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Narrowing the Marketing Capabilities Gap

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ABSTRACT

Purpose: In marketing discipline, there is considerable interest in understanding the relationship between diverse approaches of Market Knowledge Learning and Organizational Performance, and recently, how analytics and emerging revolutionary technologies are changing this relationship. To fully apprehend this relationship it is first necessary to uncover the role of Marketing Capabilities, the management mechanism that boosts Organizational Performance using Market Knowledge.

Design/methodology/approach: A new construct that embraces Analytics and Adaptive Capabilities approach (AAC) was developed to increase our comprehension of Marketing Capabilities mechanism using structural equation modeling and regressions.

Findings: The model has shown an indirect-only effect of AAC using Static Marketing Capabilities as a mediator narrowing the Marketing Capabilities Gap and avoiding any tautological capabilities pitfalls.

Research limitations: A deeper endogeneity test could be executed related to adaptive market approach as well it was an original preoccupation concerned to dynamics capabilities.

Practical implications: It enabled managers to understand what AAC are. Additionally the results suggest precaution for headhunter because AAC needs pre-existing marketing capabilities.

Social implications: It provides to managers a useful tool to assess their organizations regarding analytics in marketing realm, what makes it possible to compare with rivals and to predict the investments.

Originality/value: It lies in to appraise the Marketing Capabilities management mechanism and a step by step scale developed for AAC in different industries in Brazil.

KEYWORDS: Analytics Adaptive Capabilities. Scale development. Marketing Capabilities Gap

1. INTRODUCTION

According to the literature review of Barrales-Molina, Martínez-López, and Gázquez-Abad (2014) and Pereira & Bamel (2021), Marketing discipline increases attention in emerging revolutionary technologies of the recent data-driven decision-making scenario, in particular using the capabilities literature. To fully understand the learning and the outputs of Market Knowledge, it is first necessary to uncover the role of Marketing Capabilities and its management mechanism that allows the relationship between the new opportunities of Market Learning and Organizational Performance to exist.

The utilization of Big Data, mobile connectivity, e(m)-commerce, and the Internet of Things (IoT) has led to the emergence of revolutionary technologies that provide interactive and voluminous market information. This information is used as input to advanced analytical methods, transforming both structured and unstructured internal and external data into valuable Market Knowledge (Wedel & Kannan, 2016). These new opportunities for learning are at the forefront of recent and complex performance-driven debates surrounding emerging technologies and analytics (Chuang & Lin, 2017; Wamba et al., 2017; Donthu et al., 2021; Ahmed et al., 2022).

Revolutionary technologies have significantly improved the power of analytics, which has paved the way for the emergence of Adaptive Business Models such as experimental spin-offs, startups for industry foresight (Kiron, Prentice, & Ferguson, 2014), joint ventures, external networks, and collaborative strategies (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014). However, there is a significant literature gap in measuring the construct that represents learning capabilities related to analytics, which are used in conjunction with the adaptive approach explained in Day (2011). To address this gap, a scale for Analytics Adaptive Capabilities (AAC) has been proposed and tested as an antecedent variable to organizational performance (OP). However, the relationship between AAC and OP only exists with the mediation mechanism of Marketing Capabilities.

Also according to Barrales-Molina, Martínez-López, and Gázquez-Abad (2014) and Pereira & Bamel (2021), the integration of various marketing resources, capabilities, and processes into a common framework is hindered by the wide range of options available. This plethora of capabilities, often without clear construct content delimitation and scale validation, has led to conflicting and misleading findings regarding the nature and contributions of analytics for marketing.

While tautological research may sometimes yield positive results, it can also lead to pitfalls, such as testing correlations between similar dynamic capability scales. The present work has aimed to avoid such pitfalls by testing a new scale derived from adaptive capabilities (Day, 2011), which is an advancement related to dynamic capability.

Day (2011) differentiates between static marketing capabilities, which are stable capabilities, and dynamic marketing capabilities, which are capabilities that can be reconfigured and augmented, or as capabilities to pursue new opportunities.

In addition to the challenges related to capabilities, a multitude of recent empirical studies in Marketing and Information Systems have utilized various constructs related to analytics. These constructs include terms such as Business Analytics, Business Intelligence & Analytics (BI&A), Customer Relationship Management (CRM) Analytics, Social Media Analytics, and Big Data Analytics (Chuang & Lin, 2017; Côrte-Real, Oliveira, & Ruivo, 2017; Trainor, Andzulis, Rapp, & Agnihotri, 2014; Wamba et al., 2017).

It is important to recognize the potential pitfalls that may arise from an overemphasis on capabilities and analytics without adequate theory development. Such tautological pitfalls can occur when concepts are overused and applied without proper consideration for their underlying theoretical foundations.

The most prominent contribution of the present work is to uncover Static Marketing Capabilities mechanism between AAC and Organizational Performance. The step by step scale development of AAC and the association between this new construct to Organizational Performance was tested using Structured Equation Modeling (SEM) with Partial Least Square (PLS) and Ordinary Least Square (OLS) with SPSS PROCESS macro. In the next sections, we discuss some concepts and assumptions and after we propose the model and the new scale, and tested them. Synthetically, the paper showed an indirect only-mediation of Marketing Capabilities and discuss how to narrow the Marketing Capabilities Gap.

LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

The concept of absorptive capability (ACAP) is commonly used in traditional Marketing and Strategy literature to describe the overall learning process. This approach employs exploitative and explorative market orientation or responsive and proactive market orientation (Barrales-

Molina, Martínez-López, and Gázquez-Abad, 2014; Ozdemir, Kandemir, & Eng, 2017). While this literature is prominent, it falls short in addressing the role of analytics and relies heavily on traditional marketing methods and approaches (Wedel & Kannan, 2016), thus failing to close the marketing capabilities gap (Day, 2011).

To solve the lack of an AAC scale and test the mediation role of Marketing Capabilities we developed a new scale using the MacKenzie, Podsakoff, and Podsakoff (2011) validity framework have ten steps that were followed here and are outlined using the notation: (validity framework - step X). We followed this framework and used other scale quality tests.

Day (2011, 2014) criticize the current Resource-Based View literature, and even the current Dynamic Capabilities literature, as less dynamic theories than the market demands, suggesting the existence of the Adaptive Capabilities. Directed by the point of view of Day (2011, 2014) the present work advocate that AAC explore market opportunities. AAC reflect the **(AIQ) Analytical Information Quality**, and a **(TE) Team** exploits it with specific **Expertise** (analytical, technology, and business) improved by **(MKL) Market Knowledge Learning**. In summary, to develop a conceptual definition of the construct (validity framework - step 1), AAC can be classified as an Adaptive Capability that uses Analytics. Of course, this definition is based on two others, Adaptive Capability, and Analytics, defined in the present theoretical review.

Using MacKenzie, Podsakoff, and Podsakoff (2011) suggestions (validity framework - step 1), organizations are the AAC entity and the AAC general property are the capabilities of these organizations to use sophisticated data technology approach to boost a market openness in a continuously experimental behavior, forging partnerships, vigilantly for deep market insights. AAC is multidimensional, and its stability is across cases, where cases are, for example, projects of marketing, data science, R&D, or product/brand innovations.

In terms of dimensionality, AAC consists of three reflective first-order constructs. While information quality is a well-known and measured construct (Gorla, Somers, & Wong, 2010; Wieder & Ossimitz, 2015), it is important to note that emerging technologies handle data in novel ways, leading to an increase in **Analytical Information Quality**. Market data is no longer limited to information systems within databases but includes web and social media data, different types of data that are merged into data lakes or warehouses, and independent datasets such as texts, videos, and denormalized spreadsheets that are prepared for data science applications. The process of data engineering and cleansing gives rise to another type of data, which in turn leads to another type of information quality, which we refer to as Analytical Information Quality (Provost & Fawcett, 2013).

Teams with special **expertise** perform analytics. Updated quantitative studies provide empirical evidence that confirms the positive role developed by innovation teams (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014, Sincorá, Oliveira, Zanquetto-Filho, & Ladeira, 2018). Another example is a quantitative work executed with Chinese senior executives that identified exchange and integration of team knowledge, and by its turn, this improves the organizational financial performance because of new product development (Tseng & Lee, 2014).

Analytics can help in the **Market Knowledge Learning** (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Pereira & Bamel, 2021). Weaven et al. (2021) and Davenport (2006) exemplifies the market knowledge learning by saying that the organizations may spend many years accumulating data from different approaches before having enough information to analyze a marketing campaign in a trusting and efficient way. This market knowledge is all information that the organization has about the customer and his needs in different situations and various moments, past, present and future (Cooke & Zubcsek, 2017). AAC has a construct that responds to market accelerating velocity and complexity with a more outside-in and exploratory learning capability. This first-order construct is based on Absorptive Capability (ACAP) with the improvement of vigilant, experimental and, market openness of Day (2011).

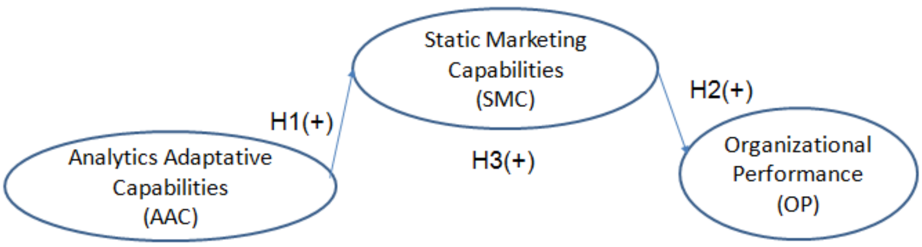
The first-order constructs do not have a causal relationship with AAC; instead, they represent the dimensions of the second-order construct. Another crucial point for defining the construct is the reflective/formative issue. It is essential to understand that whether a construct is reflective or formative is not inherent but a matter of definition (MacKenzie, Podsakoff, & Podsakoff, 2011). The three dimensions of AAC represent its manifestations. For instance, learning a new statistical method like clustering can enhance the team's expertise, which in turn can improve market knowledge learning and analytical information quality.

As part of the first step in the validity framework, which involves defining the construct, it is important to differentiate AAC from other constructs in the field of marketing capabilities (MacKenzie, Podsakoff, & Podsakoff, 2011). Figure 01 summarizes the position of AAC in relation to team expertise, which is utilized during the reconfiguration process of ACAP, and then passes through static marketing capabilities such as resource/capabilities related to customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization.

THEORETICAL MODEL AND HYPOTHESES DEVELOPMENT

Market knowledge is a crucial point of connection between the constructs discussed in this paper. The source of this knowledge can be diverse, ranging from CRM systems and social media to new technologies like IoT and big data. However, the way of learning remains the same, that is, by using quantitative evidence (Davenport, 2006). This evidence is then used to launch Adaptive Business Models, such as experimental spin-offs, industry foresight, and collaborative network strategies. The Theoretical Model is presented in Figure 01, and hypotheses are introduced in the following section.

Figure 01 – Theoretical Model



Source: Prepared by the authors

The Information System Literature has extensively used the concept of capabilities to explain the learning process (Popovič, Hackney, Coelho, & Jaklič, 2012; Teo, Nishant, & Koh, 2016; Wang & Byrd, 2017), but these approaches have not explicitly focused on the Market Knowledge learning process, which is crucial for changing/reconfiguring organizational strategies (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014). Therefore, the unique contribution of the present work lies in the utilization of Market Knowledge through AAC.

Some digital marketing technologies facilitate large-scale field experiments that produce market knowledge and become powerful tools for eliciting the causal effects of marketing actions (Wedel & Kannan, 2016). Examples are A/B tests and recommendation systems. The former started with changes in site colors for best sales, and nowadays they apply machine learning to test small details for full automated super individualized market-mix. By it turn, recommendation systems can interact directly with stock management or other Marketing capabilities like loyalty programs and Customer Relationship Management (CRM) building super segmentation approaches.

Complementary capabilities, idiosyncratic business needs, and organizational procedures\routines should be integrated by teams of technologists and scientists that leads with complex and sophisticated technological knowledge (Cohen & Levinthal, 1990). This seminal work about market information learning, before the discussions about analytics and big data boom (Ciampi et al., 2021), gives us a clue that technologies uphold the market knowledge impacting other marketing capabilities like pricing, segmentation, and personalization. From this discussion and the assumption about the capabilities tautological pitfall, the first hypothesis raises.

H1. AAC has a direct positive effect on Static Marketing Capabilities.

Marketing literature is concerned about the relationship between Marketing and performance constructs using Capabilities (Morgan, 2012; Kozlenkova, Samaha, & Palmatier, 2014) but few works measure Day's named "Static Marketing Capabilities" improvement in organizational performance (OP). OP is measured subjectively.

We assume the Marketing Capabilities importance for Performance, and the following hypothesis is declared to uncover the literature term avoidance:

H2. Static Marketing Capabilities have a direct positive effect on Organizational Performance.

Analytics can improve marketing capabilities/resources like customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization (Germann, Lilien, Fiedler, & Kraus, 2014; Wedel & Kannan, 2016). However, these capabilities/resources need to have its preexisting procedures/routines to AAC make possible disruptions or become Adaptive Business Models like experimental spin-offs, industry foresight or collaborative network strategies.

Extant literature argument that CRM systems are enablers for Marketing Capabilities (Wang, Hu, & Hu, 2013; Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Chatterjee, Chaudhuri, & Vrontis, 2022) which indicates the dependence of some technological capabilities to other sorts of capabilities. Additionally, the technology effectiveness, its output, is enabled by preexisting capabilities (Boulding, Staelin, Ehret, & Johnston, 2005; Ferreira & Coelho, 2020).

Finally, some Technology Capabilities Constructs about analytics are assumed to have a direct effect on Performance (Wamba et al., 2017; Ferreira & Coelho, 2020). On the other hand, Adaptive Capabilities constructs have no direct effect (Morgan, Zou, Vorhies, & Katsikeas, 2003). The results show a mixed behavior, and there is hardly clear evidence for a positive impact. In brief, AAC as a kind of technological Adaptive Capability depends on preexisting marketing capabilities to improve performance, and this is the reason to test the mediation and expect a not significant direct relationship to performance. Thus, we assume that AAC translates organizational performance just thru Marketing Capabilities. From this discussion, and using the Zhao, Lynch, and Chen (2010) terminology about mediation, we formulate our third and central hypothesis:

H3. Static Marketing Capabilities have an indirect-only mediating role between the AAC and Organizational Performance

The last hypothesis assumed the terminology of Zhao, Lynch, and Chen (2010) that detail three possibilities regard to mediation, (i) Complementary mediation, there are direct and indirect effects and both point at the same direction. (ii) Competitive mediation, there are direct and indirect effects, and they point in opposite directions. (iii) Indirect-only mediation, there is only the indirect effects.

METHODOLOGY

A survey was executed to test the hypotheses (validity framework - step 5) with Brazilian 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, Other Management Positions. The survey was conducted from December 2017 to March 2018, and garnered a total of 250 records for the purposes of scale validation and item purification, without any additional treatments (MacKenzie, Podsakoff, & Podsakoff, 2011). From this larger sample, a heuristic holdout sample of 200 was selected for use in step 6 of the analysis. Finally, a subsample of 195 respondents was used to validate the final model, after excluding those with IT profiles.

The AAC construct described earlier is new, and can´t be confused with the existing constructs related to Analytics which usually deal with greater technological detail (Rapp, Trainor, & Agnihotri, 2010; Wamba et al., 2017). Table 01 defines the dimensions of the three first-order AAC constructs and how to operationalize the multi-industry questionnaire.

In the validity framework, step 2 involves generating items for the AAC construct. These items are all new but were adapted from the literature review. The formal specification of the measurement model, without any formative indicators, is presented in Table 01 as part of the validity framework in step 4.

The Table 01 adaptation (i) was a change in the items that deal with data improvements due to a CRM implementation, so the new items address any data improvements. By it 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) emphasis was given to the use of quantitative sources of information.

Regarding the Team Expertise, no other questionnaire tested concepts of quantitative evidence, market immersion, and experimentation, key parts of analytics and Day(2011) concepts. This idiosyncrasy came from the AAC contextualization as an Adaptive Capability discussed in the theoretical section.

The adaptation (iii) was necessary because projects can be done by teams especially 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 team only (Kim, Shin, & Kwon, 2012).

Table 01 - AAC - Defining the first-order constructs

Defining the Constructs	Source of the indicators
Analytical Information Quality – refers to the quality of Analytical information outputs	(i) Adaptation from Chuang and Lin(2013) scale
Team Expertise– Represents the professional abilities of the project team that are fundamental to perform tasks. (ex: skills or knowledge) of three different dimensions. Dimension 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 others characteristics like data-driven learning, and experimentation (Day, 2011). Dimension 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 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).	(ii) Dimension Analytical Expertise–New scale inspired in Popovič and others (2012) and Day (2011) (iii.a) Dimension Technological Expertise–New scale inspired by Kim, Shin, and Kwon (2012) (iii.b) Dimension Expertise in Business–New scale inspired by Kim, Shin, and Kwon (2012) and Day (2011)
Market Knowledge Learning - the ability of the team to recognize the value of new external knowledge, assimilate and apply that knowledge (Cohen & Levinthal, 1990). These authors argue that the ability for assessing and using external Information is, in most part,	Adaptation from Pavlou and Sawy, (2013) and Pavlou and Sawy, (2010) scales and influenced by Day (2011)

directed by the level of previous knowledge, what is related to analytical information quality.	

Source: Prepared by the authors

The references for the other constructs are all based on established works in Marketing. The concept of Static Marketing Capabilities focuses on marketing competencies (Conant, Mokwa, & Varadarajan, 1990) and employs a multi-industry scale adapted from Song, Di Benedetto, and Nason (2007). In addition, Organizational Performance uses a scale reproduced from Jaworski and Kohli (1993) as it is challenging to obtain objective performance data in a cross-industry survey. Thus, this study measures performance subjectively.

Categorical data for multi-group analyses was based on organizational size and respondents' profile. The nonparametric equivalence analysis technique, Partial Least Square - Multi-Group Analysis (PLS-MGA), was used. This technique is considered an original extension of Henseler's (2009) MGA method. Despite hypothesis delimitation, control variables such as organizational size and respondents' profile were tested. The MGA results differentiated IT and non-IT respondents.

Aside organizational size and respondents profile, the work used only seven-point Likert scales, ranging from "totally disagree" (1) to "totally agree" (7). To test differences between early and late responders a PLS-MGA was used too, with no significant differences found. Another precaution was to assess common method bias using Harman's single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

There is no missing data. According to checked non-normality, the empirical test of theoretical hypotheses was made using structural equation modeling (SEM) on SmartPLS software (version 3.2.4).

RESULTS ANALYSIS

The univariate skewness and kurtosis, with values of 14 from 31 likert variables are out of interval from -1 to 1, indicate non-normality for the original sample, what was confirmed after executing the Shapiro-Wilks and Kolmogorov-Smirnov tests rejecting the hypothesis of normality for all 31 variables (Hair, Black, Babin, Anderson, & Tatham, 2009).

The scale purification and refinement (validity framework - step 6) resulted in the exclusion of two questions, as seen in Appendix I, due to cross-loadings tests. To gather data from new Sample (validity framework - step 7) a holdout with only 200 first registers of the original sample, we called as heuristic subsample, was used with no big difference (MacKenzie, Podsakoff, & Podsakoff, 2011). The holdout was used only to confirm refinement of step 6.

Some Multi-group Analyses was performed using organizational size and profile information. Using a data-driven approach, the SmartPLS suggested the following groups for size: (a) less than 10 employees, with 48 registers, (b) more than 1000 employees, with 52 registers, and (c) the middle, with 150 registers. The PLS-MGA and the Permutation algorithm were performed using the combination of these three size groups and two groups of profile resulting in p-values bigger than 0.05, i.e., rejecting the hypothesis of group differences about organizational size. However, for profiles assessment, the PLS-MGA shows differences from IT, 55 registers, and non-IT respondents, 195 registers (final sample), then just non-IT respondents were used as the final subsample (MacKenzie, Podsakoff, & Podsakoff, 2011) for model tests.

Using the validation/final subsample with MICOM process (Henseler, Ringle, & Sarstedt, 2016), we confirmed the possibility of pooling the data of the other profiles. 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 then measure invariance.

The AAC construct has the biggest number of variables, 19 after the deletion of 2 items. Therefore, preliminary would be 190 respondents using the rule of thumb of 10 times (Hair, Hult, Ringle, & Sarstedt, 2017). Another conservative way, making a statistical power test in 95%, and assuming an f square of 15%, the software GPower determines, for a significance of 1%, the size of the sample as 170 respondents. The GPower statistical test chosen is one that tries to maximize the multiple regressions R square adding new predictors to the solution, f^2 (Faul et al., 2007). We used 4 predictors, including 2 control variables.

Model tests

The PLS algorithm was executed with the default values following the guidelines of Hair et al. (2017). All constructs have at least three variables and are reflective according to the content definition, or *a priori* specification.

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

Still on the measurement model 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 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 multidimensional constructs of AAC (validity framework - step 8).

The structural model collinearity was evaluated using the VIF indicator, using less than 5 as a parameter, with the highest result being 4,097 (Hair et al., 2017). After, the coefficients are evaluated using the Bootstrapping procedure with 5000 subsamples with the option "no sigh changes" (validity framework - step 6). The coefficients are not significant (p-value <0.05) only for the statistical test of the relationship between AAC and Organizational Performance indicating an indirect-only mediation of Static Marketing Capabilities (H3).

For a more in-depth analysis (see Table 02 and Figure 02), the macro PROCESS of SPSS confirmed the H3, indirect-only effect for mediation, (a) and (b) <0.001 and (c´) not significant, and gave more information using Ordinary least squares (OLS) regression analysis with the latent scores outputted from smartPLS.

We used the procedures and parameters of Hayes (2013), and the results of the bootstrap with 10000 resample are summarized in Table 02 with results for R2, F statistics (degree of freedom 1 and 2) and p-values. It also includes unstandardized regression coefficients of direct paths (a, b, and c'), and the indirect path ab with significance level for bias-corrected 95% confidence intervals, and standard error(SE).

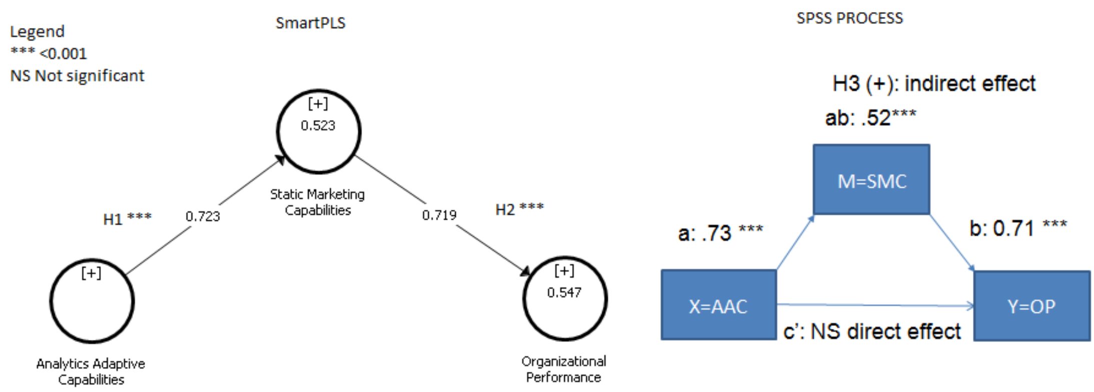
Table 02 - PROCESS OLS mediation results

	Consequent							
Antecedent	M(Static Marketing Capabilities)				Y(Performance)			
		Coeff.	SE	*p*		Coeff.	SE	*p*
X(AAC)	a	.7325	.0640	<.001	c'	.0532	.0859	NS
M(Static Marketing Capabilities)		--	--	--	b	.7084	.0865	<.001
Constant	i1	.0	.0494	1	I2	.0	.0484	1
	R2 = 0.536 p<.001				R2 = 0. 3273 p<.001			
	F(1,193) = 130,8382				F(2,192) = 90,5057			

Source: Prepared by the authors

The first two hypothesis was confirmed (see Figure 02, left side), and they gave responses to extant literature and introduced AAC as an antecedent of the realm of Marketing Capabilities. About the main test, mediation (see Figure 02, right side), the indirect effect (ab) resulted in a value of .5189 using both the normal theory test and the bootstrap confidence interval (Hayes, 2013). As H3 is the main test, to improve the robustness of the indirect effect value, another test procedure was executed using a simulation-based method, Monte Carlo using the MCMED macro (Hayes, 2013). MCMED showed the same value with confidence intervals ranging from .3734 and .6811 (Preacher & Selig, 2012), i.e., not passing thru zero.

Figure 02: SmartPLS algorithm and PROCESS SPSS outcomes



Source: Prepared by the authors

Thus H3 was confirmed, no direct significant effect, using SEM and OLS indicating an indirect-only mediation between AAC and Organizational Performance, what agree with part of literature that we assumed as correct, what has a definite impact for practice and academics. The mediation effect is most important as higher is the indirect-effect value, not the inexistence of direct-effect (Zhao, Lynch, & Chen 2010), and have to be analyzed together with the size of the effect f^2, which evaluates if any omitted constructs generate substantive impact on the endogenous constructs. This caveat is necessary to avoid the epiphenomenal association, that means a mediator correlated with another omitted construct (Hayes, 2013), but f2 results deny this association as we will see.

The indirect-effect has a value of .5189, but it is a scale bound then it is dependent on the constructs metrics, and the measurement metrics in our model are not inherently meaningful because they are responses to rating scales aggregated over multiple questions (Hayes, 2013) and standardized by SmartPLS. Thus we used the R-squared mediation effect size (R-sq_med from PROCESS) that resulted in .3260, confidence intervals ranging from .1969 and .4546, meaning that AAC explains 32.6% of Organizational Performance valiance in our final sample, that has total effect larger than the indirect effect and they have the same sign, following the restriction of Hayes (2013) for R-sq_med effect size index.

Back to the SmartPLS, the f^2 effect shown that AAC on Static Marketing Capabilities and Static Marketing Capabilities on Organizational Performance are large, bigger than 0.35 (Hair et al., 2017), meaning the contribution of the exogenous construct for the R^2 of the endogenous construct. We also evaluated the coefficient of determination that measures the model predictive power. The result was 0.523 for Static Marketing Capabilities and 0.547 for Organizational Performance, with adjusted values of 0.521 and 0.543 respectively, which is considered both moderate (Hair et al., 2017).

The predictive relevance is evaluated using the Blindfolding algorithm with default configuration, omission distance equal to seven, resulting in a Q^2 that represents great relevance 0.377 (Organizational Performance) and near to great 0.318 (Static Marketing Capabilities), with 0.35 as parameters (Hair et al., 2017) using cross-validated redundancy (validity framework - step 9). To finish the validity framework - steps 6 and 9, with standardized root mean square residual (SRMR) fit parameter as less than 0.08 (Hair et al., 2017), was found a good fit of 0.064. In summary, the analysis of SEM carried out in SmartPLS, and OLS in

PROCESS resulted in the confirmation of all three hypothesis.

DISCUSSIONS

The hypothesis H1 confirmed the importance of teams of technologists and scientists that leads with complex and sophisticated knowledge impacting in marketing capabilities (Cohen & Levinthal, 1990; Ciampi et al., 2021) with a moderated R square. By it turn, the hypothesis H2 confirmed the marketing capabilities literature (Morgan, 2012; Kozlenkova, Samaha, & Palmatier, 2014) and gives the possibility of using the term "static marketing capabilities". Additionally, H2 also resulted in a moderated R square for Organizational Performance. The parsimonious model empowers the moderated R^2.

The hypothesis H3 showed that AAC is dependent on Static Marketing Capabilities. This result gives to AAC the same enabler behavior of technological capabilities regarding preexisting marketing capabilities to improve performance (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Pereira & Bamel, 2021). These tests expand the knowledge of managers and academics. In particular to both profiles that take for granted the importance of analytics and think about it naively.

CONCLUSIONS

The present paper helps to explain organizations that continually feel and act upon the emerging technological trends using a market knowledge with the adaptive approach. The paper shows that to improve Organizational Performance using AAC it is needed static marketing capabilities. Thus, analytics can boost traditional methods of customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, personalization, which by its turns, can launch adaptive Business Models like experimental spin-offs, startups for industry foresight, they can promote joint ventures or external networks and collaborative strategies.

The results show findings both from academic and practice point of views. The academic relevance is to show how AAC acts through static marketing capabilities to become a critical and predictive element for organizational performance. Thus, the results of the research contributed to clarify the way in which the construct operates, additionally the paper escape from traps linked to tautological Dynamic Capabilities research.

Regarding the managerial context, this research effort enabled managers to understand what the Analytics Adaptive Capabilities are, as well as the static marketing capabilities that need to be developed and articulated by work teams involved in marketing activities. The expertise of these teams are used to recognize the value of new market knowledge through the use of technologies, assimilating them and applying them to new adaptive business models. Thus, AAC is a rare, valuable and adaptable capability to the market demands.

The paper provides to managers a useful tool to assess their organizations regarding AAC, what makes it possible to compare with rivals and to predict the investments to improve AAC dimensions. In particular, we highlight the new Analytical Information Quality that is different from the widespread Information Quality construct.

A limitation is that the idea of researching the adaptive market approach is not entirely new, another limitation it that deeper endogeneity test could be executed related to adaptive market approach as well it was an original preoccupation concerned to dynamics capabilities. However, as an academic contribution, the results and discussions on marketing capabilities seem to expand the field toward the emerging revolutionary technologies. For management, these results suggest precaution for headhunter because AAC needs pre-existing marketing capabilities and sometimes a step back is necessary.

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