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How does the environmental context moderate machine learning adoption?

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Dissertation presented as partial requirement for obtaining the Master’s degree in Information Management

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HOW DOES THE ENVIRONMENTAL CONTEXT MODERATE MACHINE LEARNING ADOPTION?

by

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

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DEDICATION

To my sister Daniela for all her friendship, complicity and, above all, unconditional love.

To my family, who made me who I am.

Soliloquy[1]

[1] an act of speaking one's thoughts aloud when by oneself or regardless of any hearers.

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To my entire family, for being my support and the ones I can rely on. Especially to my mother Isabel, my father Rui, and my sister Daniela.

ABSTRACT

Machine learning (ML) has become one of the hottest trends in the IT field. Knowing that ML can positively impact an organization's performance, it is, therefore, crucial that the drivers upon its adoption are studied. Using the technology-organization-environment (TOE) framework and the institutional (INT) theory, an empirical measurement of the key determinants of ML adoption was made in a single framework. A structural equation modeling (SEM) technique was used in a dataset of 319 firms to test the suggested hypotheses. The research empirically sustains the impact of the environment on ML adoption, not only as a predictor but also as a moderator of the technological context.

KEYWORDS

Machine learning; IT adoption; Technology-organization-environment (TOE) framework; Institutional (INT) theory; Environmental context

RESUMO

O *machine learning* (ML) tornou-se numa das tendências mais relevantes no campo das tecnologias de informação (TI). Sabendo que o ML pode impactar positivamente o desempenho de uma organização, é crucial que os fatores que influenciam a sua adoção sejam estudados. Utilizando o modelo tecnologia-organização-ambiente (TOE) e a teoria institucional (INT), um estudo empírico dos principais determinantes da adoção de ML foi realizado num só modelo. Uma técnica de modelação de equações estruturais (SEM) foi utilizada numa amostra de 319 empresas para testar as hipóteses sugeridas. O presente estudo sustenta empiricamente o impacto do ambiente na adoção de ML, não apenas enquanto preditor direto, mas também como moderador do contexto tecnológico.

PALAVRAS-CHAVE

Machine learning; Adoção de TI; Modelo tecnologia-organização-ambiente (TOE); Teoria institucional (INT); Contexto ambiental

PUBLICATIONS

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial intelligence
AVE	Average variance extracted
CEO	Chief executive officer
CR	Composite reliability
DOI	Diffusion of innovation
HTMT	Heterotrait-monotrait ratio
INT	Institutional
IS	Information systems
IT	Information technology
ML	Machine learning
PLS	Partial least squares
R^2	Coefficient of determination
RPA	Robotic process automation
SEM	Structural equation modelling
SME	Small and medium-sized enterprises
TOE	Technology-organization-environment
VIF	Variance inflation factor

1. INTRODUCTION

In recent years, machine learning (ML) has been pointed out as one of the most important breakthroughs for improving an organization's performance, emerging as a profitable leading edge for businesses (Jordan & Mitchell, 2015). This paradigm emphasizes the importance of applying ML methods to automate the understanding of different phenomena impacting the environment, economy, and society (Wagstaff, 2012), encouraging an increasing number of companies to adopt solutions to support regular business operations, such as finance, sales, marketing, among others. The proven applicability of ML techniques to several fields, including management science, economics, computer science, medicine, or manufacturing, foretells its applicability for addressing a vast range of real-life problems (Qin & Chiang, 2019). Despite the benefits it may bring to enterprises, the adoption of ML at the firm level has been limited and, in many cases, fallen short of expectations. Indeed, evidence suggests that a vast amount of organizations still do not consider embracing ML solutions, which can be explained by the lack of empirical work regarding the adoption stage (Rana, Staron, Hansson, Nilsson, & Meding, 2014). Drawing parallels with the cloud computing field, the main reasons may include the fact we are addressing an innovation that has not yet achieved a level of maturity, which greatly impacts the high level of risks associated to its adoption, that can be reflected in higher costs to the company (Oliveira, Thomas, & Espadanal, 2014). Other reasons might pertain to the lack of available evidence on best practices, compliance matters, compatibility, and proof from success cases (Chang, Kuo, & Ramachandran, 2016). On top of that, there is currently little understanding of the aspects influencing favorable adoption at the firm-level, as most studies disregard the organizational standpoint and focus instead on the individual level, therefore creating an opportunity for further research.

The existing literature on ML is widely concerned with technical matters, such as the development of algorithms, or the applicability of ML in a particular use case or industry. No study has ever investigated ML from an organizational standpoint, nor assessed the drivers of its adoption, or the impact exerted from the environment. Motivated by these issues, the objective of this study is to address the following research questions: "how does the environmental context influence the process of ML adoption?", which in a broader scope also helps us answer "what are the key drivers of ML adoption?". This research intends to develop a research model combining the technological, organizational, and environmental contexts of the TOE framework with the isomorphic pressures from the institutional (INT) theory, enriching the environmental perspective and better portraying the adoption phenomena. The contribution of this paper is threefold. First, by empirically examining the drivers of ML adoption on data from 319 firms, this study presents the first framework to explain ML adoption at the firm level. No previous study has assessed the influencers of ML adoption, meaning this research is adding empirical proof to a field in which the body of knowledge remains scarce. Second, by using the environment as a moderator, we complement the existent quest in IS literature to assess the impact of the environment on technology and organization perspectives, which enhances the thorough understanding of the ML adoption process and, more broadly, supports more informed scrutiny of the TOE framework itself. The inclusion of the moderating effects not only paves the way for further research but also offers a more contextualized perception on how the environment tailors the internal traits of the firm in the adoption process. Plus, it further attests to the preponderance of complementing the environmental context of the TOE framework with INT theory, providing additional proof of the benefits of integrating these two reputable theories. Third, we model the organization and environment contexts as higher-order constructs, arguing that this approach may better embed the first-order constructs to the context they are attached. By hypothesizing a new level of abstraction, we represent the organization and environment lenses as higher-level dimensions, as an alternative of purely interrelating them, which, aside from providing a new way of assessing the adoption of ML, also lays down an alternative method to approach the TOE framework in the future.

In the next section, we provide a background on ML, followed by theoretical considerations on adoption models – the TOE framework, the INT theory, and their coupling when used together. Then, we introduce the conceptual model and propose the hypotheses. The following section presents the research methodology and the analysis of results. We then discuss the managerial, practical, and theoretical implications of our paper, concluding with the limitations and recommendations for further research.

2. THEORETICAL BACKGROUND

2.1. MACHINE LEARNING

ML has been present for some years now, and many definitions have been given throughout this time, with Samuel (1959) and Mitchell (1997) standing out as classically recognized contributors. Despite the presence of ML for quite some time, its popularity has only grown in the last few years. We attribute this spawn to the availability of big volumes of data, enabling the training of large ML models with enough historical data (Kitchin, 2014); the existence of convenient, accessible and low-cost big data platforms that can deal with vast amounts of data, including faster and more efficient computational resources (Chiang, Enke, Wu, & Wang, 2016; Chilimbi, Suzue, Apacible, & Kalyanaraman, 2014); and the development of more sophisticated ML techniques to tackle more complex problems, which is enhanced by the two antecedent reasonings (Abadi et al., 2016).

The recent popularity ML has gained, starting to spread to the industry domain alongside the possibility of enhanced strategic value, triggered the need for research on ML adoption at the firm level. Indeed, the possibility of using ML methods to extract value from huge volumes of data applied to different fields of a firm's activity enables the opportunity for gaining competitive advantages (Carrasquilla & Melko, 2017). The fact that an ML program can be run in a cornucopia of different hardware or cloud computing environments has contributed to its popularity, enabling companies to choose from a wide range of offers according to their technological setup. This is especially important as ML is "hardware-agnostic but ML-explicit", meaning users can write their code independently of the programming language, as there is currently the opportunity for users to choose the application they find the best due to this vast range of offer. Using open-source software and communities of practice to share code has further empowered this spread widely, as it is now easier than ever to create an ML program that can systematize the extraction of insights from dense datasets in a precise, timely and automatic manner (Xing, Ho, Xie, & Wei, 2016).

Organizations are currently extracting value from ML techniques as they are now able to give meaning to their data, uncovering hidden patterns, and finding important insights impossible to bring to light before. This aspect is particularly important in the era of big data, as companies have a huge amount of data from which ML algorithms can retrieve fruitful knowledge (Borangiu, Trentesaux, Thomas, Leitão, & Barata, 2019; Zhou, Pan, Wang, & Vasilakos, 2017). This value-added by machine learning can be exponential when integrated with complementary technologies, such as AI, RPA, or other expert systems (Syed et al., 2020). With the stated benefits it can bring to businesses, firms can no longer disregard the possibility of using ML as a way of renovating business processes and achieving corporate efficiencies by enhancing the decision-making process (Jimenez-Marquez, Gonzalez-Carrasco, Lopez-Cuadrado, & Ruiz-Mezcua, 2019; Lismont, Vanthienen, Baesens, & Lemahieu, 2017).

Therefore, the thorough IT paradigm of firms is suffering a revolution towards a holistic ML embracement in an enterprise-wide context. This fact yields the necessity of developing a framework that can empirically sustain the main drivers that affect ML adoption.

2.2. ADOPTION MODELS

2.2.1. Technology-organization-environment (TOE) framework

The TOE framework (DePietro, Wiarda, & Fleischer, 1990) explains the process of an innovation's adoption at the enterprise level. It contemplates three contexts that influence adoption: the technological context, which describes the internal and external technologies relevant to the firm, including current practices, hardware, and software (Zhu, Dong, Xu, & Kraemer, 2006); the organizational context, which refers to descriptive measures about the organization, such as the managerial structures, resources, the process of communication and the degree of centralization (Alain & Ooi, 2008); the environmental context, which includes how a firm conducts its business, encompassing the industry, competitors, and governmental relations and regulations (Tornatzky, Fleischer, & Chakrabarti, 1990). The TOE framework offers a solid theoretical background, supported by consistent empirical measures, to study innovation adoption in different fields of IS (Chan & Chong, 2013).

2.2.2. Institutional (INT) theory

The INT theory (DiMaggio & Powell, 1983) focuses on the characteristics of the social framework, capturing the significance of external pressures in the organizational adoption of innovations. The INT theory examines how these external pressures that affect organizations result in institutional isomorphism (Yoon & George, 2013). It proposes that a firm's decision to adopt an innovation is influenced not only by rational goals but also by its surrounding environment, social, and cultural factors (Chatterjee, Grewal, & Sambamurthy, 2002; Oliveira & Martins, 2011). It also postulates that firms act as institutions in influencing behaviors and cognitions of individuals within the firm, contributing to attest the importance of organizational structures and actions (Teo, Wei, & Benbasat, 2003). Three types of external institutional (isomorphic) pressures were introduced by DiMaggio & Powell (1983): coercive pressures, based on regulations, values, and norms to the professional activity of the firm, arising from trade associations, the government, or other associations with regulatory power that exert pressures on organizations to conform how things should be done (Pearson & Keller, 2009); normative pressures, imposed on a firm by other organizations the first rely on, such as pressures from customers or suppliers (Son & Benbasat, 2007); mimetic pressures, exerted when an organization tends to mimic the behavior of another similar organization which has already adopted the innovation, usually a competitor, to reduce the uncertainty and risk of being a first adopter (Khalifa & Davison, 2006).

2.2.3. Combining TOE framework with INT theory

Combining different theories in the IS field has been a typical approach of many researchers when addressing innovation's adoption. This technique has been proven to enable a more systematic and broader understanding of the adoption phenomenon at the firm level (Hsu, Kraemer, & Dunkle, 2006; Iacovou, Benbasat, & Dexter, 1995). Despite the wideness offered by the TOE framework, it lacks important key factors, such as accounting for external pressures exerted in the organization. IS researchers recognize this limitation, and the TOE framework has been utilized as a framework to incorporate other theories to create broader spectrums of research (Puklavec, Oliveira, & Popovič, 2018). Thus, to enhance the predictive power of the research model, we combine this framework with INT theory, which has been shown to be an effective complement of the TOE framework to explain adoption (Gibbs & Kraemer, 2004; Oliveira, Martins, Sarker, Thomas, & Popovič, 2019; Soares-Aguiar & Palma-dos-Reis, 2008).

As the integration of the TOE framework and INT theory provides a better understanding of the environmental context through the inclusion of different institutional pressures, it becomes more comprehensive to explain intra-firm innovation adoption (Oliveira & Martins, 2011). With the complement of INT theory, it emerges as better able to capture the external characteristics of the environment, and therefore the combination of the two turns into a further inclusive model to expansively explain adoption (Kung, Cegielski, & Kung, 2015). There is evidence of the benefits of integrating these two well-established theories to expand the realm of the research model (Ahmadi, Nilashi, Shahmoradi, & Ibrahim, 2017; Ciganek, Haseman, & Ramamurthy, 2014).

3. RESEARCH MODEL AND HYPOTHESES

A research model combining the characteristics of the TOE contexts with the isomorphism from the INT theory was developed to create a holistic representation of the adoption of ML in today's business environment. The INT theory was used to model the environmental context of the TOE framework, therefore enriching the research model. A construct regarding the diffusion stages was added to underscore the importance of the intention to adopt and to complement the conceptual model presented in Figure 1.

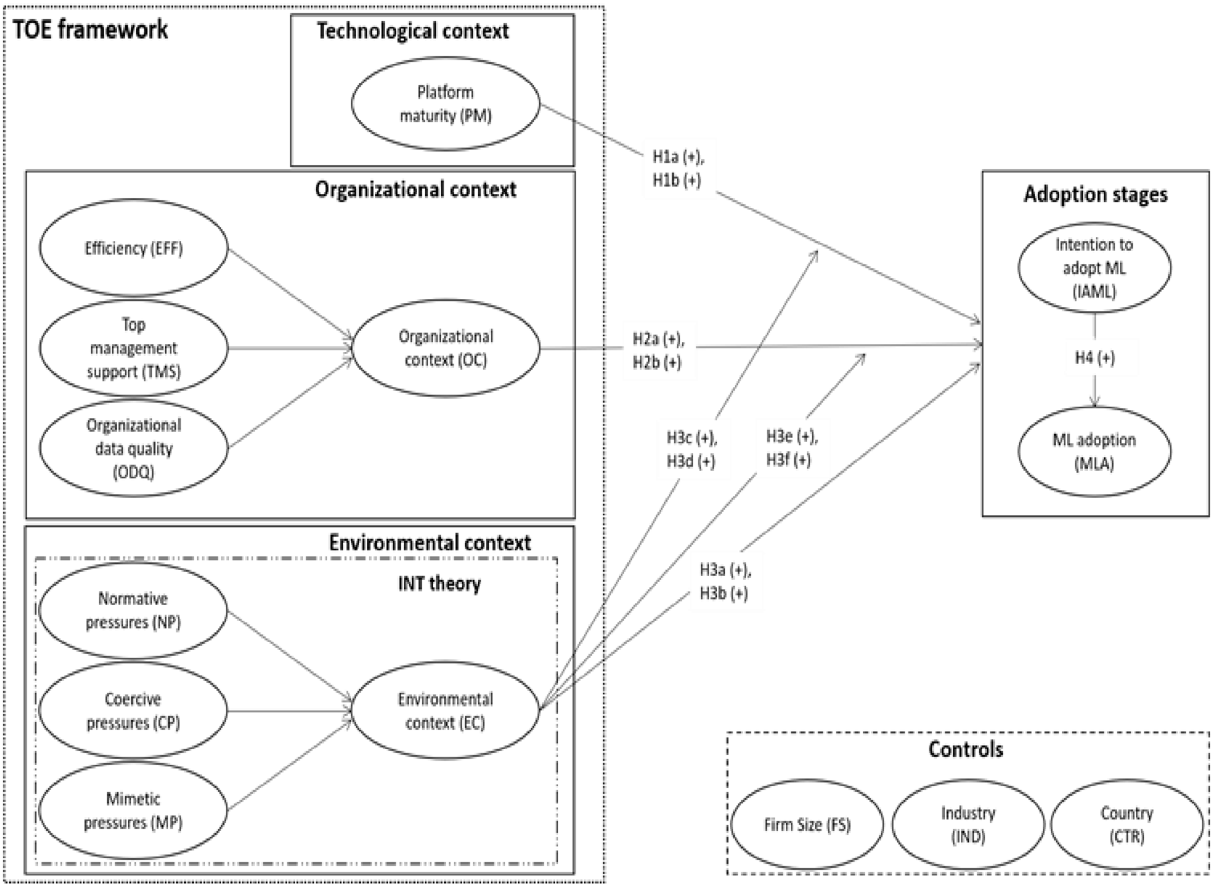


Figure 1 - Research model for ML adoption at the firm level

Therefore, to characterize the adoption of ML at the firm level, the following hypotheses are postulated.

3.1. HYPOTHESES OF THE TECHNOLOGY-ORGANIZATION-ENVIRONMENT (TOE) FRAMEWORK

3.1.1. Technological context

Platform maturity is closely linked to the extent to which an organization can use its IT infrastructure to leverage the discovery of actionable insights (Anand, Coltman, & Sharma, 2016). Having a mature platform for storing, integrating, and processing data is key to enhancing data access, integration, and value extraction (Gattiker & Goodhue, 2005). The sophistication of the platform influences how easy it is to access relevant data, integrate it with legacy systems, and translate it into faster and cost-effective business decisions (Ravichandran & Lertwongsatien, 2005). Platform maturity measures four key indicators: data management capability, system integration capability, reporting and visualization capability, and predictive discovery capability (Anand et al., 2016). We postulate that platform maturity is reflected in the eagerness to adopt ML to unlock value from stored data, implying that firms with higher levels of platform maturity are more prepared to adopt ML. Therefore,

H1a. Platform maturity positively influences the intention to adopt ML.

H1b. Platform maturity positively influences ML adoption.

3.1.2. Organizational context

Even though the TOE framework has been widely used to explain the process of IT adoption, it does not provide a tangible model for describing the factors driving the organizational adoption decision. Instead, the TOE framework provides a classification of the factors influencing adoption in their individual context, being not expansive (Bose & Luo, 2011). To tackle these shortcomings, one must take into account that various individual factors exist in themselves but affect, in a broader scope, the thorough organizational context. It is, therefore, reasonable to model efficiency, top management support, and organizational data quality as reflective in themselves, but as second-order constructs in an organizational context (reflective-formative type) (Ringle, Sarstedt, & Straub, 2012). Efficiency is measured by how easy it is for users to perform ordinary, repetitive tasks, expressing how the company can save time, money, react quickly to changes, speed up decision-making, and increase customer satisfaction (Kennedy & Fiss, 2009; Vandenbosch & Ginzberg, 1996). Top management support refers to the vision, support, and commitment provided by senior management to foster the appropriate environment for adoption (Rai, Brown, & Tang, 2009). Organizational data quality is related to the process of preparing input data for ML, considering data availability, accuracy, timeliness, integrity, reliability, standardization, security, among others (R. Y. Wang & Strong, 1996).
Using these three latent variables within the environmental context, the firm's internal attributes that may facilitate or restrain ML adoption are now embedded much more to the construct, contrarily to what happens when using various first-order reflective constructs (Ciavolino & Nitti,

2010). The elements attained to the organizational context are suggested to facilitate the adoption of innovation, as an effectively organized organizational data environment contributes to enhanced business value (Ramamurthy, Sen, & Sinha, 2008). Firms with higher levels of data quality are more prepared to use it and extract value from it to create relative advantages (Nicolaou & McKnight, 2011), which can be further enhanced by the existing efficiency within the firm and the top management support, as the decision to adopt an innovation is unlikely to become viable without their commitment (Cruz-Jesus, Pinheiro, & Oliveira, 2019; Grover, 1996; Lee & Kim, 2007). Therefore,

H2a. The organizational context positively influences the intention to adopt ML.

H2b. The organizational context positively influences ML adoption.

3.1.3. Environmental context

3.1.3.1. Direct effects

In IS literature, there is a clear reference to firms' propensity to be influenced by environmental pressures (DePietro et al., 1990; Yoon & George, 2013). However, no studies are scrutinizing their impact on ML adoption. Firms are not confined and static organizations, but rather evolving institutions that act depending on the environment they are settled in (Tornatzky et al., 1990). In fact, how firms interact with the main elements of the environment - competitors, partners, suppliers, government, or others - deeply impacts their way of doing business, either by enhancing their performance or by restraining their functioning (Camisón-Zornoza, Lapiedra-Alcamí, Segarra-Ciprés, & Boronat-Navarro, 2004; Damanpour & Schneider, 2006). The environmental context comprises the normative, mimetic and coercive pressures from INT theory (DiMaggio & Powell, 1983), and the most prominent ways of analyzing its impact on innovation adoption has been along two different means: either by using each pressure as a first-order construct or by conceiving a second-order construct of the reflective-formative type. We argue that each individual pressure variation impacts, in a broader scope, the full environmental context, therefore it is rational to model the environment as a second-order construct (Petter, Straub, & Rai, 2007). However, we claim that each pressure should be modeled as first-order formative, as an increase in one of the pressures does not imply a similar increase in another pressure. Even though this increase may occur, it does not mean it is caused by the first pressure variation. Nevertheless, in a formative indicator the existence of correlation or high internal consistency is not necessary (Chin, 1998), thus we propose that the environmental context is a second-order formative-formative construct. Therefore,

H3a. The environmental context positively influences the intention to adopt ML.

H3b. The environmental context positively influences ML adoption.

3.1.3.2. Moderator effects

There is evidence in IS research toward the benefits of integrating moderators to better portray a firm's behavior (C. H. Wang, Chen, & Chen, 2012; Yu, Ramanathan, Wang, & Yang, 2018). Given that the adoption process is not detached but rather an activity dependent on various factors that surround the organization, the environment the firm is settled in may influence the other contexts of their activity (Oliveira et al., 2019; C. H. Wang et al., 2012). This reasoning goes along with the existing research that states that a firm's internal characteristics – in which we include the technological and the organizational contexts - are not inert, but rather dependent on their interaction with the environment. This argument can be translated into different impacts of the organizational and technological characteristics on a firm, depending on the environmental characteristics in which the firm is established (Xie, Jia, Meng, & Li, 2017). Being evident that the moderator effect of the environment is present at various levels of a firm's activity, there is the expectation this impact can also be felt throughout the adoption process. Thus, we suggest innovation adoption will be impacted not only by the technology, organization or environment, but also by how the technological and organizational perspectives behave and evolve, whether the firm is established in a high or low-level environmental context (Lu, Xu, & Liu, 2009). Hence, it is valid to hypothesize that besides directly influencing ML adoption, the environment also shapes the link between the other two lenses and ML adoption, moderating this relationship. Therefore,

> **H3c.** The environmental context moderates the relationship between platform maturity and the intention to adopt ML.
>
> **H3d.** The environmental context moderates the relationship between platform maturity and ML adoption.
>
> **H3e.** The environmental context moderates the relationship between the organizational context and the intention to adopt ML.
>
> **H3f.** The environmental context moderates the relationship between the organizational context and ML adoption.

3.2. HYPOTHESES OF DIFFUSION STAGES

The intention to adopt ML (evaluation/persuasion stage), happens when the company begins to consider gathering information about ML to assess its relevance, possibly conducting pilot tests to analyze the benefits it may bring to the business (Zhu, Kraemer, & Xu, 2003). Even though an organization's intention to adopt ML does not guarantee the technology will be integrated in the end, this phase occurs immediately before adoption – being also called the pre-adoption phase - and flags the willingness to implement the innovation before its actual embracement (Chan & Chong, 2013). We argue the intention to adopt ML is a main driver of ML, as it stands as a foundation for the firm to move toward the effective adoption. We hypothesize, the stronger the intention to adopt, the more willing the firm will be to move to adoption. Therefore,

H4. The intention to adopt ML positively influences ML adoption.

3.3. CONTROL VARIABLES

Previous articles in the IS literature provide evidence towards the usage of control variables (Jeyaraj, Rottman, & Lacity, 2006; Premkumar & Roberts, 1999; Zhu, Kraemer, & Xu, 2006). We use firm size - measured by the number of employees and the annual turnover (Chwelos, 2001; Premkumar & Roberts, 1999) -, country, and industry as control variables to capture the variation of data that is not captured by the explanatory variables of the proposed research model.

4. RESEARCH METODOLOGY

4.1. MEASUREMENT

A web-survey for gathering data was conducted to evaluate the proposed constructs and the conceptual model. All the item-questions derived from published literature and were measured using a seven-point range scale on an interval level ranging from “strongly disagree” to “strongly agree” for all items (Table 1). Along with the existent literature, all items were operationalized as reflective, apart from the organizational context, being modeled as a second-order reflective-formative construct, and the environmental context, modeled as a formative-formative construct. An expert panel of five IS professionals and researchers reviewed the items to oversee possible issues with the instrument, subsequently indicating suitable amendments. We used a pilot study to test the questionnaire in a sample of 30 firms. The contemplated firms were not included in the main investigation. The results provided evidence supporting the reliability and validity of the instrument.

Constructs	Measurement items	Adapted source
Platform maturity (PM)	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 enables 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)
Efficiency (Eff)	Please indicate the extent of importance of the following reasons for your company's decision to implement ML: Eff1: Improve the technical quality of our business processes. Eff2: Improve productivity. Eff3: Improve customer satisfaction.	(Kennedy & Fiss, 2009; Vandenbosch & Ginzberg, 1996)
Top management support (TMS)	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)
Organizational data quality (ODQ)	ODQ1: The data currently available in our company is of high quality. ODQ2: The data currently available in our company is reliable. ODQ3: The data currently available in our company is up-to-date. ODQ4: The amount of data currently available in our company is huge.	(Ramamurthy et al., 2008; R. Y. Wang & Strong, 1996)
Coercive pressures (CP)	CP1: The local government requires our firm to use ML. CP2: The industry association requires our firm to use ML. CP3: The competitive conditions require our firm to use ML.	(Kennedy & Fiss, 2009; Liang, Saraf, Hu, & Xue, 2007; R. Martins, Oliveira, & Thomas, 2016)
Normative pressures (NP)	NP1: The government's promotion of Information Technology influences our firm to use ML. NP2: ML is adopted by our firm's suppliers. NP3: Our firm is under pressure from partners to adopt ML.	
Mimetic pressures (MP)	Please indicate the extent to which you agree with the following statements regarding your competitors who have adopted ML: MP1: They are favorably perceived by others in the same industry. MP2: They are favorably perceived by their suppliers and customers. MP3: Our firm is under pressure from competitors to adopt ML.	
Intention to adopt ML (IAML)	IAML1: Our company intends to use ML if possible. IAML2: Our company collects information about ML for possible intention of using it. IAML3: Our company conducts a pilot test to evaluate ML.	(Chan & Chong, 2013)
ML adoption (MLA)	MLA1: Our company invests resources to adopt ML. MLA2: Business activities in our company requires the use of ML. MLA3: Functional areas in our company require the use of ML.	

Note: all items are based on 7-point Likert scale

Table 1 - Measurement items

4.2. DATA

An online version of the questionnaire was emailed to a list of 2000 qualified companies, along with a brief description of the research scope and goals. The company and contact data were gathered with the assistance of SAP, a global IT leading company. The “key informant” methodology was followed to increase the validity and trustworthiness (Benlian & Hess, 2011; Pinsonneault & Kraemer, 1993). A clarification of ML was presented at the beginning of the questionnaire to identify respondents clearly and to eliminate misconceptions (J. Martins, Gonçalves, Oliveira, Cota, & Branco, 2016; Oliveira et al., 2014). In an endeavor to increase the response rate, we gave participants the opportunity to receive a benchmark of their responses compared to all average responses.

The data were collected using an online survey administered in two stages, both taking place in early-2019. In the first stage, 210 valid responses were received (early respondents). After the first stage was over, we sent a follow-up email to the firms who did not respond in the first stage. This action generated 109 additional valid responses (late respondents), for a combined total of 319 usable responses at the end of eight weeks. This amount yields an overall response rate of 16%, which is comparable to other studies in IS (Grover & Goslar, 2015; Oliveira et al., 2019; Ranganathan, Dhaliwal, & Teo, 2018). All respondents were qualified individuals, suggesting the good quality of data. The entire profile of the sample is presented in Table 2.

Sample characteristics	Observations (n=319)	%
Industry		
Health & Public sector	27	8.46%
Banking & Insurance	32	10.03%
Construction & Professional services	43	13.48%
IT & Telco	55	17.24%
Retail & Consumer products	62	19.44%
Production & Manufacturing	100	31.35%
Respondents position		
Board member, General Manager or CEO	33	10.34%
Manager, Business unit or Department supervisor	140	43.89%
Data scientist, Data specialist or Technical role	146	45.77%
Country		
France	34	10.66%
Germany	38	11.91%
United Kingdom	46	14.42%
Italy	51	15.99%
Canada	57	17.87%
United States of America	93	29.15%
Firm Size		
Number of employees		
Medium (50 to 249)	11	3.45%
Large (250 or more)	308	96.55%
Annual turnover		
From 10 to 50 Million Dollars	25	7.84%
More than 50 Million Dollars	294	92.16%

Table 2 - Sample characteristics

5. RESULTS

Partial least squares (PLS), a variance-based SEM technique was used to assess the proposed research model empirically, as (1) it is useful for analyzing matters that have never been tested before (Ke, Liu, Wei, Gu, & Chen, 2009; Teo et al., 2003) (2) can be used when the measurement model is complex and low theoretical background is provided (Acedo & Jones, 2007; Henseler, Ringle, & Sinkovics, 2009) (3) allows for latent constructs to be modeled as formative indicators (Goo, Kishore, Rao, & Nam, 2017; Teo et al., 2003) and (4) does not require assumptions regarding data distributions (Chin, Marcelin, & Newsted, 2003; Fornell & Bookstein, 2006; Gefen, Straub, & Boudreau, 2018). The sample consists of 319 firms, meeting the minimum requirements for using PLS - is bigger than ten times the number of formative indicators used to measure one construct and than the largest number of structural paths directed at a single latent variable (Hair, Ringle, & Sarstedt, 2011). The software used to test the research model and analyze the structural model was SmartPLS 3.0 (Ringle, Christian M., Wende, Sven, & Becker, 2015).

5.1. MEASUREMENT MODEL

A measurement model was performed to assess the construct reliability, convergent validity, indicator reliability, and discriminant validity of scales for the reflective constructs. To test the construct reliability, the composite reliability (CR) and Cronbach's Alpha should both be higher than 0.7 (Gefen et al., 2018). All constructs exhibit CR and Cronbach's Alpha higher than 0.7, indicating appropriateness and internal consistency, and suggesting all constructs are reliable. To examine convergent validity, the average variance extracted (AVE) benchmark value of 0.5 was used to account for latent variables which explain more than half of the variance of its indicators (Hair, Sarstedt, Ringle, & Mena, 2012). All constructs have AVE higher than 0.5, implying the convergent validity of the measurement model (table 3). Indicator reliability was demonstrated as all loadings are higher than 0.6. Discriminant validity was analyzed by (1) the Fornell-Larcker criteria, which postulates that the AVE squared root of each construct should be higher than the correlation between the constructs (Fornell & Larcker, 1981). In Table 3, we see that the squared AVE are higher than the construct's correlations; (2) the loadings of each indicator should be greater than the cross-loadings (Chin, 1998). As shown in Table 4, the loadings are greater than the cross-loadings; (3) the heterotrait-monotrait ratio (HTMT), which establishes a threshold of 0.9 to ensure discriminant validity (Henseler, Ringle, & Sarstedt, 2014). All constructs have HTMT values below 0.9 (Table 5), so we can confirm that our measurement model is reliable and valid by the three criteria.

Constructs	**Mean**	**SD**	**AVE**	**CR**	**PM**	**Eff**	**TMS**	**ODQ**	**IAML**	**MLA**
Platform maturity (PM)	6.017	0.720	0.885	0.969	**0.941**					
Efficiency (Eff)	6.166	0.604	0.648	0.846	0.161	**0.805**				
Top management support (TMS)	5.846	0.975	0.512	0.805	0.383	0.184	**0.715**			
Organizational data quality (ODQ)	5.754	0.548	0.864	0.962	0.137	0.437	0.177	**0.930**		
Intention to adopt ML (IAML)	6.066	0.614	0.915	0.970	0.198	0.420	0.118	0.432	**0.957**	
ML adoption (MLA)	5.903	1.020	0.962	0.987	0.111	0.378	0.275	0.677	0.501	**0.981**

Notes: Values in diagonal (bold) are the AVE square root.

Table 3 - Descriptive statistics, correlations, CR and AVE

Constructs	**Item**	**PM**	**Eff**	**TMS**	**ODQ**	**IAML**	**MLA**
Platform maturity (PM)	PM1	**0.976**	0.167	0.377	0.114	0.167	0.151
	PM2	**0.952**	0.182	0.347	0.093	0.197	0.106
	PM3	**0.861**	0.094	0.351	0.170	0.221	0.005
	PM4	**0.970**	0.155	0.369	0.146	0.165	0.152
Efficiency (Eff)	Eff1	0.017	**0.718**	0.195	0.298	0.386	0.337
	Eff2	0.099	**0.880**	0.207	0.454	0.294	0.334
	Eff3	0.292	**0.810**	0.021	0.274	0.356	0.237
Top management support (TMS)	TMS1	0.315	0.028	**0.658**	0.022	0.015	0.055
	TMS2	0.310	0.215	**0.836**	0.224	0.155	0.319
	TMS3	0.251	0.074	**0.733**	0.100	0.043	0.129
	TMS4	0.291	0.077	**0.615**	0.021	0.017	0.075
Organizational data quality (ODQ)	ODQ1	0.146	0.373	0.138	**0.927**	0.330	0.612
	ODQ2	0.109	0.415	0.168	**0.950**	0.432	0.631
	ODQ3	0.122	0.371	0.152	**0.939**	0.406	0.616
	ODQ4	0.133	0.465	0.199	**0.902**	0.434	0.656
Intention to adopt ML (IAML)	IAML1	0.211	0.384	0.100	0.426	**0.947**	0.441
	IAML2	0.170	0.403	0.110	0.432	**0.979**	0.477
	IAML3	0.187	0.416	0.128	0.381	**0.944**	0.518
ML adoption (MLA)	MLA1	0.104	0.353	0.251	0.658	0.437	**0.987**
	MLA2	0.114	0.363	0.244	0.628	0.459	**0.983**
	MLA3	0.109	0.395	0.310	0.700	0.570	**0.973**

Table 4 - Loadings and cross-loadings

Constructs	PM	Eff	TMS	ODQ	IAML	MLA
Platform maturity (PM)						
Efficiency (Eff)	0.207					
Top management support (TMS)	0.441	0.205				
Organizational data quality (ODQ)	0.146	0.512	0.141			
Intention to adopt ML (IAML)	0.209	0.515	0.092	0.454		
ML adoption (MLA)	0.116	0.444	0.214	0.700	0.514	

Table 5 - Heterotrait-Monotrait ratio (HTMT)

For the organizational and environmental contexts, modeled as second-order constructs of the reflective-formative and formative-formative types, respectively, a measurement model was conducted to evaluate the multicollinearity and the significance and sign of outer weights. For multicollinearity, we used the variance inflation factor (VIF) indicator to guarantee the values are below the threshold of 3.3 (Lee & Xia, 2017). The values are below the cutoff of 3.3 (Table 6), suggesting the absence of multicollinearity for both constructs (Diamantopoulos & Siguaw, 2006). Regarding the outer weights' significance and sign, all constructs are positive and statistically significant, indicating the organization and environment contexts can be used to test the structural model.

Formative construct (second-order construct)	**Constructs (first-order reflective)**	**Weights**	**VIF**
Organizational context (reflective-formative type)	Efficiency (Eff)	0.313***	1.255
	Top management support (TMS)	0.131***	1.048
	Organizational data quality (ODQ)	0.787***	1.251

Formative construct (first-order construct)	**Items**	**Weights**	**VIF**
Coercive pressures (CP)	CP1	0.580***	1.061
	CP2	0.882***	1.037
	CP3	0.420**	1.032
Normative pressures (NP)	NP1	0.303***	1.002
	NP2	0.890***	1.001
	NP3	0.345***	1.001
Mimetic pressures (MP)	MP1	0.351***	1.000
	MP2	0.526***	1.644
	MP3	0.516***	1.645

Formative construct (second-order construct)	**Constructs (first-order formative)**	**Weights**	**VIF**
Environmental context (formative-formative type)	Coercive pressures (CP)	0.109*	1.216
	Normative pressures (NP)	0.762***	1.415
	Mimetic pressures (MP)	0.294***	1.347

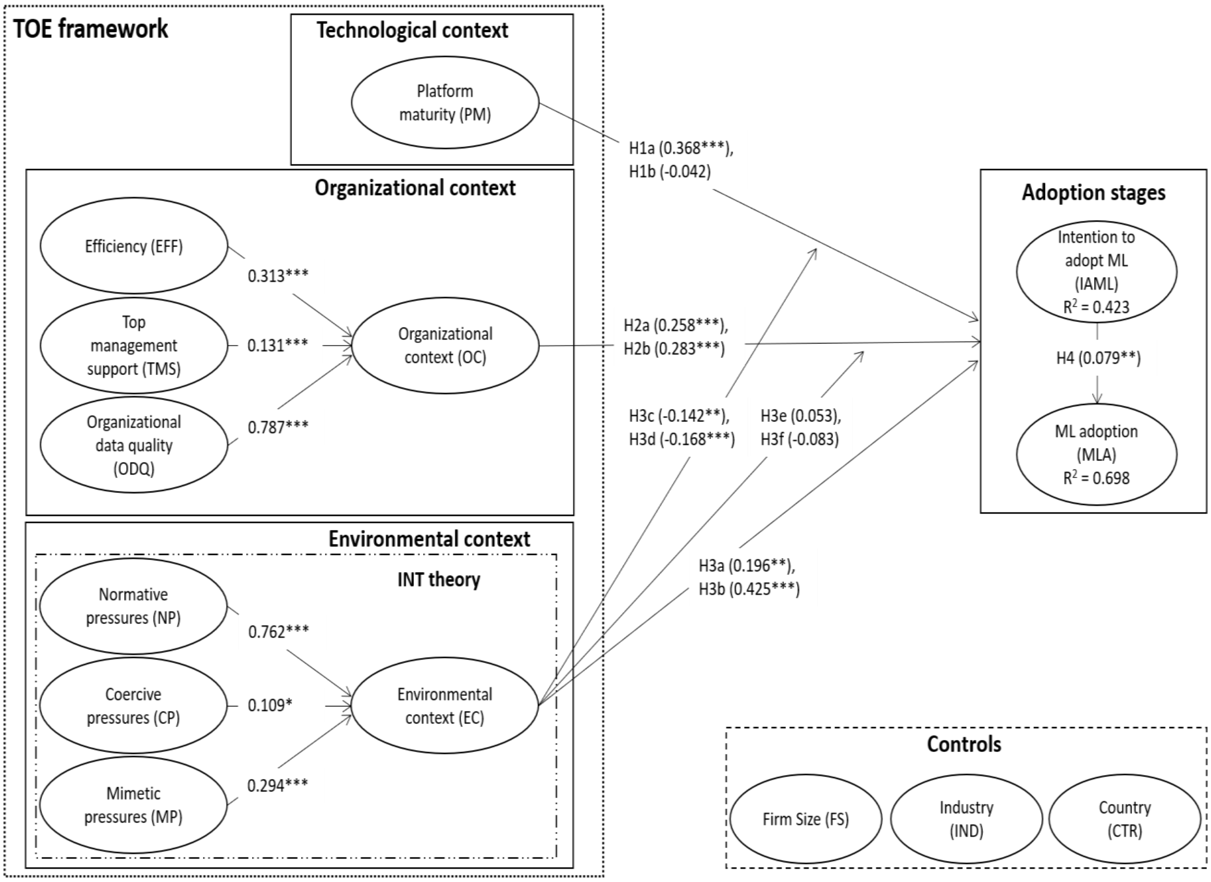
*Note: ***ρ<0.01; **ρ<0.05; *ρ<0.10.*

Table 6 - Formative measurement model evaluation

5.2. STRUCTURAL MODEL

Based on the VIF indicator, we tested all exogenous constructs for evidence of multicollinearity. The VIF values for the reflective constructs are all below 3.3, suggesting the absence of multicollinearity (Cenfetelli & Bassellier, 2017). The predictive capacity of the structural model was estimated utilizing R^2 measures and path coefficients' levels of significance, using a bootstrapping method with 5000 iterations of resampling (Hair et al., 2011; Henseler et al., 2009). Figure 2 summarizes the estimation results.

The conceptual model explains 42.3% and 69.8% of the variation in the intention to adopt ML and ML adoption, respectively. From the technological context, platform maturity is found to be statistically significant only for the intention to adopt ML ($\hat{\beta}$ =0.368; ρ<0.01). Hence, H1a is confirmed, but H1b is rejected. The hypothesized organizational context is also statistically significant for intention to adopt ML ($\hat{\beta}$ =0.258; ρ<0.01) and ML adoption ($\hat{\beta}$ =0.283; ρ<0.01), meaning that H2a and H2b are supported. Regarding the environmental context, it was found to be statistically significant to the intention to adopt ML ($\hat{\beta}$ =0.196; ρ<0.05) and ML adoption ($\hat{\beta}$ =0.425; ρ<0.01). Thus, H3a and H3b are also confirmed. For the intention to adopt ML, the study suggests its statistical significance for explaining ML adoption ($\hat{\beta}$ =0.079; ρ<0.05). Therefore, H4 is likewise supported. Regarding the moderating effects of the environment on the technological context, it is confirmed both for the intention to adopt ML ($\hat{\beta}$ =-0.142; ρ<0.05) and for ML adoption ($\hat{\beta}$ =-0.168; ρ<0.01). On the other hand, the effect of the environment on the organizational context was found to be not significant for both adoption stages. Thus, H3c and H3d are supported, whilst H3e and H3f are rejected. The main findings of our study suggest that besides explaining the intention to adopt ML and ML adoption, the environmental context also moderates the relationship between the technological context and the ML adoption stages. The investigation results provide experimental proof towards the significance of the research model to explain the intention to adopt ML and ML adoption at the firm level.



*Note: *ρ<0.10; **ρ<0.05; ***ρ<0.01.*

Figure 2 - Structural model for ML adoption at the firm level

6. DISCUSSION

6.1. DISCUSSION AND MANAGERIAL FINDINGS

The findings of this research indicate that the technological, organizational, and environmental perspectives of the firm affect the intention to adopt ML and ML adoption in singular manners. When considering the technological traits of the firm, our research reveals that firms with higher platform maturity are more willing to move towards a stage in which they intend to adopt ML, as they are more prepared to extract value from it (Côrte-Real, Ruivo, Oliveira, & Popovič, 2019). Thus, firms should ensure the readiness of a sophisticated IT infrastructure that promotes data-driven decisions (Qin & Chiang, 2019). However, there is no evidence towards a higher platform maturity leading to an increasing eagerness to adopt ML. We attribute this factor to (1) the holistic representation of the construct, that accounts for data management, system integration, reporting and visualization, and predictive discovery capabilities (Anand et al., 2016) and (2) the sample profile – we are only dealing with large companies both in number of employees and revenue. Hence, firms that are already successful in the market and have a mature infrastructure are not seeing the benefits of adopting ML, and are more commonly stopped in an early period of adoption without moving forward to the adoption stage *per se*. This research emphasizes the need for managers, practitioners, and researchers to underscore the usefulness of ML better across decision-makers to revert this situation. This call includes promoting close communication amongst key stakeholders with the IT department across all business areas to understand ML as a way of renovating business processes and enhancing strategic value (Ravichandran & Lertwongsatien, 2005).

When referring to the organization, we conclude that efficiency, top management support, and organizational data quality as a whole are a good proxy of the company's organizational context, which is found to be a facilitator of ML adoption. This factor stands out as a valuable contribution for managers, stressing the importance of evaluating the organizational characteristics of the firm prior to adoption (Alain & Ooi, 2008). This element emphasizes the need for top management support to promote the innovation's adoption, as well as to account for the necessary efficiency and to stress the need for a good organizational data environment.

With regards to the environment enclosing the firm, we state that managers ought to be especially aware and responsive to the surroundings of the firm, as it directly influences ML adoption, showing that the external characteristics affecting the firm influence organization's adoption (de Mattos & Laurindo, 2017; Khalifa & Davison, 2006). All pressures were proved to be positively significant, demonstrating that normative, coercive, and mimetic pressures drive ML adoption. This situation highlights the importance that should be given to external pressures, as it can lead the firm to go to an adoption stage when it is, in fact, not ready for it. Hence, we suggest that managers should carefully evaluate the pressures that are being exerted on the company, and ensure they are not persuading the company into a rushed adoption when all the other factors are not yet ready to accommodate it.

Likewise, the intention to adopt ML was confirmed as a driver of ML adoption. As the intention is the first step to move towards adoption and posterior assimilation (Zhu, Kraemer, et al., 2006), gathering information about the technology, evaluating the potential benefits it may bring, how to improve business performance and how to reduce costs with its usage, is proven to promote the adoption process.

As for the influence of the moderator, we found out that the environment shapes the relationship between technology and the ML adoption stages. For the intention to adopt ML, the impact of platform maturity as a predictor is shown to be higher among firms where the environmental context is lower (Figure 3a). In particular, when the environmental context is high, the platform maturity is not as relevant as when the environmental context is low since the intention to adopt ML is already elevated while in the presence of environmental pressures. For the ML adoption, we argue that the environment negatively moderates the maturity of the platform, and an increase of the environmental context levels will undermine the importance of the technology, meaning that an increasing level of external pressures will yield a diminishing focus on technology competence (Figure 3b). Such as in the intention to adopt ML, platform maturity yields a much more important effect in low environmental surroundings than in high environmental ones. This point is a major concern for managers, that should take into consideration that a mature platform is in place before moving to adoption, even though the persuasion from competitors, suppliers, partners, or even norms from the government may accelerate the need to adopt ML.

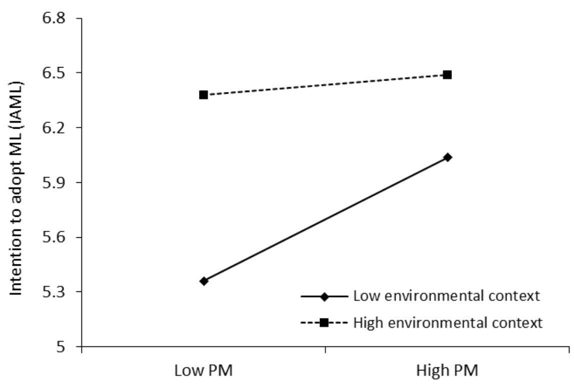


Figure 3a - Moderating effect of the environment on the intention to adopt ML

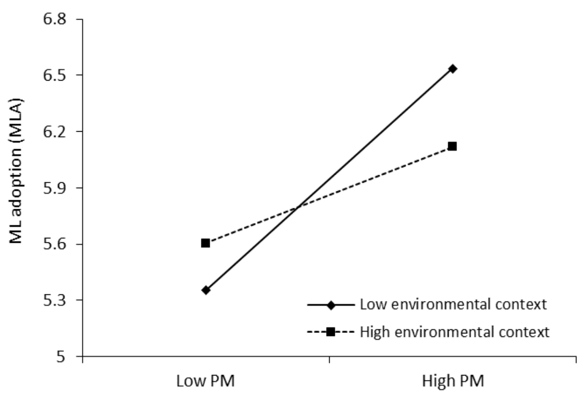


Figure 3b - Moderating effect of the environment on ML adoption

The implications arising from this research emphasize that firms are not static institutions in themselves, but rather evolving concepts that depend on the environment they are inserted in (Teo et al., 2003). Therefore, we can infer that ML adoption is, instead of a detached process, a sprouting activity that entails the interaction among the environment the firm is settled in and the technological context associated with it.

6.2. THEORETICAL FINDINGS

Grounded on the managerial and practical implications discussed above, the implications for theory coming from this study underpin the most important contributions to the literature. At the outset, this study strengthens the evidence towards the benefits of enriching the environmental context of the TOE framework with INT theory (Ahmadi et al., 2017). Moreover, to the best of the authors' knowledge, this research provides the first conceptual model for studying ML adoption, which is of paramount importance to pave the avenue for further investigation. This pioneering model conceived the need for incorporating into the TOE contexts some constructs that capture the technical components of ML, which is not common in IS research. In particular, platform maturity and organizational data quality provided a more technical assessment and conveyed more depth to the model, better capturing the essence of the technology.

Additionally, we empirically confirmed the direct effects of the technological, organizational and environmental contexts on ML adoption, further attesting the moderator effects of the environment, corroborating that the environmental conditions shape the technological context, and revealing that INT theory was essential to the research model by moderating this lens (Oliveira et al., 2019). Plus, we confirmed that the external pressures exerted may lead to adoption with less preponderancy to the technological factors. We propose to all authors to elaborate on this moderator, expounding on how the variation on the environment is reflected on technological (and also organizational) levels in other IS studies.

Lastly, we propose a groundbreaking technique of accosting the TOE framework by using second-order reflective-formative and formative-formative constructs to model the organization and environment contexts. We suggest this technique may achieve superior results than using many first-order reflective or formative constructs and yearn that this approach can set the tone for future research on the TOE framework.

6.3. LIMITATIONS AND FUTURE RESEARCH

The main limitations of this study lay the foundations for future research. The first has to do with the generalization of our findings: the sample only comprises large firms, implying that the study may not reflect the situation for smaller companies. A suggestion would be to conduct a similar investigation focused only on SMEs (Abdollahzadehgan, Che Hussin, Gohary, & Amini, 2013; Ahani, Rahim, & Nilashi, 2017). Another limitation pertains to the possibility of disregarding variables that could be appropriate for our research model. Using the Diffusion of Innovation theory to model the technological context of the TOE framework (possibly as second-order construct as well) could be a viable extension of research (Chong, Ooi, Lin, & Raman, 2009; Thong, 1999). We recommend the model proposed in this study as a baseline for upcoming endeavors in this direction.

7. CONCLUSION

The widespread of ML techniques have left exciting opportunities for researchers to draw upon the main drivers of its adoption. The impact the environment has on ML adoption has also been unclear, as it happens for similar innovation's adoption. This study emerges as the first assessment of the key influencers of ML adoption and sustains the impact of the environmental characteristics on shaping the adoption process. An integrative research model was developed to assess how the environmental context influences the process of ML adoption and moderates the other lenses of the TOE framework, steadily capturing the determinants of the technology, organization, and environment on ML adoption at the firm level, as framed in our research questions. This research confirmed that incorporating the TOE framework and INT theory better portrays the adoption phenomena, as encapsulating the environmental conditions helps to describe intra-firm adoption and contributes to a broader rationalization of ML adoption.

By empirically testing the model on a sample of 319 firms, we found out that platform maturity from the technological context, the organizational context, the environmental context, and the intention to adopt ML are predictors of ML adoption. Besides having a direct effect on ML adoption, we argue that the environment also moderates the technological context: among firms with higher levels of environmental context, the effect of platform maturity is found to be weaker, both for the intention to adopt ML and for ML adoption. Plus, the research model provides evidence towards the usefulness of modeling TOE contexts as higher-order constructs, which was found to embed the traits of the first-order constructs better into the context to which they are attained. Thus, this approach not only enhances the predictive power of the model while studying the factors impacting ML adoption but in a broader scope, helps us achieve a better understanding of IS innovation adoption.

This research is purposed to serve as a backbone for, on the one hand, decision-makers and ML practitioners who aspire to investigate ML at the firm level and, on the other hand, to IS researchers who intend for an innovative way to approach the TOE framework. We encourage all authors to elaborate on our findings.

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9. APPENDIX

Constructs	Path	Coefficients	T-value
Platform maturity (PM)	PM -> IAML	0.368***	6.589
	PM -> MLA	-0.042	0.924
Efficiency (Eff)	Eff -> OC	0.313***	12.544
Top management support (TMS)	TMS -> OC	0.131***	3.368
Organizational data quality (ODQ)	ODQ -> OC	0.787***	33.196
Organizational context (OC)	OC -> IAML	0.258***	3.927
	OC -> MLA	0.283***	3.794
Coercive pressures (CP)	CP -> EC	0.109*	1.696
Mimetic pressures (MP)	MP -> EC	0.294***	5.118
Normative pressures (NP)	NP -> EC	0.762***	15.548
Environmental context (EC)	EC -> IAML	0.196**	2.190
	EC -> MLA	0.425***	5.616
Intention to adopt ML (IAML)	IAML -> MLA	0.079**	2.132

Note: ***$\rho<0.01$; **$\rho<0.05$; *$\rho<0.10$.

Table 7 - Direct effects of the determinants on ML adoption

Constructs	Path	Coefficients	T-value
Platform maturity (PM)	PM -> IAML	0.368***	6.589
	PM -> MLA	-0.013	0.290
Efficiency (Eff)	Eff -> OC	0.313***	12.544
	Eff -> IAML	0.081***	3.720
	Eff -> MLA	0.095***	4.025
Top management support (TMS)	TMS -> OC	0.131***	3.368
	TMS -> IAML	0.034**	2.493
	TMS -> MLA	0.040***	2.691
Organizational data quality (ODQ)	ODQ -> OC	0.787***	33.196
	ODQ -> IAML	0.203***	3.943
	ODQ -> MLA	0.239***	4.215
Organizational context (OC)	OC -> IAML	0.258***	3.927
	OC -> MLA	0.304***	4.266
Coercive pressures (CP)	CP -> EC	0.109*	1.696
	CP -> IAML	0.021	1.336
	CP -> MLA	0.048	1.570
Mimetic pressures (MP)	MP -> EC	0.294***	5.118
	MP -> IAML	0.057*	1.790
	MP -> MLA	0.129***	4.297
Normative pressures (NP)	NP -> EC	0.762***	15.548
	NP -> IAML	0.149**	2.238
	NP -> MLA	0.335***	5.113
Environmental context (EC)	EC -> IAML	0.196**	2.190
	EC -> MLA	0.440***	5.766
Intention to adopt ML (IAML)	IAML -> MLA	0.079**	2.132

Note: ***ρ<0.01; **ρ<0.05; *ρ<0.10.

Table 8 - Total effects (direct and indirect effects) of the determinants on ML adoption

Direct effects						
Hypothesis	**Independent variables**	**Dependent Variables**	**Weights**	**T-value**	**Findings**	**Conclusion**
H1a	Platform maturity (PM)	Intention to adopt ML (IAML)	0.368***	6.589	Positive and statistically significant	Supported
H2a	Organizational context (OC)		0.258***	3.927	Positive and statistically significant	Supported
H3a	Environmental context (EC)		0.196***	2.19	Positive and statistically significant	Supported
H1b	Platform maturity (PM)	ML adoption (ML)	-0.042	0.924	Non-statistically significant	Not supported
H2b	Organizational context (OC)		0.283***	3.794	Positive and statistically significant	Supported
H3b	Environmental context (EC)		0.425***	5.616	Positive and statistically significant	Supported
H4	Intention to adopt ML (IAML)		0.079**	2.132	Positive and statistically significant	Supported
Moderating effects of the environmental context (EC)						
Hypothesis	**Independent variables**	**Dependent Variables**	**Weights**	**T-value**	**Findings**	**Conclusion**
H3c	Platform maturity (PM)	Intention to adopt ML (IAML)	-0.142**	2.813	Negative and statistically significant	Supported
H3e	Organizational context (OC)		0.053	0.959	Non-statistically significant	Not supported
H3d	Platform maturity (PM)	ML adoption (ML)	-0.168***	5.040	Negative and statistically significant	Supported
H3f	Organizational context (OC)		-0.083	1.325	Non-statistically significant	Not supported

Note: ***ρ<0.01; **ρ<0.05; *ρ<0.10.

Table 9 - Hypotheses conclusion