Determining factors influencing the adoption of Artificial Intelligence at a firm level and its impact on firm's performance: Empirical analysis from an emerging country

Research Project Plan

1. Abstract

The use of information and communication technologies, or ICTs, have increased over the last years at a firm level, as organizations have identified the potential advantages that their use bring to its operation. While most companies located at first world and emerging markets currently use traditional ICTs, such as personal computers, internet services, office automation software, and specialized software packages as enterprise resource planners (ERP), customer relationship managements (CRM), or supply chain managements (SCM), among others, to improve their productivity, the development of a new breed of these technologies, or "*Digital ICTs*", have changed the landscape of advanced technology adoption and its use in order to improve competitiveness. While some of these digital ICTs, including mobile, social media, cloud computing, and even big data, have grown in popularity over the last decade as their corporate use has increased due to commercial efforts made by leading IT companies, there is a subset of highly innovative and disruptive digital technologies, in particular, artificial intelligence (AI) and advanced analytics (AA), that show uneven adoption rates among various firms, especially the ones located at emerging markets, such as Latin America. Through a quantitative approach, this research project aims to identify the potential hindering or enabling factors that can impact the level of adoption of AI and AA technologies, as well as their perceived level of competitiveness, using Colombian firms as a case study.

2. Introduction

2.1. Introduction

Information Systems (IS) is the field of study on the management, use and impact of information technologies in organizations (MIT, 2021). Information and communication technologies, or ICTs, are a set of IS developments based on hardware or software systems, created with the objective to facilitate processes of transmission and reception of information and data generated by people, firms or countries (Ogunsola, 2005), and have essentially changed the way they interact. The field of ICTs has rapidly evolved as companies started to realize the potential business impact that automated information systems had, especially on overall factor productivity.

ICTs have played a fundamental role to improve business processes at a firm level over the last 70 years, allowing them to become one of the main tools used by firms to support the advanced management of its business departments such as manufacturing, finance, logistics, sales, marketing, among others. In this context, ICTs have been considered *"valuable organizational resources, that can be used to improve internal communication, enhance product design quality, reduce design cycle time, and lower product development cost"* (Liang et al., 2010, p. 1142), eventually leading to higher performance and competitivity at a firm level.

As expected, the study of ICTs has grown exponentially since the 1980s within the business management field, based on countless innovative developments created by leading IT companies that have resulted in different business use cases that aim to optimize highly inefficient and costly business processes characterized for a high level of manual and labor-intensive procedures. In this context, new disruptive digital technologies, such as advanced analytics (AA) and artificial intelligence (AI), have been designed to provide elements of evaluation, prediction, and prescription of various business dynamics by the intensive use of data and information, one of the most powerful assets in the digital era (Nadkarni & Prügl, 2020), so that the executive roles at firms can take strategic business decisions in an informed and systemic manner. Thus, the great impulse we have seen of these data driven digital ICTs, given the relevance and pertinence they have in today's business context, especially considering the exponential growth that transactional data has experienced, and the theoretical business value that firms could obtain from it. In that sense, some scholars have observed that *"the ability to obtain information about markets and customers helps to ensure that firms are more attuned to changes in the environment, and can result in a competitive advantage over slower, ill-in- formed competitors"* (Tippins & Sohi, 2003, p. 745).

Given this, firms placed in Latin America should be ideal candidates to rapidly incorporate technical advancements in AI and AA to reduce their operating costs, improve their levels of productivity and competitiveness, and strengthen their general financial performance; however, the overall levels of adoption of such technologies in the region are far from ideal, and lag when compared with firms located in similar sized economies at other regions such as North America, Asia Pacific and the European Union (Soni et al., 2020). According to the figures of the report *"The global AI agenda: Latin America"* (Bailey et al., 2020), it is estimated that on average, only 79% of organizations in Latin America are in the process of experimenting with AI in business projects, compared to 87% of organizations in North America and 95% in Asia Pacific, respectively. Considering these figures, and the fact that Colombia is currently placed as the 3rd largest economy in the region just behind Brazil and México, but presents a lower level of overall factor productivity compared to its peers in the region (Chile, Argentina and Peru), this project, through a quantitative process aims to identify the main factors that could be influencing the adoption rates of AI and AA technologies at a firm level in the Colombian market, considering its regional significance, economic size, and growth projection.

2.2. Project Motivation

Several studies have been performed both by practitioners and scholars hoping to identify the main drivers that hinder or enable firms to adopt technological innovations into their business processes successfully. While there are various highly cited and used frameworks related to technology adoption, such as the technology acceptance model (TAM), theory of planned behavior (TPB), unified theory of acceptance and use of technology (UTAUT), Diffusion of innovation (DOI) and Technological organizational and environmental (TOE), among others, only the DOI and TOE frameworks are focused on studying the adoption of ICTs at the firm level (Oliveira et al., 2011). Out of these two frameworks, TOE, initially mentioned in the book *"The Processes of Technological Innovation"* (Drazin, 1991), describes how these sort of technical innovations evolve within organizations, ranging from their creation and development, to the process of adoption and business use (Baker, 2018), and is one of the most cited and accepted in academic literature.

Currently whoever, there is a notable scarcity of studies focusing on the general factors that could influence the adoption of highly disruptive digital technologies such as AI and AA, defined as tools with the potential for *"(1) a 5–10 times improvement in performance compared to existing products; (2) create the basis for a 30–50% reduction in costs; or (3) to have new-to-the world performance features*" (Rice et al., 1998, p. 52), using firms located on emerging economies as the unit of study. So far, most of the academic work in the field have focused on a particular industry (i.g. finance, healthcare, manufacturing, tourism, etc.), a particular AI technology (i.g. chatbots, text mining, speech recognition, etc.), a particular firm size (i.g micro and small enterprises), a particular region (i.g. North America, Western Europe or south east Asian countries), or a specific set of limitations (technological ones), as noted on studies performed by (Cubric, 2020) and (Borges et al., 2020), creating a research gap that could be filled with an empirical study of such kind.

Therefore, this project aims to address this particular gap, by the creation of an adapted methodological model using a sample of Colombian firms located on across various industries and with different ages and characteristics, that have different levels of adoption on a set of AI technologies (Advanced descriptive analytics (AA), Chatbots and automated assistants, predictive and prescriptive analytics, natural language understanding and processing and Image and speech recognition), and that takes in consideration other factors different from technical ones (organizational and relational), that can hopefully result in a new generalized framework.

A study on this topic and with these particular objectives would be important for firms, because the adoption of disruptive digital technologies such as AI could allow them to improve their competitiveness, reduce complexity and costs in their operations, and improve their financial results over time, especially in a highly global integrated economy; at the same time, this study could be useful for policy makers in order to seek potential interventions or adapted models (i.g. business and/or market incentives), that could increase the use of these kind of technologies, aiming for an improved global factor productivity and general economic growth as mentioned by (Pereira et al., 2020). At the same time, determining specifical factors that could impact the general rate of adoption of AI at a firm level could prove to be of great importance for the accelerated economic development of emerging countries and enterprises placed on them, based on the projections of studies such as the ones published by (Bughin et al., 2018) and (Estevadeordal et al., 2018).

2.3. Literature Review

In the IS and business management fields, the adoption of ICTs at a business level is a topic that has growth in interest over the last two decades, as the number of applications on which a certain firm can use them to improve their operation has also increased. Scholars such as (Fishbein & Ajzen, 1975), (Davis et al., 1989), (Taylor & Todd, 1995), (Rogers, 1995), (Venkatesh et al., 2003) or (Baker, 2018), among others, have developed several general theories and frameworks aiming to explain the possible factors that could be related to the rate, level and factors that a certain group of technological innovations may be adopted both from an individual and corporate viewpoint, as discussed in detail in the following sections. These frameworks have also been used as an input for the development of derived studies that look to determine the specific factors that are related to the use of certain technological solutions such as enterprise resource planners (ERPs) (Ilin et al., 2017), customer relationship management (CRMs (Marolt et al., 2015), supply chain managers (SCM) (Cao et al., 2013), business intelligence solutions (BI) (Gudfinnsson & Strand, 2018), big data (Bremser, 2018) and cloud technologies (Bannerman, 2010), among other trending developments, and have usually included either technical, organizational or market factors to account for certain observed behaviors in particular industries, firm sizes or geographical clusters. As the academic and corporate interest in new digital and disruptive ICTs, such mobile solutions, internet of things (IoT), virtual reality (VR), augmented reality (AR), and artificial intelligence (AI) has increased, the number of published articles related to these ICTs has exponentially grown, specially over the last 10 years, as shown in figure 1. The figure displays the result of a query searching for the total number of published articles in English language between the years 2010 and 2020 in the Web of Science repository (WOS) in the fields of business, management, and economics that are directly related to those digital ICTs, and reflects that both the number of published results, peaking to a maximum of 1.384 in the year 2020, and citations, peaking to a number of 27.429 in the year 2020, had a significant growth rate over this 10-year period of time.

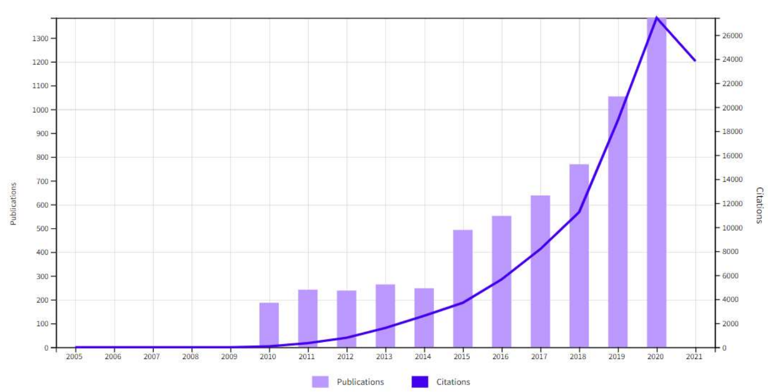

Figure 1. Number of citations and published articles in English language for articles related to disruptive digital ICTs at the Web of science (WOS) repository for the period between 2010 and 2020.

When a secondary group of terms, related to either the adoption or application of these disruptive technologies is added to the initial query we performed, a subset of the total sample is obtained, reflecting that the observed general behavior in terms of academic interest in the area of digital disruptive ICT is aligned with the interested in determining the underling factors related to their use in the real sector, and that in general, nearly 1 of out 3 published articles (452 out of 1384, or almost 33%), and nearly 1 out of 2 citations (10.736 out of 27.429, or almost 50%) for published articles in 2020 are directly or partially related to these behaviors, as seen of figure 2, reflecting also an exponential growth in both measurements in a 10-year period (between 2010 and 2020).

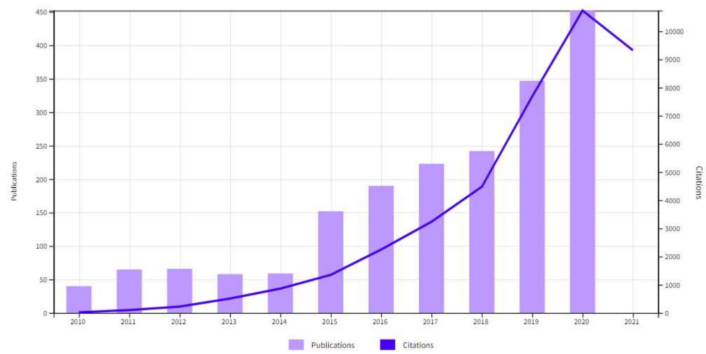

Figure 2. Number of citations and published articles in English language for articles related to disruptive digital ICT adoption or application at the Web of science (WOS) repository for the period between 2010 and 2020.

However, in relation to the specific academic interest in the field of AI and AA, this behavior is not quite like the one observed in the general field of digital disruptive technologies. This can be verified as a more specialized query is performed on the WOS repository to determine the results of the total number of published articles and total number of citations for the same period (10 years from 2010 to 2020) related with these two technologies. When we performed a query to determine the actual number of published articles in this period of time, including the terms "Artificial intelligence" or "AI" or "analytics" or "machine learning", as a point or reference, and limiting the search for the fields of business, management, economics or accounting, and English as the language for these publications, we obtained a result 5.135 articles with 75.566 citations. However, once we decide to include three additional terms in the query ("adoption" or "barriers" or "hindering") to try to limit the search to articles only related to the determination of principal factors that could either contribute or restrain the adoption of such technologies, only 310 articles with 5.988 citations were included in the WOS repository. These figures show than on average, of the total number of academic papers published in this 10-year period of time related to this specific topic, only 1 out of 15 (or roughly a mere 6%) are related to the adoption of AI and AA in WOS, a figure that is far lower than the average one we discovered for adoption of other digital ICT papers, that were close to a 33%, reflecting a notorious scarcity of this kind research projects in the field of business and management.

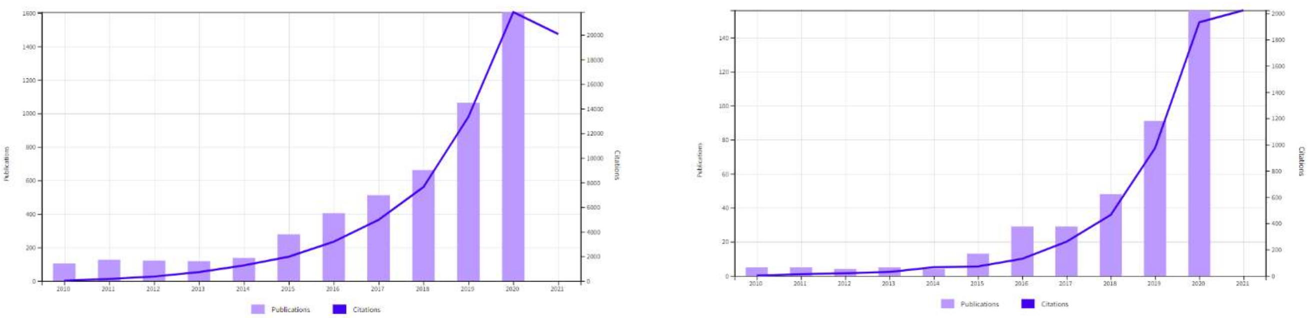

Figure 3. Number of citations and published articles in English language for articles related to AI, Artificial intelligence, analytics, and machine learning (left column) for the WOS repository, and for their adoption, barriers or hindering factors (right column) at the WOS repository for the period between 2010 and 2020.

This behavior related to AI and AA adoption is accentuated when we decide to include additional terms to segment this query for “emerging countries”, “developing countries” and for the “Latin American” region. After including these three additional terms to refine the search query, we retrieved a total of only seventy-two published articles in the WOS repository, most of which were published between 2019 and 2020, showing a potential research gap for this topic in the IS and Business management fields of study.

Having defined this subset of published articles, we performed an analysis using a technique call “natural language processing” (NLP), a machine learning application that is designed to mine and analyze unstructured text data sets in a semiautomated manner, to determine the most commonly used individual and group terms (trigrams or 3 consecutive terms, and four grams or 4 consecutive terms in our analysis) that are included in their abstract to estimate general lines of content for these articles, as well as to perform a grouping on “clustering” technique to determine similar lines of work for these research projects and possible similarities between them. This process, based on the corpus of the seventy-two abstracts of these articles, includes a preprocessing step, on which stop words, or usually common linguistic connectors that does not have any significant idiomatic value are removed, and the remaining text is stripped of punctuation and exclamation signs, unified to small caps, and tokenized (divided into single words for vectorization used by this machine learning model), in order to determine the n-grams or combinations of consecutive words that are more commonly found in this text corpus, as shown on the visualization and list displayed on figure 4.

Figure 4. Word cloud visualization containing the most common 3-grams and 4-grams (3 or 4 consecutive word combinations) present in the abstracts of resulting published articles for the refined query of AI and related technologies adoption in either emerging, developing, or Latin American countries between 2010 and 2020 in the WOS repository.

The initial three and four-grams analysis show that the most commonly consecutive terms that appear in the abstracts of these seventy-two published articles are related to the design of methodological approaches, research limitation implications of the studies performed and the originality value of the papers that are estimated by the authors. In term of the topics, we can see that many of them are related to big data analytics, AI technology talent and social media analytics. Using this analysis, we can also see that in the abstracts of those papers, there is only a marginal number of them that directly discuss the factors that could be influencing the adoption of such technologies (5), adoption of AI technologies (5), use of big data (7), usage of AI technology (4), and Usage of big data analytics (BDA) technologies (5).

Using a complementary NLP and statistical technique called "Topic modeling" based on the Latent Semantic Indexing (LSI) algorithm, that is defined as an unsupervised form of machine learning that aims to define groups or "clusters" of documents from a general collection based on similarity of the terms they contain to estimate possible topic similarities by determining a set of concepts they include, we were initially able to assess the list of seventy-two articles that resulted from the query performed on the WOS repository. Projecting a number of topics or clusters equal to five, and using the predefined structure of n-grams (three and four for this literature review) as the base for this analysis to include semantical meaning rather than just word frequency appearance as the measurement for this clustering, we were able to determine a list of general topics on which these articles could be grouped, each of them characterized by a list of key terms, as seen on figure 5.

Topics

1: health data standards, data standards healthcare, standards healthcare organisations, health data standards healthcare organisations, health data standards healthcare, data standards healthcare organisations, decision health data, adoption decision health data, adoption decision health, decision health data standards
2: technology talent acquisition, ai technology talent acquisition, ai technology talent, adoption ai technology, usage ai technology, usage ai technology talent acquisition, adoption ai technology talent acquisition, adoption ai technology talent, actual usage ai, usage ai technology talent
3: bda utilization adoption, technological organizational environmental, strategic utilization bda, adoption bda organizations, bda adoption model, big data analytics, design methodology approach, research limitations implications, originality value paper, purpose purpose paper
4: readiness big data, readiness big data iot, big data iot, health care sector, health care providers, correlated hit adoption, design methodology approach, research limitations implications, practical implications study, originality value paper
5: technology transfer barriers, barriers technology transfer, critical barriers technology, critical barriers technology transfer, supply chains manage, technology transfer critical, technology transfer critical barriers, transfer critical barriers, single numeric value, design methodology approach

Figure 5. Results of the topic modeling technique, containing the key 3-grams and 4-grams (3 or 4 consecutive word combinations) present in the abstracts of resulting published articles for the refined query of AI and related technologies adoption in either emerging, developing, or Latin American countries between 2010 and 2020 in the WOS repository.

The modeling technique shows that there are only two clear categories out of the five defined (topics two and three), that are clearly focused on determining the effective use of big data/analytics/AI technologies from a systemic viewpoint, while the other three remaining ones are related to the possible effects, business applications, related digital technologies, or business context on which these technologies are seemed to be used.

The LSI topic model outputs an estimated score for each document to be categorized in each of the five predefined topics we initially defined in the previous step, where the higher score represents a higher probability to be part of a determined topic. Using a filtering criterion of this score (higher than 0.25), we estimate the number of articles that are most likely part of both topics two and three, being the ones that contain key three and four grams directly related to our research and field of interest, obtaining a total list of twenty-four documents that met these criteria. The resulting list of articles of this exercise is shown on table 1.

Year	Topic 2 score	Topic 3 score	Authors	Title	Journal
2017	1,13	29,48	Verma, S; Bhattacharyya, SS	Perceived strategic value-based adoption of Big Data Analytics in emerging economy A qualitative approach for Indian firms	journal of enterprise information management
2019	0,10	0,53	Chopra, K	Indian shopper motivation to use artificial intelligence: Generating Vroom's expectancy theory of motivation using grounded theory approach	international journal of retail & distribution management
2018	0,13	0,29	Li, H; Dai, J; Gershberg, T; Vasarhelyi, MA	Understanding usage and value of audit analytics for internal auditors: An organizational approach	international journal of accounting information systems
2019	0,07	0,22	Wu, GJ; Xu, Z; Tajdini, S; Zhang, J; Song, L	Unlocking value through an extended social media analytics framework Insights for new product adoption	qualitative market research
2019	0,01	0,26	Behl, A; Dutta, P; Lessmann, S; Dwivedi, YK; Kar, S	A conceptual framework for the adoption of big data analytics by e-commerce startups: a case-based approach	information systems and e-business management
2018	0,24	0,50	Queiroz, MM; Telles, R	Big data analytics in supply chain and logistics: an empirical approach	international journal of logistics management
2017	0,16	0,98	Kache, F; Seuring, S	Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management	international journal of operations & production management
2018	0,21	0,61	Chaurasia, SS; Kodwani, D; Lachhwani, H; Ketkar, MA	Big data academic and learning analytics: Connecting the dots for academic excellence in higher education	international journal of educational management
2015	0,11	0,57	Kumar, S; Luthra, S; Haleem, A	Benchmarking supply chains by analyzing technology transfer critical barriers using AHP approach	benchmarking-an international journal
2019	0,14	0,24	Ray, A; Bala, PK; Dasgupta, SA; Sivasankaran, N	Factors influencing adoption of e-services in rural India - perspectives of consumers and service providers	journal of indian business research
2015	0,26	0,64	Chen, DQ; Preston, DS; Swink, M	How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management	journal of management information systems
	0,36	1,86	Alrahbi, DA; Khan, M; Gupta, S; Modgil, S; Jabbour, CJC	Challenges for developing health-care knowledge in the digital age	journal of knowledge management
2020	0,18	0,37	Bag, S; Gupta, S	Examining the effect of green human capital availability in adoption of reverse logistics and remanufacturing operations performance	international journal of manpower
2019	0,07	0,25	Agostini, L; Nosella, A	The adoption of Industry 4.0 technologies in SMEs: results of an international study	management decision
2017	0,07	0,24	Ahmed, V; Tezel, A; Aziz, Z; Sibley, M	The future of Big Data in facilities management: opportunities and challenges	facilities
2019	0,01	0,20	Phang, DCW; Wang, KL; Wang, QH; Kauffman, RJ; Naldi, M	How to derive causal insights for digital commerce in China? A research commentary on computational social science methods	electronic commerce research and applications
2020	0,08	0,49	Tupikovskaja-Omovie, Z; Tyler, D	Clustering consumers' shopping journeys: eye tracking fashion m-retail	journal of fashion marketing and management
2019	0,08	0,52	Narain, K; Swami, A; Srivastava, A; Swami, S	Evolution and control of artificial superintelligence (ASI): a management perspective	journal of advances in management research
2016	0,18	0,66	Bhadani, AK; Shankar, R; Rao, DV	Modeling the factors and their inter-dependencies for investment decision in Indian mobile service sector	journal of modelling in management
2015	0,07	0,29	Tint, BS; McWaters, V; van Driel, R	Applied improvisation training for disaster readiness and response Preparing humanitarian workers and communities for the unexpected	journal of humanitarian logistics and supply chain management
2016	0,10	0,56	Ab Talib, MS; Sawari, SSM; Hamid, ABA; Chin, TA	Emerging Halal food market: an Institutional Theory of Halal certificate implementation	management research review
2019	0,07	0,28	Seetharaman, A; Patwa, N; Saravanan, AS; Sharma, A	Customer expectation from Industrial Internet of Things (IIOT)	journal of manufacturing technology management
2019	0,09	0,47	Lima, A; Araujo, FFM	Technology environment and crowdfunding platforms in Brazil	rege-revista de gestao
2018	0,07	0,21	Wahga, AI; Blundel, R; Schaefer, A	Understanding the drivers of sustainable entrepreneurial practices in Pakistan's leather industry: A multi-level approach	international journal of entrepreneurial behaviour & research

Table 1. Resulting article list after the use of the topic modeling technique (LSI) and filtering with a criterion (higher than 0.25) from the total WOS query that are included in the topics related to big data, analytics, or AI use, that contain key 3-grams and 4-grams related to these topics.

An initial assessment of these sub-group shows that out of these twenty four articles, only two of them were located on the Latin American region (Brazil), and were mainly focused on the use of crowdsourcing platforms in operations in firms located at that country, and its apparent relation to the level of adoption of business analytics and internet technologies (Lima & Araújo, 2019), or to analyze the use of big data analytics (BDA) at Brazilian firms who were already using supply chain software packages for logistics (Queiroz & Telles, 2018) aiming to identify the awareness of Brazilian firms in the use of BDA, as well as potential barriers and difficulties to implement these tools in the logistics business field. Out of the remaining twenty-two articles, we can find projects such as the one performed by (Verma & Bhattacharyya, 2017) that discuss the factors that enable the adoption of BDA technologies at Indian firms aiming to determine a general framework applicable for emerging economies. Using the strategic value as the main driver and the TOE framework as the methodological guideline, the study uses a qualitative approach from a 22 firm sample to analyze the validity of the factors proposed by this framework in the Indian context. We can also find projects like the one published by (Agostini & Nosella, 2020) that attempts to assess the use of digital 4.0 technologies in a general matter in an international context for small and medium enterprises (SME), where one of the main conclusions is that smaller firms that have a higher levels of social capital also tend to have higher levels of adoption of 4.0 digital ITCs. Finally there is a set of articles, like the one published by (Li et al., 2018), (Behl et al., 2019), (Kache & Seuring, 2017), (Chen et al., 2015) or (Chopra, 2019), that are focused on determining potential factors, enablers and barriers for the use of BDA and AI technologies at specific industries (manufacturing, auditing, supply chain management, e-commerce, retail), specific types of firms (startups) or even at an individual level, that don't have the same scope or take into account the same level of generality of the research we propose.

Therefore, given this preliminary analysis, to the best of our knowledge this would be the first research project that would focus on integrating and adapting two highly acceptable and used general ICT adoption frameworks (TOE and DOI) at a firm level to determine the level of use of a disruptive digital ICT, such as artificial intelligence, on an emerging country placed in Latin America; additionally, this would also be the first study that would aim to link the perceived level of competitiveness of each firm as a measure of their performance to their current level of AI adoption in an effort to determine a possible relationship between the first two frameworks, and the resource based value (RBV) dynamic capabilities one, trying to determine if a possible moderation relationship between the business motivations to enhance firms competitiveness in a dynamic context and the adoption of disruptive digital ICT exists.

2.4. Problem statement

Artificial intelligence (AI) technologies, as part of a set of new disruptive digital ICTs, have the potential to positively impact the levels of productivity, efficiency, and value generation of firms, especially the ones located on emerging countries; however, the dynamics and particular factors that can hinder or incentive the adoption of such technologies at Latin American countries are still to be determined, based on an adapted version of existing methodological frameworks.

2.5. Research questions

- ¿Which are the main factors that influence the rate of adoption of a set of disruptive digital technology, such as AI, in firms located at emerging countries such as Latin America? and ¿Do these factors influence their perceived level of competitiveness?
- ¿Do these factors have a mediation relationship on the perceived level of competitiveness trough the rate of adoption of AI at any given firm located on an emerging country such as the one on Latin America?

2.6. Objectives

Main objective

- Determine, based on a statistically significant sample of firms located in the Colombian market, whether there are different factors that hinder or incentive the adoption and intensive use of AI technologies to improve their corporate processes on firms placed at emerging countries and their relation to their perceived level of competitiveness.

Secondary Objectives

- Define the potential competitive advantages and benefits that firms can obtain with the use of artificial intelligence technologies, as part of a digital transformation strategy.
- Establish the main technical, organizational, and relational requirements that firms should consider to successfully leverage strategic decision-making, with the use of data-driven digital technologies, such as AI and AA.
- Create an adapted methodological framework that summarizes the main barriers (technical, financial, knowledge, processes, etc.) that firms face to successfully adopt AI and AA technologies as a part of digital transformation strategy.

3. Conceptual framework

3.1. Technological innovation adoption models – ICTs and how firms adopt them

In a highly globalized and integrated economic environment such as the current one, firms on any given industry have to take advantage of a series of methodologies and tools that allow them to accomplish the highest levels of efficiency to improve and sustain their competitiveness, with the expectation of achieving the best possible operational and financial results (Barney, 1991). Recognizing this, several studies in the IS have focused on defining the factors that allow or prevent a successful adoption of certain technological innovations, and as a result, different frameworks that look to define the most critical ones playing a predominant role on these processes have been created. While some of these frameworks have used the individual as a unit of measurement to determine possible contextual, psychological and personal motivations to adopt a particular technological innovation, such as the technology acceptance model-TAM (Davis, 1989), theory of planned behavior-TPB (Azjen, 1985), or the unified theory of acceptance and use of technology-UTAUT (Venkatesh et al., 2003), other authors in the management field have focused particularly on the factors that potentially affect these dynamics from the firm's perspective recognizing the importance of corporate behavior and its potential impacts, such as the Diffusion of innovation-DOI and Technological organizational and environmental-TOE frameworks, and therefore, are the ones that were selected to serve as a theorical base for this research plan.

The DOI framework (Rogers, 1995), focus on the particular factors that can affect the level of adoption of ICTs at a firm level, stablishing three main elements that have a direct influence on the rate and speed for the adoption of a certain technological innovation: Individual, related to factors influencing management roles in organizations, internal, and external organizational characteristics. While this theorical framework defines that the particular propensity to adopt a certain innovation at a firm level is divided within five different groups (innovators, early adopters, early majority, late majority and laggards) that are spread across a normal distribution curve, it also recognizes that on a firm level, not only an individual motivation is taken in account to define investments in innovative technologies (propensity to change), but a rather complex mix of individual and group decisions from several key decision makers and collectives that are all influenced by their own perceptions as well as from several internal (level of centralization, complexity, formalization, interconnectedness, organizational slack and size) and external factors (system openness) inherent to each firm's organizational structure.

The TOE framework (DePietro et al., 1990) on the other hand, identifies three main elements that influence the level of adoption of a particular ICT at a firm: Technical factors, organizational factors, and environmental factors. At a technological level, the adoption of ICTs is influenced by the degree of technical maturity of a firm, defined as the kind of technologies that it has been and is actively using, the type of impact that the technology has on its operation, defined by the level of disruptive use of these technological innovations for business applications, and the impact these technologies have on its internal competences, defined by their enhancement or destruction. At an organizational level, the TOE framework focuses on measuring the capabilities and number of capabilities and resources any given firm has, specially at the structural, communication, size, and availability levels, and the impact these ICTs have on other resources. Finally, at the environmental level, the TOE framework defines certain relations between the industry the firm is embedded in, the amount of skilled personnel and companies that are available in the market to support the use of a particular ICT, and the level and state of government regulation that exist, and that can influence the general levels of adoption in a particular market.

While the TOE framework has been extensively used as a guideline to develop several empirical studies on the factors that impact the adoption of different ICTs on multiple industries, geographies and business contexts, there is still a lack of projects that focus on the dynamics and behavior of the adoption of disruptive digital ITCs, such as AI technologies, at a firm level in emerging countries, mainly because of the novelty of these sort of technical innovations, and of the lack of empirical data related to this behavior. In that sense, the aim of this study is to build a derived model, combining selected factors from the DOI and TOE frameworks, that is complemented them with a specific consideration of their relation with both AI adoption and their effect on firm's performance as a function of their perceived level of competitiveness, using three different categories (technical, organizational and relational) that have been recognized as critical when firms consider adopting disruptive digital technologies, as well as their interaction and their relationship with business strategy, value creation and competitiveness (Borges et al., 2020).

3.2. Factors that enable or hinder the adoption of disruptive digital ICTs: Technical, organizational, and relational – A derived view from the DOI and TOE frameworks.

While the DOI and TOE frameworks can provide some initial indications on the main factors that influence the adoption of general technological innovations at a firm level, highly innovative and disruptive ICTs such as AI are seem to have a particular behavior that requires the definition of a differentiated list of factors that may have a direct relation with their adoption, considering not only the technical capabilities that any firm might have formed over time, as some studies has focused on until now, but the internal, functional, organizational and relational capabilities they have either built or reconfigured dynamically over time to gain or sustain competitive positioning in their markets, as well as the extended relations they have with other firms in their extended ecosystem, including partners and competitors.

Initially, as shown on the literature review section, scholars have extensively reviewed the influence that technical factors have on the rate of adoption of digital ICTs, and therefore we recognized their importance in our model. However, AI technology adoption in particular seems to have a positive correlation with some factors such as the level of technical maturity of a firm, defined as the kind and level of penetration of traditional technologies that a firm have been actively using to support their core operations as they provide a foundational base for the use of more complex and disruptive digital ICTs, as shown by authors such as (Bughin et al., 2018) and (Chui & Malhotra, 2018). At the same time, as AI technologies have a notable technical dependence on data and information as an input to provide valuable business insights, factors such as IT and data complexity, data integration, and the ease of access that functional and technical roles have of data in usable formats, seem some level of relation with the rate of adoption of these technologies, as noted by (Zhu et al., 2006) and (Cubric, 2020). Therefore, to summarize these technical factors we have formulated the first hypothesis for this project as:

Hypothesis 1. *There are technical factors, such as the level of complexity and integration of IT and data systems, that could have a negative relationship with the level of adoption of AI technologies for Colombian firms.*

Hypothesis 1a. *There are technical factors, such as the level of complexity and integration of IT and data systems, that could have a negative relationship with the perceived level of competitiveness (as a measurement of their performance) of Colombian firms.*

At the same time, some research has shown that factors related to the internal characteristics of a firm might have some relation to the propensity to use a given technical innovation. Technical competence and digital skills, defined as the general level of knowledge on the use of digital technological innovations for business applications and processes, have been identified in various studies to have a positive relation with the rate of adoption of disruptive digital technologies such as AI, as it enables their acceptance and use by the general workforce at any given firm, as noted by the work performed by (Eller et al., 2020) and (Markus, 2004). Organizational culture, defined as *"the deeper level of basic assumptions and beliefs that are shared by members of an organization, that operate unconsciously, and that define in a basic 'taken-for- granted' fashion an organization's view of itself and the environment"* (Schein, 1985, p. 26), has been identified by multiple authors as a critical factor that fosters the adoption of disruptive technical innovations at a firm level, and is believed to have a positive relation with their general use, as it creates an internal environment that nurtures individual and group efforts related to this task. Finally, the definition of a global digital strategy and IT championing by first and second-line management, as a part of a wider corporate business strategy have been widely studied as means to increase, support, and facilitate the adoption of disruptive ICTs with the objective of gaining competitive advantages and improve business and operational results when used as cross organizational resources, as noted by authors like (A. Bharadwaj et al., 2013) and (Bassellier et al., 2003). Therefore, the second hypothesis we have formulated for this project is:

Hypothesis 2. *There are organizational factors, such as the level of an open and risk-taking organizational culture, that could have a positive relationship with the level of adoption of AI technologies for Colombian firms.*

Hypothesis 2a. *There are organizational factors, such as the level of an open and risk-taking organizational culture, that could have a positive relationship with the perceived level of competitiveness (as a measurement of their performance) of Colombian firms.*

Finally, factors that reflect the strategic relations that firms have established with their direct business environment, including business partners, technology providers, competitors, and non-profit organizations like R+D government agencies, universities, think tanks and startups, that constitute digital ecosystems, have started to caught the attention of several scholars, as they have shown some potential effects on the propensity of adoption of disruptive digital ICTs at a firm level, providing either positive incentives for these technological developments to be used in their core processes at a result of functional consulting, technical assistance and development of business use cases and applications, or negative ones, as a result of low levels of collaboration with third-party entities to foster the internal R&D of these ICTs, or as the level of competitive pressure in their natural markets is lower when compared with other industries as shown by (Thompson et al., 2019), (Ross et al., 1998), (Zakrzewska-Bielawska, 2019) and (Ilin et al., 2017). Therefore, the third hypothesis we have formulated for this project is:

Hypothesis 3. *There are relational factors, such as the level of open innovation at a firm, that could have a positive relationship with the level of adoption of AI technologies for Colombian firms.*

Hypothesis 3a. *There are relational factors, such as the level of open innovation at a firm, that could have a positive relationship with the perceived level of competitiveness (as a function of their performance) of Colombian firms.*

3.3. Disruptive ICTs, firm value creation, and performance: A possible linkage between them

While the adoption of disruptive digital ICTs has been a topic of high interest among scholars over the last years, the field of business and management have mainly focused on the apparent relation those technologies may have on the financial results, competitiveness, and efficiency levels of firms as a result of the optimization and automation of highly manual, repetitive, or basic tasks, on which integrated technological systems usually provide superior results compared to manual and human resources. However, until know, there is not a clear opinion among academics on whether the adoption of these kind of innovations have a positive relation with improved financial performance and added-value generation. Given the division of opinions mainly due to questionable empirical approaches used to measure such kinds of correlations between technology adoption and firm performance, and the fact that many technological developments have a short lifecycle after becoming obsolete by further subsequent innovations, the connection between strategic resource and value generation frameworks such as the resource-based view (RBV) (Barney, 1991) or the Dynamic Capabilities (Teece et al., 1997), and technological innovation adoption ones at a firm level, such as TOE and DOI, is proving to be of high interest to truly estimate the impact of technological capabilities in competitive positioning and value creation at a firm level (Liang et al., 2010).

The RBV framework proposes that value generation and performance of firms depends on their ability to develop *"unique"* resources (including technological ones) based on their capabilities, that are valuable, rare, difficult to imitate and non-substitutable by other ones (Barney et al., 2001), and that in that sense these resources are distributed among firms in a rather heterogenous form that is constant or "sticky" over time. While resources can be tangible or intangible depending on their nature, they are the building blocks on which firms form business value and competitive advantage as they facilitate the definition of organization capabilities, especially functional ones such as marketing, sales, and manufacturing (A. S. Bharadwaj, 2000). While in this context, information technologies and ICTs may appear as functional capabilities that could potentially interact with other ones to create value and improve a firm's performance, it is true that modern firms have started to use digital ICTs, such as AI and AA as a cross functional tools, aiming to significantly improve their most critical internal resources, making them a strategic asset to achieve *"competitive advantage"*, a term that is defined as mainly to measure firm's success relative to its competitors. (Porter, 1985).

The dynamic capabilities framework, on the other hand, is a *"potentially integrative approach to understand new sources of competitive advantage"* (Teece et al., 1997, p. 510) that derives from the resource base perspective approach, and therefore it is considered an extension of the RBV framework (Barreto, 2010). This framework, as en evolution of the RBV one, recognizes that firms are facing a rapidly changing business environment, instead of a static or "sticky" one on which disruptive technological innovations such as AI and AA, new business demands from customers, and global competitors demand timely strategic changes to maintain a competitive advantage in the market, requiring the formation and renewal of these competences to achieve congruence with the dynamic scenario by the exploitation of internal and external specific capabilities, and the development of new ones in a fashionable time in a strategic manner. This framework also assumes that dynamic capabilities are heterogeneously spread across firms, and that they are specific and unique among them, allowing that a particular configuration at a firm result in the achievement of a higher level of competitive advantage over time when compared to others, and that even firms with similar initial sets of dynamic capabilities build different levels of resources that result in different patterns of performance, and that these differences are enabled by the organizational processes a certain firm defines, shaped by its specific assets (technological, intellectual property, complementary assets, customer base and external relations) position, and the paths defined for their use.

In the context of dynamic capabilities, it is important to differentiate three particular categories of ICT resources, and their relation with the resource value approach at a firm level (Ross et al., 1998): The first one, infrastructure technologies, are traditional physical or tangible resources such as servers, storage, networking, telecommunications, personal computing, middleware or software systems, that act as the foundation base for all IT operations and projects. And while this layer of ICTs has a high level of importance in the overall technical, and therefore, business strategy of a particular firm in relation to the complexity, time and cost that is demanded to create and manage it, some novel business models such as third-IT service providers and new developments such as cloud computing have commoditized it, reducing the impact that IT infrastructure has on the ability of certain firms to adopt other disruptive ICTs, and therefore adapt to changing environments to create value.

The second category -knowledge, related to the learning component of the dynamic capabilities view, is represented on both technical, digital, and managerial skills and their formation trough the definition of a global digital strategy, and is presented in this context as a critical factor that serves as a foundation for both technology exploitation, dissemination and use among firms in a business plane. General IT skills are usually formed across time, and require a high level of specialization, and capital investment that not all companies are able to achieve rapidly or easily. Without this knowledge, firms typically experience a series of limitations to build an integrated set of disruptive technological systems, and therefore are less prone to be open to invest and implement in innovative technologies with successful business results (Ong & Ismail, 2008). Technical competence is of great importance, because it allows to create new patterns of activity or "*routines*" within firms, that can result in a new logic of organization that is more efficient, customer or result centered and therefore, achieves improved results in a timely fashion.

Finally, a third key aspect of the value creation at a firm level based on technological resources is related to the "*IT-Enabled intangibles*", a term that encompasses several non-physical resources such as organizational culture, know-how, reputation, process management and orientation, participation in R&D ecosystems, definition of a relational strategy, among others. In this scenario, it is important to determine how does these intangible factors are directly related to the physical ones, and how to they impact the business operations in areas such as customer orientation, knowledge assets and synergy. These group of technical resources usually act as enablers for firms to focus on their customers, experience, and overall satisfaction, streamlining the direct relation they have, and expanding the knowledge on their behavior, interaction with other customers, and what they expect of firms in terms of new products and services in a rapidly changing environment. Taking in consideration these three categories of technological resources from the dynamic capabilities view, and their apparent alignment with the three main factors that we have defined in our model for AI adoption (technical, organizational and relational), we hope to determine if technical resources allow organizations the reconfiguration of their asset structure, allowing for their internal and external transformation, taking in consideration that *"change is usually costly so firms must develop processes to minimize low pay-off change"* (Teece et al., 1997, p. 521).

At the end, we are hoping that this project can prove that together, these resources (IT infrastructure, organizational knowledge and intangibles) create a unique set of technical and business networks, relations, capabilities and efficiencies that are very particular and difficult to imitate, allowing firms to differentiate, and therefore, create value by transforming and adapting on a timely basis given the changes they experience, obtaining improved financial results either by boosting their total incomes, or reducing their total costs, even though there is still a general perception that ICT impact on a firm performance is still a black box, as the results of other empirical studies are yet inconclusive or inconsistent (Liang et al., 2010). In that sense, this research project will try to address the mediation effect that the use of a digital disruptive technology, such as AI and AA would have on the performance level of a firm, given the three sets of factors (technical, organizational, and relational) that we have defined as potential influencers on the level of adoption of these technologies and their role as potential resources for value creation and competitive positioning from a RBV perspective. Therefore:

Hypothesis 4. *The relationship between technical, organizational, and relational factors and the perceived level of a firm's performance (competitiveness) is mediated by the level of adoption of AI technologies.*

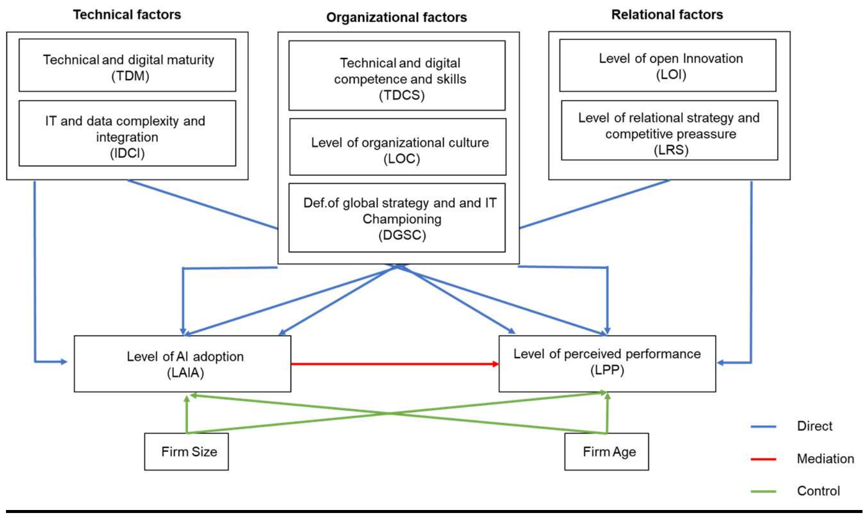

Figure 6. Proposed PLS structural equation model.

4. Methodology

4.1. Sample

In accordance with the research question and objectives that were defined for this project, the following are the main characteristics for the sample that is intended to be used as part of the quantitative analysis.

- ***Unit of analysis:*** Colombian firms from various industries, sizes, and ages.
- ***Space:*** Colombian business market.
- ***Period:*** Survey will address existing AI initiatives deployed at 2020 (Pre-pandemic), at selected firms.
- ***Data gathering method:*** Online survey.
- ***Sample size:*** Yet to be determined, based on a 20% expected respond rate from the total sample of surveyed firms; technical and business management roles will be invited to participate on a 50%-50% proportion, seeking to reduce possible bias in the responses obtained.
- ***Secondary data:*** Information regarding number of employees and date of foundation, for participating firms in the study.

4.2. Method

For this research project, a quantitative analysis approach has been projected, using primary and secondary data sources. The method for the primary data source collection will be the design and delivery of an online survey, being the tool that better adjusts to the proposed objectives, and the one that have been widely used in the similar studies performed in Latin America for the last 20 years according to the work by (Martinez & Kalliny, 2012) in the field of international business. The survey will be sent to at a number yet to be determined of randomly selected business managers from diverse Colombian firms, in different industries, sizes, ages, and geographical locations, hoping to achieve at least a 20% response rate, which is in the low average figures for this colleting method, according to multiple studies, like the one performed by (Yang et al., 2006), hoping to acquire a statistically representative sample size. As for the secondary data sources, the project will use publicly available data sets.

The survey will include a series of questions to assess the overall adoption state for artificial intelligence technologies at selected Colombian firms, as well as a series of technical, organizational, and relational factors that could influence the adoption of these technologies and the level of perceived competitiveness each respondent estimates for its organization (as a measurement of the firm's performance), using a 6 level Likert-scale questions, that will divide into different categories for each of these factors. This scale has been chosen to maximize first and second factor eigen values obtained when applying factor analysis, as noted by (Leung, 2011), and to reduce possible fatigue in the participants looking to maximize the overall response rates and avoid potential neutral.

For technical factors, the survey will try to address the technological and digital maturity including the use of other digital technologies besides artificial intelligence (cloud computing, office automation, mobile and cybersecurity), information systems integration and complexity, as well as current state of data and information availability and integration for each firm; for the organizational factors, the survey will try to address the general level of technical and digital competences of the workforce, IT managerial skills and championing for first and second line management, level of organizational culture related to fostering IT-based innovation, and the organizational adaptation to digitalization and digital strategy in each firm. Finally, on a relational level, the survey will try to address factors such as the level of open innovation at a firm level (collaboration with other firms and organizations to develop AI-related projects), competitive pressure to adopt AI technologies based on similar strategies from firms placed in the same market and industry segments, and the level of relational strategy and collaboration with external firms.

The project, based on the work performed by (Ilin et al., 2017) and (Eller et al., 2020) contemplates an initial statistical exploratory analysis of the information that will collected in the survey and complemented with the secondary data sources, to determine the main trends, significance, and consistency of the information that is integrated between the two data sources. After this initial exploratory analysis, a factor and correlation analysis will be performed, to determine which of the variables selected will have a better explanatory capability (summarization of the total variance of the model) against the independent ones, and the results will be used to construct a partial least square (PLS) structural equation model, that will be designed to determine the possible effects (positive of negative), and statistical significance of each general factor (thar are built as constructs), taking into consideration the different control variables as comparison points, on the independent one.

4.3. Technique

This research study will use the following quantitative techniques to analyze the results of the primary data source (survey) in conjunction with the secondary one (public data sources).

- Estimation of general descriptive statistics (mean, median, standard deviation, variance), to determine possible trends and apparent relations between variables, analysis of statistical significance for each variable using the chi-squared tests, and consistency of the answers, using the Cronbach's alpha test.
- Analysis of correlation of each of the variables using the Pearson's or Spearman's correlation matrix, and factor analysis (principal component analysis or PCA) of each of the variables, to be grouped in a particular category (technical, organizational, and environmental).
- Definition of a PLS structural equation model, to assess the general relation between the three general defined factors, and the dependent construct, as well as the goodness of fit and explicability.
- Mediation analysis to determine the relation and impact of each of the general factors on the dependent variable (construct).

4.4. Variables

Dependent variables (constructs):

- ***Level of adoption and effective use of AI technologies*** (data analytics, chatbots, predictive modelling, NLP/NLU systems for text analysis, speech recognition and image recognition) for Colombian firms.
- ***Perceived level of competitiveness***, for each surveyed Colombian firm.

Independent variables (constructs):

- ***Technical factors:*** Technical and digital maturity (Bughin et al., 2018) and (Chui & Malhotra, 2018), complexity and integration of current IT systems and available data sources (Zhu et al., 2006) and (Cubric, 2020).
- ***Organizational factors:*** Technical and digital competence and skills (Eller et al., 2020) and (Markus, 2004), level of organizational culture (Teichert, 2019), definition of a global digital strategy and IT championing (A. Bharadwaj et al., 2013) and (Bassellier et al., 2003).
- ***Relational factors:*** Level of open innovation and participation on existing digital technology ecosystems (Thompson et al., 2019) and (Ross et al., 1998), level of relational strategy and competitive pressure (Zakrzewska-Bielawska, 2019) and (Ilin et al., 2017) .

Control variables:

- ***Firm size.*** (Eller et al., 2020)
- ***Firm age.*** (BarNir et al., 2003)

5. Findings

Yet to be determined.

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