization needs to improve its analytics results. Alternatively, the organization can change the culture and/or increment its marketing capabilities and/or absorptive capacity.

In summary, the mechanism engenders a fit construct, measured as covariation, marketing capabilities, and absorptive capacity on a multi-industry effort in the European Union and Brazil. The thesis shows a complex mechanism that explains better the impact of analytics on performance than the direct effect. The fitted culture and analytics with a parallel mediation result expands analytics role on theory and interconnects, even more, the information systems and marketing strategy literature.

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APPENDIX A - R CODES

Code of Tables 1-8

library(bibliometrix) # package load

biblioshiny()

Code of Figure 1 and 2

D1 <- readFiles("/scopus.bib")

D2 <- readFiles("/savedrecs.bib")

A <- convert2df(D2, dbsource = "scopus", format = "bibtex")

B <- convert2df(D1, dbsource = "isi", format = "bibtex")

M <- mergeDbSources(A, B, remove.duplicated = TRUE)

NetMatrix<- biblioNetwork(M, analysis = "co-occurrences", network = "keywords", sep = ";")

calculate jaccard similarity coefficient

S <- normalizeSimilarity(NetMatrix, type="jaccard")

#openVosViewer

net=networkPlot(S , n =5000 , type = "vosviewer", vos.path = "/home /VOSviewer/")

Example code how to discover the best number of clusters

nbc<-NbClust(variaveis_influencia, diss=NULL, distance="euclidean", min.nc=2, max.nc=5, method="centroid", index="all")

[1] "Frey index : No clustering structure in this data set"

*** : The Hubert index is a graphical method of determining the number of clusters.

In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure, i.e. the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.

In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:

* 11 proposed 2 as the best number of clusters

* 6 proposed 3 as the best number of clusters

* 1 proposed 4 as the best number of clusters

* 5 proposed 5 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 2

Code of Table 22

```
boxplot(ED ~  Location + Cluster, data=variaveis_influencia)

wilcox.test(variaveis_influencia$ED~variaveis_influencia$Cluster)

group =       compareGroups(Cluster~., data=variaveis_influencia)

clustab       =       createTable(group)

clustab
```

Code of appendix D figures

```
clusplot(variaveis_influencia,variaveis_influencia$cluster)
```

APPENDIX B - RESEARCH QUESTIONNAIRE

First, thank you for your contribution to science. This research aims at understanding how analytics impacts performance. The results obtained will compose an organizational **benchmark available for your consultation** (updated every response) and, in the future, it can **HELP YOU DECIDE HOW TO INVEST IN ANALYTICS AND/OR MARKETING**.

When answering the following questions, think about a data-driven project or another kind of initiative, finished or not. A project that you participated in, or supported, technically or as a business knowledge source.

Only a few examples of these project types: From diverse possibilities of KPIs (largest buyers, VIP customers, average ticket, etc.) using only spreadsheets or even Business Intelligence, passing by georeferencing data analysis, market segmentation for advertising, Google Analytics, customer profile analysis, sales trends or tendencies of new products/services/customers/markets. **OF COURSE, IT IS NOT RESUMED TO THIS SHORTLIST**. It is essential to understand that we want to cover everything from the use of data in a rudimentary way using spreadsheets with purchases data until the use of elaborate quantitative methods with the support of data science, artificial intelligence, or machine learning.

The scale of 1 to 7 means that 1 is when you strongly disagree with the question; 2 disagree, but not completely; 3 disagree more than agree; 4 neither agree nor disagree; 5 agree more than disagree; 6 agree but not completely, and 7 strongly agree.

1 - SIZE

Approximately what is the organization's number of employees?

Aproximadamente qual é o número de funcionários da organização?

2 – AGE - Organization Age (in years)?

2 - Idade da organização (em anos)?

3 – B2BXC Your Organization prevalent Business is?

B2B or B2C

3 - O negócio da sua organização predominante é?

B2B ou B2C

4 –FOCUS - What is your organization's focus?

Service / Product

Qual é o foco da sua organização?

Serviço / Produto

5 - From what country is the most prevalent culture of your organization?

5- De qual país é a cultura mais predominante da sua organização?

6 –HIGHTECH - Our Organization is high-tech(has a high dependence of science and technology)?

Nossa Organização é high-tech (tem alta dependência de ciência e tecnologia)?

7 – JOB What is your job/position?

<Marketing Manager/Analyst - Product/Brand Manager/Analyst - Marketing Research Manager/Analyst - R&D Manager/Analyst - Top Management Innovation Manager/Analyst - IT Manager/Analyst - Data Analyst/Scientist - Other>

7 - Qual o seu cargo / posição?

<Gerente / Analista de Marketing - Gerente / Analista Produto/de Marca - Gerente /Analista de Pesquisa de Marketing- Gerente / Analista - de P & D - Gerente/ Analista de Inovação - Alta Gestão - Analista / Gerente de TI - Analista / Cientista de Dados - Outros>

8 – STARTUP Is your organization a Start-up OR spin-off (Y/N)

Sua organização é uma start-up ou spin-off (S / N)

AIQ - Indicators of Analytical Information Quality - Dimension of Adaptive Analytics

9-Our team has efficiently combined transaction data with external data. (AIQ1)

9-Nossa equipe tem combinado eficientemente dados transacionais com dados externos. (AIQ1)

10- Analytical information has become more relevant to the organization. (AIQ2)

10- Informações analíticas tornaram-se mais relevantes para a organização. (AIQ2)

11- Analytical information has become more accurate for the organization. (AIQ3)

11- Informações analíticas tornaram-se mais precisas para a organização. (AIQ3)

12-Our team provides Analytical information promptly to the organization. (AIQ4)

12-Nossa equipe fornece prontamente informações analíticas para a organização. (AIQ4)

TE - Indicators of Team Expertise- Dimension of Adaptive Analytics

13-In our team, the problem-solving process involves experimentation with quantitative evidence (TE1)

13-Em nossa equipe, o processo de solução de problemas envolve experimentação com evidências quantitativas (TE1)

14-In our team, we consider experimentation with quantitative evidence regardless of the type of problem to be solved. (TE2)

14-Em nossa equipe, consideramos a experimentação com evidências quantitativas, independentemente do tipo de problema a ser resolvido. (TE2)

15-Our team is competent regarding statistical abilities. (TE3)

15-Nossa equipe é competente quanto a habilidades em estatística. (TE3)

16-Our team is competent regarding programming abilities. (TE4)

16-Nossa equipe é competente quanto a habilidades em programação. (TE4)

17-Our team shows a superior comprehension of technological tendencies. (TE5)

17-Nossa equipe mostra uma compreensão superior sobre tendências tecnológicas. (TE5)

18-Our team shows superior skills to learn new technologies. (TE6)

18-Nossa equipe mostra habilidades superiores para aprender novas tecnologias. (TE6)

19-Our team is very capable of dealing with data. (TE7)

19-Nossa equipe é muito capaz ao lidar com dados. (TE7)

20-Our team understands our organization plans. (TE8)

20-Nossa equipe entende nossos planos organizacionais. (TE8)

21-Our team is competent in interpreting business problems. (TE9)

21-Nossa equipe é competente na interpretação de problemas de negócios. (TE9)

22-Our team has an open mind to the organization’s customer’s necessities. (TE10)

22-Nossa equipe tem mente aberta às necessidades do cliente da organização. (TE10)

23-Our team is immersed in the observation of the organization’s business environment. (TE11)

23-Nossa equipe está imersa na observação do ambiente de negócios da organização. (TE11)

ACAP-Indicators of Exploitative Learning of Absorptive Capacity

24-Our team has effective routines to identify new market data. (MKL1)

24-Nossa equipe possui rotinas eficazes para identificar novos dados do mercado. (MKL1)

25-Our team has adequate routines to assimilate new market data. (MKL2)

25-Nossa equipe possui rotinas adequadas para assimilar novos dados do mercado. (MKL2)

26-Our team is effective in transforming existing market Information. (MKL3)

26-Nossa equipe é eficaz na transformação de informações existentes no mercado. (MKL3)

27-Our team is effective in experimenting market Information into new products/services. (MKL4)

27-Nossa equipe é eficaz em experimentar informações de mercado em novos produtos / serviços. (MKL4)

(STATIC) MARKETING capabilities (Song et al., 2007)

28- Our organization has knowledge of competitors. (MC1)

28- Nossa organização tem conhecimento sobre concorrentes. (MC1)

29- Our organization has effectiveness in advertising programs. (MC2)

29- Nossa organização tem eficácia em seus programas de publicidade. (MC2)

30- Our organization has integrated marketing activities. (MC3)

30- Nossa organização tem atividades integradas de marketing. (MC3)

31- Our organization has skills to segment and target markets. (MC4)

31- Nossa organização tem habilidades para segmentar seu público-alvo. (MC4)

32- Our organization has effectiveness of pricing programs. (MC5)

32- Nossa organização tem eficácia em seus programas de precificação. (MC5)

33- Our organization has knowledge of customers. (MC6)

33- Nossa organização tem conhecimento sobre seus clientes. (MC6)

ORGANIZATIONAL performance (Law & Ngai, 2007)

34-Compared to our competitors, customers perceive that in our organization they receive their money's worth for purchasing our products/services (OP1)

34-Em comparação com nossos concorrentes, nossos clientes percebem que recebem o valor do dinheiro ao comprar nossos produtos / serviços (OP1)

35-Our customer retention rate is as high as or higher than that of our competitors. (OP2)

35-Nossa taxa de retenção de clientes é tão alta, ou mais alta, que a de nossos concorrentes. (OP2)

36-Our sales growth rate is as high as or higher than that of our competitors. (OP3)

36-Nossa taxa de crescimento de vendas é tão alta, ou mais alta, que a de nossos concorrentes. (OP3)

37-Our overall competitive position is strong in our business sector. (OP4)

37-Nossa posição competitiva geral é forte em nosso setor de negócios. (OP4)

38-The profitability of our organization is good relative to the overall performance of our business sector (OP5)

38-A rentabilidade da nossa organização é boa em relação ao desempenho geral do nosso setor de negócios (OP5)

39-Our organization achieved its goal in terms of market share? (OPM1)

39-Nossa organização atingiu seu objetivo em termos de marketshare?

ORGANIZATIONAL CULTURE (Cameron & Quinn, 2011)

43- Our organization is a very personal place. It is like an extended family. People seem to share a lot of themselves. (OCD1)

43- Nossa organização é muito pessoal. É como uma continuação da família. As pessoas parecem compartilhar muito de si mesmas. (OCD1)

44- Our organization is a very dynamic entrepreneurial place. People are willing to stick their necks out and take risks. (OCD2)

44- Nossa organização é um lugar muito dinâmico e empreendedor. As pessoas estão dispostas a se arriscarem e assumirem riscos. (OCD2)

45- Our organization is very results oriented. A major concern is with getting the job done. People are very competitive and achievement oriented. (OCD3)

45- Nossa organização é muito focada em resultados. Uma grande preocupação é com a realização do trabalho. As pessoas são muito competitivas e focadas nas realizações. (OCD3)

46- Our organization is a very controlled and structured place. Formal procedures generally govern what people do. (OCD4)

46- Nossa organização é um lugar muito controlado e estruturado. Procedimentos formais geralmente controlam o que as pessoas fazem. (OCD4)

47-The organization emphasizes human development. High trust, openness, and participation persist. (OCS1)

47-Nossa organização enfatiza o desenvolvimento humano. Confiança, abertura e participação são valorizadas. (OCS1)

48-The organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued. (OCS2)

48-Nossa organização enfatiza a aquisição de novos recursos e a criação de novos desafios. Há valor em experimentar coisas novas e prospectar oportunidades . (OCS2)

49-The organization emphasizes competitive actions and achievement. Hitting stretch targets and winning in the marketplace are dominant. (OCS3)

49-Nossa organização enfatiza ações competitivas e resultados. Priorizam-se atingir objetivos ambiciosos e vencer no mercado. (OCS3)

50-The organization emphasizes permanence and stability. Efficiency, control and smooth operations are important. (OCS4)

50-Nossa organização enfatiza permanência e estabilidade. Eficiência, controle e operações dentro das regras são aspectos importantes. (OCS4)

ENVIRONMENTAL DYNAMISM (Jayachandran, Sharma, Kaufman, & Raman, 2005)

51-In our business, customers' product/service preferences change substantially over time. (ED1)

51-No nossa ramo de negócios, as preferências por produto / serviço dos clientes mudam substancialmente ao longo do tempo. (ED1)

52-We are witnessing demand for our products and services from customers who never bought them before. (ED2)

52-Estamos testemunhando demanda por nossos produtos / serviços de clientes que nunca os compraram antes. (ED2)

53-The technology in our industry is changing rapidly. (ED3)

53-A tecnologia em nosso ramo de negócios está mudando rapidamente. (ED3)

54-Technological changes provide big opportunities in our industry. (ED4)

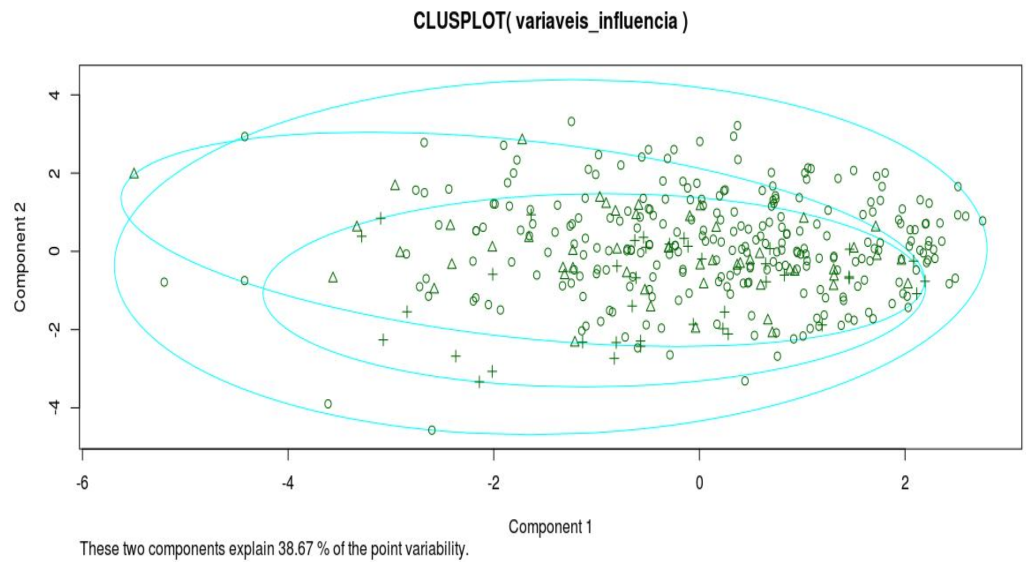
54 - As mudanças tecnológicas proporcionam grandes oportunidades em nosso ramo de negócios. (ED4)

55-A large number of new product\services ideas have been made possible through technological breakthroughs in our industry. (ED5)

55 - Um grande número de novas idéias de produtos / serviços foi possível graças a avanços tecnológicos em nosso ramo de negócios. (ED5)

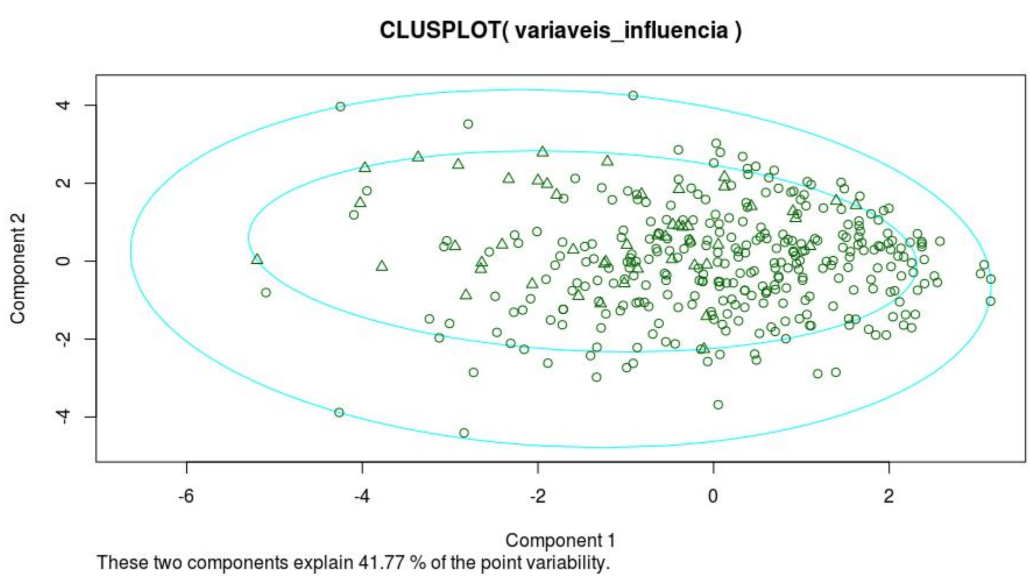
APPENDIX C FIMIX-PLS VERSUS TRADITIONAL CLUSTER ANALYSIS

3 Clusters Solution



Source: Prepared by the author (2019) using R

2 Clusters Solution



Source: Prepared by the author (2019) using R

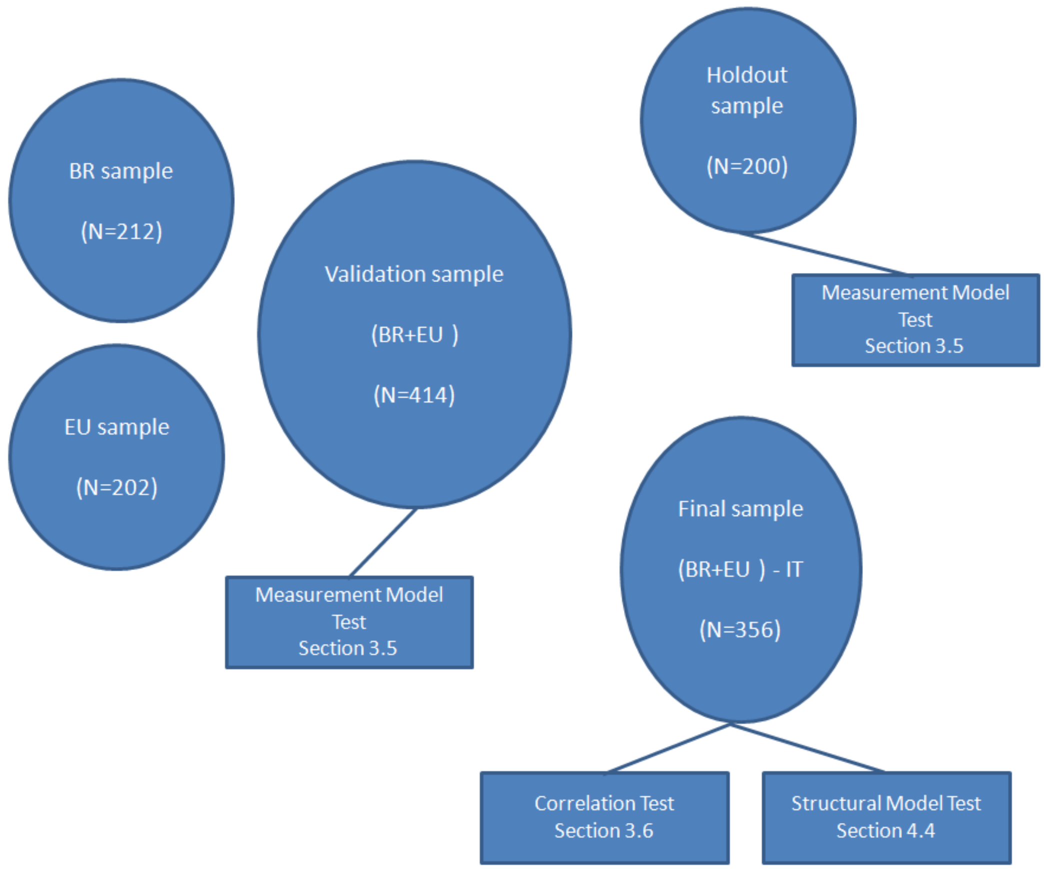
APPENDIX D - DESCRIPTIVE STATISTICS

Descriptive Statistics

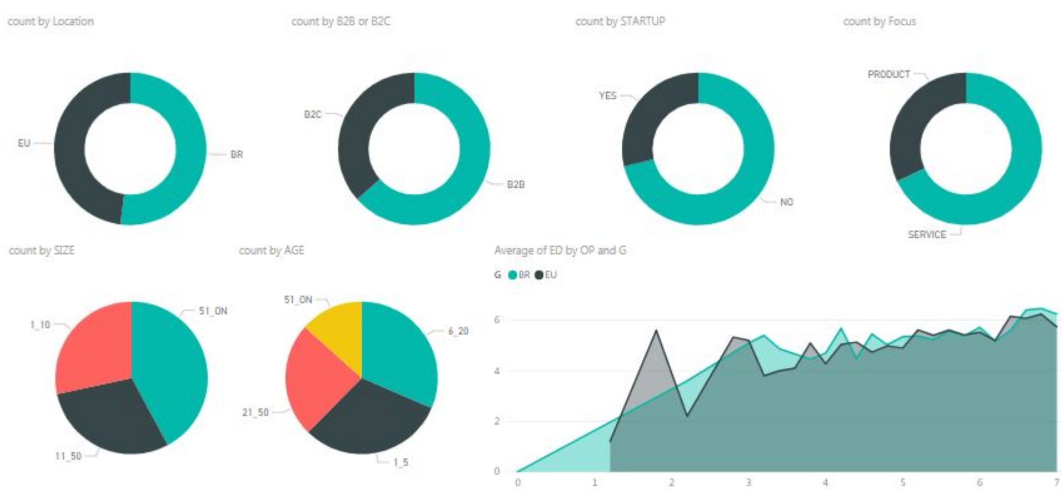
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LOG_SIZE	359	0,000	5,398	1,81455	1,175656	,798	,129	,264	,257
AGE	359	1,0	300,0	25,240	34,0090	3,242	,129	15,944	,257
STARTUP	359	0	1	,29	,453	,946	,129	-1,111	,257
B2BC	359	0	1	,36	,482	,564	,129	-1,692	,257
FOCUS	359	0	1	,32	,467	,773	,129	-1,410	,257
AIQ1	359	1	7	4,57	1,646	-,373	,129	-,645	,257
AIQ2	359	1	7	5,62	1,483	-1,196	,129	,970	,257
AIQ3	359	1	7	5,39	1,432	-,874	,129	,319	,257
AIQ4	359	1	7	4,87	1,538	-,631	,129	-,113	,257
TE1	359	1	7	4,84	1,570	-,598	,129	-,310	,257
TE2	359	1	7	4,74	1,581	-,488	,129	-,357	,257
TE3	359	1	7	4,73	1,585	-,493	,129	-,486	,257
TE4	359	1	7	4,63	1,820	-,395	,129	-,923	,257
TE5	359	1	7	5,15	1,521	-,816	,129	,145	,257
TE6	359	1	7	5,26	1,441	-,916	,129	,709	,257
TE7	359	1	7	5,05	1,572	-,556	,129	-,535	,257
TE8	359	1	7	5,27	1,410	-,812	,129	,287	,257
TE9	359	1	7	5,38	1,356	-,980	,129	,825	,257
TE10	359	1	7	5,65	1,310	-1,147	,129	1,526	,257
TE11	359	1	7	5,04	1,388	-,597	,129	-,071	,257
MKL1	359	1	7	4,69	1,588	-,353	,129	-,564	,257
MKL2	359	1	7	4,58	1,566	-,348	,129	-,573	,257
MKL3	359	1	7	5,05	1,440	-,686	,129	,028	,257
MKL4	359	1	7	4,93	1,545	-,564	,129	-,315	,257
MC1	359	1	7	5,53	1,257	-,963	,129	,756	,257
MC2	359	1	7	4,79	1,556	-,503	,129	-,358	,257
MC3	359	1	7	5,22	1,636	-,835	,129	-,055	,257
MC4	359	1	7	5,46	1,413	-1,018	,129	,809	,257
MC5	359	1	7	4,75	1,499	-,537	,129	-,122	,257
MC6	359	1	7	5,53	1,287	-,893	,129	,521	,257
OP1	359	1	7	5,50	1,248	-,848	,129	,577	,257
OP2	359	1	7	5,08	1,321	-,464	,129	-,120	,257
OP3	359	1	7	4,76	1,522	-,417	,129	-,344	,257
OP4	359	1	7	5,50	1,270	-,819	,129	,394	,257
OP5	359	1	7	5,17	1,415	-,857	,129	,566	,257
ED1	359	1	7	4,81	1,578	-,392	,129	-,642	,257
ED2	359	1	7	5,11	1,528	-,694	,129	-,116	,257
ED3	359	1	7	5,50	1,524	-,823	,129	-,209	,257
ED4	359	1	7	5,80	1,333	-1,153	,129	,927	,257
ED5	359	1	7	5,25	1,523	-,821	,129	,118	,257
OCD1	359	1	7	4,96	1,736	-,627	,129	-,552	,257
OCD2	359	1	7	4,87	1,754	-,596	,129	-,668	,257
OCD3	359	1	7	5,21	1,473	-,660	,129	-,215	,257
OCD4	359	1	7	4,16	1,754	-,101	,129	-,935	,257
OCS1	359	1	7	5,32	1,603	-,901	,129	,139	,257
OCS2	359	1	7	5,32	1,539	-1,001	,129	,307	,257
OCS3	359	1	7	5,29	1,455	-,792	,129	,256	,257
OCS4	359	1	7	5,16	1,420	-,665	,129	-,019	,257
Valid N (listwise)	359								

Source: Prepared by the author (2019) using SPSS

APPENDIX E- SAMPLES DESCRIPTIONS



Final Sample by Location, B2B or B2C, startup or no, service or product, size, age, and dispersion of organizational performance and environmental dynamism by location.



Source: Prepared by the author (2019) using PowerBI