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Assessing machine learning adoption at the firm level: the moderating effect of the environmental context

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Abstract

Granted that Machine learning (ML) can positively impact an organization's performance, it is crucial to understand the technological, organizational, and environmental drivers upon its adoption. Using the technology-organization-environment (TOE) framework and the institutional (INT) theory, a measurement of the determinants of ML adoption and an evaluation of the moderating effects of the environmental context were made in a single framework. Partial least squares, a structural equation modeling 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, both as a predictor and as a moderator of the technological context. Moreover, it suggests that external pressures may lead to a rushed adoption of ML when the firm is not yet prepared to accommodate it.

Keywords: Machine learning; Information technology (IT) adoption; Technology-organization-environment (TOE) framework; Institutional (INT) theory; Environmental context.

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1. Introduction

The recent ML popularity is spreading to the industry domain, alongside with the C-suite perception of ML as a way to renovate business processes and achieve strategic value [1]. This paradigm emphasizes the importance for companies to embrace the digital transformation, having in ML a centerpiece to automate the understanding of different domains [2,3]. This 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 [4]. Nevertheless, evidence suggests that a vast number of organizations still do not consider embracing ML, mainly because of: the uncertainty around today's business environment [5]; managerial reservations on how to manage risks and justify investment [6]; insufficient ML know-how [7]; and disparate IT landscapes [8]. On top of that, there is a lack of empirical work on the aspects influencing favorable adoption at the firm-level. Motivated by these issues, the objective of this study is to address the following research question: "how does the environmental context influence ML adoption?", which also helps us answer "what are the key drivers of ML adoption?". The authors developed a research model that enriches the environmental perspective of the TOE framework with INT theory, better portraying the adoption phenomena.

The contribution of this paper is threefold. First, this study presents a framework to explain ML adoption at the firm-level by empirically examining data from 319 firms. Second, we assess the impact of the environment as a moderator, paving the way for further research. Third, we model higher-order constructs, as theory suggests that hypothesizing this additional level of abstraction may enhance parsimony and reduce model complexity [9].

In the next section, we provide a background on ML, followed by theoretical considerations on adoption models. Then, we introduce the conceptual model, propose the hypotheses, present the research methodology and the analysis of results. Lastly, we discuss the implications and conclude with the limitations and next steps for research.

2. Theoretical Background *(abbreviated)*

2.1. Machine Learning

ML is a data-driven computational technique that uses algorithms to automate knowledge acquisition from examples [10]. ML algorithms automatically learn from data and adapt to it over time without being explicitly programmed [11,12]. ML uncovers patterns and provides actionable insights with minimal human intervention [13].

ML is a subfield of artificial intelligence, and some categorizations have been made in order to organize ML methods by their desired outcomes or, instead, the amount of supervision they need during training [14]. Generally speaking, supervised, unsupervised, semi-supervised, and reinforcement learning are the acknowledged ML categories. Each category relies on a specific set of ML algorithms, even though some ML algorithms are used with different purposes across categories (e.g., neural networks have applications in all said types of ML). Throughout this study, we will be referring to ML in its broader connotation, without particularizing any category or algorithm.

2.2. Technology-organization-environment (TOE) framework

The TOE framework [15] explains the process of an innovation's adoption at the firm level by means of three contexts: the technological context, which describes the internal and external technologies relevant to the firm, including practices, hardware, and software [16]; the organizational context, which refers to descriptive measures such as managerial structures, resources, and processes of communication [17]; and the environmental context, which includes how a firm conducts its business in relation to the industry, competitors, and regulations [15]. The TOE framework offers solid theoretical background and consistent empirical measures to study adoption in different fields of IS [18].

2.3. Institutional (INT) theory

The INT theory focuses on the external pressures in the organizational adoption of innovations. It proposes that a firm's decision to adopt an innovation is influenced not only by rational goals but also by its surroundings [19]. It contemplates three types of isomorphic pressures [20]: coercive, based on regulations, values, and norms, arising from trade associations, the government, or other associations with regulatory power [21]; normative, imposed on a firm by other organizations the first rely on, such as customers or suppliers [22]; mimetic, exerted when a company mimics the behavior of other organization, usually a competitor, to reduce the risk of being a first adopter [21].

3. Research model and hypotheses

With such an extended theoretical foundation and consistent empirical sustenance – for instance, in CRM, SCM, ERP, BI, e-banking, cloud computing, blockchain, among others – there is a clear opportunity to extend TOE's realm of research to ML adoption. With the complement of INT, it emerges as better able to capture external factors affecting adoption [23]. Also, since the environment is characterized by its uncertainty and intricate dynamism, the authors suggest it can also act as a moderator [24]. The conceptual model developed is presented in Fig. 1.

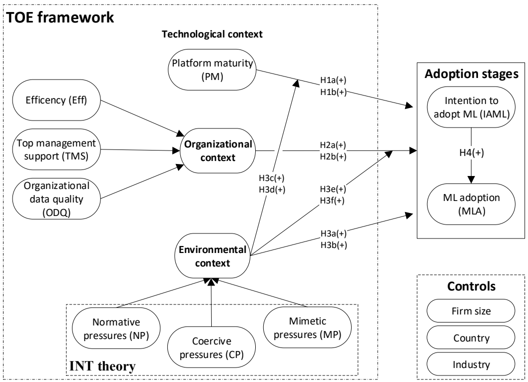

Fig. 1. Research model for ML adoption at the firm level.

A mature and sophisticated platform for storing, integrating, and processing data is key to value extraction, as it will potentiate the usage of ML [25]. Hence, we postulate that platform maturity empowers a firm to adopt ML and unlock value from stored data. Therefore,

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

H1b. Platform maturity positively influences ML adoption.

It is reasonable to assume that various individual factors exist in themselves but affect, in a broader scope, the thorough organizational context – an intangible concept that should be analyzed as a combination of its sub-dimensions. Each one of the sub-dimensions is reflective in itself and does not share a common cause, whereas together they contribute to form a wider concept – the organizational context – being, thus, modeled as a reflective-formative construct [26]. Efficiency is measured by how users are able to use ML methods to perform ordinary, repetitive tasks, expressing how the company can speed up decision-making by automating processes [27]. Top management support refers to the vision and commitment provided by senior management to foster ML adoption [28]. Organizational data quality is related to data availability, accuracy, timeliness, integrity, reliability, and security [29]. The elements attained to the organizational context are suggested to facilitate ML adoption. Therefore,

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

H2b. The organizational context positively influences ML adoption.

The way firms interact with the main elements of the environment deeply impacts their way of doing business [30]. We argue that each individual pressure impacts the full environmental context, therefore being rational to model it as a second-order construct [31]. The authors 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. While this increase may occur, it does not mean it is caused by the first pressure variation [32]. Hence, we propose that the environmental context is a second-order formative-formative construct and that it has a positive effect on ML adoption. Therefore,

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

H3b. The environmental context positively influences ML adoption.

The environment the firm is settled in influences the other contexts of their activity, with research stating that a

firm's internal characteristics are dependent on their interaction with the environment [33]. Hence, it is valid to hypothesize that the environment shapes the link between the other two TOE lenses and ML adoption. Therefore,
H3c. The environmental context moderates the link between platform maturity and the intention to adopt ML.
H3d. The environmental context moderates the link between platform maturity and ML adoption.
H3e. The environmental context moderates the link between the organizational context and the intention to adopt ML.
H3f. The environmental context moderates the link between the organizational context and ML adoption.

The intention to adopt ML (evaluation/persuasion) happens when the company begins to gather information to assess its relevance and analyze its benefits [34]. Even though intention does not guarantee the technology will be integrated in the end, this phase occurs immediately before adoption and flags the willingness to implement it [18]. 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.

3.1. Control variables

IS literature provides evidence towards the usage of control variables. To understand if ML adoption is undergone differently by the nature of the industry, country, or firm size – measured by the number of employees and the annual turnover – we introduce these variables as control variables [16].

4. Research methodology

A web-survey was conducted to evaluate the proposed constructs and the conceptual model. Item-questions were derived from literature and measured using a seven-point scale ranging from "strongly disagree" to "strongly agree" (measurement items are available from the author on request). An expert panel of five IS professionals and researchers reviewed the items, indicating suitable amendments. We used a pilot study to test the questionnaire in a sample of thirty firms, which were not included in the main investigation. The results provided evidence supporting the reliability and validity of the instrument.

An online version of the questionnaire was emailed to qualified personnel from a list of 2000 companies gathered with the assistance of SAP, a leading software company. 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 in 2019. In the first stage, 210 valid responses were received. The second stage generated 109 additional valid responses, for a combined total of 319 usable responses. This yields a response rate of 16%, comparable to other IS studies. The Kolmogorov-Smirnov test confirmed the absence of non-response bias [35]. The authors used Harman's one-factor test [36] to test for common method bias, confirming that none of the factors individually explains the majority of the variance. The profile of the sample is presented in Table 1.

Table 1. Sample characteristics.

Sample characteristics		Observations (n=319)	Percentage (%)
Industry	Health & education 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%
	Business unit manager 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	50 to 249	11	3.45%
	250 or more	308	96.55%
Firm Size: Annual turnover	10 to 50 million dollars	25	7.84%
	More than 50 million dollars	294	92.16%

5. Results

Partial least squares was used to assess the proposed research model as (1) it is useful for analyzing matters that have never been tested before [37] (2) the measurement model is complex and low theoretical background is provided [37] (3) allows for latent constructs to be modeled as formative indicators [19] and (4) does not require data distribution assumptions [38]. The software used to test the research model and analyze the structural model was SmartPLS 3.0 [39].

All constructs exhibit composite reliability and Cronbach's Alpha higher than 0.7, indicating appropriateness and internal consistency [40]. Likewise, all constructs display average variance extracted (AVE) values higher than 0.5, implying convergent validity [37], as per table 2. Indicator reliability was demonstrated as all loadings are higher than 0.6. Discriminant validity was verified by (1) the Fornell-Larcker criteria [41], as the AVE squared root of each construct is higher than the construct's correlations (Table 2); (2) the loadings of each indicator are greater than the cross-loadings [32], as per Table 3; (3) all constructs have heterotrait-monotrait ratio values below 0.9 (Table 4).

Table 2. Descriptive statistics, correlations, CR, and AVE (note: bold values in diagonal are the AVE square root).

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

Table 3. Loadings and cross-loadings.

Constructs	Item	PM	Eff	TMS	ODQ	IAML	MLA
Platform maturity	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	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	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	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	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	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. Heterotrait-Monotrait ratio (HTMT).

Constructs	PM	Eff	TMS	ODQ	IAML	MLA
Platform maturity						
Efficiency	0.207					
Top management support	0.441	0.205				
Organizational data quality	0.146	0.512	0.141			

Intention to adopt ML	0.209	0.515	0.092	0.454	
ML adoption	0.116	0.444	0.214	0.700	0.514

For the second-order constructs, a measurement model was conducted to evaluate the multicollinearity and the significance and sign of outer weights. The variance inflation factor (VIF) [42] shows all values are below the threshold of 3.3, suggesting the absence of multicollinearity. Regarding the outer weights' significance and sign, all constructs are positive and statistically significant, indicating they can be used to test the structural model (Fig. 2).

The explanatory 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 [37]. Fig. 2 summarizes the results. The conceptual model explains 42.3% and 69.8% of the variation in the intention to adopt ML and ML adoption, respectively. 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 statistically significant for the intention to adopt ML ($\hat{\beta}$=0.258; ρ<0.01) and ML adoption ($\hat{\beta}$=0.283; ρ<0.01), hence H2a and H2b are supported. The environmental context 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 confirmed. The intention to adopt ML is also statistically significant for explaining ML adoption ($\hat{\beta}$=0.079; ρ<0.05). Hence, H4 is supported. The moderating effects of the environment on technology is confirmed for the intention to adopt ($\hat{\beta}$=-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. Thus, H3c and H3d are supported, whilst H3e and H3f are rejected.

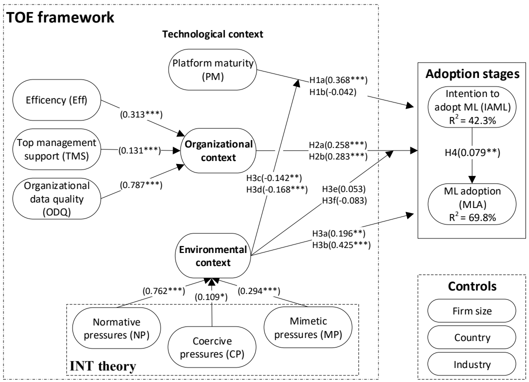

Fig. 2. Structural model for ML adoption at the firm level (note: *ρ<0.10; **ρ<0.05; ***ρ<0.01).

6. Discussion *(abbreviated)*

6.1. Discussion and managerial findings

When considering the technological traits of the firm, this 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 [43]. However, there is no evidence towards higher platform maturity leading to increased ML adoption. Hence, firms that already have a mature infrastructure are not perceiving the benefits of ML and are more commonly stopped in an early period of adoption. This research emphasizes the need to highlight ML across decision-makers as a way of renovating business processes and enhancing strategic value to revert this situation.

When referring to the organization, we conclude that efficiency, top management support, and organizational data quality are a good proxy of the company's organizational context, which is found to be a facilitator of ML adoption. This underlines the need to evaluate if the right organizational features are in place prior to adoption [17,44].

Regarding the environment, we state that the C-level ought to be aware and responsive to the firm's surroundings, as it directly influences ML adoption [45]. All pressures were proved to be positively significant, indicating that managers should ensure they are not persuading a rushed adoption when the firm is not yet ready to accommodate it.

Likewise, intention was proven to promote adoption, representing the first step toward ML embracement [34].

As for the influence of the moderator, we found that in the intention stage, the impact of platform maturity is higher among firms where the environmental context is lower (Fig. 3a). When the environmental context is high, platform maturity is not as relevant as when the environmental context is low. For ML adoption, the environment negatively moderates the platform maturity, and an increase of the environmental context levels will undermine the importance of technology. This means that an increasing level of external pressures will yield a diminishing focus on technology competence (Fig. 3b).

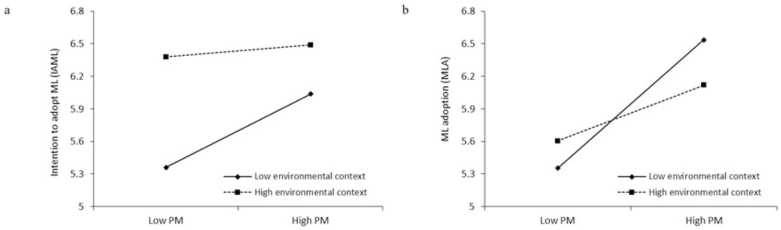

Fig. 3. (a) moderating effect of the environment on the intention to adopt ML; (b) moderating effect of the environment on ML adoption.

Such as in the intention to adopt ML, platform maturity yields a more important effect in low environmental surroundings. This is a major concern for the C-suite, that should ensure that a mature platform is in place before adoption, even though external persuasions may accelerate the need to adopt ML.

6.2. Theoretical findings

At the outset, this study strengthens the evidence towards the benefits of enriching the environmental context of the TOE framework with INT theory. Moreover, this research empirically confirmed the moderating effects of the environment, corroborating that it shapes the technological context [46]. We confirmed that the external pressures may lead to adoption with less preponderancy to the technological factors. Lastly, we build upon the benefits of higher-order modeling by using second-order constructs. We suggest this technique may achieve superior results to explore complex relationships in IT adoption and hope this approach can set the tone for future research on TOE.

6.3. Limitations and future research

The limitations of this study lay the foundations for future research. The first limitation has to do with the sample only comprising large firms, leaving the opportunity to conduct a similar investigation on SMEs. Other limitation pertains to the possibility of disregarding variables that could be appropriate for our model. Using the Diffusion of Innovation theory to model the technological context of the TOE framework could be a viable extension of research.

7. Conclusion

This study empirically sustains that each TOE context is a predictor of ML adoption. Besides having a direct effect on ML adoption, the environmental context also moderates the technological lens, as framed in our research questions. 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. This approach helps achieving a better understanding of IT adoption in general, and of ML in particular.

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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