Assessing the Drivers of Machine Learning Business Value

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This is the accepted author manuscript of the following article published by Elsevier:

Reis, C., Ruivo, P., Oliveira, T. & Faloreiro, P. (2020). Assessing the drivers of machine learning business value. *Journal of Business Research*, Vol. 117, September 2020, Pages 232-243.

Doi: https://doi.org/10.1016/j.jbusres.2020.05.053

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Abstract

Machine learning (ML) is expected to transform the business landscape in the near future completely. Hitherto, some successful ML case-stories have emerged. However, how organizations can derive business value (BV) from ML has not yet been substantiated. We assemble a conceptual model, grounded on the dynamic capabilities theory, to uncover key drivers of ML BV, in terms of financial and strategic performance. The proposed model was assessed by surveying 319 corporations. Our findings are that ML use, big data analytics maturity, platform maturity, top management support, and process complexity are, to some extent, drivers of ML BV. We also find that platform maturity has, to some degree, a moderator influence between ML use and ML BV, and between big data analytics maturity and ML BV. To the best of our knowledge, this is the first research to deliver such findings in the ML field.

Keywords: Machine learning; business value; competitive advantage; dynamic capabilities theory

1 INTRODUCTION

The current wave of the industrial revolution has flooded every single business with the next generation of technology (Xu, Xu, & Li, 2018), from emerging solutions that gather significant data, such as the Internet of Things (Rehman, Chang, Batool, & Wah, 2016), to the advanced analytics that retrieve relevant insights from these data, such as machine learning (ML) (Antons & Breidbach, 2018). However, as business processes become more complex and stored data greater, serious problems arise (Hernández, Perez, Gupta, & Muntés-Mulero, 2018; Sivarajah, Kamal, Irani, & Weerakkody, 2017). While awash in data, companies are still starving for insights (Ferraioli & Burke, 2018).

Steady advances in digitalization made big data analytics (BDA) become the new key driver of value creation within organizations (Côrte-Real, Ruivo, Oliveira, & Popovič, 2019; Sivarajah et al., 2017). In fact, companies that use data and analytics become 5% more productive, and 6% more profitable than their competitors (McAfee & Brynjolfsson, 2012). However, modern companies need to continue investing in more complex techniques to overcome the present intense competition (D. Q. Chen, Preston, & Swink, 2015; Jimenez-Marquez, Gonzalez-Carrasco, Lopez-Cuadrado, & Ruiz-Mezcua, 2019).

ML stands out as one of the best-suited advanced analytics for dealing with big data (Bose & Mahapatra, 2001; Lismont, Vanthienen, Baesens, & Lemahieu, 2017). This branch of artificial intelligence (AI) (Michalski, Carbonell, & Mitchell, 1983) has emerged due to recent advances in computational capabilities that have dramatically decreased the costs of its algorithms (Agrawal, Gans, & Goldfarb, 2017; Kwak, Lee, Park, & Lee, 2017). Now, recent studies suggest ML will completely revolutionize the business landscape in the near future (Jimenez-Marquez et al., 2019). Its wide range of applications has been reported to actually foster labor disruption and business model redefinition within organizations (Wright & Schultz, 2018). Successful stories such as the ML deployment on Walmart’s search engine have provided early evidence that ML can improve performance and create competitive advantage (CA) (Raguseo & Vitari, 2017). Nevertheless, academics and practitioners still hesitate to embrace ML. While scholars call for more extensive research on ML to match the growing relevance of this technology in businesses (Nascimento, Cunha, Meirelles, Scornavacca, & De Melo, 2018), companies continue to struggle to deploy ML (Table 1) thoroughly.

Table 1 - Organizations grouped by their judgment of ML potential

Cluster	Adapted Source	Description
No ML	(Lismont et al., 2017)	Organizations either unaware of ML or still investigating it.
ML Bootstrappers	(Economist Intelligent Unit & SAP, 2018; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Lismont et al., 2017)	Organizations that already decided to implement ML systems through a gradual process. They have attained low positive outcomes.
ML Fast Learners	(Economist Intelligent Unit & SAP, 2018; Hernández et al., 2018; LaValle et al., 2011; Lismont et al., 2017)	Organizations that have fully embraced the ML solution. It has already paid off.

These showcase that both academics and practitioners share the same unanswered question: *What are the key drivers of machine learning business value?* Moreover, academics and practitioners might have gone further and detected a potential moderator of ML BV. Moderators are rarely perceived associations that provide an important contextualization and, thereby, produce invaluable insights. Scholars postulate that the IT infrastructure existing in an organization has an enabler effect on the integration of new analytics solutions (Nwankpa & Datta, 2017). At the same time, companies conjecture that more mature platforms speed up new innovation developments (Anand, Coltman, & Sharma, 2016). Translating this judgment to the implementation and further enhancement of ML algorithms, a second research question worthy of investigation arises: *Does platform maturity have a catalytic effect on machine learning business value?*

The contributions of this article are fourfold. First, this is a pioneering investigation of important antecedents of ML BV, which aims to uncover how firms can gain CA from ML specifically. So far, no research has focused on providing an ML BV integrative model, uncovering key determinants with direct and moderator effects. Second, the provided model and conjectured hypotheses are substantiated by a large sample of 319 firms based in Europe and North America, which grants our research discoveries an empirical corroboration. Third, our findings are of interest to a wide range of companies, as the firms we examine are spread across six different types of industries. Fourth, we explore an important moderator of ML BV, platform maturity. Most standard technology models only incorporate direct effects. Therefore, we see these added hypothesis paths as rare and influential additional insights. Overall, with this study, we contribute to the positive loop existing between academia and industry that continuously triggers new breakthroughs for our future (Zhu, Huang, Chen, & Gao, 2018).

To eliminate ambiguity, we use our literature review to define the terms "ML," "BV," and "ML BV." We then provide an overview of the dynamic capabilities theory (DCT) as our theoretical paradigm. In the following section, we propose our conceptual model, which is then assessed through a large-scale survey. Each significant finding is discussed regarding the earlier literature pertaining to it. We conclude with academic and managerial implications, limitations, and avenues for future research.

2 Literature Review

2.1 Machine Learning

ML is herein defined as a system fueled by data (Jimenez-Marquez et al., 2019; Thomas, Abraham, & Liu, 2018) that uses algorithms but does not rely on rule-based programming (Kaplan & Haenlein, 2019). Its ability to learn and improve (Gollapudi & Phillips, 2016; Kwak et al., 2017) allows ML to detect hidden patterns (Bose & Mahapatra, 2001) and make decisions (Gollapudi & Phillips, 2016) with minimal human intervention (Kwak et al., 2017), providing knowledge and data-driven insights that are crucial to business (Bohanec, Borštnar, & Robnik-Šikonja, 2017; Jarrahi, 2018).

A more profound approach to the term ML subdivides this discipline into three categories based on the type of observation: supervised learning, unsupervised learning, and reinforcement learning (Jimenez-Marquez et al., 2019; Kaplan & Haenlein, 2019). In turn, each observation type embraces a set of ML algorithms.

Earlier studies have used the term ML referring to only a specific subfield or algorithm of the discipline (e.g., Antons & Breidbach, 2018). In this research, ML is used in its broader sense, and no emphasis will be given to a category or algorithm. The same sense is used in Bose & Mahapatra (2001).

2.2 Business Value - Achieving Competitive Advantage

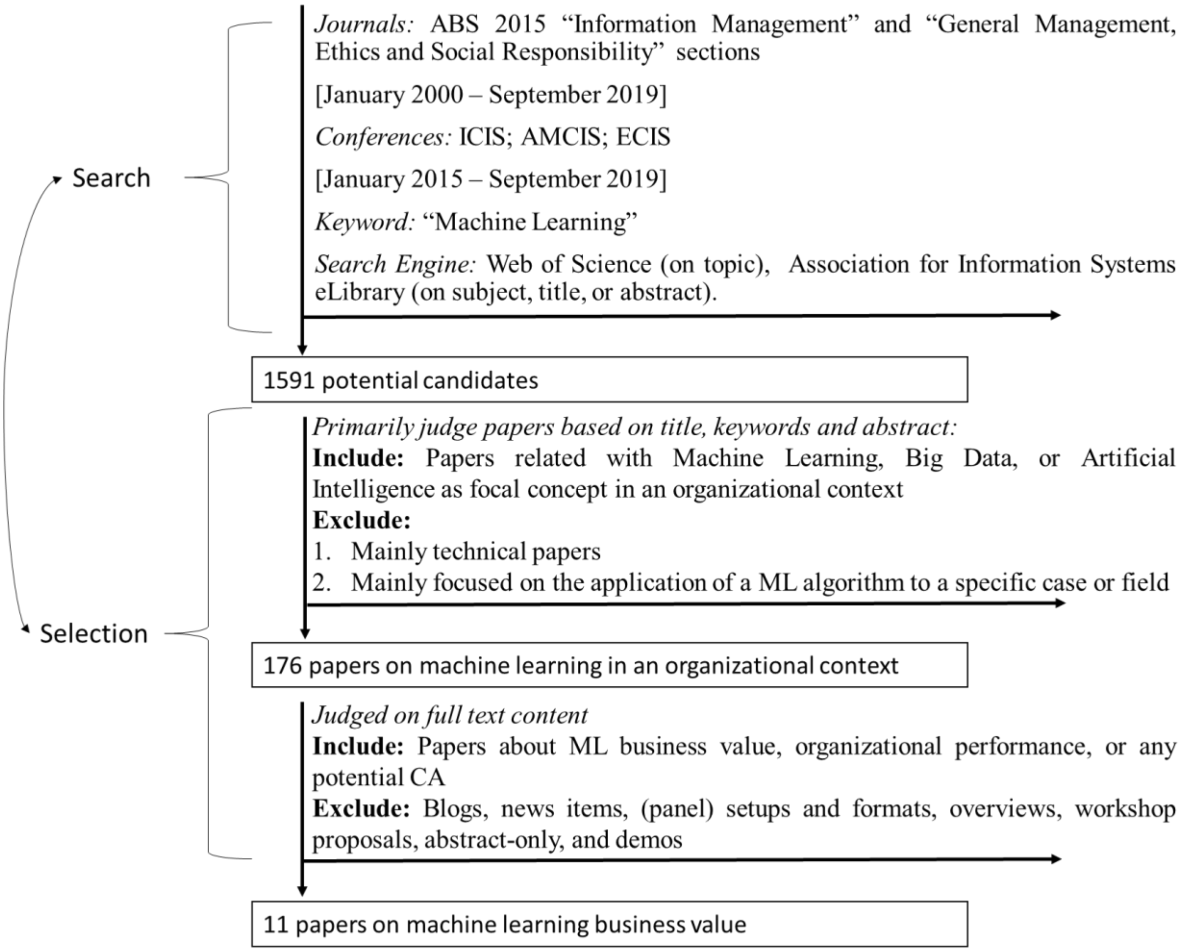
The ultimate goal of any BDA investment lies in achieving BV, which provides the firm with enduring CA (Côrte-Real et al., 2019; Grover, Chiang, Liang, & Zhang, 2018). The process to attain BV involves continuously developing and deploying the resources and capabilities (R&C) that support dynamic business models that bring firms stable and long-lasting profitability (Shan, Luo, Zhou, & Wei, 2019; Teece, 2018). In the current fast-paced landscape, it has become harder for companies to cultivate such R&C (Shan et al., 2019; Teece, Pisano, & Shuen, 1997). The solution seems to include the exploration and exploitation of innovations that overcome the usual rigidity of core competencies (Shan et al., 2019; Teece et al., 1997). By building the capacity to sense opportunities and reconfigure knowledge base assets, firms can achieve enduring performance and, thereby, CA (Shanks, Gloet, Someh, Frampton, & Tamm, 2018).

2.3 Machine Learning Business Value - Achieving Competitive Advantage

Achieving CA through ML, refers to the creation of BV which includes finding new revenue streams (Schreck, Kanter, Veeramachaneni, Vohra, & Prasad, 2018), restructuring current business models (Nascimento et al., 2018), and reinventing existing products and services (Schreck et al., 2018). ML BV can also represent the improvement of a firm's internal processes (Schreck et al., 2018) at efficiency and quality levels. Additionally, ML BV can equally provide unexpected insights regarding buying behavior patterns (Stormi, Laine, & Elomaa, 2018). Overall, the potential of ML BV conveys financial (Beath, Tarafdar, & Ross, 2018) and strategic results (Bose & Mahapatra, 2001) that will ultimately lead a firm to attain CA (Jimenez-Marquez et al., 2019; Schreck et al., 2018).

Based on the above considerations of ML BV, we reviewed the literature to assess our standpoint. Our structured review is similar to the one performed by Günther, Mehrizi, Huysman, & Feldberg (2017). In our case, the process involved reviewing relevant journals and conferences that bring insights about ML BV within organizations. We found eleven papers while applying the search process illustrated in Figure 1.

Figure 1 - Search and Selection Processes



Bose & Mahapatra (2001) exposed the strengths and weaknesses of ML techniques in business data mining contexts – "finance and marketing lead other areas in application count. Two characteristics of these areas may explain the widespread use of data mining. First, the computerization of transaction processing activities has created large databases ready to be mined. Second, these areas offer high potential payoff for data mining applications." Merkert, Mueller, & Hubl (2015) showcased how ML may bring different results based on task, decision-making phase, and technology. Nascimento et al. (2018) presented AI and its subfields as solutions with ever more applications for management – "Our review of the articles, however, reveals encouraging results regarding AI research on decision making…, supply chain management…, financial time series forecasting…, market predictions…, innovation…, and helping sustainable development goals".(Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira, 2016)(Jimenez-Marquez et al., 2019)(Jimenez-Marquez et al., 2019) Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira (2016) developed an ML review concerning financial markets. Jimenez-Marquez et al. (2019) focused on ML deployment on social media content and the consequent potential for enhancing customer relationships. Stormi et al. (2018) used a case study to evaluate the ML BV in B2B marketing management. Beath et al. (2018) presented an in-depth description of a firm's successful ML deployment within their business processes – "Not surprisingly,… attitude toward the use of ML had received a positive boost". Savage (2012) documented ML potential in medicine. Zhao & Siau (2017) focused on emotion classification (ML algorithm). Lismont et al. (2017) conducted a descriptive survey in which ML emerged as the best technique for decision-making support. In contrast, Parnas (2019) exposed his belief that ML problems can be solved through conventional hardware and programming language.

To the best of the authors' knowledge, the few existing articles tackling the potential of ML inside an organization share the disadvantage of being limited to a particular ML subfield, an ML algorithm, or a specific task, department area, or industry. Moreover, none of the studies provide a theoretical model uncovering variables with direct or moderator effects on ML BV.

Motivated by these gaps in the literature and grounded in DCT lenses, this research seeks to determine the keychain that unlocks ML BV for organizations in general. Ultimately, the outcomes are expected to contribute with crucial insights for real business discussions on how to generate results from ML solutions while balancing the company's financial and strategic performance.

3 INTEGRATIVE MODEL OF MACHINE LEARNING BUSINESS VALUE

3.1 Dynamic Capabilities Theory

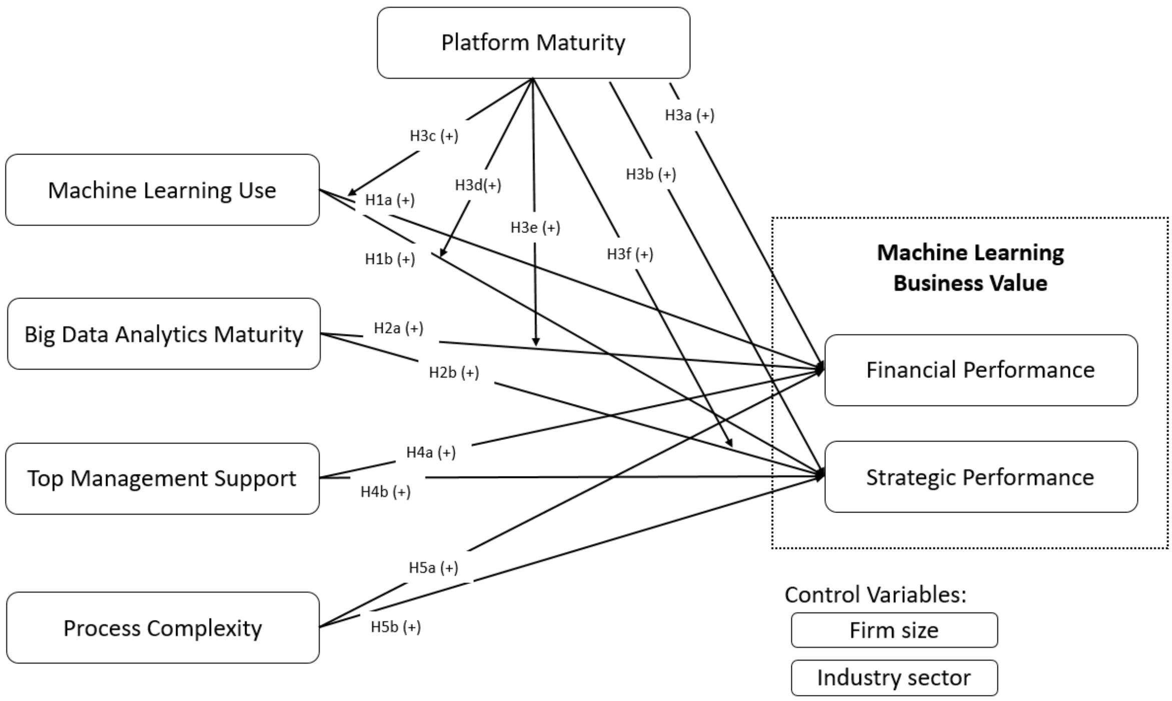
Over the years, researchers have employed different theoretical paradigms to assess the performance impact of technologies. Earlier theoretical approaches, such as Porter's five forces, have emphasized the exploitation of market power strategies to attain CA (Teece et al., 1997). Eventually, these tactics turned out flawed in scenarios where rivals had deep-seated CA. Over time, the understanding of the true source of CA evolved and, more focus was built around the development and combination of a firm's unique set of skills (Barney, 1991). The renowned resource-based view recognizes that the R&C of each firm determine their ability to achieve CA (Barney, 1991). To be considered a CA source, resources must be valuable, rare, imperfectly imitable, and non-substitutable. Nevertheless, this theory also revealed limitations when companies with similar R&C achieved different CA outcomes (Shan et al., 2019).

The DCT emerged in response to this limitation integrating two additional factors on top of the resource-based view (Teece et al., 1997). This theory presumes the marketplace conditions will influence the process to achieve CA. Here, it is acknowledged that we live in an innovation-based industry alongside a much more demanding clientele (Setia, Venkatesh, & Joglekar, 2013; Teece et al., 1997). Second, it assumes that firms need to continuously update their resources and develop new capabilities to maintain ownership of the scarce R&C that provide them CA (Shan et al., 2019; Teece et al., 1997). As a result, the DCT can be seen as the emerging paradigm to understand the newest sources of CA in the present landscape (Teece et al., 1997). Following this paradigm perspective, we present the model below.

3.2 Integrative Model and Hypotheses

According to the literature mentioned above, ML applications may have a positive, negative, or null effect on firm performance. Furthermore, this effect may be strongly influenced by specific actions or developments realized within the organization. In response, an integrative model was developed with the core purpose of assessing the potential antecedents of ML BV. Figure 2 presents our proposed conceptual model.

Figure 2 - Conceptual Model: Machine Learning Business Value



The right-hand side of our conceptual model shows how ML can impact firm performance and create BV. Through our understanding, an organization's performance becomes CA when it achieves BV in terms of financial and non-financial outcomes (Côrte-Real et al., 2019; Galy & Sauceda, 2014). Financial performance relates to profitability ratios measured against a sector or an industry benchmark (Côrte-Real et al., 2019), while non-financial benefits account for R&C intangible effectiveness (Galy & Sauceda, 2014) on creating new opportunities that ultimately lead to value creation (Teece et al., 1997), and thereby improvements in marketing, finance, operations, and other core business areas (D. Q. Chen et al., 2015; Gold, Malhotra, & Segars, 2001). According to the DCT, it has actually become more critical for companies to find these new opportunities through data-driven insights than to pursue standard "business-as-usual" practices (Teece et al., 1997). Indeed, an organization's performance goes beyond financial or strategic performance domination. It entails a comprehensive and complex decision process where trade-offs between short-term and long-term results are weighted in real business scenarios. In an attempt to capture the most out of an organization's performance potential to become CA, we portrayed ML BV as a combination of both financial and strategic performance.

The left-hand side of the conceptual model shows the antecedents and the moderator of ML BV under review. Through an extensive literature review of BDA, AI, and ML value, we collected a large initial pool of potential factors that might have a significant effect over ML BV. From this set, we selected the five antecedents and the one moderator that exhibited the highest potential. Following Teece et al.'s (1997) line of thought, we make a leap in the understanding of our constructs and portray these adjacent independent variables as dynamic capabilities themselves, as we anticipate that they will allow firms to achieve new and innovative forms of ML BV in this rapidly changing environment. The selected variables for analysis are ML use, BDA maturity, platform maturity, top management support, and process complexity. The rationale for each construct and structural path is described in the following sub-sections.

3.2.1 Machine learning use

ML use is the extent to which ML applications are being deployed to support the activities inside the organization (Côrte-Real et al., 2019). This concept becomes vital when the literature discloses that companies are not deriving BV from this solution as they are actually not working with the technology (Ruivo, Oliveira, & Neto, 2015). This aspect means that they are not further developing their expertise in the matter. However, without a greater awareness of how to bridge the gap among algorithms, working models, and real problems, no tangible results will emerge (Schreck et al., 2018).

In order to attain value, companies must evolve their actual applications of the innovation in question to their business processes (Lismont et al., 2017).

H1a: ML use has a positive effect on financial performance.

H1b: ML use has a positive effect on strategic performance.

3.2.2 Big data analytics maturity

Some researchers believe that the earlier companies implement analytics on their organizational processes, the earlier they will advance to more complex techniques (Lismont et al., 2017). In general, innovation is more likely to occur in organizations that have a more conducive environment for innovation in place (Fichman, 2001). More compelling reasons appear when we understand that these companies must have broken down the organizational silos that typically constrain data sharing and analytics across functional boundaries (Kitchens, Dobolyi, Li, & Abbasi, 2018).

Synergies of centralized capabilities structures can help firms attain a sustainable environment faster (Günther et al., 2017). In the same vein, it has been proven that BDA and digitalization have a positive incremental effect on business models (Rehman et al., 2016).

H2a: BDA maturity has a positive effect on financial performance.

H2b: BDA maturity has a positive effect on strategic performance.

3.2.3 Platform maturity

Deploying the right technology architecture and capabilities is considered to be very important (if not the main criterion) for obtaining value from data and analytics (Barton & Court, 2012). The competence to incorporate data from multiple sources and the ability to share data are seen as crucial requirements (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011; Lismont et al., 2017). Researchers have even found that mature platforms are able to leverage and re-use more data (Anand et al., 2016). This capability can lead to further discoveries of actionable insights (Anand et al., 2016) without compromising the current business needs.

A higher line of thought holds that the construct in question may play an even greater role in our model. Earlier literature has emphasized the importance of data quality and data management for companies to realize BDA results (Côrte-Real et al., 2019; Wamba et al., 2017). In fact, the most common challenges for analytics have been the ability to share and integrate data (Lismont et al., 2017).

H3a: Platform maturity has a positive effect on financial performance.

H3b: Platform maturity has a positive effect on strategic performance.

H3c: Platform maturity has a positive moderator effect on the relationship between ML use and financial performance.

H3d: Platform maturity has a positive moderator effect on the relationship between ML use and strategic performance.

H3e: Platform maturity has a positive moderator effect on the relationship between BDA maturity and financial performance.

H3f: Platform maturity has a positive moderator effect on the relationship between BDA maturity and strategic performance.

3.2.4 Top management support

The literature suggests that active senior management has the power to enhance the signification, legitimization, and domination of a technology inside a firm (Rai, Brown, & Tang, 2009). The endorsement of an innovation in public by executives will influence the proactiveness of organization members toward that exact solution (Rai et al., 2009; Ramamurthy, Sen, & Sinha, 2008). In other words, it will diminish the resistance that normally accompanies organizational innovation. At the same time, managerial competence to assess and redefine business models seems to have a great impact on a technology's potential to seize actual opportunities (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Teece, 2018).

H4a: Top management support has a positive effect on financial performance.

H4b: Top management support has a positive effect on strategic performance.

3.2.5 Process complexity

Advancements in digitalization have further increased the complexity of companies' processes (Shan et al., 2019). This on-going tendency is making it impossible for companies to base their business model on subjective notions (Bohanec et al., 2017). Intelligent systems are being incentivized to introduce more data-driven insights into business decisions (Bohanec et al., 2017; Jarrahi, 2018). BDA, such as ML, has the power to optimize business processes and increase business opportunities (Côrte-Real et al., 2019; Rehman et al., 2016). In fact, ML algorithms have been singled out to support business model definitions in scenarios where complexity is the main inhibitor (Jarrahi, 2018; Kuzey, Uyar, & Delen, 2014).

H5a: Process complexity has a positive effect on financial performance.

H5b: Process complexity has a positive effect on strategic performance.

Control variables are essential to capture variations of data that are not explained by constructs. We use firm size and industry sector as in previous studies (Martins, Oliveira, & Thomas, 2016; Rai et al., 2009).

In the next section, we present the elected research methodology to validate our conceptual model and its hypotheses.

4 RESEARCH METHODOLOGY

4.1 Measurement

A survey was the selected research strategy to assess the conceptual model. This approach has been recommended to academics as it allows them to foster a relationship with organizations (Flynn, Sakakibara, Schroeder, Bates, & Flynn, 1990) and to gather the perceptions of key personas that hold extensive field experience (Rungtusanatham, Choi, Hollingworth, Wu, & Forza, 2003). Therefore, this data collection methodology empowers researchers to corroborate their conceptual model through real-world data (Flynn et al., 1990).

Our questionnaire was developed, assuming that it would target companies that were already using ML. Through this process, we would be able to assess this technology's drivers of value creation within organizations. To attain significant results, we based our constructs on past literature (Appendix 1). By the same token, we measured those constructs using a well-established seven-point range scale, ranging from "strongly disagree" to "strongly agree."

At an early stage, an expert panel of five individuals with extensive experience in survey development in the information systems area reviewed our questionnaire. Minimal adjustments were made to anchors and item questions, so the overall concepts best match the domain under review. We conducted a pilot survey among 30 organization members to test the instrument.

These responses were not included in our principal analysis. Their purpose was to test our inquiry's reliability and validity and the consensus around the definition of terms. Proposed adjustments were implemented.

4.2 Data

An online version of our questionnaire was made available and sent in January 2019 to 2,000 companies. Given the complexity involved in data collection when targeting a large number of subjects, a professional market research organization was involved in the process. The targeted representative sample included organizations based in North America and Europe, across a mix of small, medium, and large companies. The following set of criteria was ensured to induce data quality and data relevancy: companies should have an ML solution in place (regardless of the software provider), the respondent should be familiar with ML algorithms, ML principles, or with how ML data-driven insights can be interpreted. In order to reduce latent biases, the respondents were assured that their inquiries and identities would remain confidential and that only aggregate information would be shared. In an effort to foster the organizations' interest in completing the full questionnaire, a benchmark report would be sent afterward to those who completed it so that they could assess their position against the average reply in a detailed analysis until the item question level.

In a first wave during the month of January, we received 210 valid responses. After a follow-up email at the beginning of February, a second one-month wave resulted in an additional 109 valid responses. We confirmed the absence of non-respondent bias between the early and the late respondent sets through the Kolmogorov-Smirnov (K-S) test (Ryans, 1974). An overall 16% response rate was achieved (319 responses), summarized in Table 2.

Table 2 - Sample composition

Sample characteristics (n=319)	Observations	(%)
Respondent position		
Board member, general manager, CEO	33	10.3%
Manager of business unit or department supervisor	140	43.9%
Data scientist, data specialist, or technical role	146	45.8%
Industry Sector		
Banking & insurance	32	10.0%
Health & education public sector	27	8.5%
Retail & consumer products	62	19.4%
Construction & professional services	43	13.5%
Production & manufacturing	100	31.3%
IT & telco	55	17.2%
Firm size		
# of employees		
50 to 249	11	3.4%
250 or more	308	96.6%
Annual turnover		
From 10 to 50 million dollars	25	7.8%
More than 50 million dollars	294	92.2%
Country		
North America		
USA	93	29.2%
Canada	57	17.9%
Europe		
Germany	38	11.9%
Italy	51	16.0%
France	34	10.7%
United Kingdom	46	14.4%

The respondent profile was approximately 10% board members, 44% managers, and 46% data scientists. It could be verified that the more technical the job profile, the greater was their knowledge about ML (Appendix 2). Most of the organizations surveyed were large corporations across a spectrum of industry sectors. In terms of their ML structure (summarized in Table 3), most companies had adopted ML 2 years earlier. The sample comprised companies having from 1 to 5 years of ML experience.

Table 3 - Sample ML Composition

Sample ML Characteristics (n=319)	Observations	(%)
Time since ML adoption		
1	6	
2	102	
3	65	
4	82	
5	64	
ML Types		
Supervised		38.1%
Unsupervised		37.8%
Reinforcement		24.1%
Data types		
Structured		39.7%
Unstructured		60.3%
ML Landscape		
Off-the-shelf ML packages		53.2%
Predictive Analytics		
Applications on predictive analytics		63.2%

These companies applied all three types of ML. Their data type usage was slightly more unstructured than structured data. Regarding the ML landscape, half of their ML algorithms came from off-the-shelf ML packages, and more than half of their overall applications were predictive analytics.

5 RESULTS

We used the partial least squares variance-based technique to test the conceptual model as our goal was to maximize the R^2 values of the dependent variables of the model and thereby its predictability (Henseler, Ringle, & Sinkovics, 2009). The partial least squares application has been explicitly pinpointed (i) for investigations where not all items in the data are distributed normally ($\rho<0.01$ based on the Kolmogorov–Smirnov test), (ii) for research models that have not yet been tested and, (iii) for conceptual models that are considered complex. In particular, the SmartPLS 3.0 software (Ringle, Wende, & Becker, 2015) was the program used to analyze the relationships within our proposed model.

5.1 Measurement Model

Our first assessment focused on the indicator reliability of our measurement items, which is verified when their loadings are higher than 0.7 (Henseler et al., 2009). This test evaluates the absolute correlation between a construct and each of its measurement items. The only measurement item with a loading lower than the threshold 0.7 was eliminated (TMS2) (Appendix 2). In this manner, our model presents good indicator reliability (Table 4). Next, we assessed the internal consistency of our reflective constructs through the composite reliability coefficient (CR). This measure considers that constructs are composed of measurement items with different loadings. The construct's CR value should be higher than 0.7 to verify good internal consistency (Henseler et al., 2009). This criterion was confirmed across all constructs (Table 5).

Table 4 - Loadings and Cross Loadings

Constructs	Item	MLU	BDAM	PM	TMS	PC	FP	SP
ML Use (MLU)	MLU1	**0.878**	-0.174	0.053	0.030	0.011	0.188	-0.043
	MLU2	**0.898**	-0.140	0.153	-0.018	-0.064	0.195	-0.029
	MLU3	**0.762**	0.115	-0.091	0.139	0.008	0.142	0.024
BDA maturity (BDAM)	BDAM1	-0.005	**0.963**	0.031	0.045	0.009	0.388	0.031
	BDAM2	0.135	**0.888**	-0.008	0.062	0.050	0.367	0.052
	BDAM3	-0.287	**0.954**	0.129	-0.028	0.000	0.471	0.041
	BDAM4	-0.150	**0.910**	0.148	-0.018	-0.015	0.460	0.040
Platform Maturity (PM)	PM1	-0.018	0.073	**0.971**	-0.317	-0.178	0.409	-0.011
	PM2	-0.037	0.073	**0.942**	-0.310	-0.170	0.375	-0.006
	PM3	0.259	0.086	**0.879**	-0.297	-0.130	0.459	-0.044
	PM4	-0.000	0.096	**0.967**	-0.310	-0.163	0.457	-0.012
Top Management Support (TMS)	TMS1	0.064	-0.041	-0.315	**0.952**	0.228	-0.247	0.101
	TMS3	-0.045	0.131	-0.253	**0.807**	0.219	-0.123	0.086
	TMS4	0.080	-0.012	-0.292	**0.869**	0.194	-0.159	0.106
Process Complexity (PC)	PC1	-0.002	0.016	-0.117	0.209	**0.853**	-0.055	0.622
	PC2	-0.033	0.047	-0.110	0.170	**0.930**	-0.041	0.841
	PC3	-0.024	-0.031	-0.203	0.241	**0.924**	-0.128	0.596

	PC4	-0.011	-0.014	-0.205	0.274	**0.897**	-0.121	0.556
Financial Performance (FP)	FP1	0.100	0.398	0.230	-0.050	-0.016	**0.746**	-0.014
	FP2	0.139	0.496	0.464	-0.206	-0.070	**0.921**	0.002
	FP3	0.287	0.244	0.416	-0.251	-0.135	**0.834**	-0.069
Strategic Performance (SP)	SP1	-0.011	-0.020	-0.020	0.040	0.520	-0.037	**0.869**
	SP2	-0.015	0.077	-0.014	0.137	0.707	-0.037	**0.932**
	SP3	-0.036	0.049	-0.023	0.115	0.792	-0.015	**0.972**

Notes: Loadings in bold.

Table 5 – CR, AVE and Fornell-Larcker criterion

Constructs	Mean	SD	CR	AVE	MLU	BDAM	PM	TMS	PC	FP	SP
MLU	6.246	0.781	0.884	0.719	**0.848**						
BDAM	5.870	0.704	0.962	0.864	-0.100	**0.929**					
PM	6.017	0.720	0.968	0.885	0.061	0.088	**0.940**				
TMS	5.922	0.963	0.910	0.771	0.047	0.012	-0.328	**0.878**			
PC	5.442	0.736	0.945	0.813	-0.021	0.010	-0.170	0.241	**0.902**		
FP	6.000	0.609	0.874	0.700	0.209	0.459	0.456	-0.212	-0.091	**0.837**	
SP	5.687	0.622	0.947	0.856	-0.024	0.044	-0.021	0.111	0.743	-0.030	**0.925**

Notes:(1) Diagonal elements (in bold) are square root of average variance extracted (AVE), (2) Off-diagonal elements are correlations; ML Use (MLU), BDA Maturity (BDAM), Platform Maturity (PM), Top Management Support (TMS), Process Complexity (PC), Financial Performance (FP), Strategic Performance (SP).

Our third assessment focused on the convergent validity through the average variance extracted (AVE) calculation. According to the literature, AVE should be higher than 0.5 (Fornell & Larcker, 1981). This criterion was also fulfilled in our model (Table 5). Lastly, discriminant validity is assessed through three criteria: (i) square root of AVEs should be higher than the correlation between constructs (Fornell & Larcker, 1981) (Table 5), (ii) loadings should be higher than cross-loadings (Chin, 1998a) (Table 4), and (iii) the heterotrait-monotrait ratio of correlations (HTMT) value should be below 0.90 (Henseler, Ringle, & Sarstedt, 2015) (Table 6). All three criteria are satisfied. In the end, all constructs attested to indicator reliability, internal consistency, convergent validity, and discriminant validity.

Table 6 – HTMT criterion

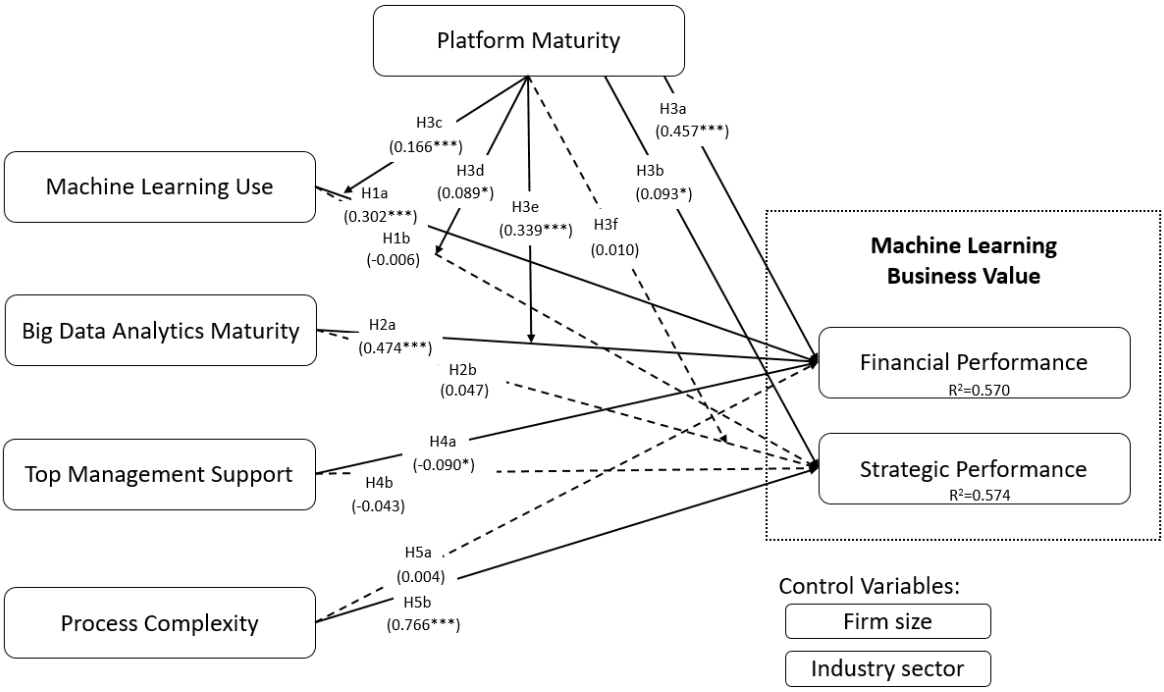
Constructs	MLU	BDAM	PM	TMS	PC	FP	SP
ML Use (MLU)							
BDA Maturity (BDAM)	0.227						
Platform Maturity (PM)	0.162	0.095					

Top Management Support (TMS)	0.120	0.091	0.361			
Process Complexity (PC)	0.041	0.039	0.188	0.281		
Financial Performance (FP)	0.262	0.522	0.507	0.241	0.116	
Strategic Performance (SP)	0.044	0.058	0.022	0.120	0.770	0.044

5.2 Structural Model

Moving forward, we applied the partial least squares method. Collinearity was analyzed through the inner variance inflation model indicator, where the highest result (1.177) was lower than the conservative threshold of 3.3 (Diamantopoulos & Siguaw, 2006). To test our hypotheses' level of significance, we performed the bootstrapping technique with 5000 iterations of re-sampling. Figure 3 shows our model estimation. This model explains 57% of financial performance and 57.4% of strategic performance in terms of ML CA. Both R^2 are considered adequate (Chin, 1998b). Regarding financial performance, ML use (H1a) ($\rho<0.001$), BDA maturity (H2a) ($\rho<0.001$), platform maturity (H3a) ($\rho<0.001$), the moderator effect of platform maturity in the relationship between ML use and financial performance (H3c) ($\rho<0.001$), the moderator effect of platform maturity in the relationship between BDA maturity and financial performance (H3e) ($\rho<0.001$), and top management support (H4a) ($\rho<0.05$) have statistical significance. In turn, strategic performance is explained by the antecedents' platform maturity (H3b) ($\rho<0.05$), process complexity (H5b) ($\rho<0.001$), and by the moderator effect platform maturity in the relationship between ML use and strategic performance (H3d) ($\rho<0.05$). The remaining structural paths (H1b), (H2b), (H3f), (H4b), and (H5a) could not be supported as they did not obtain statistical significance ($\rho>0.05$). All the relevant results are discussed in the next section.

Figure 3 - Structural Model: Machine Learning Business Value



*Note: Significance at * p<0.05;**p<0.01;*** p<0.001.*

6 DISCUSSION

Through our examination of supporting publications, we augment the existing understanding of the ML subject. The following discussion is presented in the order of our findings.

First, ML use has a positive effect on financial performance. This influence has been demonstrated among multinationals such as eBay and Walmart, which implemented ML algorithms in their business processes and subsequently witnessed financial growth and online sales growth (Grover et al., 2018). In the same vein, 85% of America's largest corporations have ranked AI and ML as the most disruptive forces in our future (Jarrahi, 2018). At the same time, a global survey has shown that executives are projected to invest heavily in ML algorithms within the next three years (Jarrahi, 2018). This detail aligns with our results, as companies are just now starting to adopt ML, but are eager to advance and increase their ML plans.

Second, BDA maturity has a positive effect on financial performance. BV through BDA has been widely reported by providing opportunities for companies to differentiate themselves from their peers and attain greater financial results (McAfee & Brynjolfsson, 2012; Wamba et al., 2017). BDA and digitalization have also been registered to provide a positive incremental effect on business models (Günther et al., 2017; Rehman et al., 2016). In this case, we infer that they accelerate ML deployment (Lismont et al., 2017).

Third, platform maturity has a positive effect on financial performance and on strategic performance. Breaking this down, we understand that there are key components of any platform for companies to attain tangible and intangible returns. The abilities to share, integrate, and exploit multiple systems are important stimulators of companies' performance in general (Anand et al., 2016; Vidgen, Shaw, & Grant, 2017). These capacities have been reported to stimulate not only financial and market performance (Wamba et al., 2017) but also provide insightful intuitions for marketing purposes (Kitchens et al., 2018). Nowadays, managers must leverage and re-use real-time and static data to attain higher insights to underpin state-of-the-art products and services (Anand et al., 2016). An eminent example emerged alongside the digitalization of every aspect of our contemporary life. From GPS coordinates to social media, humans are currently a walking data generator of unstructured data for companies (McAfee & Brynjolfsson, 2012). More than ever, firms must enhance their ability to integrate and transform all this data into actionable insights to fully understand customers' needs (Bose & Mahapatra, 2001; H. Chen, Chiang, & Storey, 2012). Next, we encounter reporting and visualization skills. They constitute the bridge across the clear and understandable ML knowledge gap between general managers and data scientists (LaValle et al., 2011) (Appendix 2). Last, the ability to proactively deliver fresh data-driven insights is revealed to provide financial and strategic outcomes (Schreck et al., 2018; Stormi et al., 2018).

On supplementary grounds, platform maturity has a positive moderator effect on the relationships between ML use and financial performance (Figure 4a), ML use and strategic performance (Figure 4c), and BDA maturity and financial performance (Figure 4b). In other words, the effect of ML use as a predictor for financial and strategic performance, as well as the effect of BDA maturity as a predictor for financial performance will be stronger among organizations with a higher level of platform maturity. Thus, when platform maturity increases, the importance of ML use for financial and strategic performance, as well as the importance of BDA maturity for financial performance, are also enhanced. More compelling evidence arose when more mature platforms were leveraging predictive and prescriptive competences at a proficient level (Anand et al., 2016), while legacy systems revealed substantial difficulties to adopt and develop the new cutting-edge analytics further (Nwankpa & Datta, 2017).

Figure 4a - Moderation effect of platform maturity and ML use on financial performance

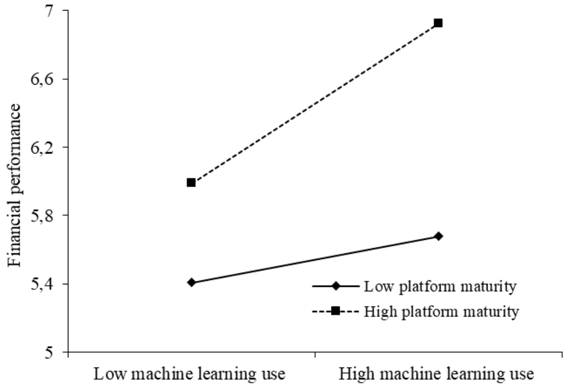


Figure 4b - Moderation effect of platform maturity and BDA maturity on financial performance

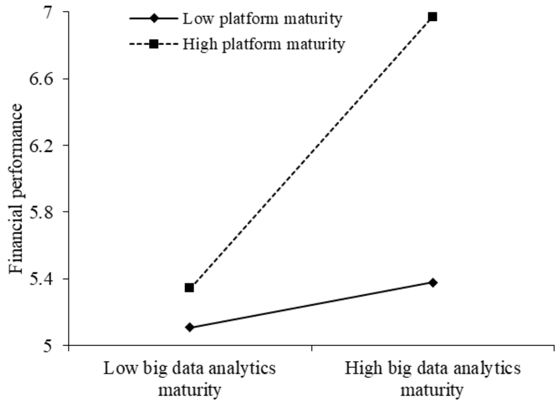
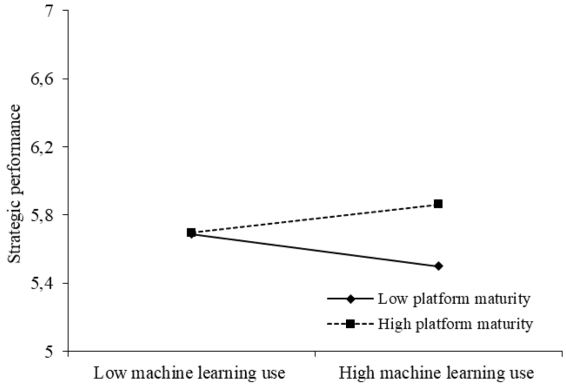


Figure 4c - Moderation effect of platform maturity and ML use on strategic performance



Fourth, top management support has a negative impact on financial performance. This result was a startling finding as we grounded our rationale on the idealization that top management sets the significance and the credibility of a new technology within a firm (Anand et al., 2016; Rai et al., 2009). Nonetheless, this finding does not, otherwise, makes us challenge such ideas. It does, however, make us question what then constitutes ideal top management support (Galy & Sauceda, 2014; Sarker & Lee, 2003). Henceforward, based on our results set, we advance three logical hypotheses to why a type of action might produce an unexpected outcome in a particular context. One explanation relates to the high pressure that comes from general managers that generate anxiety in first-line managers and data scientists. As companies reported to have, at best, five years of ML experience, the eagerness of executives to start deploying data-driven insights and get ahead of the competition (Beath et al., 2018) might trigger a detrimental effect. In accordance, we encountered a study by Galy & Sauceda (2014) that realized long-term plans have a negative impact on EBIT. Alternatively, Weill & Ross (2004) postulate the issue most likely resides in the information technology governance misalignment with the business strategy or even in the inexistence of such plans. This obstacle prevents further ML deployment by executives and impedes ML deployment by employees. Another justification involves addressing our respondent profile, in which 90% of our sample translates managers' and data scientists' perceptions of reality. This element becomes relevant when the literature identifies the existence of a discrepancy between the message sent by executives and the actual message apprehended by workers (Beech, 2000). Thus, the problem may not reside in the inexistence of a vision, goals, and standards, but rather in how they are being expressed and spread across the company. In a nutshell, top management's strategic foresight to overcome the volatility and uncertainty of future business landscapes through the deployment and proliferation of technologies is not put under distrust in this investigation. The present findings serve, however, as a signaling factor to leadership as it invites them to check the resilience that exists within their firms as well as it calls for a reevaluation of the type of actions that have been taken so far to demonstrate their support to the current business model transformation.

Fifth, process complexity has a positive effect on strategic performance. In the new wave of digitalization, companies have the possibility to be in close contact with the environment status at all times (Teece, 2018). However, it comes with the cost of interpreting the tsunami of information that enters their IT infrastructure. ML algorithms have been reported to address all this complexity efficiently. In the finance area, predictive applications are successfully handling risk and credit assessment (Bose & Mahapatra, 2001), while other ML methods are effectively managing financial decision-making dilemmas (Kuzey et al., 2014). In the marketing & sales area, market basket definition and product and services development are being refined by supervised and unsupervised ML algorithms fueled by customers' feedback and their search history information (Singh et al., 2017; Stormi et al., 2018). In the same area, we encounter reinforcement learning applications on websites so organizations can track user behavior and their interests (Rovira & Slater, 2017). In the operations area, machinery data history is being used to refine equipment maintenance (D. Q. Chen et al., 2015; Jarrahi, 2018). The existing complexity and uncertainty of business processes open the space for ML to not only uncover new mapping and trends in data sets (Antons & Breidbach, 2018) but also to make sense of complex problems that might even result in new business models for the long run (Günther et al., 2017).

Taking the above debate into account, we disclose the implications of our work for academic and managerial environments. We equally expose our work's limitations and postulate future research paths.

6.1 Academic Implications

To the best of the authors' knowledge, this is the first paper to present an ML BV conceptual model. Indeed, the presented representation can carefully be adjusted to a common technology BV model. Nevertheless, it must be borne in mind that the present model has deeply taken into consideration the distinctive characteristics of ML technology. It not only takes into account ML's growing potential based on the catalyst effect that data quality has on its algorithms (platform maturity moderator effect), but it also weighs the incredible potential that emerges from making sense of complex tasks that humans and other analytics might just overlook (process complexity direct effect). We also theorize that it is the first study to substantiate its ML BV model through an empirical approach.

By providing constructive answers to our research questions, we are creating a foundation to fill the knowledge gaps identified in the literature. However, there is still a long path ahead to fully understand the ML BV process. Therefore, we also formulate new hypotheses and directions that can be advanced through future works.

6.2 Managerial Implications

Our findings provide important insights on how firms can achieve ML BV. By uncovering significant antecedents and a major catalyst, we are delivering a keen blueprint of directives for companies to foster the ML CA in particular.

With the proliferation of analytics, the low-hanging fruit is no longer there (Kitchens et al., 2018). From this point on, companies must focus on dynamic competencies that provide new actionable insights to continuously outperform their peers (Kitchens et al., 2018). ML surfaces with a potential that surpasses humans and other analytics on complex tasks (Antons & Breidbach, 2018; Bose & Mahapatra, 2001). Moreover, ML is already predicted to change the business landscape in the 21st century entirely (Jimenez-Marquez et al., 2019; Wright & Schultz, 2018). Therefore, we are providing valuable guidelines for pertinent solutions in the current and future managerial environment.

6.3 Limitations and Future Research

Our research has some limitations that can be overcome through future work. As a one-time survey across time, we understand that we are only providing a snapshot of reality. Through a longitudinal assessment, it is possible to analyze the sustainability of the ML BV creation process. Moreover, the list of antecedents can be extended through exploratory research. Also, the list of dependent variables can be further investigated where the concept’s ramifications can enrich our understanding of ML, ML BV, and ML CA. In the future, our model could be matured to a more diversified sample in terms of size. At this stage, our analysis can only be generalized to large corporations. Any beyond sample diversification will entail meaningful contributions to the ML domain.

Regarding our model, we attained a surprising finding regarding top management support's negative effect on financial performance. Therefore, we welcome academics to investigate this relationship further. Regarding the platform maturity moderator effect, we invite researchers to expand these findings to other analytics BV models. Last, ML BV's indirect and mediator variables were not monitored, and these associations may be explored in future ML BV studies.

7 CONCLUSION

ML can spread BV across industries and domains. Through a well-developed trail of ML use, BDA maturity, platform maturity, process complexity, and adjusted top management support, firms can speed up the ML BV process, and ultimately, grasp CA.

This study was able to answer the research questions posed. First, it uncovered key antecedents for companies to achieve ML BV. Second, it demonstrated the catalytic effect of platform maturity on ML BV. Ultimately, the work and its intrinsic practical experience have provided convincing evidence that ML is playing an ever-increasing role in firms' financial and strategic performance. Moreover, it has provided evidence that platform maturity has a key role within this process.

This research has greatly enriched the current literature. It has showcased how to enhance the ML potential across business processes and companies in general. It has also brought together technical and business understandings. Nevertheless, there is still much to expose concerning the newest vital element of the academic and business landscapes. Therefore, we close this piece by inviting others to join in the ML quest.

ACKNOWLEDGMENTS

The authors acknowledge the importance of the established partnership with SAP to achieve the present investigation. Any opinions, findings, and recommendations expressed here are from the authors and not necessarily from the supporter of this research. Equally, we gratefully acknowledge the reviewers' shared valuable comments and suggestions throughout the review process.

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APPENDIX

Table A.1 - Survey Questionnaire

Constructs	Measurement Items	Adapted Source
Machine Learning Use	Please classify the following sentences regarding the machine learning use: MLU1. If ML is a superior solution, it should be used as the application domain I am in charge of. MLU2. Our company should increase the existing level of adopting ML-based applications. MLU3. Our company supports the further adoption of ML-based applications.	(Benlian & Hess, 2011)
Big Data Analytics Maturity	Please indicate the extent to which you agree with the following statements regarding big data analytics maturity: BGAM1. Rules, procedures, and organizational activities are documented with formal paperwork with respect to Big Data & Analytics systems. BGAM2. Big Data & Analytics systems planning are connected with organizational planning. BGAM3. Our organization employs rules and procedures in Big Data & Analytics system's development and use. BGAM4. Our organization uses any Big Data & Analytics systems for creating competitive advantage.	(Grover, Jeong, Kettinger, & Lee, 1993)
Platform Maturity	Please indicate the extent to which you agree with the following statements regarding platform maturity: PM1. The current platform has the capacity to extract, integrate and convert data from multiple digital data streams. PM2. The current platform allows the corporation to seamlessly integrate data from several static and real-time data sources. PM3. The current platform tools enable to both report and visualize data and, from them, retrieve relevant data-driven insights. PM4. The current platform allows to proactively retrieve new insights as well as uncover future trends and patterns.	(Anand et al., 2016)
Top Management Support	Please indicate the extent to which senior management in your firm actively participates in: TMS1. Articulating a vision for our organization of ML systems. TMS2.* Formulating a strategy for the organizational use of ML systems. TMS3. Establishing goals and standards to monitor ML systems. TMS4. Deploying ML technology in our organization.	(Rai et al., 2009)
Process Complexity	Please indicate the extent to which you agree with the following statements regarding organizational process sophistication: PC1. The business processes often cut across multiple functional areas. PC2. We frequently deal with ad-hoc, non-routine business processes. PC3. We generally have a high extent of uncertainty in our business processes. PC4. A majority of our business processes are quite complex.	(Setia et al., 2013)

Financial Performance	Please indicate the extent to which you agree with the following statements regarding financial performance: FP1. EBIT (earnings before interest and taxes) is continuously above industry average. FP2. ROI (return on investment) is continuously above industry average. FP3. ROS (return on sales) is continuously above industry average.	(Côrte-real et al., 2019)
Strategic Performance	Please indicate the extent to which you agree with the following statements regarding strategic performance: SP1. The use of ML offers new opportunities in finance business processes. SP2. The use of ML offers new opportunities in marketing & sales business processes. SP3. The use of ML offers new opportunities in operations business processes.	(Gold et al., 2001; Segars & Grover, 1998; Subramani, 2004)
Firm Size	SIZ1 Annual turnover SIZ2 Number of employees	(Son & Benbasat, 2007)
Industry Sector	IND1	N/A

*Note:*items eliminated due to low loadings.*

Figure A.2 – Perceived machine learning knowledge by respondent position