BIG DATA AND TV MEDIA: GOING BEYOND TRADITIONAL SEGMENTATION

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ABSTRACT

The aim is to show the benefits of a model of advanced segmentation based on big data, that improves results for advertisers and brings new relevance to linear and video-on-demand TV operators. The paper also assesses the subjacent importance of three main Dynamic Capabilities (i.e. sensing, seizing, transforming) to the described process.

Results suggest that the advanced segmentation model is able to impact marketing performance, by doubling the percentage of consumers that visited the advertiser's website in the first 24 hours. The advertising pressure, below which consumers would not react, is also established. These results constitute a proof that new segmentation models based on big data are able to improve marketing campaign results, as well as able to address the loss of relevance of TV to advertisers.

The business case analyzed proves that a TV campaign result can be optimized and better measured, thanks to the use of big data on a new segmentation model. It also brings new relevance to TV as a media that can compete with digital investments.

Keywords: Attention economy, Segmentation, Media, Big Data Analytics, Marketing Performance, Dynamic Capabilities.

INTRODUCTION

Digital media, including social media, is enabling advertisers to deploy better targeted content to consumers. Additionally, results can be measured. And there is more: The measurement of results can be continuously fed into a marketing information system, since technology implementation is carried out by companies through digital marketing to support marketing information systems (Alamsyah et al., 2021). This is a key advantage of digital media for marketeers, versus TV where content could not be fully targeted and results (other than advertising pressure) could not be measured. As a consequence, TV broadcasters are losing effectiveness and looking for new forms of advertising (Arrazola et al., 2013; Rubinson, 2009). Moreover, the surge of subscription video on demand (SVOD) platforms is having a disruptive effect on traditional TV scheduling, ratings, and advertising (Matrix, 2014). And it has formed a new competitive landscape in Spain as shown in Figure 1.

TV broadcasters are now forced to look for unique systems and practices in order to remain attractive to the audience (Given, 2016). However, the problem stays unresolved even if they manage to remain attractive for viewers. Reach –Viewing rating or exposure– still remains the most popular criterion for media space buying and selling, and the clearest quantitative criterion for evaluating advertising effectiveness (Bína et al., 2019). However, a reach-driven plan does cover a lot of viewers, but without discriminating them by anything else than basic demographic criteria (Büger & Hylkè, 2017). The TV industry now plays in the content industry, a competition arena that for some authors is now solidly in the attention economy, which positions consumers' attention as the most valuable commodity (Zulli,

2018). New and related realities, like the new role of media viewers becoming producers and the opportunities for converging contents to niche markets, have also been addressed (Salamzadeh et al., 2019).

Group	Type	Description	Examples	Content served through...	Smart TV required?
Traditional →	Off-line TV	Linear traditional TV	Antena3, Tele5…	Antenna	NO
Hybrid →	Subscription	Linear AND on-demand	Movistar +	Decoder	NO
			Movistar+ Lite	Internet	YES
Connected →	AVOD (Advertising video on-demand)	Broadcasted content is monetized through advertising	YouTube	Internet	YES
	BVOD (Broadcasters video on-demand,)	Linear TV that also offers broadcasted content on-demand	A3Player (A3Media), MiTele (Mediaset)	Internet	YES
	SVOD (Subscription video on-demand)	Non-linear. Subscription based.	Netflix, Amazon PrimeVideo, Rakuten	Internet	YES

FIGURE 1
THE CURRENT TV COMPETITIVE LANDSCAPE IN SPAIN

Focusing on advertising, this paper illustrates how the use of big data analytics can create a more effective allocation of advertising investment. Underlying this process is the development of Dynamic Capabilities-sensing, seizing and transforming-, all of them related to data management, technological infrastructure and personal talent. Results suggest that the development of Dynamic Capabilities have helped the use of big data analytics to improve segmentation and consequently advertising performance, whilst offsetting the lack of effectiveness of traditional TV advertising. We show an experimental case where three distinct and powerful players (a leading advertiser in the tourism industry, a leading Travel Agency Network and a leading TV broadcaster) were involved in a TV Campaign that runs until November 2019. The advertiser: A key player in the cruise industry was concerned about not being able to improve campaign results due to the limitations of traditional segmentation techniques. The advertiser was trying to ascertain if the use of more sophisticated data (behavioral) on a TV campaign could achieve better results. A market sensing drive was initiated, looking for a segmentation solution that overcame this hurdle. The Travel Agency Network: The leading Company in the Travel and Tourism distribution in Spain. They were persuaded by the advertiser about the need to look beyond traditional segmentation techniques, in order to become much more effective when investing together on advertising. The Media: A leading linear and on-demand TV provider in Spain, also providing internet and mobile telecommunications, generating vast amounts of big data on their subscriber's behaviour all three parties agreed to test-pilot a TV campaign where big data could be used, after anonymization, for segmentation. Our analysis begins by reviewing literature around the concept of Dynamic Capabilities, then around the current challenges around advertising effectiveness, and then around how big data analytics can overcome these challenges related to advertising effectiveness. Then, we review the method used to create high-affinity clusters, followed by the results achieved. Finally, the combined effect of big

data analytics and Dynamic Capabilities has academic and professional implications that are discussed. Future research opportunities are also identified.

Dynamic Capabilities

Managers in turbulent environments need to make sound decisions quickly to better suit to the environment (Pavlou & El Sawy, 2011). The ability to respond to changes is a complex process can only be achieved when firms develop and apply capabilities sooner, more astutely, or more fortuitously than their competitors (Eisenhardt & Martin, 2000). This stream of reasoning has also been referred to as the Dynamic Capabilities view (Teece et al., 1997). Dynamic Capabilities address this need by building different types of capabilities that make use of real-time information, simultaneously explore multiple alternatives, rely on quickly created new knowledge, are governed by very few simple rules, do not get stored in the organizational memory and thus, do not produce predictable outcomes (Eisenhardt & Martin, 2000). The main functions of Dynamic Capabilities are (1) sensing environmental changes that could be threats or opportunities, by scanning, searching, and exploring across markets and technologies; (2) responding to the changes by combining and transforming available resources in new and different ways; and (3) selecting the organizational configuration and business model for delivering value to customers and then capturing the economic profit (Teece, 2007). Based on the concept of big data emerges Big Data Analytics (BDA) to refer the holistic approach to managing, processing and analyzing big data. BDA creates actionable ideas for delivering sustained value, measuring performance and establishing competitive advantages (Wamba et al., 2015). BDA are taxonomized as descriptive, predictive and prescriptive (Wang et al., 2014). The ability to manage the information technology is called Big Data Analytics Capability or BDAC (Mikalef et al., 2019).

Firms that develop strong big data analytic capability have shown to be better positioned to sense emerging market opportunities and threats (Akter & Wamba, 2016) and to better understand consumer behavior, interactions, and experiences with a product or service. Dynamic companies are constantly sensing the market for new opportunities, seizing them inside their organizations and transforming the working processes to improve performance as a result. In the case presented in this paper, the use of BDA for marketing purposes was a current capability in the advertiser, and prompted the company to try to figure out if the use of BDA by a TV broadcaster could result in performace gains for the advertiser and the distributor. The lookout in the market for a TV provider with the right technology is an example of the Sensing capability. Once found, the adaptation of the new technology to the company's goals is an example of the Seizing capability. And the creation of a seven-step model to design, implement and evaluate the campaign is an example of the Transforming capability, as shown in Figure 2.

Advertising Effectiveness

The impact of television advertising has been mostly measured in terms of advertising recall (Mehta, 2000). Scholars and practitioners share little consensus as to how the effectiveness of TV can be measured in other terms, like engagement (Kim et al., 2017).

Recently, TV advertising effectiveness has also been measured in terms of incremental online searches elicited by TV ads (Hill et al., 2019) enabled by the use of a second screen while watching TV (Coates & Dozier, 2017; Qing & Prado, 2020). Some studies have attempted to prove the link between TV advertising and the increase of internet queries (Zigmond & Stipp, 2010). It has been argued that TV advertising has a positive instant effect on online browsing, prompting impacted consumers to tend to use branded

keywords instead of generic keywords (Joo et al., 2013). ROI in terms of sales revenue has also been studied as a measure of the effectiveness of TV advertising, concluding that slightly less than half of all brands earn a positive ROI on their total advertising spending during the sample period, and the vast majority of brands over-invest in advertising and could increase profits by reducing their advertising spending (Shapiro et al., 2020).
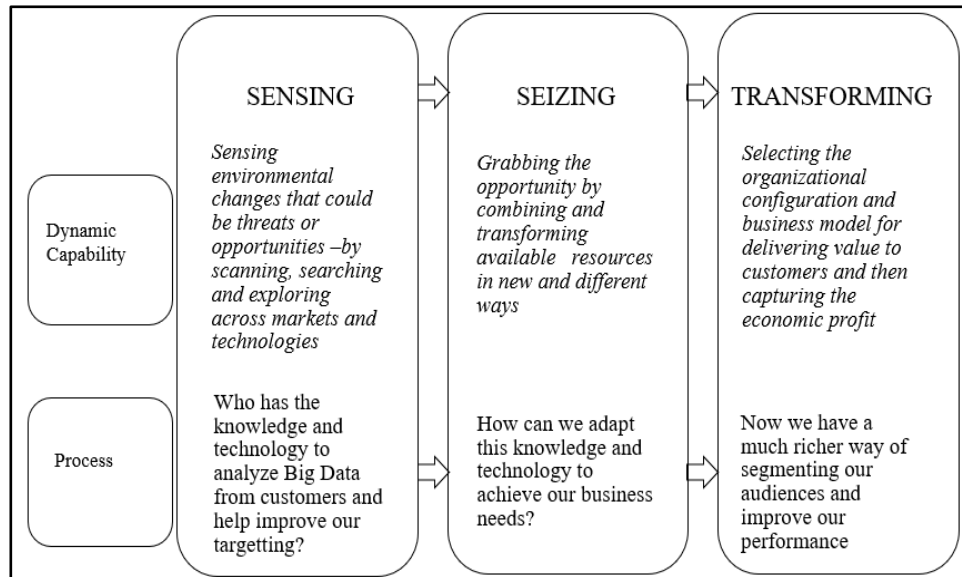

FIGURE 2
HOW DYNAMIC CAPABILITIES ARE SUBJACENT TO THIS PROCESS

Despite the economic importance of TV advertising investment within a Marketing Investment Plan addressed to impact on brand's choices, a proper causal relation between TV advertising investment and brand choice is seen as weak and rarely significant (Tellis & Weiss, 1995). One possible reason could be that TV advertising investments have traditionally lacked true segmentation power. Segmentation variables like demographic are proved to be insufficient, because consumers in the same demographic group have very different psychographic makeups (Lin, 2002). Traditional television-advertising has lost relevance. The success or failure of a communication effort is grounded on audience segmentation (Atkin & Freimuth, 1989; Maybach, 1995; McQuail, 1997). Demographic is the most common approach to audience segmentation (Maybach, 1995). However, using demographics as a primary basis for segmentation is error-ridden to the degree that the relations between demographics and the actual determinants of the behaviour are imperfect (Sondhi & Chawla, 2016; Barwise & Ehrenberg, 1988; Maybach, 1995). Therefore, a new form of segmentation is needed, that pays attention to the consumer contexts and his/her mind-sets associated with the new and emerging viewing behaviours, such as time-shifting on online versions of traditional TV or streaming through different fixed or mobile devices. Segmentation aims to deliver value, instead of merely exposure, to consumers (Kim, 2008). Addressability is now allowing advertisers to target to segmented audience by personality and interest, rather than only demographics. New metrics allow connecting advertising exposure to results in real time, thus identifying better working ads. Innovations in the way we can segment are making TV advertising more compelling (Sondhi & Chawla, 2016; Mulhern, 2009). The growing presence of consumer-generated big data, especially when it pertains to attitudes and behavior, could be used to improve the approach to segmentation and achieve better marketing performance.

Big Data Analytics and Advertising Effectiveness

While the hype around big data Analytics is continuously growing, the conditions under which such investments lead to business value remain largely unexplored in empirical research (Mikalef et al., 2019). Big data analytics is the ability to capture and to analyse big data generated by consumers' behaviour and personality. Organizations can now leverage the new information eco-system arising from big data adoption due to the real time information and the quality of the knowledge generated: a better understanding of customers, the design of better targeted products and services with better chances to win and develop the critical insights for decision making (Wamba et al., 2015). The new big data ecosystem is impacting the way marketing organizations adopt strategic decisions and optimize marketing communication channel performance, optimizing predictive models for better targeted marketing (Jobs et al., 2015; Martens et al., 2016). Traditional broadcasting would only survive if it continued to experiment with content innovation and new programming and employed big data analytics with a view to increasing performance (Bughin, 2016). And increased performance is exactly what the advertiser was looking for.

METHODOLOGY

The goal of this study was to test if the use of big data analytics could improve the effectiveness of a TV advertising campaign, using the following hypothesis:

H_1 *Thanks to an advanced segmentation based on big data analytics, the percentage of impacted viewers that visit the advertiser's website within the first 24 hours can be higher than the norm (0.12%)*

To test this hypothesis, seven steps were agreed between the parties and carefully followed when designing, implementing and measuring the test campaign (Figure 3):
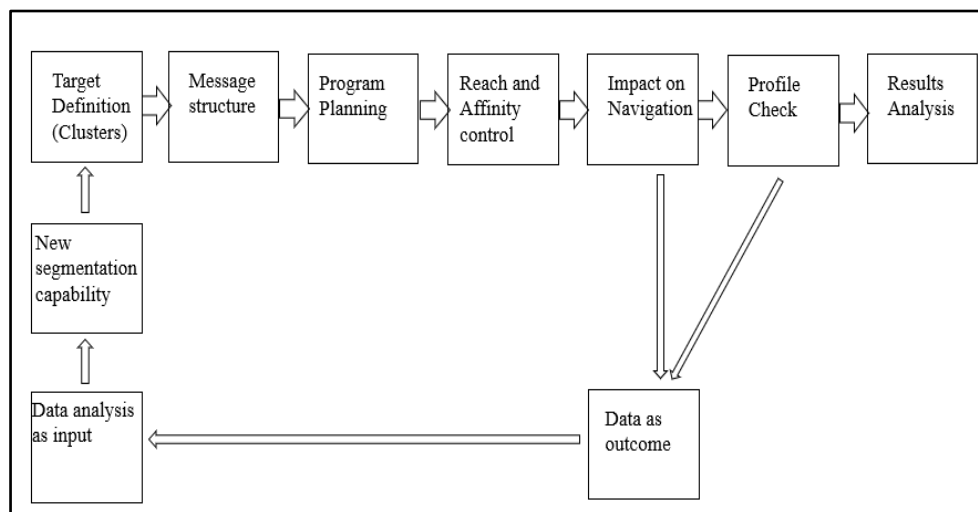

FIGURE 3
THE SEVEN STAGE PROCESS

Target Definition

TV operators are moving towards behavioral data collected from panels or in real-time from viewers who consume video content across formats, platforms, and screens. Behavioral data is also key to unlocking new insights by placing viewer habits in context, enabling a better understanding of the audience and emerging trends (Murschetz & Schlutz, 2018). In our case, the advertiser was looking for very specific behavioral data: actively

interested in travel, actively interested in gastronomy, interested in true, memorable experiences, and active users of social networks, on top of socio-demographic attributes like being 35 to 70 years old, medium and medium-high class, with children. Through big data analysis, all TV subscribers' data was screened from diverse touch point's such as platform subscriptions, browsing history, response to interactive campaigns, place of residence, type of decoder (standard or premium), geo-location, roaming activity.

Audiences were then clustered; combining three socio-demographic dimensions (age and gender, and having kids) with five new psychographic ones (see Figure 4).
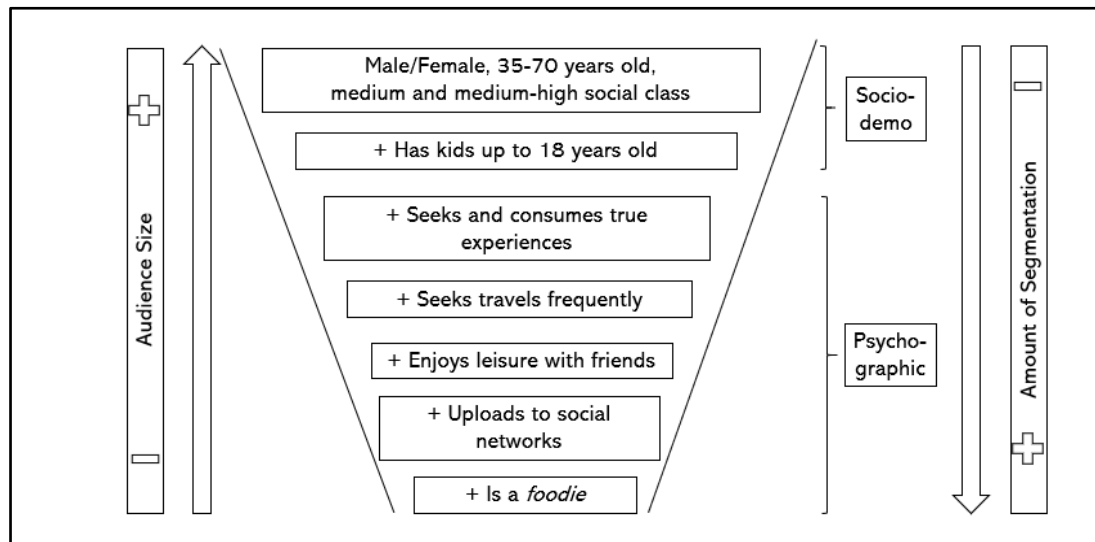

FIGURE 4
SOCIO/PSYCHOGRAPHIC SEGMENTATION FUNNEL

Message Design

Brands generate true value to consumers when consumers perceive them in a differentiating, special and attractive way versus competing rivals (Vera, 2008). To achieve this, the message was built around several key drivers aimed at further engaging such a well-segmented target, like clear references to new and memorable experiences, to travelling with kids, and to high-end gastronomy. The message was a 20 spot and was displayed across several timeframes and channels within the TV platform, both on linear TV (live) and on Video on demand.

Planning

The acquired data was downloaded to an RPD (Return-Path Data) system, using its capability and learned experience for planning the content in the best possible way to the newly formed psychographic clusters.

The content was then displayed in two ways: Commercial breaks during a list of programs, based on affinity with the cluster, and Video on Demand where the 20'' spot was served as a mandatory pre-roll to any person belonging to the defined cluster that would wish to see any already broadcasted program, or a film.

Reach and Affinity Control

Along the campaign, reach (the absolute number of customers to which the message has been served, and the % number *vs.* total audience) and affinity (proximity between the final audience of the program and our targeted cluster).

Impact on Navigation

The system monitored the number of households that visited the brand site in the first 24 hours after being impacted, and the total number of households that visited the brand site during the campaign, as a percentage of total households impacted. These metrics generate data as an output that once fully analysed is fed as input onto the continuum process of cluster definition, to further improve the segmentation ability.

Profile Check

Once the campaign is finished, a full assessment of the customers visiting the brand's site was conducted and compared with the initial target profile, to identify any key difference and feed-back this data into a new segmentation process.

Analysis of the Outcome

The final analysis is quantitative and is carried out as a final stage of the process, to assess whether the hypothesis was validated.

RESULTS

The new psychographic segmentation that was implemented using big data Analytics led to a better targeted campaign with the following outcome and results:

1. *H1 hypothesis was validated*: The percentage of viewers that went to the advertiser's website in the first 24 hours after being impacted grew from 0.12% (norm) to 0.24% thanks to the advanced segmentation model. *According to the TV provider, this percentage set a record of immediate effect on consumers' behaviour, being twice as much as what they had previously achieved on prior general campaigns with other advertisers, thanks to the new way of segmenting the audiences.*
2. A further new contribution to advertisers is coming from the cross-analysis of impacted audience and navigation data. Results indicate how many impacts were needed to 'move' a customer into the website: customers that visited the website were impacted an average of 2.38 times, versus 1.75 times for customers who did not visit the web. This powerful insight enables future advertisers to know, for specific psychographic or lifestyle audiences, the amount of advertising pressure below which consumers will not react, as well as the sufficient number of impacts needed to obtain a response from consumers, thus avoiding unnecessary spend above that figure.

DISCUSSION & CONCLUSION

Our theoretical contribution proposes a new concept that addresses the existing literature that signals the loss of effectiveness of traditional TV advertising (Arrazola et al., 2013; Given, 2016; Rubinson, 2009). Our study responds to this challenge with an actionable and innovative way of segmenting audiences based on big data. It overcomes the traditional problem of achieving reach but without discriminating audiences with anything more than basic sociodemographic criteria (Büger & Hylkè, 2017). The biggest practical implication is that advertisers can now design much better targeted campaigns to better reach the target with the highest affinity to the advertising message, thanks to the analysis of big data about consumers. Big data can enable a better understanding of the audience and emerging trends (Murschetz & Schlutz, 2018). The exercise shown in this study is an example of how TV broadcasters are being forced to look for new practices that can deliver results to advertisers and maintain the relevance of TV to consumers (Given, 2016). Against those who signal the loss of effectiveness of TV, we have been successful with our method.

Moreover, with our study we are offering new and more tangible ways of measuring advertising effectiveness, which traditionally was measured only in terms of reach (Bína et al., 2019). We are now able to measure TV advertising effectiveness with consumer

behaviour as a consequence of the campaign. This way, it is no longer a question of measuring the effort (how many people have we reached, and how many times) but also measuring the result (what have they done as a consequence of our effort). Our study is an example of how consumers have become a factory of data, and how big data has the potential to transform the art of management. Big data has the ability to change the decision-making process, enhancing visibility of firm operations and improving performance measurement mechanisms (Wamba et al., 2015; Erevelles et al., 2015).

Our study also suggests that companies are able to react to a fast-changing and very competitive external environment by using dynamic capabilities (i.e. sensing, seizing, transforming) (Teece, 2007). These dynamic capabilities find on big data new ways to address the marketing challenges around improving performance and establishing new competitive advantages. Managers in turbulent environments need to make sound decisions quickly to better suit to the environment (Pavlou & El Sawy, 2011). In the case we study, the advertiser was proactive in sensing the market to find available solutions to its needs of increasing performance. . The lookout in the market for a TV provider with the right technology is an example of the Sensing capability. Once found, the adaptation of the new technology to the company's goals is an example of the Seizing capability. And the creation of a seven-step model to design, implement and evaluate the campaign is an example of the Transforming capability. The sensing activity is also related to an entrepreneurial approach to leadership, needed to survive the challenging business environment (Fatoki, 2021). Dynamic companies like the one we are studying are constantly sensing the market for new opportunities, seizing them inside their organizations and transforming the working processes - to improve performance as a result (Teece, 2007; 2014). The ability to respond to changes is a complex process can only be achieved when firms develop and apply capabilities sooner, more astutely, or more fortuitously than their competitors (Eisenhardt & Martin, 2000). Firms that develop strong big data analytics have shown to be better positioned to sense emerging market opportunities and threats (Akter & Wamba, 2016). As we have shown in this case report, merging big data analysis and Dynamic Capabilities helped to successfully address one of the biggest marketing conundrums: how to go beyond traditional socio-demo segmentation in non-connected TV, and how to measure the investment results in terms of consumer behaviour (web visits) and not just in terms of advertising pressure

Our study is not exempt of limitations, since it relates to a group of companies from the tourism industry that joined efforts to overcome the loss of effectiveness of traditional TV advertising. The study could be run across different industries to prove that the use of big data analytics can improve audience segmentation to address the right message to the right consumer and consequently achieve better campaign results.

There are some further researches avenues that can be derived from this case, as further empirical studies are needed that carefully examine how organizations actually realize value from big data in practice (Gunther et al., 2017). We also suggest a need for research to define a cross-industry model where the use of big data analytics achieves improvement on marketing communication performance. Big data analysis should be able to define more accurate targets (beyond socio-economic), impact them in a better targeted moment and in a way that is able to prompt action from consumers. This case report also suggests theoretical implications referred to the attribution model (Nisar & Yeung, 2018). Since consumers are exposed to many messages from the same advertiser across a number of channels and moments, including the powerful nature of social media as a two-way communication tool between consumers and brands (Khadim et al., 2018), one of the most important questions facing the advertising industry today is to explain the which of the impacts is responsible for the final purchasing decision. As such, a conversion may be the result of a series of ads that

were displayed to the consumer (Abhishek et al., 2014). Normally, companies attribute this responsibility to the last impact received by a consumer before purchasing. It should be researched if big data analytics is able to reduce the number of impacts to achieve a sale, thanks to an improved segmentation capability, and also if it is able to change the attribution model from the usual *"last impact received"* to *"best targeted impact"*.

The role of individual managers seems to be key in this case and could also be the subject of further research. This subject has begun to assume greater importance as the micro foundation of dynamic capabilities (Teece, 2007) for organizational adaptation and change (Adner & Helfat, 2003). Some managers may have *"dynamic managerial capabilities"* with which to build, integrate, reconfigure, and competitively reposition organizational resources and capabilities, and have more effective capabilities than others for anticipating, interpreting, and responding to the demands of an evolving environment (Helfat & Peteraf, 2014). Additionally, further research could address the opportunity and impact of merging communication strategies directed to consumers from a brand perspective with those from a company perspective, especially given the broad use of social networks by corporations (Ratliff & Kuntz, 2014). Finally, further research could analyse the new opportunities for improved marketing performance that are arising from the current pandemic. Covid-19 has forced new behaviours that are feeding a whole new set of big data to better understand consumers. It could be researched how specific industries are taking advantage of this, and what is the impact on marketing performance, cost reduction and consumer satisfaction.

As time passes, the possibility to add new segmentation variables will improve. Digitization and the ability to extract value from the analysis of big data is still emerging, will keep growing and could have a substantial impact at all levels of business management – and in our lives.

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