Influencing factors for the adoption of Artificial Intelligence at a firm level: Empirical exploratory analysis for Colombian organizations

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"If I have seen further, it is by standing on the shoulders of giants"(Sir Isaac Newton)

To my parents, who instilled in me the value of continuous learning and knowledge building as the most important tools to become the man I am today.

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Abstract

The proliferation of Information and Communication Technologies (ICTs) has fundamentally reshaped organizational operations. While conventional ICTs, such as personal computers, office automation suites, and customer relationship management (CRM) systems are deeply established, the emergence of novel, disruptive digital ICTs is altering the landscape and our understanding of adoption and diffusion dynamics. Although novel technologies such as mobile, social media, and cloud computing have achieved widespread adoption fueled by marketing efforts, highly disruptive technologies such as Artificial Intelligence (AI), advanced analytics (AA), and machine learning (ML) are experiencing varying adoption rates, particularly in emerging markets like Latin America when compared to developed nations. This research project employs a quantitative methodology to identify the factors that either hinder or enable the adoption of these advanced technologies and to assess their impact on the competitiveness of Colombian organizations.

Keywords:

Artificial Intelligence adoption, Disruptive digital ICTs, Digital ICT application, Colombian AI adoption.

CONTENTS

LIST OF ABBREVIATIONS

AI – Artificial intelligence

AA – Advanced analytics

AVE – Average variance extracted

BA – Business analytics

BCa - Bias-corrected and accelerated bootstrapping

CB-SEM - Covariance-based Structural Equation Model

CONPES - *Consejo Nacional de Política Económica y social*

CRM - Customer relationship manager

DA – Data analytics

DL - Deep Learning

DOI - Diffusion of innovation model

DSGC - Digital Strategy and Governance

EMDE - Emerging and developing economies

ERP - Enterprise resource planners

HTMT - Heterotrait-monotrait ratio

IADB – Inter-American Development Bank

ICT - Information and communication technologies

IDCI - IT and Data Complexity & Integration

IS – Information Systems

IT – Information technology

KPI – Key performance indicators

LAIA - Level of Artificial Intelligence Adoption

LOC - Level of Organizational Culture

LOI – Level of open innovation

LPP - Level of Perceived Performance

LRS - Level of Relationship Strategy

ML – Machine learning

MAE - Mean absolute error

MVP – Minimum viable product

NN – Neural networks

PLS – Partial least squares

PLS-SEM - Partial least squares structural equation model

RBV - Resource-based value

RMSE - Root-mean-square error

SCA - Sustainable competitive advantage

SCM - Supply chain managers

SEM – Structural equation model

SME -Small and medium enterprises

TAM - Technology acceptance model

TDCS - Technical and Digital Skills and Competence

TDM – Technical and digital maturity

TPB - Theory of Planned Behavior

TOE - Technological, organizational, and environmental model

UTAUT - Unified theory of acceptance and use of technology

VIF - Variance Inflation Factor

WoS - Web of Science

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1. INTRODUCTION AND APPROACH

Information systems (IS) is a multidisciplinary field of study focusing on the management, use, and impact of information and communication technologies (ICT) within the organization. According to the Michigan Institute of Technology (MIT), IS integrates knowledge from fields such as economics, management science, computer science, organizational behavior, and psychology (MIT, 2021). ICTs are a set of technological developments encompassing hardware or software systems designed to facilitate the transmission and reception of information and data generated by individuals, firms, or countries.

ICTs are designed to reduce complexity and expedite communication and information sharing. Their evolution has been driven by incremental and disruptive innovations that emerged during the First Industrial Revolution, when enterprises recognized the potential business impact that automated mechanical and electronic devices had to enhance factor productivity and began to introduce them as strategic tools to increase efficiency and competitiveness in their markets.

The adoption of electricity in the industrial era, coupled with new technical developments such as vacuum tubes and transistors, allowed the first information technology (IT) companies in North America, Europe, and Asia to create a series of innovative hardware and software developments. These IT companies designed systems to address highly manual, inefficient, and labor-intensive tasks. For the first time in human history, a set of highly innovative and disruptive devices was available outside manufacturing firms to optimize their daily operations and to achieve differentiation based on factors other than scale or capital.

As a result, ICTs have played a fundamental role in transforming business processes at a firm level over the last seven decades. The rise of the first commercial computing and information processing equipment in the early 1950s marked a milestone, allowing the management of several functional areas within organizations, including manufacturing, finance, logistics, sales, and marketing, among others. As Liang et al. (2010, p. 1142) emphasize, ICTs have become invaluable organizational assets, enhancing internal communication, product design, and development efficiency, while reducing costs and boosting overall performance.

The IS field has grown since the 1980s, driven by successive technological innovations designed by leading IT companies. These advancements have resulted in numerous business use cases designed to optimize internal and external manual, inefficient, costly, and unautomated processes for firms. The constant search for increased business productivity and competitiveness in the context of a highly demanding, global, and integrated economic environment forced firms to rapidly adopt ICT to meet demanding business needs and to generate substantial improvements in their management processes.

Digital technologies, a subset of ICTs, emerged in the business and IT markets in the late 1990s and the early 2000s. These technologies, driven mostly by internet-based companies, are defined by the Australian government as: *"electronic tools, systems, devices, and resources that generate, store or process data"* (Victoria State Goverment, 2019). Digital ICTs can be categorized into several types:

- Mobile technologies: mobile phones, mobile technologies, and mobile applications.
- Social media platforms: Facebook, Twitter, WhatsApp, LinkedIn, etc.
- Web services: websites, portals, and platforms.

- Data analytics tools: Big data and analytics.

These rapidly evolving and extremely innovative technologies are transforming all domains of economic, sociopolitical, biotechnological, and environmental aspects of society, providing innovative ways for people and firms to interact, communicate, and operate. (Pereira et al., 2020).

In recent years, and especially over the last decade, there has been an explosion of new digital technologies, such as business analytics (BA), advanced analytics (AA), and artificial intelligence (AI), that are designed to offer elements of evaluation, prediction, and prescription of various business dynamics, relying intensively on data and information, one of the most powerful assets in the digital era (Nadkarni & Prügl, 2020). As a result, executive roles at firms are enabled to take strategic business decisions in an informed manner.

1.1 Artificial intelligence, a new breed of digital ICTs

AI, an interdisciplinary field of study encompassing mathematics, engineering, philosophy, biology, and economics, originated in 1956 at Dartmouth College. Professor John McCarty from Stanford University held the first official conference on this topic and coined the term as we know it today.

Defined as *"the science and engineering of making intelligent machines, especially intelligent computer programs."* (Kurzweil, 1985, p. 2), AI aims to replicate human intelligence without biological constraints. The field experienced technical and academic advancements between the 1960s and the 1970s while facing a subsequent 20-year period of stagnation defined as the "*AI Winter*", characterized by reduced academic interest and investments that resulted in little significant technical and commercial development.

However, breakthroughs in the design and manufacturing of microprocessors and computer memory devices have reduced costs in specialized hardware platforms.

Additionally, the establishment of other digital ITCs, such as cloud computing and big data, has allowed for a resurgence of the field, allowing for several academics, such as Joshua Bengio, Yann LeCun, and George Hinton, to make significant advancements in the fields of machine learning (ML), neural networks (NN) and deep learning (DL), adapted by IT firms to create business cases that were rapidly commercialized in the market.

Speech recognition, computer vision, natural language understanding and processing, expert systems, and heuristic classification were among the initial AI generic use cases, hoping to automate repetitive and manual tasks within organizations. Over time, these general business cases have evolved over the last years into industry-specific solutions designed to address unique business challenges in sectors such as retail, CPG, transportation, baking, finance, and manufacturing, among others.

The rapid advancement of these technologies is particularly relevant in the business field, especially considering the exponential growth of transactional data generated by business operations, and the fact that firms could potentially gain significant business value from it. In fact, some scholars, such as Tippins & Sohi, (2003, p. 745) 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-informed competitors"*

Since most AI research and development is currently concentrated mainly in North America, the European Union, and China, observed levels and rates of adoption at a firm level are significantly higher in these clusters compared with emerging countries. As mentioned by authors such as Kelly et al. (2023), Schwaerzler et al. (2024), or Fatima et al. (2022). The proximity to main research centers, allowing for higher awareness of new developments, massification of knowledge and workforce training, and higher levels of technological maturity of those firms could explain this behavior. While numerous studies have explored AI adoption within these leading regions, research focusing on firm-level adoption in emerging markets and across diverse industry sectors remains limited at this time.

In this context, Latin American organizations have lagged behind their North American, European, and Asia-Pacific counterparts in relation to AI-related technology adoption. According to the figures published in the report *"The Global AI Agenda: Latin America,"* (The Global AI Agenda, 2020) it is estimated that, on average, only 79% of organizations in Latin America are in the process of experimenting or implementing AI projects, compared to 87% in North America and 95% in Asia Pacific, respectively.

Recent studies have shown significant levels of disparity in the rate of change of total productivity factors for South American countries when compared with similarly sized economies in Southeast Asia. According to Ovanessoff & Plastino, (2017), Colombia even lags behind its regional peers, Argentina, Chile, and Perú. This productivity gap, characterized by low levels of labor and capital, highlights the potential use of disruptive digital technologies such as AI to drive economic transformation.

The same study projects substantial economic growth derived from full AI technologies, estimating an average year-on-year GDP growth of 4.5% for Colombia, a figure remarkably close to the growth projected for developed economies such as the United States (4.6% on average), surpassing the average GDP growth rate the country has had over the last 5 years (pre-pandemic) by almost 1%.

Labor productivity in emerging and developing economies (EMDEs) such as Colombia is less than one-fifth of advanced countries (Solow, 1956), even though the unconditional productivity convergence theory specifies that it should be closing over time.

This productivity gap is caused, among other factors, by barriers to technology transference (adoption) in low-income countries, extending the estimated period of this gap to fully close to more than 140 years, according to Kindberg-Hanlon & Okou (2020).

Despite Colombia's recognized labor productivity improvements over the past 40 years (1970-2010), placing it within the same cluster of South American countries as Argentina, Peru, Brazil, and Uruguay in recent World Bank estimations, the nation still lags behind Chile, a subcontinental leader. Currently, Colombia's labor productivity remains approximately half that of the Chilean economy (Castellano Montiel & Orozco Suárez, 2022).

Considering the transformative potential of AI to drive economic growth in emerging and developing countries, alongside the acknowledged risk of exacerbating the digital divide through inequitable distribution of social and economic benefits, this project employs a quantitative and qualitative research approach.

It aims to identify the primary factors driving or hindering the firm-level adoption of AI technologies, including business analytics, data analytics, and artificial intelligence, within Colombia. It is anticipated that this project will contribute to developing strategies for promoting equitable AI adoption and fostering the development of a knowledge-based economy (Ogunsola, 2005).

Additionally, this research aims to develop an adapted methodological framework derived from an explorative analysis that enables firms to evaluate the best practices and identify key organizational, technical, and market factors for successful AI implementation. The framework will guide organizations in optimizing their AI initiatives for enhanced competitiveness.

1.2 Digital ICTs at a firm level and the process of "*digital transformation*"

The emergence of digital ICTs has had an impact on the operation of firms. These organizations have recognized the potential value that these tools have in improving their agility and reducing time-to-market. This is achieved through deep transformations in processes, organization, and culture, as these changes create an environment of innovation and overall improvement, with ICTs acting as key enablers.

Digital ICTs differ from more traditional ICTs because their physical form separates from their logic layer, allowing for higher adaptability and reprogramming. This allows for information to be transmitted between devices and networks in a more homogeneous and agile manner, resulting in extended use that can result in noticeable positive externalities for organizations (Matthess & Kunkel, 2020).

Given these unique properties, digital transformation has been a growing topic of interest in the managerial field over the last decade. Digital transformation is defined as the process of changes that digital technologies can bring about in a company's business model, products, or organizational structures (Nadkarni & Prügl, 2020). Academics have been working to identify the potential implications of ICT use for both incumbent and non-incumbent firms on their competitive performance.

Digital strategy, defined by A. Bharadwaj et al., (2013, p. 472) as an *"organizational strategy formulated and executed by leveraging digital resources to create differential value"* is a key element on which organizations across industries and geographies develop a structured plan to align business objectives with available digital resources and capabilities to enhance digital transformation. However, the digital transformation journey varies between organizations, depending on industry type and organizational maturity, among other factors.

Calvino et al. (2018) found significant variability of penetration for digital ICTs at a global firm level. Defining an index of *"digital intensity"* composed of elements such as total ICT investment, software investment, ICT intermediate goods, ICT intermediate services, robot use, online sales, and ICT specialists, they find that firms can be catalogued into three different stages (primary, secondary, and tertiary) and four digital intensity levels (low, medium-low, medium-high, and high).

As expected, firms in sectors such as agriculture, mining, and food products exhibit low penetration in this index, while others in telecommunications, finance, advertising, and insurance demonstrate high levels. Surprisingly, industries with complex operations and substantial data generation, such as transportation, tourism, public facilities, and pharmaceutical and petrochemical production, also display low or medium-low adoption levels of digital ICTs. These findings suggest that digital transformation processes are not only dependent on the technical or financial capabilities but also on the environmental, organizational, and cultural factors complementing functionalities delivered by digital ICTs.

Both academics (Hjort & Poulsen, 2019) and practitioners (Matthess & Kunkel, 2020) have estimated the significant impact of digital transformation and digitalization on the levels of productivity, competitiveness, and overall performance at a firm level. Despite this evidence, a significant group of firms across different industries has yet to embark on digitalization projects. Potential barriers such as lack of financial resources, skills, competitive pressure, organizational complexity, or low cost of manual labor, among others, have been identified as elements firms face when trying to define digital strategies aligned with their business strategy.

This is particularly true in traditionally low-productivity sectors of emerging economies like agriculture and manufacturing. Also, authors such as Eller et al. (2020)

established that digitalization varies by firm size and that small and medium enterprises (SMEs) show heterogeneity in terms of digital ICT adoption when compared with large enterprises. This disparity is amplified in emerging economies with their predominantly SME-based economic structures.

1.3 Digitalization and adoption levels of digital ICTs in the Latin American region and Colombia

Latin American countries have made a significant effort to advance in the adoption of digital ICTs over the last decade, given the developments that have emerged with technologies such as cloud computing, mobile, social media, the internet of things, big data, advanced analytics, and artificial intelligence, among others. However, the overall use figures are still behind when compared with other regions due to serious limitations in terms of access to such technologies and even more basic ones, such as broadband internet.

According to the Corporación Andina de Fomento - CAF (2020), the penetration of basic ICTs constitute the base foundation for all other digital technologies; in this context, the penetration of technologies such as internet was approximately 68% in the Latin American region in 2021, with almost 32% of the total population in the region not covered by this basic technological service, compared with a worldwide average of 59.5% and a North American average of 90% (Statista, 2021).

The same study notes that this limitation is creating a digital gap, as the composite index for digital resiliency of the households, which measures the use of internet access to download health apps, access and buy from e-commerce sites, and use fintech services in any given household, is only of 30.7 (on a scale from 1 to 100), compared to an average index of 53.78 for the OECD countries.

At the same time, there is a high disparity in terms of the proportion of rural and urban users that have access to internet services in the region, with less than 40% of rural users having the possibility to use internet services compared to 70% in urban areas, a figure that is highly concerning given the geographical distribution of the population in the region (OECD, 2020).

Even so, levels of digital skills and digital ICT knowledge among adults are considerably lower in the Latin American region. On average, only one-third of employees in the region are proficient in using personal computers, cell phones, or other digital ICT tools in their work. This contrasts with almost half of the workers in Europe.

Furthermore, only an average of 25% of the region's workforce utilizes digital ICT for simple tasks, while a mere 10% employs these tools for advanced tasks such as programming and communication (OECD, 2020).

Although this context seems to be different at an organizational level, as it is estimated that almost 85% of the firms placed in the region have access to the internet, the level of use of advanced digital ICTs at regional firms is not particularly high. The overall level of digitalization of the Latin America region is estimated to be around 49.92 (on a scale from 1 to 100), behind regions such as North America (80.85) and Western Europe (71.06), placing it in the same group with other regions such as Eastern Europe (52.90) and the Arab states (55.54). At the same time, the year-to-year growth rate for this indicator between the years 2004 and 2018 (6.21%) is below the average of comparable regions such as Asia Pacific (9.39%), Africa (8.27%), and Eastern Europe (6.89%) (Katz et al., 2020).

According to studies performed by the Inter-American Development Bank (IADB), the diffusion of digital ICTs in Latin American firms does not follow a linear path and varies by industry type, firm size, geographical location, and type of business application that they have. In fact, it has been identified that micro and SME enterprises in the region have a lower level of ICT adoption, given the technological and financial barriers that they face when compared with large enterprises.

Typically, only advanced small, medium, and large enterprises have successfully invested in and adopted certain technologies such as cloud computing, customer relationship managers (CRM), enterprise resource planners (ERP), and supply chain managers (SCM). Given this scenario, the path that enterprises follow is not necessarily sequential in terms of technological adoption, as many of them jump from one stage of technical maturity to a more advanced one directly (Gallego & Gutiérrez, 2015).

The Latin American IT industry is highly concentrated in Brazil and Mexico, with limited domestic production of ICT technologies at other locations. Most countries in the region rely on imports for ICT solutions (hardware, software, and professional IT services) (Gallego & Gutiérrez, 2015).

The IT market in Latin America was projected to grow 4.8% annually in 2020 (pre-pandemic), with third-pillar platforms (cloud computing, social media, big data/analytics, and mobile) accounting for 58% of total expenditure and an expected growth at an 8.5% year-to-year rate. Additionally, firms in the region planned to increase their ICT investments from 17% to 27% between 2021 and 2026, with AI leading the growth at 44.2% in 2020 (IDC, 2019).

Colombia has made progress in digitalization, according to the report "*Economía digital*" (Consejo privado de competitividad, 2020), but challenges remain. The government has expanded broadband internet connectivity, doubling active subscribers between 2010 and 2019. However, Colombia lags in mobile user penetration and broadband speed compared to regional and OECD averages, placing 13th out of 17 countries included in measurement, and presenting an average broadband speed that is below the regional average and one-third of the average for OECD countries.

Digital penetration varies significantly within Colombia, with higher rates in urban areas and lower rates in rural regions, creating a digital divide. While Bogotá boasts a 22.7% broadband penetration rate, more than ten departments (Colombian regional administrative units) have rates below 5%, often coinciding with lower GDP, GDP per capita, and higher poverty levels.

And despite increased digitalization efforts from 2005 to 2019, Colombia has slipped in the global electronic government index due to fragmented digital systems. While the government has implemented policies to improve public institution productivity and reduce complexity, only 35% of public procedures could be initiated digitally in 2019, and only 15% could be fully completed electronically. This pales in comparison to Brazil (85%), Mexico (88%), and Uruguay (100%).

To address these challenges, the Colombian government issued the CONPES (*Consejo Nacional de Política Económica y Social*) number 3975, and article 147 of the general law 1955, outlining a national policy for digital transformation and AI adoption in both public and private sectors. For public entities, CONPES defines guidelines for creating integrated digital transformation plans that streamline processes and services, aiming to add economic value and adopt emerging technologies (MINTIC, 2020).

Colombian firms have lagged in adopting digital ICTs, even particularly basic tools such as e-commerce platforms. A study by the *Cámara Colombiana de Comercio Electrónico* (CCCE) found that only 3 out of 10 Colombian firms had active e-commerce platforms and only 20% offered electronic payments, with higher adoption rates among medium and large enterprises. In 2017, Colombia ranked fifth in regional e-commerce participation (CCCE, 2019). Regarding advanced digital ICTs, the "*Digital Economy Observatory*" reported for 2017 low penetration rates among Colombian firms, except for cybersecurity and cloud computing, which were primarily adopted by large enterprises.

In terms of data-driven technologies such as big data and AI, adoption rates among Colombian firms were low in 2020. Large enterprises had limited adoption (18% for big data, 10% for AI), while micro-enterprises had virtually no adoption (Consejo privado de competitividad, 2020).

This impacted Colombia's competitiveness compared to other Latin American countries. The "*Global Competitiveness Report for 2019*" (Schwab, 2019), ranked Colombia 57th worldwide (up from 60th in 2018), with a regional ranking of fourth behind Chile, Mexico, and Uruguay.

The report measures ICT adoption, which is a key factor in efficient resource utilization. The Latin American region averaged 50.9 (out of 100) in this indicator, lagging behind Europe and North America (70.4), even though its percentage change on a year-to-year basis was the highest among all regions (9.8%). In the same report, Colombia scored 50, ranking 87th out of 141 countries.

1.4 Digital Divide and ICT Use

Information has become increasingly valuable and significant in the context of technological advancement and rapid entrepreneurial innovation. While digital ICTs offer efficient tools for information creation and sharing, their disruptive nature has created disparities among individuals, firms, and countries. As a result, barriers and limitations in adopting these technologies have hindered access to their benefits.

The term "*digital divide*," characterized by disparities in access to and utilization of technology among people, regions, or firms, has gained prominence over the last years

(Mendoza-Ruano & Caldera-Serrano, 2014). While the potential economic and social benefits of the use of digital ICTs are widely recognized among scholars and practitioners, the reality is that the digital divide can persist or even widen as these technologies become more prevalent. This highlights the challenges faced by individuals, firms, and regions in effectively leveraging digital ICTs.

The lack of infrastructure, education, and financial resources are key factors contributing to the digital divide. Limited access to physical resources, digital literacy, and the ability to generate economic value from digital tools prevent individuals and firms from fully benefiting from digital technologies.

Research has shown three main approaches to addressing the digital divide: infrastructure, formative, and resources. The infrastructure approach focuses on physical resources (hardware and software) and their impact on the digital divide. The formative approach emphasizes digital literacy and its impact on limited digital ICT use. The resource approach recognizes the importance of generating economic value through digital entrepreneurship, derived from the other two approaches, limiting "*the ability to process, select, and produce information as a factor of social development.*" (Mendoza-Ruano & Caldera-Serrano, 2014, p. 129).

While the digital divide is often discussed at the individual level, firms also experience its effects, as factors such as size, age, regional location, and industry can influence a firm's ability to effectively access and utilize digital ICTs. Research has shown that digital ICTs can significantly impact productivity and financial results by facilitating connections with customers and other firms globally, expanding their reach and market size. (Bach et al., 2013).

Academia has identified two (first and second) levels of the digital divide: access and use. Analyzing these levels at an organizational standpoint reveals the competitive advantages gained by firms that effectively utilize digital ICTs, as well as the negative effects that laggards face against leaders in this field, especially due to internal factors such as "*vertical integration, education of employees, and usage of other technologies*" or external factors such as "*size, geographical area, region, and industry.*" (Bach et al., 2013, p. 126). These contribute to a growing productivity gap between digital leaders and laggards globally.

Studies have defined a four-level methodology to assess the digital divide. In addition to the first and second levels mentioned above, the third level, representing an 11% to 15% deviation from average digital ICT use and adoption, is associated with challenges in creating new technology-based enterprises. The fourth level, with variations exceeding 16% from the mean values, can disrupt the overall performance of a regional economy, limiting global interaction, commerce, economic growth, and social welfare. (Bach et al., 2013).

Studies have shown that firms with higher levels of digital ICT adoption often exhibit higher levels of internal and open innovation. This can lead to market concentration and increased markup differences between digital leaders and laggards.

Rückert et al. (2020) identified the characteristics of EU and US firms that are more likely to have higher levels of digitalization, including industry, size, current digital technology usage, and planned investments. Their analysis revealed that the digital divide among firms in these regions is associated with lower productivity, growth rates, innovation, markups, and employment rates for digital laggards compared to leaders. This economic divide widens over time as digital leaders possess more structured internal and external capabilities compared to laggards.

Digitalization and digital ICT adoption should be strategic priorities for both new and established firms seeking to maintain a competitive edge and achieve sustainable growth. Policymakers must identify and encourage firms with low levels of digitalization to mitigate the digital divide and promote economic growth.

1.5 Problem Statement

Artificial intelligence (AI) technologies, as disruptive digital ICTs, offer the potential to enhance productivity, efficiency, and value generation for firms, particularly in emerging economies. However, the specific factors influencing AI adoption in Latin American countries are still not fully understood within existing methodological frameworks.

1.6 Relevance

In today's highly globalized and integrated economic environment, firms must adopt efficient methodologies and tools to remain competitive and achieve optimal operational and financial results. Data, a frequently underutilized resource, offers significant potential for innovation and addressing operational complexities. As a result, many organizations recognize the value of data-driven strategies for operational optimization and for achieving their strategic business objectives.

Based on this, Latin American firms are well-positioned to leverage data analytics and AI to enhance productivity, efficiency, and competitiveness. However, adoption rates for these technologies remain relatively low compared to firms in regions like North America, Asia Pacific, and the European Union.

Given Colombia's relatively low overall factor productivity compared to its regional peers, this research aims to identify key factors influencing AI technology adoption among Colombian firms. The objective is to develop a methodological framework that facilitates AI adoption and enhances competitiveness at the regional level.

Understanding the factors influencing AI adoption is crucial for firms and policymakers in emerging economies. AI can enhance competitiveness, reduce operational complexity and costs, and improve financial results. For firms, this research can inform strategies for leveraging AI to achieve these goals. For policymakers, it can guide the development of targeted interventions and incentives to promote AI adoption and drive broader economic growth.

1.7 Objectives

Building upon the project's defined scope, one primary and three secondary research objectives were formulated. These objectives were developed by considering established methodological frameworks and theories on ICT adoption and its business-level impact, the characteristics of the anticipated statistical sample (as described in subsequent sections), and the proposed statistical analysis methods:

Main objective

- Conduct an exploratory analysis of Colombian firms to identify factors influencing AI technology adoption and their relationship with perceived competitiveness.

Secondary Objectives

- Identify potential competitive advantages that organizations can gain through AI adoption as part of a digital transformation strategy.
- Establish key technical, organizational, and relational requirements for successful AI implementation and strategic decision-making.

- Develop an adapted methodological framework for Colombian organizations to assess barriers to AI adoption and inform effective digital transformation strategies.

1.8 Research questions

Following the outline of the primary and secondary research objectives, two main research questions were defined to summarize and reflect the main conclusions and findings of this project. These research questions were derived from the main theoretical gaps found in the literature review section of this dissertation and are deeply aligned with the objectives and methodological framework on which the project is developed:

Research question 1: Factors influencing the adoption of AI technologies.

- What are the main factors that may influence the adoption of AI technologies in organizations located in emerging countries such as Colombia?

Research question 2: Potential relation between these factors and the level of perceived performance at an organizational level.

- Do these factors influence the perceived levels of competitiveness for Colombian organizations?

Research question 3: Potential direct and indirect relations between latent variables for the proposed model.

- Is there a mediating relationship between these factors, the level of adoption of AI technologies, and the perceived level of competitiveness in organizations located in emerging countries such as Colombia?

1.9 Summary

This research study of this thesis aims to explore the impact of digital technologies, particularly AI, on firms in Latin America, with a specific focus on Colombia. It delves into the challenges faced by organizations in adopting advanced digital technologies due to economic disparities and barriers. The research also aims to identify factors influencing AI adoption at the firm level and its relationship with organizational competitiveness. For this purpose, it discusses the importance of digital transformation strategies and the role of three kinds of factors (technical, organizational, and relational) and their influence on ICT adoption to enhance productivity and competitiveness in emerging markets.

Highlighting the significance of digitalization and ICT adoption for firms in Colombia, this study addresses the digital divide present in Latin American countries, where access to technologies such as AI lags behind other regions. It outlines how low adoption rates of AI technologies in the region are impacting productivity and economic growth, emphasizing the importance of promoting digital transformation and AI adoption in both public and private sectors to bridge the economic disparities prevalent in the region. By addressing these challenges, firms in Colombia and other emerging markets may potentially enhance their competitiveness and operational efficiency.

Furthermore, this research explores the evolution of digital technologies, including AI, and their potential to enhance business productivity and competitiveness. It underscores the importance of information systems and ICTs in driving organizational efficiency and performance. As a result, the main objective of the thesis is to identify organizational barriers and enablers for AI adoption, particularly for Colombian firms, and propose an adapted methodological framework to propose strategies to leverage AI for strategic business decision-making. By promoting digital transformation and addressing technological barriers, firms in Colombia, and hopefully in other emerging regions, will be able to improve their operational efficiency and bridge the economic disparities with their counterparts in first-world countries.

In conclusion, this research emphasizes the critical role of digital technologies, especially AI, in shaping the competitiveness and productivity of firms in Latin America, with a specific focus on Colombia. It underscores the importance of several organizational factors, as well as the importance of digital and business strategies to promote ICT adoption and digital transformation to enhance operational efficiency and bridge economic disparities. By addressing barriers and enablers of AI adoption and leveraging digital technologies effectively, firms in emerging markets can hopefully improve their competitiveness and contribute to economic growth and development in the region.

2. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK DEVELOPMENT

The purpose of this literature review is to provide an overview of the current state of academic production on digital ICT adoption at an organizational level, its relationship with organizational performance and value creation, and the factors that have been identified to have possible impacts on AI adoption at a firm level.

The review begins by defining the topic and its key terms. Afterward, it discusses the history of research on the topic, highlighting the major findings and contributions of each study. The review also tries to identify gaps in the literature and defines the implications of these gaps for future research.

The topic of digital ICT adoption in the context of the business and management field is a rather complex one, where multiple theories have been developed, followed by a great number of empirical studies trying to prove their validity using a series of methodological approaches, units of measurement, and data-gathering methods, among other factors. Therefore, the literature review of this dissertation will focus on the following areas, following the outline and recommendations made by Mohamed Shaffril et al. (2021):

1. The definition of the term "*adoption*" within the scope of the dissertation and the fields of IS and business management.
2. Levels of academic research on digital ICT and AI technological adoption at a firm level in emerging and Latin American countries, with special focus on Colombia.
3. Main theoretical frameworks that have been defined to study digital ICT technological adoption, specifically at a firm (business) level.

4. Main theoretical frameworks that have been defined to study the potential impacts of digital ICT adoption on firms' competitiveness, performance, and value creation.
5. Main factors that have been determined to influence digital technological adoption at a firm level from a technical, organizational, and relational point of view.
6. Potential research gaps that could be addressed with the development of this thesis.

The review will conclude by summarizing the key findings of the literature and discussing the implications of these findings for future research.

2.1 Literature review process

The study of digital ICT adoption within the fields of information systems and business management has gained significant attention in recent decades, as organizations increasingly leverage these technologies to improve their operations. Researchers such as Fishbein & Ajzen, (1975), Davis et al., (1989), Taylor & Todd, (1995), Rogers, (1995), Venkatesh et al., (2003) or Baker, (2012) among others, have developed various theories and frameworks to explain the factors influencing individual and corporate adoption of technological innovations.

These general models and frameworks have been used as a foundation for developing more specific studies that focus on particular technological solutions. For example, researchers have used these models to examine factors influencing the adoption of specific technologies such as enterprise resource planners, or ERPs (Ilin et al., 2017), customer relationship management, or CRMs (Marolt et al., 2015), supply chain management systems, or SCM (Cao et al., 2013), business intelligence, or BI (Gudfinnsson

& Strand, 2018), big data (Bremser, 2018), and cloud technologies (Bannerman, 2010). These studies have often focused on technical, organizational, or market factors to explain observed behaviors in specific industries, firm sizes, or geographical clusters.

The growing interest in emerging digital technologies like mobile solutions, the Internet of Things (IoT), virtual reality (VR), augmented reality (AR), and AI has led to a surge in academic research. The number of published articles on these topics in the fields of business, management, and economics has increased exponentially over the past decade, as illustrated in Figure 1. This figure shows the total number of published articles in English between 2011 and 2023 in both the Web of Science (WoS) and Scopus repositories, focusing on areas directly related to these digital ICTs. For this initial query, the following is the defined subset of search terms used on the WoS database:

- *"cybersecurity" OR "internet of things" OR "IoT" OR " virtual reality" OR "VR" OR "augmented reality" or "AR" OR "mobile" OR "cloud" (All Fields) and Articles (Document Types) and English (Languages) and Business or Management or Economics (Web of Science Categories) and 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013 or 2012 or 2011 (Publication Years)*

For the Scopus database, this was the defined list of terms for the initial query:

- *ALL ("cybersecurity" OR "internet of things" OR "IoT" OR "virtual reality" OR "VR" OR "augmented reality" OR "AR" OR "mobile" OR "cloud") AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)*

OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA , "BUSI"))

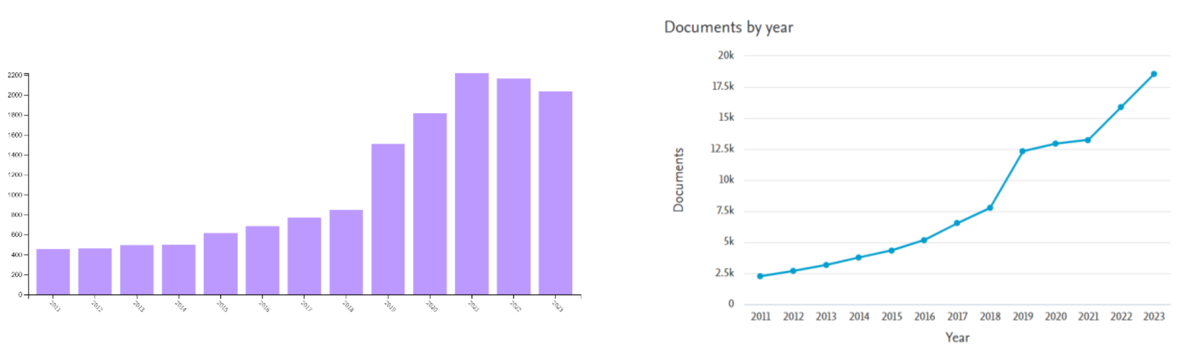

***Figure 1** - Number of published articles in the English language related to disruptive digital ICTs at the Web of Science and Scopus repositories between 2011 and 2023, Source: WoS and Scopus repositories*

The exponential growth in the number of published articles related to innovative digital ICTs has been accompanied by a similar trend in studies focusing on adoption and use factors in the business and management fields. Adding the terms “*adoption*” or “*use*” in the first two queries for the WoS and Scopus databases shows that almost 38.90% of the published articles for the WoS repository (5,667 out of 14,576), and nearly or 67.29% of all published articles on the Scopus repository (73,188 out of 108,758) between the years 2011 and 2023 were directly or partially related to these behaviors, as seen in Figure 2, reflecting also an exponential growth in both measurements in the same period.

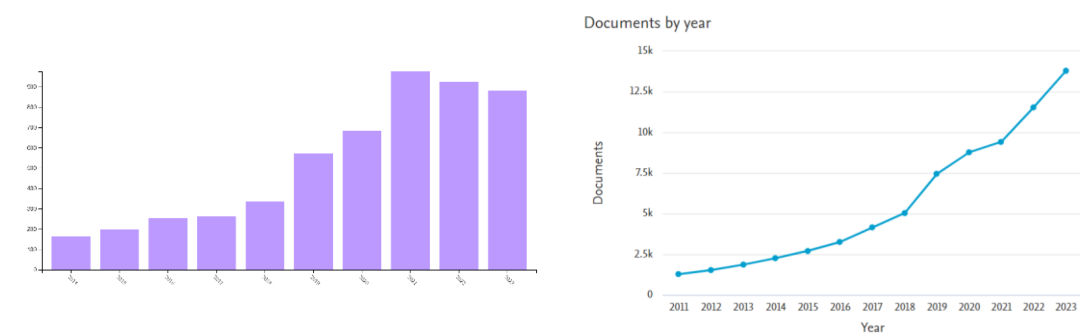

Figure 2 *- Number of published articles in the English language related to disruptive digital ICT adoption or use at the Web of Science and Scopus repositories between 2011 and 2023, Source: WoS and Scopus repositories*

The academic interest in AI and AA is distinct from other broader digital disruptive technologies. This is evident when comparing publication trends in bibliographic databases such as WoS and Scopus for the period between the years 2011 and 2023 to determine the total number of published articles and citations for those technologies compared to other disruptive digital ICTs.

To identify research on AI and AA adoption in business, a set of queries on the WoS and Scopus repositories was performed, searching for articles published between 2011 and 2023. The initial search added the terms "*artificial intelligence*", "*AI*", "*analytics*", or "*machine learning*" within the fields of business, management, or economics, and limited results to English-language publications. This yielded 12,617 articles in WoS and 19,480 in Scopus. To refine the search and focus on factors influencing adoption, I added the terms "*adoption*" or "*use.*" This resulted in 4,101 articles in WoS and 6,760 in Scopus, respectively.

For the secondary queries, I defined the following subset of search terms for the WoS database:

- *"Artificial intelligence" OR "AI" OR "analytics" OR "machine learning" OR "ML" (All Fields) and 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013 or 2012 or 2011 (Publication Years) and Articles (Document Types) and English (Languages) and Business or Management or Economics (Web of Science Categories).*

For the Scopus database, I defined the following query:

- *((ALL ("artificial intelligence" OR "AI" OR "analytics" OR "machine learning" OR "ML"))) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SUBJAREA , "BUSI")) AND (LIMIT-TO (PUBYEAR , 2023) OR (PUBYEAR , 2022) OR (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011)) AND (LIMIT-TO (LANGUAGE , "English")).*

The search results in WoS and Scopus reveal a significant research gap for AI and AA adoption within the business, management, and economics fields. While a substantial number of articles address AI and AA in general (12,617 in WoS and 19,480 in Scopus), a rather small proportion of them focus on adoption factors (4,101 in WoS and 6,760 in Scopus).

These results represent only 32.50% (WoS) and 34.70% (Scopus) of broader AI/AA research, compared to an average of 38.90% and 67.29% for other trending digital ICTs. These figures suggest a scarcity of research, specifically concerning the examination of potential factors that may be influencing the adoption of AI and AA in business contexts.

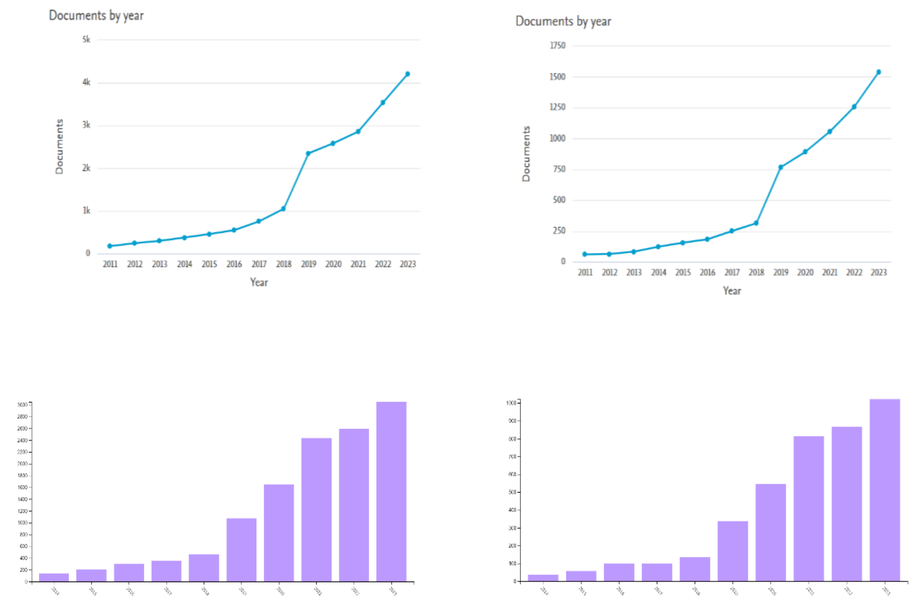

***Figure 3** - Number of published articles in the English language related to AI, analytics, and ML at the WoS and Scopus repositories (left column), and for their adoption or use (right column) between 2011 and 2023. Source: WoS and Scopus repositories*

To delve deeper into the possible barriers hindering AI adoption at the firm level, a refined query for the Web of Science (WOS) repository was developed. This third query incorporated additional terms aligned with the research scope and focused on identifying potential obstacles to AI adoption. This refinement yielded a total of 990 articles published between 2011 and 2023.

For this third and final query, I used the following subset of search terms for the WoS database:

- *"artificial intelligence" OR "AI" OR "analytics" OR "machine learning" OR "ML" (All Fields) and "adoption" or "use" (All Fields) and "organization" OR "company" OR "firm" OR "institution" (All Fields) and 2011 or 2012 or 2013 or 2014 or 2015 or 2016 or 2017 or 2018 or 2019 or 2020 or 2021 or 2022 or 2023 (Publication Years) and Articles (Document Types) and English*

(Languages) and Business or Economics or Management (Web of Science Categories) and Management or Business (Web of Science Categories).

Given time and resource constraints, the focus of this literature review was on the WoS database. WoS is known for having higher requirements for journal and document indexing, as noted by scholars such as Stahlschmidt et al. (2020), ensuring the quality and depth of included articles. This aligns with using high-quality research for the proposed methodological framework.

The following sections of this chapter summarize the key theoretical insights derived from a detailed analysis of the resulting literature obtained from WoS. These insights served as the conceptual framework for the research methodology. The literature review involved a two-step sorting process: 1) relevance to key terms and 2) academic impact based on citations and references within this repository. (Xiao & Watson, 2019).

2.2 Main Theories on ICT adoption

Research on technology adoption, especially digital ICTs, has evolved over decades, with scholars from various fields like cognitive science, sociology, psychology, and behavioral economics contributing to our understanding. Pedersen (2005) identifies three common approaches: diffusion, adoption, and domestication. The diffusion approach focuses on how technological innovations spread within organizations, recognizing that communication is just one component of a broader process involving evaluation, perception, and decision-making. (Rogers et al., 2019).

Adoption has been defined in the context of ICTs as the individual or organizational decision to accept or reject an innovation, including its implementation, discontinuance, or modification, and it has been seen as a process that leads to the broader diffusion of technology within a social system.

From the view of technology acceptance models, adoption has been seen as a complex, developmental, and social process where individuals form perceptions about a technology that influences their decision to use it. This process involves cognitive, emotional, and contextual factors.

In terms of organizational capability building, ICT adoption is not a single event but a dynamic, recursive process with multiple stages, where different factors may influence decisions at each stage. This perspective emphasizes the evolving and interactive nature of ICT adoption, especially in organizations.

From a social computing context, ICT adoption includes both the embracement of technology by individuals and its embedment in society, highlighting the role of group consensus, cooperation, and social influence in shaping adoption behaviors.

However, for the sake of this thesis, adoption will be related to the cognitive and decision-making processes that occur after a technological innovation is established within an organization. It involves the effective application and use of technology to support functional and technical processes. Domestication, on the other hand, refers to the integration of technological development into the organization's daily operations, making it an essential part of its routines and capabilities, having a direct relation with organizational performance.

Concerning the adoption dimension, several academic studies have tried to identify the main factors that enable or prevent firms from adapting and adopting ICTs successfully. While there are several highly cited and used frameworks related to studying technology adoption, such as the Technology acceptance model (TAM) (Davis et al., 1989), Theory of planned behavior (TPB) (Fishbein & Ajzen, 1975), Unified theory of acceptance and use of technology (UTAUT) (Taylor & Todd, 1995), Diffusion of innovation (DOI) and Technological organizational and environmental model (TOE), only the DOI and TOE frameworks are focused on studying the adoption of ICTs at the firm level (Oliveira et al., 2011).

The TOE framework, introduced in "*The Processes of Technological Innovation*" (Drazin, 1991), is a widely used model for understanding technology adoption at the organizational level. This framework highlights the evolution of technological innovations from their creation by leading IT companies to their adoption and practical implementation within organizations. (Baker, 2012). TOE identifies three key factors influencing technology adoption: technical, organizational, and environmental.

Comparably, the DOI framework (Rogers, 1995), focuses on individual factors influencing technology adoption at the firm level. It identifies three key elements: (1) individual (leadership), (2) internal organizational characteristics, and (3) external organizational characteristics. While DOI recognizes individual motivations, it also acknowledges that at a firm level, technological adoption is also influenced by a rather complex mix of group decisions from several key decision makers influenced by their perceptions. This framework categorizes firms into five adoption groups: innovators, early adopters, early majority, late majority, and laggards, distributed along a normal curve.

The TOE framework establishes a segmentation on the intent to adopt and use a particular technological innovation based on the three main factors: At a technological level, for instance, the adoption of ICTs is influenced by the degree of technical maturity of any given firm, the kind of technologies that it is actively using and has been using, the type of impact that the technology has on its operation or how disruptive the ICT is in terms of technological use for business applications, and the impact these technological innovations have on its internal competences, either enhancing or destroying them.

From an organizational viewpoint, this framework emphasizes the importance of capabilities and resources in technology adoption. It considers factors like structure, communication, size, and availability. Decentralized and organic structures may be more conducive to experimentation and innovation, while formal structures are beneficial during implementation for order and control. However, organizational structures can also hinder mechanisms like sponsors, innovation champions, or gatekeepers that influence strategic ICT adoption decisions. These informal linking agents play a crucial role in facilitating or hindering technological adoption within organizations.

The TOE framework also considers the environmental context, including industry-specific factors, skilled personnel availability, external support from IT providers, and government regulation. These factors can significantly influence the level of ICT adoption in a particular market. While the framework does not explicitly mention government regulation, it is clear that regulatory policies can create favorable or unfavorable conditions for technology adoption. Additionally, the size of the industry and the availability of IT infrastructure can play a crucial role in supporting or hindering ICT adoption efforts.

Some studies suggest that the TOE framework is an adaptation of the DOI model, given their similarities in focusing on three main factors or three main characteristics to explain technology adoption. However, TOE complements DOI by incorporating some potential gaps, such as technical factors not included in Rogers' original work, and expanding the range of internal and external factors considered relevant for intra-firm ICT adoption explainability. (Oliveira et al., 2011).

This TOE framework has been widely applied to study the adoption of various ICTs, including cloud computing (Low et al., 2011) , big data (Angwar, 2018) , business intelligence (Bhatiasevi & Naglis, 2020), CRM (Marolt et al., 2015), or ERP (Ilin et al., 2017). While there is a wealth of research on these topics in industries such as manufacturing (Aboelmaged, 2014), retail (Ramanathan et al., 2017), finance (Koh et al., 2019), telecommunications (H. Chen et al., 2021) or healthcare (Damali et al., 2021), and in regions such as India, China, the US, and the EU, empirical studies focusing specifically on AI adoption at the firm level in emerging countries remain relatively limited due to the novelty of AI technologies.

Therefore, to identify recent research on AI adoption in emerging countries, the search criteria were expanded to include specific terms related to the Global South as a derivation from the third query that was performed solely on the WoS repository, including the terms “*emerging*” or “*developing*.” This resulted in a significantly smaller sample of 198 articles published between 2011 and 2023, highlighting the limited research on AI adoption for this region compared to the broader field of business and management.

These results might showcase that while the TOE framework offers valuable insights on ICT adoption, a new adapted model may be necessary to understand AI adoption in emerging countries, especially Latin American ones. AI's disruptive nature and its potential impact on productivity, comparable to labor and capital, require a tailored approach. This new model should consider the unique factors influencing AI adoption in emerging economies and the potential positive or negative effects on firm behavior and performance.

As a result, the TOE framework may require adaptation to fully understand AI adoption dynamics. While TOE provides valuable insights, additional factors not considered in the original model may be crucial in determining the specific factors influencing AI adoption at the firm level. Therefore, a new adapted framework is necessary for this analysis.

2.3 Competitive advantages, positioning theories, and their evolution

Competitive advantage is a crucial concept in business management, reflecting a firm's ability to outperform competitors and create superior value. It involves a unique combination of internal and external factors that contribute to a firm's competitive boundary. Academics and practitioners have both studied competitive advantage as a tool to assess the effectiveness of a firm's resources and capabilities and unique configuration for achieving superior results.

Competitive advantage is a complex concept that requires a multidimensional approach. Falciola et al. (2020) emphasize the importance of an innovative approach to it, departing from a dynamic perspective on competitiveness, recognizing that firms strive to maintain a competitive edge in a constantly evolving market. Their framework integrates microeconomic (intra-firm) and macroeconomic (environmental and socioeconomic) factors, highlighting the role of information as a key determinant. This results in a three-pillar scheme that includes competence, change, and connectivity.

Strategic management research has explored various factors contributing to competitive advantage and value creation, resulting in multiple theories explaining the exploitation of market power by certain groups of firms in the market they operate when compared to others. The competitive forces approach (Porter, 1985) remains a foundational framework for understanding competitive positioning, emphasizing the role of industry environment and a firm's relationship within it.

Porter's five forces analysis (entry barriers, threat of substitution, bargaining power of buyers, bargaining power of suppliers, and rivalry among industry incumbents) provides a framework for understanding industry attractiveness and competitive dynamics. By analyzing these forces, firms can determine the rational decisions they will face when potentially entering a business market based on its profit potential, estimating the sources of competition and the nature of their strategic definitions. (Teece et al., 1997).

This theory takes an industry-level perspective rather than an enterprise one, assuming that differences in firm performance within a market are primarily driven by scale and industry-specific factors. While the framework recognizes the role of firm-level capabilities derived from the unique combinations of the five forces it achieves, it primarily focuses on the industry environment and its impact on competitive positioning. The interplay of the five forces creates a dynamic landscape where the relative importance of each force can change over time as industries evolve. This highlights the interdependence between firms and their industry context rather than their internal capabilities.

The theory of strategic conflict (Shapiro, 1989) complements Porter's five forces analysis by focusing on a firm's ability to control its environment and competition. Using game theory concepts derived from economics, this framework involves firms identifying their desired market position and anticipating competitor moves to develop their strategies. It defines that firms aim to maximize profits with minimal cooperation, leading to dynamic strategic interactions. These strategies are long-term commitments, distinct from tactical decisions, and are influenced by internal factors such as the firm's capabilities, externalities, and imperfect information flow.

Competitive advantage, from the perspective of strategic conflict, is "*a function of the effectiveness on with which firms keep their rivals off balance through strategic investments, pricing strategies, signaling and the control of information.*" (Faulkner, 2002, p. 344). This requires internal capabilities adapted to these tasks and can lead to increased competitive value generation.

Strategic conflict involves step-based scenario modeling, where firms make strategic decisions in response to competitors' moves within a specific timeframe. This dynamic process highlights the importance of strategic thinking and adaptability in achieving competitive advantage.

While the strategic conflict approach assumes homogeneity of capabilities and resources among firms, limitations arise when one firm dominates the market over others. Despite lacking complete information about competitors, the dominant firm may maintain its position due to cost advantages.

A third line of thought, the resource-based strategic approach, has gained prominence over the last years. This approach departs from the limitations of the competitive forces and strategic conflict theories by emphasizing the role of firm-specific resources in achieving sustained competitive advantage, based on two empirical generalizations:

- "(*1) there are systematic differences across firms in the extent to which they control resources that are necessary for implementing strategies, and,*
- *(2) that these differences are relatively stable*" (Foss, 1998, p. 135).

These assumptions suggest that firms can achieve competitive advantage by leveraging their distinctive resources and capabilities, which are relatively stable and difficult for competitors to replicate.

The resource-based approach emphasizes the role of heterogeneous resources in achieving sustainable competitive advantage. These resources are firm-specific, rare, valuable, and difficult to imitate. By leveraging these distinctive capabilities, firms can differentiate themselves from competitors and create long-term competitive advantages. This approach departs from traditional perspectives that primarily focus on external factors like industry conditions. It highlights the importance of internal resources and capabilities in shaping a firm's competitive position instead of relying only on external factors.

Given the nature of the assumptions used to build this conceptual theory, there are two main variants: the standard economic theory and the dynamic or evolutionary view. The standard economic theory views firms as relatively static or "*sticky*," with limited ability to change or acquire resources due to organizational or financial constraints. In contrast, the dynamic or "*evolutionary*" view recognizes firms as adaptable and flexible entities that can adjust their capabilities based on their organizational structure, knowledge, culture, and procedures (defined as an *idiosyncrasy*) to align with changing market conditions.

2.4 Technical factors for digitalization and disruptive ICT adoption

One of the main characteristics essential for successful AI adoption, as noted by scholars, is a robust, scalable, and flexible IT platform. Organizations must progress through various stages of "*technological maturity*", from embryonic to mature, to effectively leverage AI. This involves building a solid foundation of IT capabilities and aligning them with business objectives.

As outlined by Curley et al. (2013), firms often progress through stages of ICT adoption, including initiation, control, integration, data administration, and maturity. This evolution enables organizations to leverage ICTs for business continuity, change, and growth, ultimately contributing to sustained value creation and competitive advantage.

As a result, the concept of integration in IT platforms extends beyond mere technical compatibility. It encompasses the ability of systems to share information, capabilities, and support common business processes. A well-integrated platform architecture can significantly enhance a firm's ability to respond to business needs and achieve strategic goals.

Therefore, to facilitate the adoption and diffusion of disruptive technologies, organizations need to ensure that their IT platforms are not only internally integrated but also compatible with external ecosystems. This requires standardization, orchestration, and interoperability of systems and processes across industries and geographical regions (A. Bharadwaj et al., 2013).

The emergence of flexible, granular, and "*on-demand*" IT platforms, such as cloud computing and big data analytics, has significantly lowered the barriers to entry for firms of all sizes. These platforms enable organizations of different sizes and antiquity to rapidly adopt and deploy innovative technologies like AI, accelerating their digital transformation and improving their competitiveness. (Bughin et al., 2018).

While these new as-a-service technologies offer significant benefits, they also present challenges for large, established firms. These firms may struggle to adapt to the new paradigm due to their existing "*in-house*" IT infrastructure and organizational structures. Integrating cloud-based solutions with existing legacy systems can be complex and costly. Additionally, the required technical skills and organizational agility may not be readily available within these organizations, increasing complexity from the IT operations viewpoint.

The adoption of disruptive ICTs can pose significant risks to organizations, particularly if their existing infrastructure is not adequately prepared. Misalignment between the capabilities of the new technology and the organization's needs can lead to costly and time-consuming adjustments in terms of technological, financial, or organizational factors. Additionally, if the technological platform fails to deliver expected results or is difficult to integrate, it can erode trust and hinder the adoption of other highly disruptive technologies.

In this context, not only technical maturity but also technical complexity is of critical importance, as A poorly integrated IT infrastructure can lead to delays and increased costs and can limit value creation because of misalignment between technical capabilities and business demands (Leukert et al., 2011). To mitigate these risks, organizations must prioritize technical maturity and ensure that their infrastructure can support the demands of AI technologies rapidly to avoid potential deviations between the design phases and their deployment and implementation.

Consequently, a well-designed IT project is crucial for successful AI implementation, especially one that mitigates "*exported problems*". Markus (2004) characterizes these as early implementation issues in digital ICT that, if not promptly detected or resolved, become prohibitively costly or complex in later phases. A flexible, scalable, and integrated IT infrastructure can significantly reduce implementation complexity and accelerate the realization of projected business benefits. By carefully planning and executing projects, organizations can minimize risks and maximize the value derived from AI technologies.

Since technical maturity and integration are complex concepts that are not easily measured at an organizational level, scholars have defined different dimensions that can be used as proxy indicators:

- **IT Investment:** The level of investment in IT infrastructure and personnel.
- **IT as a Core Competency:** The extent to which IT is used as a strategic differentiator (Curley et al., 2013).
- **IT Governance:** The existence of a dedicated IT function and a strategic IT plan (Soh & Markus, 1995).
- **Digital Interactions:** The frequency and nature of digital interactions with customers, partners, and suppliers.
- **Digital Workforce:** The proportion of tasks performed digitally (Kotarba, 2017).
- **Technology Usability:** The ease of use and user-friendliness of IT systems (Leukert et al., 2011).

- **IT Infrastructure Flexibility:** The ability to adapt and scale IT infrastructure to meet changing business needs.

These indicators can provide valuable insights into an organization's level of technical maturity and its potential to leverage technology for competitive advantage, and therefore are the ones selected to be used as part of this project.

It is crucial to recognize that misalignments between digital ICT projects and business needs often stem from organizational, cultural, and procedural issues, rather than purely technical ones such as complexity or maturity. Focusing solely on technical solutions may lead to wasted resources and limited impact. Understanding the underlying organizational challenges is key to successful ICT implementation.

Therefore, prototyping is a crucial practice for mitigating the risk of misalignment between technical and business aspects of digital ICT projects. Unlike traditional, sequential development methodologies focused on the implementation of monolithic software architecture, agile development approaches, such as the use of minimum viable products (MVPs), allow for rapid iteration and validation of disruptive technical solutions. This approach helps to ensure that the final product meets the specific needs of the business and avoids costly mistakes with an approach of continuous improvement and monitoring to ensure that the technical features obtained from technical solutions are aligned with the project’s business needs.

However, successful prototyping requires a strong technical foundation, low levels of IT complexity, and a high level of technical maturity. Therefore, organizations must have the necessary skills and infrastructure to rapidly develop and deploy innovative solutions through iterative processes that include prototyping phases.

2.5 Data availability, integration, quality, and literacy: Foundations for strategic informed decision-making.

While several technical factors, such as IT infrastructure maturity and complexity, play a crucial role in adopting disruptive digital ICTs like AI, ML, and AA, data is the fundamental fuel that drives these technologies. As digitalization advances, the volume and variety of data generated by organizations have increased significantly, creating both opportunities and challenges.

AI's reliance on high-quality data is a critical factor in its success, requiring organizations to prioritize data quality, diversity, and privacy to ensure that AI models are accurate, unbiased, and representative. Addressing these challenges is essential to realize the full potential of AI and avoid negative consequences (Aldoseri et al., 2023).

Studies such as the ones performed by Balakrishnan et al. (2020) and Chui & Malhotra (2018) highlight that a lack of usable data is a common challenge for firms struggling with AI adoption. Difficulty in accessing, integrating, and utilizing existing data can hinder the development and deployment of effective AI solutions.

Two prominent approaches derived from this view for AI development are data-centric AI and data-driven AI:

- **Data-centric AI:** Prioritizes data quality and reliability, focusing on the entire data lifecycle, from collection and preparation to exploration and storage. The goal is to create a unified data repository that can support multiple AI models. (Zha et al., 2023).
- **Data-driven AI:** Emphasizes the development of custom AI models and applications for specific decision-making tasks. This approach involves the

entire model lifecycle, including validation, deployment, and continuous improvement. improvement (Aldoseri et al., 2023).

Both approaches recognize the critical role of data in AI development and highlight the importance of data quality, accessibility, and governance.

In terms of data access, the data-centric approach emphasizes the importance of both data quantity and quality, with the definition of two dimensions for data: data refinement, which focuses on improving the quality of existing data, and data extension, which involves acquiring additional data to enhance predictive capabilities.

While the accuracy of AI systems can be affected by incomplete data, cross-organizational data sharing and collaboration can further improve the performance of AI models by providing a wider range of data and fostering a culture of trust and knowledge sharing. As a result, this approach results in the definition of technology assets as a series of highly integrated and connected platforms that include the definition of a clear architectural orientation and a standardized data platform set of standards (Zha et al., 2023).

Another factor that enables the adoption and use of AI technologies is data management, which can be defined as the *"development and execution of architectures, policies, practices and procedures for ensuring the availability, usability, integrity and security of data."* (Angwar, 2018, p. 8). Surbakti et al. (2020) indicate that data quality, privacy, security, and governance are all critical factors in enabling the adoption and use of these technologies, complemented by elements such as data completeness, currency, access, relevance, accuracy, and consistency.

Consequently, a strong data foundation characterized by well-defined architecture, standards, and practices is essential for ensuring data availability, usability, integrity, and security. By prioritizing data quality and governance, organizations can unlock the full potential of AI and other disruptive technologies.

In today's rapidly changing business landscape, data has become a valuable asset. By leveraging data-driven insights, organizations can make informed decisions, improve operational efficiency, and gain a competitive edge. Galbraith (1974, p. 28) highlighted that *“the greater the task uncertainty, the greater the amount of information that must be processed among decision makers during task execution in order to achieve a given level of performance”*, while Ross & Goodhue (1995) further emphasized the link between information-based decision-making and long-term competitiveness.

The same study identified three key information technology assets that contribute to sustainable competitive advantage, as they appear to be distinctive and difficult to replicate, a concept that is closely linked to the RVB framework:

1. **Human Assets:** A skilled and motivated workforce with critical business, technical, and teamwork knowledge.
2. **Relational Assets:** Strong relationships with internal and external stakeholders that facilitate risk management and collaboration.
3. **Technological Assets:** A well-integrated IT platform with standardized data and processes, enabling efficient operations and innovation.

When effectively managed and leveraged, these assets can provide firms with a significant competitive edge.

While the first two assets of these models are discussed in detail in the following sections of this chapter, several authors identified the importance of human and technological assets concerning data and information, and the impact they have on AI adoption. Human assets, particularly data skills and literacy, are crucial for leveraging AI technologies. These skills enable organizations to effectively collect, clean, analyze, and interpret data, leading to informed decision-making and improved business outcomes. By connecting existing knowledge with new insights derived from data, organizations can foster innovation and drive growth based on data skills.

Data literacy can be defined as the ability of employees of an organization to access, process, analyze, and interpret various sources of information to generate value from it. This asset has been linked in several studies to the propensity to adopt and use data-based drive technologies such as big data and AI in a business context (Alsheiabni et al., 2019). Thereby is considered a crucial skill for organizations seeking to leverage AI and big data technologies.

However, according to Alsheiabni et al. (2019) a significant number of firms lack the necessary data skills to evaluate, build, and deploy data-driven technologies. Brock & von Wangenheim (2019) further emphasized the importance of data skills, highlighting their impact on critical organizational capabilities (strategic, technological, data, and security) over other factors such as sector, industry, country, firm characteristics, and respondent characteristics.

As a result, the increasing adoption of AI requires a data-literate workforce. This involves equipping employees with the skills to manage, analyze, and interpret data effectively. By fostering a data-driven culture, organizations can enhance decision-making, innovation, and overall competitiveness, as they are more open to using disruptive digital ICTs, leading to a higher willingness to invest in these technologies. This, in turn, can significantly influence an organization's level of sustainable competitiveness (Ong & Ismail, 2008).

Key challenges in the adoption of AI include the need for continuous upskilling and reskilling of employees to adapt to evolving technologies and the potential obsolescence of certain skill sets (Paschen et al., 2020). Organizations must invest in training programs to develop data literacy and AI skills across all levels of the workforce, including data management and governance.

Therefore, within the scope of this project, the following is the first set of hypotheses related to technical factors and their potential impacts on the levels of AI adoption as well as the perceived level of competitiveness at assessed Colombian firms:

Hypothesis 1

- ***Hypothesis 1A.*** Technical factors positively influence the levels of IA adoption of Colombian firms.
- ***Hypothesis 1B.*** Technical factors positively influence the levels of perceived competitiveness of Colombian firms.

2.6 Digital, business, and organizational strategies

The increasing adoption of digital ICTs, particularly AI, is driving significant improvements in operational efficiency and financial performance. By automating routine tasks, AI can help organizations reduce costs, improve productivity, and enhance decision-making. Additionally, AI can enable the development of innovative products and services, leading to new revenue streams and increased market competitiveness.

Digital strategy and transformation involve a comprehensive set of organizational processes and activities to leverage digital technologies for continuous optimization. A true digital strategy aligns with the overall corporate and business strategy and goes beyond isolated IT projects or marketing initiatives (Gobble, 2018). It focuses on transforming the organization's relationship with external actors and leveraging digital and physical resources (including data) to create value and drive financial performance.

Digital strategies can catalyze innovation and differential value creation. By leveraging disruptive technologies like AI, firms can achieve significant improvements in performance, cost reduction, and the development of entirely new products and services to enhance these capabilities (Wang et al., 2020).

As Rice et al. (1998, p. 52) highlighted, disruptive technologies such as AI have been characterized as game changers, with the potential to revolutionize industries by offering "*(1) 5–10 times improvement in performance compared to existing products; (2) to create the basis for a 30–50% reduction in costs; or (3) to have new-to-the world performance features*".

While disruptive digital technologies like AI offer significant potential, their impact on financial performance may not be immediate. Organizations must make significant operational adjustments and invest in training and infrastructure to fully realize the benefits of these technologies aligned with a vision of a digital strategy. Additionally, the specific impact of AI can vary depending on the type of application and the industry context (Bayo-Moriones et al., 2013).

Therefore, digital strategies can significantly impact value creation by enabling organizations to redefine their value propositions, transform their value networks, and enhance customer interactions. By leveraging disruptive technologies like AI, firms can improve agility, ambidexterity, adaptability, and innovation.

In fact, as a result of this behavior, many organizations have established dedicated digital transformation teams to oversee the strategic direction and operational implementation of digital initiatives. This dual mechanism, combining strategic vision and operational execution, represents an organizational culture approach that is essential for successful digital transformation.

Therefore, it is important to notice that traditionally rigid organizational structures often hinder the development and implementation of innovative digital projects. Large, established companies (i.e., Fortune 500 firms) may struggle to adapt to the rapid pace of technological change and foster a culture of innovation. To address these challenges, organizations must create flexible structures that encourage cross-functional collaboration and empower teams to experiment and innovate (Dremel et al., 2017).

With this in mind, firms from different industries and with different characteristics have been highly motivated not only to invest in (and therefore adopt) digital technologies but also to develop organizational capabilities from such technologies to generate value and obtain improved financial results. Indeed, the latter is one of the most cited reasons among leaders and managers to embark on digital transformation, for which it is important to integrate of two main resources, organizational and technical views, to generate a tangible business benefit from digitalization.

However, a truly effective digital strategy should be cross-functional and integrated into the overall business strategy. Instead of being siloed within specific departments, digital initiatives should be aligned with the broader organizational goals. By adopting a holistic approach that considers the rates, modes, and procedures required for the adoption of digital ICTs such as AI, firms can maximize their impact and achieve sustainable competitive advantage.

Given this, digital technologies "*are considered a major asset for leveraging organizational transformation, given their disruptive nature and cross-organizational and systemic effects*" (Nadkarni & Prügl, 2020, p. 3). Nowadays, digital technologies have the potential to revolutionize organizations. However, to fully realize these benefits, firms must undergo significant transformations, including adopting digital technologies at the core of their business, reconfiguring processes, and fostering a digital culture. By embracing these changes, organizations can unlock new opportunities and achieve sustainable competitive advantage.

AI stands out as a particularly disruptive and novel digital technology with a wide range of applications and the potential to significantly impact businesses. But to fully leverage AI, organizations must first establish a strong foundation of digitalization and a well-defined digital strategy. This involves creating a digital culture, investing in infrastructure, and developing the necessary skills and capabilities to effectively adopt and implement AI solutions.

Therefore, digitalization and digital strategy provide the foundation for successful AI adoption. By fostering a data-driven culture, investing in IT infrastructure, and developing the necessary skills, organizations can create the conditions for successful AI implementation. This involves building a strong foundation of technical capabilities, data assets, and strategic alignment to ensure that AI projects deliver value (Chui & Malhotra, 2018).

The rapid pace of technological advancement of AI puts significant pressure on organizations to adopt and adapt to new technologies quickly. This requires firms to be agile, innovative, and able to respond to changing market conditions to have a *"first-mover advantage*" against competitive companies in the market. However, this rapid pace of change can also lead to challenges, such as the need for significant investments, skill shortages, and organizational restructuring.

While many organizations are eager to adopt AI and other disruptive technologies, they often fall into the trap of treating them like traditional IT projects, exposing themselves to undesired results in terms of setbacks in the implementation phase, unintended consequences and results, and potential delays for project completion (Markus, 2004). This can lead to significant challenges, as AI projects require a different approach, focusing on organizational impact and user experience. Traditional project management methodologies may not be sufficient for complex AI initiatives.

It is crucial to recognize the unique characteristics of AI projects and adopt appropriate methodologies to ensure successful implementation. This involves a strong focus on data quality, model development, and deployment, as well as ongoing monitoring and refinement.

In this sense, while traditional IT projects often focus on incremental improvements to existing processes, disruptive technologies like AI can have a profound impact on organizational structures and processes. Successful AI implementation requires significant changes, including but not limited to *“organizational or business process restructuring, change in reward systems, job redesign, training, etc.”* (Markus, 2004, p. 7). This can be challenging for organizations, as it requires significant effort and investment.

Therefore, organizations must be prepared to embrace change and adapt to the new opportunities and challenges presented by AI. This includes developing a clear vision for the adoption of AI, building the necessary skills and capabilities, and fostering a culture of innovation and experimentation.

The successful deployment of disruptive technologies like AI often requires collaboration between business and IT teams. While IT teams play a crucial role in the technical aspects of implementation, business leaders should take the lead in defining the strategic direction and desired outcomes, a role that is analyzed in the following section of this document. This collaborative approach ensures that the technology aligns with the organization's overall goals and delivers the expected business value.

Therefore, is has been noted that It is important to bridge the gap between business and IT to ensure that technical capabilities are aligned with strategic objectives. By working together, organizations can maximize the benefits of disruptive technologies and avoid potential pitfalls.

2.7 “*Digital leadership*” and managerial skills

The shift towards disruptive digital technologies has led to a significant change in leadership roles. While traditional IT leaders focused on technical implementation, modern digital leaders must possess a blend of technical and business acumen to drive digital transformation. They are responsible for aligning technology with business strategies, fostering innovation, and ensuring that digital initiatives deliver tangible value.

The emergence of personal computers in the 1980s marked a significant shift, highlighting the need for IT and business leaders to collaborate to ensure that technology effectively supports strategic business objectives, considering IT planning, adoption, and implementation (Bassellier et al., 2003). This collaboration is essential for optimizing operations and achieving a competitive advantage.

The rapid evolution of digital technologies demanded the emergence of a new type of leadership known as "*digital leadership*", defined as the use of organizational digital resources to fulfill business processes and characterized by rapid optimization and decision-making based on data and information. Digital leaders possess a strong understanding of both technology and business, enabling them to drive digital transformation initiatives and align IT strategies with broader business goals in the so-called “*Digital business strategy*”

(A. Bharadwaj et al., 2013). They are skilled in data-driven decision-making, agile methodologies, and effective communication.

Digital leaders play a pivotal role in shaping the future of organizations by fostering innovation, driving digital transformation, and creating new business opportunities. To achieve this, digital leaders must possess a range of skills (Marcel De Araujo et al., 2021), including:

- **Visionary Leadership:** The ability to articulate a clear vision for the organization's digital future.
- **Innovation and Experimentation:** Encouraging a culture of innovation and experimentation.
- **Collaboration and Teamwork:** Fostering cross-functional collaboration and building strong relationships.
- **Strategic Thinking:** Aligning digital strategy with the overall business strategy.
- **Effective Communication:** Communicating the vision and goals of digital transformation.

By developing these skills, digital leaders can empower their organizations to thrive in the digital age.

Recognizing limitations in traditional management structures, the emergence of new C-level roles such as the CDO (Chief Digital Officer), CTO (Chief Transformation Officer), CAO (Chief Analytics Officer), and CDO (Chief Data Officer) reflects the increasing importance of digital transformation. These roles demand a unique blend of technical and business skills to drive digital innovation and ensure alignment with the overall business strategy. Upskilling existing executives or hiring external consultants can help organizations bridge the knowledge gap and successfully navigate the complexities of digital transformation.

Given the rapid pace of technological change, organizations are under increasing pressure to adopt disruptive technologies like AI to remain competitive. However, the complexity and potential impact of these technologies are making decision-making processes quite challenging. Leaders must carefully weigh the potential benefits and risks, considering both short-term and long-term implications.

Therefore, to navigate the complexities of digital transformation, organizations need to adopt an "*ambidextrous*" approach, balancing the exploitation of existing capabilities with the exploration of new opportunities. This requires a dual-structure strategy that allows firms to manage both traditional and innovative activities simultaneously, fostering a culture of innovation and experimentation, allowing organizations to unlock the full potential of disruptive technologies such as AI (Duerr et al., 2018).

Building on these new theories, digital leaders should adopt a holistic approach to AI implementation (Markus, 2004), considering both technical and organizational factors. By fostering a culture of innovation, empowering employees, and adopting agile methodologies, organizations allow for the maximization of AI benefits and risk minimization.

Additionally, a clear alignment between AI initiatives and business objectives is crucial. Organizations should establish clear key performance indicators (KPIs) and regularly monitor the impact of AI projects to ensure they are delivering value.

In this context, middle management plays a critical role in the successful adoption and implementation of AI technologies. However, this segment often faces challenges in balancing the need for innovation and risk-taking with the pressure to maintain operational efficiency and meet performance targets. These challenges may include risk aversion, lack of technical expertise, resistance to change, or fear of failure, among others.

To foster successful digital transformation, executive leadership must empower middle management to take calculated risks and engage in experimentation. This involves providing clear incentives, support, and training to provide middle managers with the necessary digital skills and knowledge (Gobble, 2018).

As highlighted by Bassellier et al. (2003, p. 317) ICT competence, defined as "*the set of IT-related knowledge and experience that a business manager possesses*", is crucial for business managers. By developing these skills, middle managers can take on leadership roles in ICT adoption projects, reducing the reliance on centralized decision-making and accelerating the diffusion of innovation within their teams (Rockart, 1988).

The ability to assess risks and manage complex projects is essential for middle managers in the age of digital transformation. By combining technical expertise with business acumen, they can effectively lead their teams and drive positive outcomes.

Given this, ICT competence, encompassing both knowledge and experience, is a critical factor for middle managers in driving digital transformation. A strong understanding of technology, coupled with practical experience in its application, enables managers to assess risks, make informed decisions, and "*champion*" the adoption of disruptive technologies such as AI. By developing their ICT competence, middle managers can play a pivotal role in bridging the gap between technical experts and business leaders, ensuring that technology is effectively leveraged to achieve strategic goals.

Thus, the concept of "*IT championing*", defined as *"a role in promoting or advocating the use of technological or other innovations in organizations."* highlights the importance of advocating for the adoption of technological innovations within organizations. (Bassellier et al., 2003, p. 322).

Middle managers and executives, with their understanding of both business and technology, are well-positioned to champion the adoption of disruptive technologies like AI. By collaborating with IT departments, they can drive innovation, improve organizational performance, and build a more resilient and adaptable business (Rockart, 1988).

2.8 New digital literacy, skills, competence, and knowledge management.

In the same manner that leadership and executive roles are required to build a new set of digital expertise to successfully manage disruptive ICT projects, digital literacy, skills, and competence are essential for individuals to thrive in the digital age. While digital literacy refers to basic digital skills, such as using computers and the internet, digital skills encompass more advanced technical abilities, like programming and data analysis. Digital competence, on the other hand, is a broader concept that includes not only technical skills but also the ability to apply these skills to solve problems and create value (Iordache et al., 2017).

As technology continues to evolve, organizations must invest in developing the digital skills of their workforce. This will enable employees to adapt to change, innovate, and contribute to the organization's success.

One of the challenges in implementing disruptive ICTs is ensuring user adoption and proper usage. Lack of user interest or misuse of technology can hinder the realization of expected benefits. To address this, organizations need to invest in "*IT education*" and training programs to equip their workforce with the necessary skills and knowledge. This includes providing formal training, certifications, and ongoing learning opportunities. By investing in IT education, organizations can improve user adoption, enhance productivity, and maximize the return on their technology investments.

Even highly experienced firms with significant investments in advanced technologies may struggle to realize the full potential of these technologies if they lack a skilled workforce. Resistance to change, lack of user adoption, and a mismatch between technology capabilities and organizational needs can hinder the realization of benefits (Ong & Ismail, 2008).

To address these challenges, organizations must invest in employee training and development, fostering a culture of continuous learning and adaptation. Additionally, a strong organizational culture that supports innovation and experimentation is essential for successful technology adoption (Cetindamar Kozanoglu & Abedin, 2021).

Higher education institutions play a vital role in disseminating knowledge about disruptive digital technologies, including AI. Integrating relevant topics into non-technical courses, such as business and entrepreneurship, can help equip a broader audience with the necessary understanding and skills to leverage these technologies effectively. By promoting digital literacy and fostering a culture of innovation, universities can contribute to the development of a skilled workforce and drive technological advancement that can leverage this knowledge to secure intra-firm value creation.

Disruptive digital ICTs, such as AI, can significantly transform business processes. Its rapid adoption, however, has sparked concerns about job displacement. While AI can automate routine tasks, it also creates new opportunities in areas like data analysis, AI development, and maintenance. An estimation made by Press (2019) shows that as many as 20.3 million workers could be displaced from their jobs only in the US, and almost 75 million workers worldwide by 2030, as a result of the automation of clerical and low-skilled roles due to the adoption of AI technologies.

To address the skills gap created by the rapid adoption of AI and other disruptive technologies, organizations must invest in comprehensive training and development programs. This includes reskilling and upskilling employees to equip them with the necessary digital competencies. While traditional corporate training programs may be helpful, they may not be sufficient to address the specific needs of AI-driven transformations, as organizations may need to partner with educational institutions, online learning platforms, or external training providers to access specialized expertise and accelerate the development of AI skills.

As a result, to bridge the skills gap and accelerate digital transformation, organizations are increasingly collaborating with external partners such as IT providers, consulting firms, and academic institutions. These partnerships can provide access to specialized expertise, advanced technologies, and innovative training programs. As mentioned by Press (2019), both organizations and employees must embrace a culture of continuous learning and adaptation. By investing in training and development, organizations can ensure that their workforce is equipped to thrive in the digital age.

Knowledge management, defined as *"the set of management activities that enable the firm to deliver value from its knowledge assets."* (Andreeva & Kianto, 2012, p. 618), plays in this scenario a crucial role in the successful adoption and utilization of disruptive digital technologies. By enabling the sharing, creation, and application of knowledge, organizations can maximize the benefits of these technologies and mitigate potential risks.

Key elements of knowledge management in the context of digital transformation include digital enrichment of resources, collaboration and networking, leadership and learning, and knowledge-intensive value creation (de Bem Machado et al., 2022). By focusing on these elements, organizations can harness the power of digital technologies to drive growth and innovation.

And while traditional ICTs can facilitate knowledge management by enabling the storage and dissemination of information, disruptive technologies like AI offer even greater potential. AI-powered systems can analyze and interpret vast amounts of data, identify patterns, and generate insights that can drive innovation and improve decision-making (Andreeva & Kianto, 2012). By automating routine tasks and providing valuable insights, AI can free up employees to focus on higher-value activities and foster a culture of continuous learning and innovation.

The integration of AI into knowledge management practices can help organizations to enhance knowledge creation and sharing by facilitating collaboration, knowledge sharing, and the creation of new knowledge; improve decision-making by providing data-driven insights to support better decision-making; automate routine tasks; and personalize learning by tailoring training programs to individual needs. By leveraging AI, organizations can build a more agile, innovative, and data-driven workforce.

Therefore, to ensure the successful adoption and utilization of disruptive digital technologies, organizations must prioritize employee training and development. By investing in knowledge management practices, organizations can foster a culture of learning, innovation, and adaptation. This involves providing employees with the necessary skills and knowledge to effectively use new technologies, as well as creating opportunities for continuous learning and development.

As Zahra et al. (1999) emphasized, a culture of learning and knowledge sharing is essential for driving experimentation, developing new skills, and redefining competitive positioning. By embracing digital transformation and empowering employees, organizations can unlock new opportunities and achieve sustainable growth.

2.9 Organizational culture as an enabler for digitalization

Organizational culture plays a crucial role in driving innovation and digital transformation. Shared values, beliefs, and assumptions shape the organization's behavior and its ability to adopt and leverage new technologies. Organizational culture can be 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). A strong organizational culture can foster a climate of innovation, experimentation, and collaboration, which is essential for successful digital transformation (A. Bharadwaj et al., 2013).

Organizational culture has different components and representations within the corporate environment:

1. Artifacts, represented by visible elements of the company such as the organizational hierarchy, technological infrastructure, manners,

2. Structural elements, beliefs, and values represented by goals, ideas, norms, or principles, and

3. Underlying assumptions, represented by unexplainable occurrences outlined within organizational culture.

These three components of organizational culture are influenced by the use of disruptive digital technologies and denote a certain degree of variance when a firm is working to adopt them, making the level of flexibility related to organizational culture a critical factor for their success.

While organizations have invested heavily in data and analytics, they often struggle to fully leverage this data to drive business value (A. S. Bharadwaj, 2000). A key challenge is the lack of a strong data-driven culture, which is essential for effectively utilizing data-driven technologies like AI.

To maximize the value of data, organizations must foster a culture that prioritizes data-driven decision-making, encourages data literacy, and supports the development of data-driven capabilities (Dremel et al., 2017). By creating a data-centric culture, organizations can unlock the full potential of AI and other data-driven technologies.

The availability of massive amounts of data, often referred to as "*big data*," has revolutionized the way organizations make decisions compared to the past. By harnessing the power of big data analytics, firms can gain deeper insights into customer behavior, market trends, and operational efficiency instead of relying solely on perceptions or experience. This data-driven approach can lead to improved customer experience, better decision-making, and increased competitiveness (A. Bharadwaj et al., 2013).

Studies have shown that one of the primary motivations for adopting digital technologies is to gain deeper customer insights and improve customer experience. By leveraging data analytics and AI, organizations can personalize products and services, tailor marketing campaigns, and provide superior customer support (Teichert, 2019).

As a result, AI technologies have emerged as powerful tools for creating value from data. By enabling personalized experiences, data-driven decision-making, and improved customer engagement, AI can significantly impact business outcomes.

However, successful AI adoption requires a comprehensive organizational transformation. This includes changes to organizational structure, culture, processes, and capabilities. Effective communication, collaboration, and alignment between business and

IT teams are essential to overcome challenges and realize the full potential of AI (Dremel et al., 2017).

As Ghafoori et al. (2024) noted, many organizations struggle to fully benefit from AI due to limitations in organizational culture, such as poor communication and a lack of cross-functional collaboration. Addressing these cultural challenges is crucial for successful AI implementation.

The adoption of disruptive digital technologies can create tensions between traditional and innovative approaches within organizations. Older, more established firms may struggle to adapt to the rapid pace of change, particularly if their organizational culture is resistant to innovation.

To overcome these challenges, organizations must foster a culture of innovation and continuous learning. This involves empowering employees, providing opportunities for skill development, and encouraging experimentation. By embracing a data-driven approach and promoting digital literacy, organizations can ensure that their workforce is equipped to thrive in the digital age.

Additionally, organizations should focus on bridging the generational gap and fostering collaboration between younger and older employees. By sharing knowledge and experience, employees of all ages can contribute to the organization's success by leveraging a general set of data skills that allow them to be autonomous.

Thus, a strong organizational culture is essential for fostering continuous learning and innovation. By encouraging employees to acquire new digital skills and knowledge, organizations can ensure that their workforce is equipped to adapt to the rapidly changing technological landscape, as well as to avoid potential knowledge gaps between employees.

Knowledge management plays a crucial role in this process. By facilitating the acquisition, sharing, and application of information, organizations can accelerate innovation and improve decision-making. A data-driven culture, where data is seen as a valuable asset, is also essential for driving digital transformation. By leveraging data analytics and AI, organizations can gain valuable insights and make more informed decisions, resulting in differentiation and competitive advantage when compared with firms that are only focusing on ICT adoption by itself (Tippins & Sohi, 2003).

Consequently, organizational development is crucial for successful digital transformation, and it includes *“managers’ attitudes and behaviors, human resource development and training, reward systems, job redesign, organizational structure.”* (Markus, 2004, p. 7). Accordingly, a supportive organizational culture, characterized by employee empowerment, collaboration, and innovation, can facilitate the adoption and effective use of digital technologies.

Research by Ghafoori et al. (2024) suggests that certain cultural factors, such as employee focus, development opportunities, strong teamwork, flexible management, market orientation, rationality, and open communication, are positively correlated with effective data-driven digital transformation that also results in enhanced operational performance.

Kane et al. (2015) highlighted the importance of a culture that embraces experimentation and open communication for successful disruptive ICT adoption. By creating a safe space for failure and learning, organizations can foster innovation and accelerate the development of new solutions. A tolerant and communicative environment allows for rapid iteration, enabling teams to quickly adapt and improve their approach as part of the organizational knowledge management strategy.

While a culture of experimentation is essential for innovation, it is important to strike a balance between risk-taking and responsible decision-making. Organizations should establish a framework for measuring the success of AI projects, including key performance indicators (KPIs) and metrics. This will help identify areas for improvement and inform future decisions, weighing in detail the potential cost of inaction against the cost of actually developing new offerings based on these developments and tools to draw useful knowledge.

It's also crucial to create a supportive environment where teams can learn from failures and use these experiences to drive future innovation. By fostering a culture of continuous learning and adaptation, organizations can mitigate the risks associated with the adoption of AI and maximize the potential benefits.

In the same line, prototyping and an agile mindset are essential for successful ICT adoption. By enabling experimentation and learning, prototyping allows organizations to gradually introduce and refine innovative technologies. This agile organizational culture approach helps to mitigate risks, address user needs, and ensure a smooth transition (Markus, 2004).

Also, mentorship and championing from both mid- and top management are crucial to fostering a culture of innovation and experimentation. By providing guidance, support, and resources, leaders can empower employees to take risks and embrace new technologies.

Additionally, to effectively implement disruptive digital technologies, organizations need to create a strong “*digital culture*” and establish dedicated teams to oversee digital initiatives. This may involve creating new organizational structures, such as digital transformation offices or digital innovation hubs. By investing in digital talent and fostering a culture of innovation, organizations can position themselves for success in the digital age.

These dedicated teams, often led by experienced digital leaders, can drive the development and implementation of innovative solutions, ensuring alignment with the organization's overall business strategy. By creating a clear vision and providing the necessary resources, organizations can accelerate digital transformation and achieve significant competitive advantages.

A flexible and adaptive organizational culture is essential for the successful adoption and utilization of disruptive technologies like AI. By embracing innovation, experimentation, and continuous learning, organizations can create a positive feedback loop that drives further innovation and growth.

When AI is effectively implemented and integrated into business processes, it can lead to significant improvements in decision-making, productivity, and customer experience. These positive outcomes, in turn, reinforce the value of a flexible and innovative culture, encouraging further investment in technology and digital transformation, creating a virtuous circle (Dremel et al., 2017).

Finally, a collaborative and cross-functional culture is essential for successful digital transformation. By fostering collaboration between teams with diverse skills and perspectives, organizations can generate innovative ideas, improve problem-solving, and accelerate the development of new products and services.

Effective communication, trust, and mutual respect are key to building strong collaborative teams. By breaking down silos and encouraging open dialogue, organizations can create a culture of rapid innovation and continuous improvement for creative and impactful product development.

As a result, modern organizations are increasingly adopting flatter, less hierarchical structures to foster innovation and agility. This empowers employees to take ownership of projects, make decisions, and collaborate effectively. Agile methodologies, such as Scrum and Prince, are well-suited for this approach, as they emphasize iterative development, continuous improvement, and rapid response to change.

By empowering employees and fostering a collaborative culture, organizations can accelerate the development and deployment of disruptive technologies like AI. This can lead to improved product development, faster time-to-market, and increased customer satisfaction.

Therefore, as part of the scope of this research, the following is the second defined hypothesis, related both to organizational factors and their potential impacts on the levels of AI adoption and perceived level of competitiveness at assessed Colombian firms:

Hypothesis 2

- ***Hypothesis 2A.*** Organizational factors positively influence the levels of IA adoption of Colombian firms.
- ***Hypothesis 2B.*** Organizational factors positively influence the levels of perceived competitiveness of Colombian firms.

2.10 Open Innovation, relational capital, and digitalization

The rapid advancements in digital technologies, particularly the internet, have significantly transformed the way knowledge is shared and accessed. Electronic and digital ICTs have dramatically reduced transmission costs and increased transfer speeds (H. W. Chesbrough, 2003). This democratization of knowledge has empowered individuals and organizations, enabling them to collaborate, innovate, and create value. By reducing barriers to information and facilitating knowledge exchange, digital technologies have become a powerful driver of economic and social progress.

Open innovation, defined as *“the distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization’s business model.”* (H. Chesbrough & Bogers, 2014, p. 12). This powerful approach to innovation leverages knowledge flows across organizational boundaries. By collaborating with external partners, such as customers, suppliers, and academic institutions, organizations can access a wider pool of ideas and accelerate innovation.

Relational capital, which refers to the value derived from relationships with external stakeholders, plays a crucial role in open innovation. By building strong relationships with partners, organizations can gain access to valuable knowledge, resources, and capabilities (Matos et al., 2022).

Open innovation ecosystems are essential for the development and deployment of AI technologies, as these benefit from collaboration and knowledge sharing. By fostering collaboration between internal and external stakeholders through a "*coupled process*", organizations can access a wider pool of expertise, accelerate innovation, and create more valuable solutions (Gassmann & Enkel, 2007).

This process of knowledge acquisition and sharing is critical to the success of open innovation. By integrating external knowledge with internal capabilities, organizations can develop innovative AI applications that address real-world business challenges, ensuring that they are both technically viable and commercially relevant.

To successfully adopt disruptive digital ICTs, organizations must make significant adjustments to their organizational structures and processes (Urbinati et al., 2020). This includes reorganizing R&D efforts, standardizing technical features, and establishing new procedures for digital innovation. Firms can either proactively prepare for these adjustments (enabled capacities) or respond to them as needed (enabling capacities). A proactive approach can help organizations to be more agile and responsive to technological change.

The reorganization of R&D capacities is a critical step in the adoption of disruptive digital ICTs. It involves assessing the organization's current capabilities and identifying gaps that need to be addressed. This may require investments in new technologies, infrastructure, and talent. Additionally, organizations may need to reorganize their teams and processes to effectively leverage these technologies.

By carefully analyzing their current state and future needs, organizations can develop a comprehensive plan for R&D transformation and ensure that they are well-positioned to capitalize on the opportunities presented by digital innovation.

Once an organization has assessed its existing capabilities, it can identify the gaps and determine the necessary resources to fill them. This may involve acquiring new technologies, hiring skilled talent, or partnering with external organizations. By leveraging a network of partners, organizations can access specialized expertise and resources, accelerating their digital transformation journey.

While many organizations recognize the value of external partnerships in driving innovation, they often overlook the importance of fostering a culture of open innovation within their organizations. By promoting collaboration, knowledge sharing, and experimentation within their structure, firms can unlock the full potential of their internal resources and capabilities (Dremel et al., 2017). In that sense, data sharing across departments is particularly crucial for AI initiatives. By breaking down silos and enabling the free flow of information, organizations can accelerate innovation, improve decision-making, and gain valuable insights.

Therefore, data sharing constitutes a crucial component of a data-driven culture, which is essential for effective AI adoption. By encouraging data sharing across departments and breaking down silos, organizations can create a more comprehensive and accurate view of their business. This, in turn, enables data-driven decision-making, leading to improved outcomes.

In this context, top management plays a critical role in fostering a data-driven culture by setting the tone and prioritizing data initiatives. By emphasizing the importance of data and analytics and by providing the necessary resources and support, leaders can drive data-driven decision-making throughout the organization.

Therefore, the interconnected nature of the global digital market underscores the importance of collaboration and open innovation even among competitors (i.e., coopetition). By partnering with other organizations, firms can access a wider pool of knowledge, resources, and expertise. This collaborative approach can accelerate innovation, reduce costs, and improve the overall quality of products and services. In that sense, open innovation ecosystems are essential for driving digital transformation. By fostering collaboration between competitors, suppliers, and customers, organizations can create innovative solutions and capture new market opportunities.

At the same time, the importance of "*human and psychological capital*" in open innovation ecosystems cannot be overstated. Strong relationships between individuals across organizations can facilitate knowledge sharing, collaboration, and the development of trust (Sartori et al., 2013). Social research methods can be used to identify the best practices and foster a culture of innovation.

By focusing on social evolution and execution, management roles at organizations can ensure that new technologies are effectively integrated into their operations and that employees are equipped with the necessary skills and knowledge to use them effectively. This collaborative approach can accelerate the adoption of disruptive technologies and drive innovation.

This behavior is incentivized by network effects that play a crucial role in the success of digital technologies. As more firms adopt technologies, their value increases, creating a virtuous cycle of growth and innovation. Collaboration and partnership among them are essential for leveraging network effects and accelerating the adoption of disruptive technologies by working together, sharing knowledge, resources, and risks, leading to faster innovation and greater impact.

The increasing interconnectedness of businesses and the emergence of digital ecosystems have transformed the competitive landscape. AI, as a powerful driver of digital transformation, is reshaping industries and creating new opportunities for collaboration and innovation.

The complexity of these ecosystems, coupled with the emergence of new complementarities between products and software, requires firms to adopt a strategic approach to digital transformation. By positioning themselves effectively within digital ecosystems, organizations can leverage the collective intelligence and resources of multiple stakeholders to drive innovation and create a sustainable competitive advantage (Appio et al., 2021).

The rapid advancement of AI and other disruptive technologies has significantly reshaped the innovation landscape. Firms are increasingly turning to open innovation ecosystems to access new ideas and technologies instead of relying solely on their internal resources (Thompson et al., 2019).

This shift is driven by the need to accelerate innovation, reduce costs, and stay ahead of the competition. By collaborating with external partners, such as universities, startups, and crowdsourcing platforms, organizations can tap into a diverse pool of talent and expertise. This collaborative approach can lead to the development of innovative products and services that drive growth and create new business opportunities.

While open innovation can be a powerful tool for driving innovation, it's important to recognize its potential limitations. For digital laggards, overreliance on external partners can hinder their ability to develop core competencies and differentiate themselves.

Digital leaders, on the other hand, often adopt a hybrid approach that combines internal and external resources. By leveraging their internal capabilities and collaborating with external partners, they can tailor innovation efforts to their specific needs and maintain a competitive edge. As a result, innovation labs can serve as a valuable platform for fostering innovation and experimentation. By providing a dedicated space for innovation, organizations can encourage cross-functional collaboration and accelerate the development of new products and services.

Therefore, the rise of open innovation ecosystems has fundamentally changed the way organizations approach innovation. By collaborating with a diverse range of partners, firms can access a wider pool of knowledge, talent, and resources. This collaborative approach can accelerate innovation, reduce costs, and increase the likelihood of success. Thus, a balanced approach that combines internal and external resources is key to effective innovation. By leveraging the strengths of both internal and external partners, organizations can create a more robust open ecosystem.

Governments also play a crucial role in fostering innovation by providing incentives, regulations, and funding. By creating a supportive environment, governments can encourage the development and adoption of new technologies. Open innovation ecosystems can facilitate the creation and implementation of new business models by providing access to knowledge, resources, and expertise. By collaborating with other organizations, firms can develop innovative solutions that address real-world challenges and create organizational value.

Therefore, as part of the scope of this research project, the following is the third defined hypothesis, related both to relational factors and their potential impacts on the levels of AI adoption and perceived level of competitiveness at assessed Colombian firms:

Hypothesis 3

- ***Hypothesis 3A.*** Relational factors positively influence the levels of IA adoption of Colombian firms.
- ***Hypothesis 3B.*** Relational factors positively influence the levels of perceived competitiveness of Colombian firms.

2.11 ICTs, value creation, and a firm's performance

The resource-based value (RBV) framework proposes that value generation and general performance of firms depend on their ability to develop "*unique*" resources based on their capabilities, which must be valuable, rare, difficult to imitate, and non-substitutable by other resources (Barney, 1991). This view considers that resources are distributed among firms in a rather unequal form that is constant over time.

Resources, both tangible and intangible, are the building blocks of business value and competitive advantage, as they facilitate the development of organizational capabilities, including functional areas like marketing, sales, and manufacturing (A. S. Bharadwaj, 2000). While information technologies and ICTs can be viewed as functional capabilities, they increasingly serve as cross-functional resources, significantly enhancing core functionalities. This strategic role of ICTs is crucial for achieving competitive advantage, defined as "*the value that a firm is able to create for its buyer that exceeds the firm's cost of creating it.*" (Porter, 1985, p. 3).

Given this, it is important to differentiate three categories of key IT resources and their relationship with the resource value creation framework at a firm level, as mentioned by Ross et al. (1998): The first resource is infrastructure technologies such as servers, storage, networking, telecommunications, personal computing, and middleware. These technologies form the foundation of IT operations. While these physical or tangible resources are crucial, their impact on business strategy has been mitigated by factors like third-party IT services and cloud computing. This commoditization has reduced the barriers to adopting innovative ICTs for many firms.

Despite this commoditization, IT infrastructure remains a critical factor for C-level executives. The ability to adapt and configure IT infrastructure effectively can provide significant competitive advantages, as firms that are able to integrate systems from various IT providers seamlessly can often outperform those with challenges in this area, given the cost and time it may demand to reach the same levels of technical efficiency.

The second resource is IT knowledge, which encompasses both general employee skills and specific managerial skills and is a foundational factor for successful technological exploitation and dissemination within firms. Developing IT skills requires time, specialization, and significant investment, making it challenging for many companies to acquire these capabilities quickly or easily. Without adequate IT knowledge, firms may face limitations in configuring integrated systems, effectively utilizing technology, and adopting innovative technologies with positive business outcomes.

In this context, managerial skills are essential for coordinating and motivating technical teams to adapt to change and embrace agile methodologies. This results in the *"creation of an environment in which IT personnel can leverage not only their technical skills, but also effectively bring to bear the assets of entire socio technical network to which the member belongs."* (A. S. Bharadwaj, 2000, p. 174).

The third and last resource is IT-enabled intangibles, such as organizational culture, know-how, knowledge management, reputation, and orientation. This is another critical aspect of value creation within the RBV framework. These non-physical resources interact with IT resources to influence business operations, particularly in areas like customer orientation, knowledge assets, and synergy.

All three IT resources enable firms to focus on their customers by gathering and analyzing information to understand their needs, defining their expectations, and designing new offerings to enhance their overall satisfaction. For this purpose, effective customer management with deep integration of processes and systems is required to leverage data for informed decision-making.

As a result, IT resources play a crucial role in managing knowledge assets within firms. By storing data, information, and know-how in unified repositories and facilitating communication, IT enables knowledge dissemination and fosters a collaborative organizational culture. This "*synergy*" represents an intra-firm capability to share information and resources among its different departments in an effective manner to respond faster to market needs. Moreover, it enhances a firm's unique ability to respond quickly to market needs and creates a competitive advantage that is difficult to replicate.

IT resources, including infrastructure, knowledge, and intangibles, create a unique set of capabilities that differentiate firms and drive value creation. These resources can enhance financial results by increasing net income or reducing costs, as demonstrated by studies such as the one performed by A. S. Bharadwaj (2000).

However, the overall impact of ICTs on firm performance remains a subject of debate, with some studies suggesting inconclusive “*black box*” or inconsistent results. This highlights the need for further research to better understand the complex relationship between ICTs and firm performance (Liang et al., 2010).

While some authors have argued that sustainable competitive advantage (SCA) is challenging in highly dynamic markets driven by innovative ICTs, studies suggest that firms can achieve differentiation through rapid adaptation and responsiveness. By leveraging disruptive ICTs to support agility and adaptability, firms can create competitive advantages that are difficult to imitate. However, the effectiveness of this approach may vary depending on specific market conditions and context, and therefore, is not completely generalizable (Barney et al., 2001).

The RBV framework highlights the importance of “*corporate governance*” and “*organizational capabilities*” in achieving SCA. Corporate governance, which involves effectively managing resources and assets, plays a crucial role. Organizational capabilities, the firm's unique characteristics for interacting with the environment, also mediate the relationship between ICTs and firm performance.

Subsequently, ICTs may enhance organizational capabilities and corporate governance, leading to improved overall performance. By enabling effective decision-making and resource management, ICTs can positively impact firms at various levels Liang et al. (2010, p. 1151) concluded that ICTs can “*significantly improve (internal and external) organizational capabilities*”, suggesting that an indirect RBV model can be used to assess the impact of ICTs on firm performance, considering factors like efficiency, financial metrics, and value creation.

AI is a disruptive technology that has garnered significant attention for its potential to impact value creation at the firm level. And while AI can optimize internal operations and drive new product or service development, it also carries the risk of value destruction. Firms can achieve value creation through cost reductions or increased revenue from new offers that address specific market needs and differentiate them from competitors.

Conversely, the adoption of disruptive technologies such as AI can also lead to value destruction, with the risk varying across industries and firms. To mitigate potential negative outcomes, careful planning is essential before deploying AI solutions. By anticipating potential challenges and developing strategies to address them, firms can minimize the risks associated with the adoption of AI.

The development, adoption, and implementation of IA technologies involve investing in hardware, software, consulting, design, training, and process reengineering. Given this significant effort, it is crucial for organizations to carefully estimate costs and align project expectations with potential benefits. By carefully assessing costs and benefits, firms can ensure that AI investments deliver the desired value.

To maximize value creation from disruptive digital ICTs, firms must ensure a strong technical foundation to define clear expectations for the solutions being developed or acquired. Success should be measured not only in terms of technical performance but also in terms of business impact and alignment with key performance indicators (KPIs). This helps to mitigate the risk of unintended negative consequences and ensures that the technology delivers the desired value (Canhoto & Clear, 2020).

A significant challenge for AI adoption is the difficulty in measuring return on investment (ROI). Unlike traditional ICTs, the benefits of AI are often less tangible and harder to quantify. Without clear metrics to assess the impact of AI, organizations may struggle to justify continued investment and risk losing momentum (MIT Technology Review, 2017).

2.12 Value creation in non-static markets: The theory of dynamic capabilities

While the RBV framework offers valuable insights into the impact of disruptive digital ICTs on firm performance, it has limitations related to the assumption of resource immobility. The framework often struggles to account for the rapid changes and adaptations required in dynamic markets, especially when dealing with disruptive technologies. The difficulty in modifying, trading, or mixing resources, including scenarios where they acquire developments rather than developing them in-house, can hinder a firm's ability to respond quickly to evolving market conditions (Teece et al., 1997).

The assumption of resource immobility within the RBV framework may not fully align with the realities of today's dynamic and globalized markets. Firms are constantly adapting to technological advancements and shifting market conditions. This requires flexibility and agility to acquire, develop, and deploy resources effectively to either build or maintain their competitive position in their markets.

To address the limitations of the traditional RBV framework, the dynamic capabilities framework (Teece et al., 1997) has emerged. This framework emphasizes the importance of a firm's ability to adapt and evolve its capabilities. Dynamic capabilities are defined as "*a firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end*" (Barreto, 2010, p. 259), to respond to changing market conditions. Unlike the static view of resources in the traditional RBV, the dynamic capabilities framework recognizes that firms need to continuously develop, integrate, and reconfigure their capabilities to maintain a competitive advantage.

The dynamic capabilities framework is based on the following assumptions:

1. Firm-Specific Capabilities: Firms possess unique capabilities that are formed or managed to adapt their initial base of resources, and
2. Internal Development: Developing these capabilities internally is often more advantageous than acquiring them externally, as they are tailored to the firm's specific context and are a key element to help them integrate, build, and reconfigure resources to respond to changing environments, resulting in an ability to maintain a sustainable competitive advantage (Barreto, 2010).

The dynamic capabilities framework highlights the importance of strategic choices and path dependencies. Firms' past decisions and actions shape their current capabilities and future options. The paths they choose can limit or expand their strategic options, influencing their ability to adapt to changing market conditions and maintain a competitive advantage.

The dynamic capabilities framework emphasizes the uniqueness of firm-specific capabilities and the difficulty of imitation. These capabilities are shaped by a firm's internal characteristics, organizational structures, and managerial processes. It mentions that "*the competitive advantage of firms lies with its managerial and organizational processes, shaped by its (specific) asset position, and the paths available to it.*" (Teece et al., 1997, p. 518).

Three key factors influence a firm's dynamic capabilities:

- Processes: The firm's ability to integrate, build, and reconfigure resources.

- Positions: The firm's strategic assets and market positions.
- Paths: The firm's history, culture, and institutional context.

By effectively managing these factors, firms can sustain a competitive advantage in dynamic markets.

Concerning the first factor (processes), routines, as part of a firm's organizational processes, play a crucial role in adapting to rapid technological changes, such as the adoption of AI. The integration of AI requires the development of new routines and their alignment with existing processes across various functional areas. This interdependency is essential for ensuring smooth operations and maximizing the benefits of AI implementation.

The ability to adapt to routines and processes is crucial for firms to embrace radical innovations such as AI. Younger firms, with fewer established routines, often have an advantage in adopting new technologies. However, established firms can also adapt by fostering a learning culture and promoting knowledge sharing and management. This involves developing new routines, reconfiguring existing processes through repetition and adaptation, and collaborating with external partners to acquire new knowledge and skills.

The ability to reconfigure resources and adapt to changing environments is crucial for firms facing disruptive technologies like AI. Organizational learning plays a key role in this process, enabling firms to develop new routines and processes. However, rapid reconfiguration can be costly and challenging, requiring careful planning and a flexible organizational structure.

While organizational learning is essential, it's important to note that it may not always be sufficient. Firms need to actively monitor market trends and anticipate potential disruptions to stay ahead of the curve. This proactive approach, combined with a flexible organizational structure, can help firms navigate the complexities of digital transformation.

Therefore, as part of this research scope, the fourth and final hypothesis is defined. It concerns the potential direct impact of AI adoption on the perceived level of competitiveness for assessed Colombian firms and the possible mediating relationship between levels of AI adoption, technical organizational factors, relational factors, and the level of perceived competitiveness.

Hypothesis 4

- ***Hypothesis 4A:*** Levels of AI adoption positively influence the levels of perceived competitiveness of Colombian firms.
- ***Hypothesis 4B*.** The relationship between technical, organizational, and relational factors and the level of perceived performance (as a proxy for competitiveness) at Colombian organizations is mediated by the level of adoption of AI technologies.

2.13 Summary

The literature review performed as part of this research, related to the process of digital ICT adoption, reveals a growing academic interest in this area over the past two decades. Several influential theoretical frameworks have been established and developed for studying ICT adoption at both the individual and firm levels. These include the Technology Adoption Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT). However, the review also identifies a gap in firm-level ICT adoption frameworks, as it reveals that only two frameworks have been specifically designed for this context: the Technological, Organizational, and Environmental (TOE) framework and the Diffusion of Innovation (DOI) model.

The review methodology relied on replicable search queries conducted in highly respected academic databases such as WoS and Scopus. This search strategy identified a significant increase in published studies on firm-level digital ICT adoption within the fields of business, management, and economics over the past decade. Furthermore, the review revealed a potential research gap when comparing it to other emerging technologies like cloud computing, big data, and the Internet of Things. There appears to be a lower volume of research specifically focused on factors influencing the adoption of AI, AA, and ML within businesses, which is important to address and provides additional incentive for the development of this research.

A close examination of the articles from the WoS database allows for a comparison of the TOE and DOI frameworks. The TOE framework identifies three key factors influencing firm-level ICT adoption: technological factors, organizational factors, and environmental factors.

In contrast, the DOI model focuses on individual-level factors such as leadership, internal characteristics, and external influences. The review suggests that the TOE framework is more widely used for empirical studies on specific ICT adoptions due to its focus on directly relevant factors, while the DOI model offers broader insights into organizational readiness for disruptive innovation, not just technological change. This suggests the potential value of a hybrid approach for studying AI adoption in Colombian organizations, with a model that combines elements from both frameworks to provide a more comprehensive understanding of the key influencing factors of this process.

The literature review also highlights several key technological factors influencing AI adoption in businesses, echoing insights from both academics and practitioners in recent years. These factors can potentially be adapted from broader digital ICT adoption considerations, including (1) Robust, Integrated IT Infrastructure: Strong, interconnected, and adaptable IT platforms are essential to support the demanding requirements of disruptive ICTs like AI. (2) Technological Maturity: Firms progress through various stages of ICT use, from initial adoption to mature integration, and the success of AI adoption can be influenced by a firm's existing technological maturity, and (3) Data Foundation: Availability, high-quality data, seamless data integration, and data literacy within the organization are critical for effective AI and ML implementation.

The literature review also identifies three key organizational factors influencing AI adoption, such as firstly. Process and Structure Adjustments: AI adoption often necessitates innovative adjustments to processes and structures. This may involve reorganizing R&D departments, defining new ones, or adapting existing ones to address skill gaps and meet AI integration needs. Secondly. Cross-Functional Digital Strategy: A collaborative, "*transfunctional*" approach to digital strategy is crucial.

Leadership and managers need to bridge the gap between IT and business strategies to drive digital transformation. This includes fostering digital leadership skills to oversee AI investment and adoption effectively, and thirdly. Empowering Middle Management: Empowering middle management, both from a decision and from a skill-based point of view, and allowing for calculated risks and experimenting with AI can be critical for successful implementation.

Finally, the process of literature review also highlights the importance of two relational factors, such as: Firstly. Digital Culture and Knowledge Management: A supportive organizational culture is essential for successful AI adoption. This includes adapting the culture to embrace disruptive ICTs and fostering knowledge management practices to capture lessons learned from previous digital initiatives. A strong culture can reinforce the value of successfully deployed AI technologies, and secondly, open innovation and relational capital. Open innovation and relational capital are interconnected. By cultivating high-value networks, organizations can leverage external knowledge, experience, resources, and capabilities to facilitate AI adoption at an organizational level.

3. METHODOLOGY

Considering the research objective of determining the factors influencing AI adoption in emerging countries, specifically Colombian firms (included in the first section of this document), and their possible impact on competitive advantage and intrafirm value creation, a robust methodological design was crucial. This design would help to establish the relationships between technical, organizational, and relational factors, AI adoption levels, and perceived competitiveness.

This chapter outlines the methodological approach adopted for this research project. It begins by defining the primary and secondary research objectives, the main research question, and the hypotheses to be tested. It also focuses on describing the data collection strategy used, which involved the development and administration of an online survey instrument and the processing of this information to create a structured database suitable for quantitative analysis.

The chapter is followed by defining the analytic processes used as part of the project, which included statistical descriptive techniques to explore the data, followed by structural equation modeling (SEM) using partial least squares (PLS) to assess the direct and indirect relationships between the identified variables. These variables were selected based on a comprehensive literature review on ICT adoption and the specific characteristics of Industry 4.0 technologies.

The methodology section concludes by discussing the specific tools used for data collection, processing, and analysis. It also addresses the limitations of the study and the generalizability of the findings to other contexts within the fields of IS and business management.

By following a rigorous methodological approach, the research aims to provide valuable insights into the factors influencing AI adoption in emerging markets and their impact on organizational performance.

3.1 Selection of the methodological approach for the project

Researching complex phenomena like the adoption of disruptive technologies (complex systems that are open and continuously dynamic) requires a robust methodological approach. Given the challenges associated with measuring organizational factors and their impact on the adoption of AI, the design of a research methodology is not a simple task. Such methodology must successfully contribute meaningful insights to generate new knowledge in the academic fields of IS and business and management while offering practical implications and guidelines for organizational leaders and public planners in emerging economies.

Therefore, several methodological approaches were considered, based on the work of authors such as Swanson & Holton III (2005), including:

1. Quantitative methods of research.
2. Qualitative methods of research.
3. Combined (or mixed) methods of research.

Mohajan, p. (2020, p. 59) defines the first type of methods (quantitative) as a "*systematic observation and description of the characteristics or properties of objects or events to discover relationships between a series of independent (predictor) variables and a dependent (outcome) variable within a population*".

Qualitative research, which is often referred to as interpretative research, "*relies heavily on observers defining and redefining the meanings of what they see and hear*" based mainly on human behaviors (Stake, 2010). It involves collecting and analyzing data through methods such as interviews, observations, and document analysis. Lewis (2015) identifies the difference between the quantitative and qualitative methodologies and relates each of them to the type of questions that they can answer: Quantitative methods typically aim to answer closed questions to prove hypotheses, while qualitative methods tend to answer open ones that often have multiple interpretations.

Thus, given the research objectives and questions defined for this research, a quantitative approach represents the best-suited option. This approach allows for a deeper exploration of the complex factors influencing AI adoption, their relations, and impact on organizational performance, while considering a very concise information data source derived from an automated and online data-gathering method. This methodology offers the elements of reliability, reproducibility, and rigor required by both scholars and practitioners who aim for a theory-research-development-practice cycle.

Quantitative research can be classified into various types based on the scope and methodology employed. While there are different categorizations proposed by various authors, this research adopted the classification provided by Swanson & Holton III (2005) as follows:

- **Experimental:** Researchers have direct influence and control over the types of variables or phenomena they want to measure, allowing for change and adaptation of different conditions to prove some of these relationships between independent and dependent variables.
- **Non-experimental:** It derives conclusions from existing phenomena. Researchers use observations to determine possible relations between a dependent variable and a set of independent variables as a result of the impossibility of carrying out active experimentation. In this category, studies

such as correlational, causal-comparative, and descriptive (survey) studies can be found.

- **Quasi-experimental:** This last category aims to determine the relations of causality between an independent and a dependent variable without the use of randomization, often used in social fields of study.

Considering the reach and scope for the adoption of AI as a disruptive technology, the quantitative research category that best suits this project is the non-experimental, as the nature of the relations that are expected to be measured (defined at a firm level) cannot be controlled by any means or design. Therefore, the variables that are expected to be included as part of the analytical model derive from their observation in a natural state.

Given the definition of a quantitative, non-experimental nature of this research, the choice of data collection method was crucial. According to Hill (1993), non-experimental quantitative studies in business management often employ surveys, case studies, or participant observation. While each method has its merits and limitations, none is inherently superior for establishing causal relationships. Since this research focuses on identifying correlations and mediation effects rather than causation, all three methods are potentially viable options for data collection.

To rigorously assess the suitability, advantages, and limitations of surveys, case studies, and participant observation for this non-experimental quantitative research, a detailed analysis was conducted. The key findings of this analysis are summarized in Table 1:

Non-experimental types of methodologies			
Type	**Survey**	**Case-Study**	**Personal Observation**
Main Characteristics	Systematic, standardized approach to the collection of information, through the questioning of systematically identified samples of individuals for a phenomenon observed in a real-life context	An empirical study that investigates the occurrence of a phenomenon in a real-life context	Uses the exploration of the perspective of insiders or members of situations in a real-life context, with an active role of participant from the researcher with subjects in the field. It represents a method of enquiry that is open-ended, flexible, and opportunistic, employing direct observation
Advantages	Very cost-effective	Can generate both qualitative and quantitative insights, making it a powerful method	Can provide access to situations that in other methodologies could not be observable or measured
	Highly scalable	It can be used as a complement for other quantitative and qualitative methods to provide additional insights	It can be a powerful tool to measure relationships among individuals or communities in comparison to other methodologies
	Functional to gather information on existing patterns of social behavior	Can be used to measure causal or relational effects where other methods or experimentation seem impossible to carry out	It has a clear focus on measuring real-life occurrences of situations of interest for the researcher
	Allows for descriptive or analytical data collection in an agile manner	This method represents a holistic Investigation of contemporary events in the real world	It can provide insights to generate descriptive analysis and theories from observable phenomena
Limitations	High complexity for the design of effective and low-bias surveys	As a research method, it lacks some credibility among authors	It's a very difficult methodology to carry out properly and effectively
	May result in considerable irrelevant information gathering	Results are often not generalizable and therefore lack general validity	Since it requires active participation in the research on the phenomenon studied, it carries a high risk
	Low response rates among participants	Building theoretical conclusions that are not only "descriptive" from this methodology can be challenging	Recording the amount of information generated by this methodology can be quite challenging
	The definition of a suitable sample size for generalizable results is not simple	Design of a case study can be difficult and may present multiple considerations	Building theoretical conclusions that are not only "descriptive" from this methodology can be challenging

***Table 1 -** Characteristics, advantages, and limitations of non-experimental types of methodologies*

Based on the analysis, both survey and case study methods were deemed suitable for this research project. However, given the research's objective to derive generalizable results from a statistically significant sample of Colombian firms, the survey method was selected. In particular, data was gathered using an online instrument. This method offers several advantages, including a wider reach, efficiency in terms of data gathering, including reduced cost, and the potential to obtain a diverse sample representing various industries, sizes, ages, and regions within Colombia.

However, as highlighted in the comparative analysis, potential limitations and challenges could arise during the design of the online survey instrument and the identification of a sample with an adequate pool of respondents, and the choice of a response rate to define a usable database. The design phase, detailed in subsequent sections of this chapter, requires careful consideration. Additionally, securing a sufficient response rate to draw statistically significant conclusions within the framework of the chosen modeling technique presents a significant challenge.

3.2 Data gathering methodology:

Following the selection of a quantitative research approach, the next step involved as part of this project was designing a survey instrument to collect data to assess possible relations of the variables defined for the proposed model. While surveys offer advantages in terms of reach, speed, and cost, careful consideration must be given to question formulation, type, and overall questionnaire structure to maximize data quality, as noted by Janes (1999). As a result, the initial step in this process was to determine the specific survey type, its key characteristics, and the overall design.

Two primary survey methods, paper-based and online, are commonly employed in organizational and academic research. While online surveys have gained popularity in academic research due to their efficiency, as noted by Greenlaw & Brown-Welty (2009), they also present challenges related to response rates and data quality. Studies have shown that average response rates for online surveys average around 39.6%, with even lower rates (34.6%) when accounting for missing or incomplete data. Additionally, poor survey design can lead to data collection errors and potentially misleading conclusions, as highlighted by Balch (2010).

Another set of limitations that scholars have identified for online surveys is that they often rely on non-probability sampling, where respondents are not selected randomly by researchers, increasing the risk of sampling bias and compromising the validity of the results. Additionally, response bias can occur due to factors such as confusing or inaccurate questions, excessive survey length, or a lack of respondent motivation. Finally, privacy concerns related to personal information may deter potential participants, further affecting response rates and data gathering and accuracy.

Despite these limitations, online surveys remain a preferred method for many researchers due to their streamlined data lifecycle management (collection, storage, processing, visualization, and analysis) compared to traditional methods like mail or telephone surveys. Participants often find online surveys less intrusive and time-consuming. Studies have shown that when given the choice, respondents tend to favor online or electronic surveys over paper or telephone-based options.

In fact, Fang et al. (2013) note a significant increase in the use of internet and web-based surveys for the research performed in the IS field. While these methods offer convenience, they also present challenges. Respondents may be more prone to distractions such as social media usage and thus may devote less attention to questions, potentially affecting data quality. However, the anonymity offered by online surveys may encourage more honest responses.

At the same time, cost is a crucial factor in designing and implementing any data collection instrument. The overall cost extends beyond the tools themselves and includes expenses related to data storage, integration, processing, and administrative tasks (labor and manual) involved in collection, analysis, and interpretation.

On this matter, paper-based surveys are generally more expensive than electronic ones due to material costs such as paper, printing, and envelopes, as well as delivery by post or mail, and the manual effort required for collection and data entry, including digitization for further analysis. Telephone and in-person surveys also incur significant costs related to personnel, infrastructure, and materials. While the design costs of paper-based, telephone, and online surveys may be initially comparable, the delivery and administration costs of online surveys are significantly lower, making them a more attractive option for IS, business, and management research.

When considering online survey methods, researchers typically have three main options: email, custom applications, and web pages. As noted by Balch (2010), several key factors should be considered when selecting the most appropriate method among them:

- Adherence to known best practices in survey design,
- Ease of creation,
- Data collection options,
- Ease of delivery,
- Acceptability to participants,
- Ease of data collection.

Table 2 summarizes the characteristics, advantages, and drawbacks for each online data gathering methodology:

Method	Characteristics	Advantages	Drawbacks
Email	Low-cost, easy to use, and can reach a large audience	High response rate, flexible, and can be personalized	Low response rate if not well-targeted, can be difficult to track responses, and is not as interactive as other methods
Web-based	High-response rate, interactive, and can collect a variety of data	Easy to use, can reach a large audience, cost-effective	Can be difficult to create, not as personal as email, and can be difficult to track responses
Application-based	Highly interactive, can collect a variety of data, can be used on mobile devices	Personalized, easy to use, and can track responses	It can be expensive to develop, not as widely used as other methods

***Table 2** - Characteristics, advantages, and drawbacks of online data gathering methodologies.*

Therefore, considering all these factors, an electronic-based survey was selected as the primary data collection method. This approach offers significant advantages over paper-based or other survey methods in terms of efficiency, cost-effectiveness, and the potential to collect a statistically significant sample size, which is crucial for drawing generalizable and replicable conclusions.

Once the type of survey methodology was defined, the next step involved designing the actual questionnaire, considering factors such as the number, wording, and type of questions. It was essential to ensure clarity, maximize response rates, and maintain validity and rigor in data collection, keeping in mind best practices as outlined by authors such as Fielding et al. (2017) or Krosnick & Presser (2009).

The initial step in the questionnaire design process involved determining how to operationalize the abstract concepts from the structural equation model into measurable variables. It was crucial to select a potential tool capable of capturing highly quantitative and abstract data related to personal, organizational, and structural behaviors.

3.3 Measurement for non-directly observable processes: Organizational Constructs

After defining the research methodology and data collection approach, the next step involved selecting an appropriate analysis technique to address the research questions and objectives. This technique needed to be capable of identifying correlations and potential mediation effects among the variables of interest, as measured by the online survey instrument.

To determine the most suitable analytical technique, it was necessary to establish whether direct or indirect measurements were required for the business variables included in the analytical model. This decision was based on the nature of the variables, the data collection method, the research objectives, and the desired outcomes and conclusions expected from the research project.

As discussed in the conceptual framework section of this document, ICT adoption has been examined from various perspectives within IS and business administration, considering factors such as technology, organization, performance (financial and non-financial), relationships, and environment. Many of these factors are not directly observable and require the use of valid, reliable, and sensitive proxies or indicators. These proxies often aggregate multiple sub-categories or characteristics that reflect collective practices, which are inherently difficult to observe directly (Polites et al., 2012).

Given this context, measures are defined in the context of academic research as *“quantifiable records, or datums, taken as an empirical analog to a construct”,* not directly related to the instrument of the process of data gathering itself but to the score they represent, while constructs are defined as a *“conceptual term…. That refers to phenomena* *that are real and exist apart from the awareness and interpretation of the researcher and the individuals that are under study."* (Edwards & Bagozzi, 2000, pp. 156–157).

Therefore, given the abstract nature of the organizational, environmental, and relational variables under investigation and their relation to and impact on AI adoption at a firm level, it was necessary to consider both measurement and construct development concepts as part of the methodology for this project. Measures and constructs are deeply entangled and provide a valuable capability to researchers in social sciences to infer information and possible relationships based on observations from human or organizational occurrences.

However, constructs, while not directly observable, in this context allow researchers to represent and measure complex phenomena like organizational culture or digital technology leadership that are not easily measured using a direct approach. By using a combination of indicators and scales, researchers can quantify these constructs, which can be either formative or reflective depending on their nature, and examine their relationships with other variables in an analytic quantitative model.

Reliability, on the other hand, is a critical consideration in measuring business variables. Indirect measures, which often rely on multiple indicators, tend to be more reliable than direct measures. This is because direct measures are susceptible to errors, such as respondents misreporting, while indirect measures can mitigate these risks by averaging across multiple observations. For example, assessing digital technology leadership through a single direct question on a scale from 1 to 10 may be less reliable than using a composite measure based on multiple related questions on different dimensions, each one using the same assessment scale.

Constructs also offer greater granularity and sensitivity in measuring business variables. Direct measures, such as a single 1-10 rating scale, may struggle to capture subtle variations in perceptions. In contrast, indirect measures, composed of multiple items, can provide a more detailed understanding of the phenomenon. For example, using multiple questions to assess digital technology leadership can reveal finer distinctions in perceived levels across different samples.

As explained by Edwards & Bagozzi (2000), construct indicators can be either reflective or formative. In reflective measurement, the latent construct itself exists in an independent space and is the underlying cause of the observed variables, making its indicators just effects or reflections that measure its existence. In contrast, in formative measurement, the latent construct is a consequence of its constituent indicators and cannot exist by itself. While reflective indicators are manifestations of the latent construct, formative indicators constitute the latent construct itself (Diamantopoulos et al., 2008).

Thus, the key difference between reflective and formative constructs lies in the direction of causality. In reflective measurement, the latent construct causes the observed variables to covary. In contrast, in formative measurement, the observed variables constitute the latent construct. Reflective constructs are more prevalent in business and management research as they are often used to measure abstract concepts that cannot be directly observed.

Formative constructs, while less common in business and management research, have gained increasing attention in recent years as *“scholars have begun to challenge the blind adherence to Churchill’s procedures”* (Coltman et al., 2008, p. 8). Koh et al. (2019) highlighted the growing acceptance of formative measurement in IS research, particularly after 2003. However, the empirical application of formative measurement remains relatively limited, with most studies focusing on theoretical discussions. Despite this, the majority of business and management researchers (approximately 95%) still rely on reflective measurement models. Therefore, the initial step in the questionnaire design process was to define the formative indicators for each construct within the SEM model.

Given the decision to use an online survey and formative constructs to measure latent constructs like organizational, technical, and relational processes, a quantitative analysis technique needed to be defined. This technique would enable the analysis of the collected data to identify relationships between these constructs, AI adoption levels, and perceived firm performance in the Colombian context, to draw generalizable conclusions.

3.4 Quantitative analytical methodology: Structural Equation Modeling (SEM) based on partial least squares (PLS) as a method for data analysis:

Considering the choice of a non-experimental quantitative methodology and an online survey as the data collection method, the next step involved identifying suitable data analysis techniques. This selection was based on the types of variables involved and the construct-based measurement approach.

First, as noted by Little (2013), Osborne (2008), and Swanson & Holton III (2005), several quantitative analysis methods are available to researchers in business, management, IS, and social sciences. The choice of method depends on the specific research question, data sources, and desired outcomes. Some common techniques include:

- **Descriptive statistics:** Descriptive statistics are a fundamental technique used to summarize and describe data. It provides insights into data distribution, such as mean, median, and standard deviation, as well as possible correlations. By analyzing these measures, researchers can identify trends and patterns relevant to their research questions and hypotheses.

- **Inferential statistics:** Inferential statistics allow researchers to conclude a population based on sample data. These techniques are used to test hypotheses, estimate population parameters, and make predictions. By analyzing sample data, researchers can determine whether observed differences or relationships are statistically significant.

- **Regression analysis:** Regression analysis is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. It is often used for predicting the value of the dependent variable based on the values of the independent variables. Regression analysis offers various techniques, including linear regression for continuous variables and logistic regression for categorical variables. Linear regression assumes a linear relationship between variables, while multiple regression can handle multiple independent variables and potentially nonlinear relationships. Logistic regression is used when the dependent variable is binary.

- **Structural equation modeling:** Structural Equation Modeling (SEM) is a multivariate statistical technique used to analyze complex causal relationships between non-observable latent variables. It is commonly used to test theoretical models that hypothesize relationships between constructs. The two primary SEM approaches are covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is primarily used for theory confirmation, while PLS-SEM is well-suited for prediction and causal explanation, especially in cases of small sample sizes, non-normal distributions, and reflective constructs.

Among various quantitative analysis techniques, PLS-SEM is widely used in business administration to examine relationships between constructs, such as customer satisfaction, employee engagement, and firm performance. This technique is particularly suitable for studying latent variables that are not directly observable. PLS-SEM is capable of testing mediation and moderation effects, developing predictive models, and validating measurement models (Hair Jr et al., 2022).

There are several reasons why PLS-SEM is considered a particularly suitable technique for analyzing data collected through online surveys. It is robust to analyze and draw statistically significant results from small sample sizes, which is advantageous given the typically low response rates of online surveys. Additionally, PLS-SEM can handle non-normally distributed data, a common characteristic of survey data

Third, PLS-SEM is versatile in handling various combinations of constructs (reflective-reflective, reflective-formative, formative-reflective, or formative-formative). Unlike CB-SEM, PLS-SEM does not require the strict assumption of perfectly correlated observed variables demanded under confirmatory factor analysis (CFA) assumptions, making it a more flexible and robust technique for modeling complex relationships

PLS-SEM has gained significant popularity in fields like IS, marketing, and management due to its advantages over CB-SEM. It offers higher reproducibility, strong predictive capabilities, the ability to explain complex relationships between constructs (a high number of constructs and estimators), and the flexibility to handle ordinal or nominal data. These factors have contributed to widespread use in high-impact journals such as *MIS Quarterly and Industrial Management & Data Systems* (J. Hair et al., 2017).

CB-SEM and PLS-SEM are complementary techniques with distinct strengths. CB-SEM is better-suited for theory confirmation and factor-based models, both common use cases in academia. In general, as discussed by Dash & Paul, (2021, p. 8) *“If the researchers’ primary objective is to estimate a factor-based model, CB-SEM is the preferred one. On the other hand, if the primary aim is to estimate a composite-based model, PLS-SEM should be considered*, while PLS-SEM is ideal for prediction, theory development, and composite-based models.

PLS-SEM offers greater flexibility, handling both formative and reflective measurement, and is capable of conducting mediation and confirmatory factor analysis. These advantages make PLS-SEM a powerful tool for researchers seeking to explore complex relationships and test theories, particularly in situations where data may not perfectly adhere to the assumptions of CB-SEM. Based on these features, and the potential relations to be assessed, PLS-SEM was the selected technique for data analysis.

3.5 SEM-PLS model development

Building upon the literature review and research objectives, the next step involved designing an SEM to identify potential enablers and barriers to AI adoption and their impact on organizational competitiveness in Colombia. Given the complexity of the relationships and the potential for latent variables, PLS-SEM was selected as the appropriate technique.

Following Hair Jr et al. (2022), the first step in designing the structural equation model was to define the latent variables and their corresponding formative indicators. Latent variables, representing abstract concepts like technical, organizational, and relational factors, were defined as composites of multiple observed variables. The model also included exogenous and endogenous latent variables, where exogenous variables were used to explain endogenous variables.

Technical factors

Based on the literature review, the SEM model included for simplicity two primary latent variables: Technical and Digital Maturity (TDM), related to the level of organizational knowledge and dissemination of several ICTs apart from AI technologies, and IT and Data Complexity & Integration (IDCI), related to the accessibility, use, and trustworthiness of different ICT and data sources as part of organizational business processes. Table 3 provides a summary of the formative indicators used to measure each latent variable.

Latent variable	Indicators
Technical and digital maturity (TDM)	- Definition of an IT Management department (TDM1) - Presence of a digital initiatives department (TDM2) - IT infrastructure robustness (TDM3) - ICT investments in the last 5 years (TMD4) - Intensity of use of deployed digital ICTs for business purposes (TMD5) - Usability of deployed digital ICTs (TMD6) - Presence of physical and data security protocols for deployed ITCs (TMD7)
IT and data complexity & integration (IDCI)	- Data sources accessibility (IDCI1) - Data sources integration (IDCI2) - Data sources dissemination (IDCI3) - Data sources completeness (IDCI4) - Data sources trustworthiness (IDCI5) - Data sources usage for decision making (IDC6)

Table 3 *- Technical latent variables and indicators for the SEM-PLS model*

Organizational factors

Regarding organizational factors, the SEM model incorporated three latent variables: Technical and Digital Skills and Competence (TDCS), Level of Organizational Culture (LOC), and Digital Strategy and Governance (DSGC). Table 4 provides a summary of the formative indicators used to measure each of these latent variables.

Latent variable	Indicators
Technical and digital competence and skills (TDCS)	- Ability for ITC use for basic business purposes (TDCS1) - Skill level for basic ICT use (TDCS2) - Skill level for advanced ICT use (TDCS3)

	- Skill level for data management tools use (TDCS4)
Level of organizational culture (LOC)	- Definition and dissemination of an organizational purpose statement linked to a digital strategy (LOC1) - Levels of work climate linked to the definition of a digital strategy (LOC2) - Levels of flexibility and tolerance to failure (LOC3) - Levels of intra-entrepreneurial spirit development (LOC4) - Levels of organizational communication (LOC5)
Definition of IT and business strategies & alignment with levels of management support, knowledge, and IT championing (DSGC)	- Definition of a strategic plan linked to a digital strategy (DSGC1) - Level of expected customer attraction based on digital ICT use (DSGC2) - Presence of a digital skills formation area (DSGC3) - Presence of a data competence formation area (DSGC4) - Level of management support for development of digital projects (DSGC5) - Level of digital skills and digital championing at a management level (DSGC6)

Table 4 - *Organizational latent variables and indicators for the SEM-PLS model*

Relational factors

Finally, the SEM model incorporated two relational factors: Level of Open Innovation (LOI), representing collaboration with external entities that could aid for ICT adoption such as consulting companies, IT vendors, start-ups, public and academic institutions, and Level of Relationship Strategy (LRS), reflecting the organization's strategic approach to collaboration and competition in the digital domain. Table 5 summarizes the formative indicators for these two latent variables

Latent variable	Indicators
Level of open innovation (LOI)	- Level of open innovation driven by top management (LOI1) - Level of collaboration with non-IT organizations for digital ICT adoption at a business level (LOI2) - Level of collaboration with IT vendors and consultants for digital ICT adoption at a business level (LOI3) - Level of integration of digital-led start-ups for value creation (LOI4)
Level of relational strategy and competitive pressure (LRS)	- Level of coopetition strategies (LRS1) - Level of relational capabilities of top management for business collaboration (LRS2) - Level of alignment between digital and business strategies for enhanced business capabilities (LRS3)

	- Level of market maturity (LRS4) - Level of digital-based capabilities innovation among direct competitors (LR5)

Table 5 *- Relational latent variables and indicators for the SEM-PLS model*

Endogenous variables

The proposed SEM model for the project includes two endogenous latent variables: Level of Perceived Performance (LPP) and Level of Artificial Intelligence Adoption (LAIA). These variables are expected to be influenced by the seven exogenous latent variables (technical, organizational, and relational factors). The model also explores potential mediation effects, where the three exogenous factors may indirectly influence LPP through LAIA. This proposed framework aligns with established theoretical frameworks like TOE and RVB.

Perceived level of AI technological adoption

The first endogenous variable, Level of Artificial Intelligence Adoption (LAIA), serves as both a dependent and mediating variable as part of the three versions of the SEM-PLS model defined for this research project. It is influenced by the seven exogenous variables representing technical, organizational, and relational factors. To measure LAIA, six indicators were used, ranging from the most disseminated and basic application of AA, ML, and AI models and techniques (descriptive analytics) to the most advanced one (image and video processing and analysis). Table 6 provides a summary of these indicators.

Latent variable	Indicators
Level of adoption and use of AI technologies (LAIA)	- Level of use of descriptive analytical tools (Dashboards) (LAIA1) - Level of use of chatbots or virtual assistants (LAIA2) - Level of use of predictive analytics (ML models) (LAIA3) - Level of use of Natural Language Processing (Text) models (LAIA4) - Level of use of Natural Language Understanding (speech or sound) models (LAIA5)

	- Level of use of Image and video processing models (LAIA6)

Table 6 *- First endogenous variable and indicators for the SEM-PLS model (LAIA)*

Perceived level of competitiveness

The second endogenous variable, Level of Perceived Performance (LPP), represents the organization's perceived ability to create value and achieve financial performance and competitive positioning relative to its competitors. Seven formative indicators were used to measure LPP, as summarized in Table 7:

Latent variable	Indicators
Level of perceived competitiveness (LPP)	- Level of comparative income growth in the last 5 years against direct competitors (LPP1) - Level of comparative market share growth in the last 5 years against direct competitors (LPP2) - Level of comparative human-resource productivity against direct competitors (LPP3) - Level of comparative innovation and creativity against direct competitors (LPP4) - Level of labor attraction against direct competitors (LPP5) - Level of suitability of products or services offered against direct competitors (LPP6) - Levels of customer loyalty compared to direct competitors (LPP7)

Table 7 *- Second endogenous variable and indicators for the SEM-PLS model (LPP)*

Finally, a control variable was included as part of the SEM-PLS model to assess its potential impact on the relationships between the endogenous and exogenous variables. This control variable (organization size), defined as a categorical variable, is summarized in Table 8:

Control variable	Type of variable
Firm Type (FT)	- Size of the organization based on the number of employees it has (categorical variable – 4 Options: *Micro (1-10 employees), Small (11-50 employees), Medium (51-200) or Large (201 or more) enterprises.*

Table 8 *- Control variables defined for the SEM-PLS model*

Figures 4, 5, and 6 provide a visual representation of the three proposed SEM models. These figures illustrate the relationships between the endogenous and exogenous latent variables, as well as the corresponding formative and reflective indicators. The arrows in the diagrams represent the hypothesized relationships, both direct and indirect, between the variables.

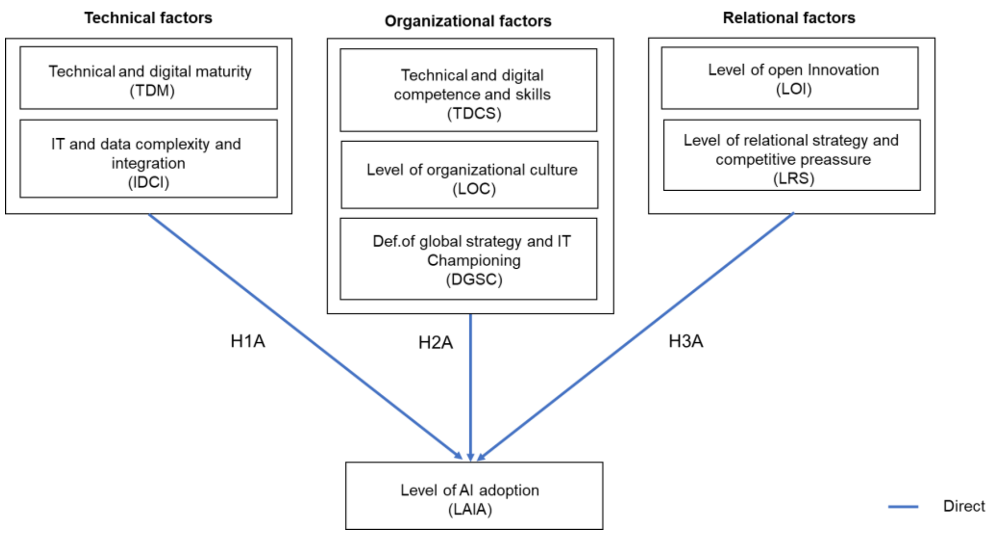

Figure 4 *- Visual representation of the first proposed SEM-PLS model*

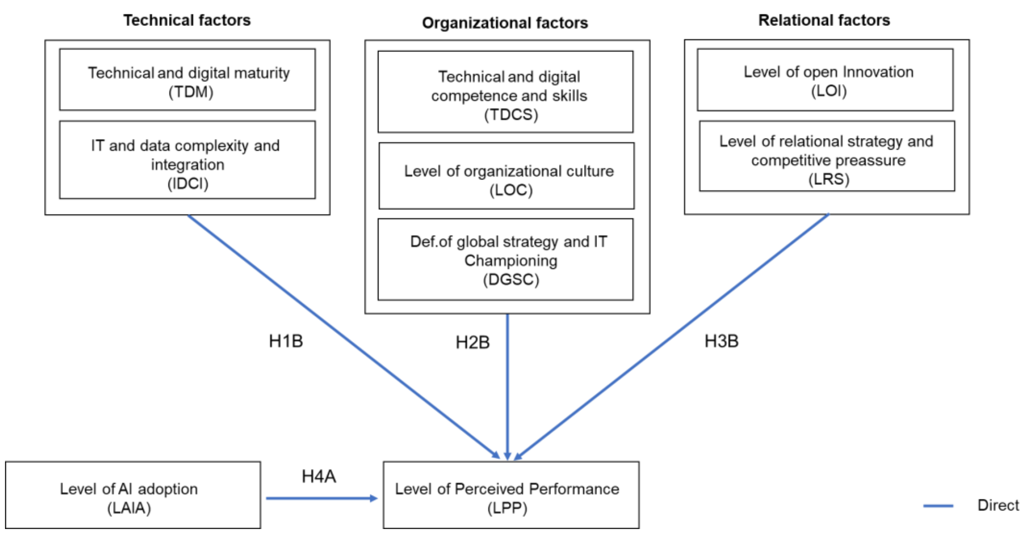

Figure 5 - *Visual representation of the second proposed SEM-PLS model*

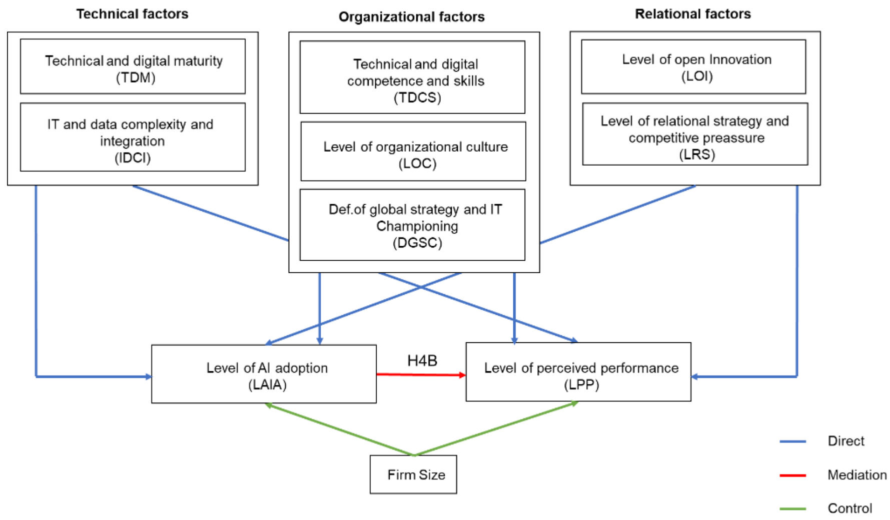

Figure 6 *- Visual representation of the third proposed SEM-PLS model*

3.6 Online survey design

As discussed earlier, an online survey was selected as the most suitable data collection method for this project given its novelty and theme. To maximize response rates and minimize costs, a user-friendly survey design was developed, drawing on insights from previous studies. The goal was to create a clear and concise survey that would encourage high participation rates.

As noted by Janes (1999), surveys are effective for gathering current opinions and perceptions. When designing surveys, two key considerations are question quality and questionnaire structure:

1. Definition of good questions, and

2. The design of well-structured questionnaires.

Thus, to ensure a successful survey, researchers should review existing literature, define clear objectives, develop a pool of potential questions, design the questionnaire, conduct pilot tests, and refine the instrument before administering it to the target population, keeping in mind that the value of survey research lies not only in the data collection process itself but also in the broader research methodology, including problem identification, literature review, methodology selection, data collection, analysis, and evaluation.

Drawing on these precepts, the online survey for this research project was designed to gather perceptions from Colombian professionals across various industries regarding technical, organizational, and relational factors; AI adoption levels; and perceived organizational competitiveness, which could serve to assess the defined hypothesis and research questions. The goal was to collect quantitative data that would inform the SEM-PLS model, allowing for the identification of significant relationships and potential mediation effects among the variables of interest.

After defining the survey's main objective, a pool of potential questions was developed. This question bank would serve as the foundation for the final questionnaire, which would be refined through expert feedback before being administered to the target population.

Initially, 2-3 questions were developed for each indicator of each of the latent variables defined for the SEM-PLS model. This allowed for flexibility in question selection and testing. Additionally, demographic questions were included to collect information on the respondent's role, department, seniority, organization's location, size (based on its number of employees), industry, and age. This demographic data would be used for further analysis and potential sample segmentation.

Finally, the survey included optional fields for participants to provide their full name, email address, and organization name. This information was collected to share a summary report of the study's findings with participants, as suggested by E. Ryu et al. (2006). While this incentive may result in boosting participation rates, it also aids in mitigating potential biases that may arise from such practices, such as response bias and low-quality responses.

The initial question bank comprised 86 items. To quantify respondents' perceptions, Likert scales were selected as the measurement technique. As noted by Nemoto & Beglar (2013) Likert scales offer several advantages, including the ability to efficiently collect data from large populations, ensure data quality and reliability, and create multiple types of measurements to facilitate comparisons with other data collection methods such as interviews and case studies.

Likert scales are widely used in social sciences to measure abstract concepts, including individual perceptions. Given their validity and reliability, they were chosen as the measurement technique for the online survey. Leung (2011) provides insights into the psychometric properties and normality of different Likert scale options, guiding the selection of an appropriate scale for this study.

He notes that social science research commonly employs Likert scales with 4 to 7 points, with some studies using 10-point scales. However, longer scales may compromise reliability. There is ongoing debate regarding the inclusion of a neutral midpoint in Likert scales, with some researchers advocating for forced-choice responses to encourage more decisive answers.

After careful consideration of these findings, a 6-point Likert scale was selected for the survey questions, balancing data reliability and respondent fatigue. This scale was chosen to maximize factor analysis results and promote normal distribution. Tables 9 and 10 provide details of the 6-point Likert scale used in the different sections of the online survey:

Point	Label
1	Strongly Disagree
2	Disagree
3	Partially Disagree
4	Partially Agree
5	Agree
6	Strongly Agree

Table 9 *- Defined Likert scales for online instrument questions*

Point	Label
1	Haven't been used (No usage)
2	Its use has been discussed but not yet defined (Usage under consideration)
3	Currently experimenting with it (Usage under experimentation)
4	At least 1 test project under development (Usage under test)
5	At least 1 productive project under development (Intermediate usage)
6	2 or more productive projects under development (Full-scale usage)

Table 10 - *Defined Likert Scales to measure AI adoption levels for online instrument questions*

The next step involved designing the online survey questionnaire itself. Following Balch (2010), the survey was structured into sections to enhance clarity and understanding, although this approach has been related to increased response time and potential drop-out rates. The sections were organized as follows:

1. **Welcome screen:** This initial screen provided an overview of the study, including its objectives, data handling procedures, estimated duration, and contact information for the researcher if doubts arose. Participants were also informed about their right to withdraw from the study at any time if they chose to.
2. **Section 1 – Demographic data:** This screen consisted of two mandatory subsections: Organization Information and Job Information. Additionally, an optional sub-section for personal information was included.

3. **Section 2 – Technical factors:** This group would include questions related to several indicators, such as the technical and digital maturity of the organization and technical and data complexity.
4. **Section 3 – Organizational factors:** This group would include questions related to several indicators, such as technical and digital skills, organizational culture, and definition of global strategy and ICT championing.
5. **Section 4 – Relational factors:** This group would include questions related to several indicators, such as the level of open innovation, relational strategy, and competitive pressure.
6. **Section 5 – Perceived level of competitiveness:** This group would include questions related to respondents' perceptions of their organization's competitive position relative to industry peers.
7. **Section 6 – Level of AI adoption:** This group assessed respondents' perceptions of their organization's AI adoption level. For organizations with AI projects, questions were included to understand the motivations behind these initiatives.
8. **Section 7 – Impacts of AI adoption**: This group explored the perceived business impacts of AI implementation in organizations with ongoing AI projects.
9. **Section 9** – **Survey's end screen**: This group thanked participants for their time and provided information about the next steps, including how their personal information would be used if they had chosen to share it.

After outlining the survey structure, the next step involved selecting a suitable web-based platform to host the online survey. Several platforms were evaluated based on their features and capabilities. The results of this evaluation are summarized in Table 11.

Tool	Cost	Ease of use /Administration	Functionalities provided
Google forms	Free to use (Google account needed)	Basic/intermediate knowledge needed	Basic: No direct data analysis, limitations on survey design, question typology, or rules, low data retention, and protection.
Microsoft forms	Free to use (MS 365 account needed)	Basic/intermediate knowledge needed	Basic: No direct data analysis, limitations on survey design, question typology, or rules, low data retention, and protection.
LimeSurvey	Low / Intermediate – Dependent on various subscription tiers	Intermediate/Advanced knowledge needed	Advanced: data analysis, survey, and question design based on rules included (branching). Integrated data protection, advanced features for data retention and protection. Offers Open-source capabilities
Qualtrics XM	Highest – Dependent on various subscription tiers	Intermediate/Advanced knowledge needed	Highest: Advanced Data analysis, survey, and question design based on rules included (Branching). Advanced data protection, advanced features for data retention and protection. Proprietary solution.

Table 11 - *Summary of features and capabilities offered by various online survey platforms*

Google Forms was initially selected to be used as part of the test phase of the online instrument for its ease of use and integration with the Universidad de Deusto online platform, including free use. However, limitations in customization, branching logic, and data privacy compliance according to Colombian regulation led to the selection of LimeSurvey, allowing for differentiation depending on the role of the respondents (technical or functional). As a publicly accessible platform for faculty members at Pontificia Universidad Javeriana, LimeSurvey offered advanced features and the necessary flexibility to implement the desired survey design and, therefore, was the selected tool for this task.

To validate the survey of the draft online instrument, a pilot test was conducted with a group of six experts, including both practitioners and academics. The experts were selected based on their diverse backgrounds, seniority, and areas of expertise to ensure a comprehensive evaluation. The goal was to gather feedback on the survey's clarity, relevance, and user experience. A list of their profiles is offered for reference:

List of practitioners

- Marketing manager for a global CPG company (15 years of experience).

- Chief information officer for a public sector institution (14 years of experience).
- Chief planning officer for a private, non-profit higher education institution (25 years of experience).

List of faculty members

- Associate professor, Organizational Strategy, Business Department (20 years of experience).
- Associate professor, behavioral economics and business analytics, business department (9 years of experience).
- Full professor, Advanced Analytics and Machine Learning, Industrial Engineering department (18 years of experience).

Based on feedback from these expert reviewers, several modifications were made to the survey instrument. Questions were prioritized, refined, or removed to improve clarity, relevance, and survey length. The final version of the survey incorporated these changes to enhance the overall user experience.

To improve clarity and reduce respondent fatigue, the survey was divided into sections, each focusing on a specific theme. This approach enhanced the overall user experience and encouraged higher completion rates.

To accommodate respondents with varying levels of technical knowledge, a "*Don't Know/No Reply*" option was added to the 6-point Likert scale for specific questions. This option was particularly relevant for functional roles that may not have a deep understanding of technical aspects. Branching logic was implemented using LimeSurvey's advanced logic functions in the survey to selectively display this option based on the respondent's role, ensuring that the survey remained relevant and engaging for all participants.

Detailed results of these sessions, the final version of the questionnaire, and sample print screens for its design from the LimeSurvey platform are offered for reference in Annexes 7.1 and 7.3.

3.7 Sample size and characteristics definition

Following the development of the SEM-PLS model and online survey instrument, the next step involved defining the target population. Given the study's focus on AI adoption in Colombian firms, the sample selection was crucial to ensure representativeness and maximize response rates.

As mentioned by Terhanian & Toluna (2012), there are several challenges to achieving high response rates in online surveys, even though this method has gained popularity. They propose a sample selection methodology that considers consistency and interchangeability of new and existing potential respondents, complementarity of different sources used to find potential respondents, and representativeness from off-line sources. However, they acknowledge the limitations of this approach and the potential for sample bias.

As a result, to ensure the validity and robustness of the survey results, a combination of sampling techniques was employed. The target population was carefully selected based on the specific information required to measure the latent and observed variables in the SEM-PLS model. This involved considering the demographic characteristics of potential respondents and their knowledge of the relevant topics.

As the study focused on Colombian firms, the online survey was distributed to a select group of professionals. Respondents were chosen based on their academic background (with a minimum level of academic acumen at least at a graduate level), professional experience, and role within their organizations. The goal was to include individuals with both technical and functional expertise to ensure a comprehensive understanding of the three key factors: technical, organizational, and relational.

Given the target profile, one potential source of respondents was the pool of students and alumni from postgraduate programs (MBA, M.Sc. in Banking and Finance, M.Sc. in Innovation and Competitiveness, and specialized programs in economics and management) at a large private university in Colombia. These individuals met the criteria of academic background, work experience, and business acumen.

To obtain the necessary permissions and ensure ethical compliance, the research project was presented to the university's ethics committee within the business school. After a thorough review by a panel of experts, including the dean, full tenured faculty members, and an independent reviewer from the engineering school, the project and data collection process were approved.

To supplement the online survey and mitigate potential low response rates, an affordable secondary data source was sought. This additional source aimed to identify individuals who met the specific profile requirements outlined for the study. Dusek et al. (2015) propose a cost-effective approach for doctoral students to gather quantitative data using a combination of targeted sampling and snowball sampling. They suggest leveraging professional networking platforms like LinkedIn to reach a wider audience and facilitate respondent referrals. Out of the different social media alternatives (i.e., Facebook, Instagram, X, TikTok) that offer alternatives and means for informal interactions between their members, LinkedIn's specialized nature and global reach make it a suitable platform for academic research.

As a result, LinkedIn was chosen as the secondary data source for this study. A targeted group of approximately 1,000 contacts, aligned with the desired respondent profile, was selected. A brief post was shared on LinkedIn, outlining the study's objectives, potential benefits, survey link, and an invitation to share the link with other relevant individuals.

Once the sample source was defined, the next step was to determine the minimum sample size that was required for the SEM-PLS model to have the desired levels of statistical significance (95%) and explicability power (80%). To determine the minimum sample size for the SEM-PLS model, the "*Rule of 10*" is a highly recognized and used methodology, as suggested by J. F. Hair et al. (2011). This rule involves multiplying the largest number of formative indicators or structural paths to a construct by 10 to obtain the required sample size.

While the *'Rule of 10'* is a commonly used guideline, it has limitations in terms of statistical power, resulting in problems of validity and applicability. Therefore, authors such as Hair Jr et al. (2022) recommend using the inverse square root method developed by Kock & Hadaya (2018) for a more accurate estimation of sample size, considering factors like standard error and desired statistical power.

Using various Monte Carlo simulations, the authors demonstrate that the "*Rule of 10*" can lead to significant underestimations of sample size, proving that the 10-fold method results in great underestimations of the sample size to sustain a threshold of 0.8 and a 0.05 significance level, particularly when considering the magnitude of path coefficients. They propose the inverse square root method as a more accurate approach. By applying this method, along with the guidelines provided by Hair Jr et al. (2022), a suitable sample size was determined for the SEM-PLS model used in this study, as illustrated in Figure 7.

Defined parameters for the sample definition of the PLS-SEM model:

- Statistical desired power level: 80%
- Statistical significance level: 5% (p = 0.05)

- Minimum path coefficient: 0.21 to 0.3
- Estimated minimum sample size: 69 complete observations.

p_{min}	Significance level		
	1%	5%	10%
0.05–0.1	1004	619	451
0.11–0.2	251	155	113
0.21–0.3	112	69	51
0.31–0.4	63	39	29
0.41–0.5	41	25	19

Source: Hair et al. (2022), Chap. 1; used with permission by Sage

Figure 7*- Estimated Sample sizes based on the minimum square root method for SEM-PLS models based on power level, statistical significance, and desired path coefficients.*

3.8 Summary

This research project aims to examine the factors influencing the adoption of IA technologies in emerging countries, using Colombian firms as a proxy. The methodology focuses on defining objectives, research questions, and hypotheses. Data collection strategies included an online instrument and statistical analysis using structural equation modeling (SEM) based on partial least squares (PLS). The selection of the methodological approach, given the project's scope, was key. The options considered were quantitative, qualitative, and combined methods of research. Quantitative methods involve systematic observation to establish relationships between variables, while qualitative methods emphasize interpretative research.

As the project aims to determine correlations, quantitative methods were deemed the most suitable as they provide insights into theory and practice. This research project explored different types of quantitative methods: experimental, non-experimental, and quasi-experimental. Considering the project's characteristics, the non-experimental quantitative method was selected. In this category, surveys, case studies, and participant observations were identified as the most viable options for data collection. Survey methodology was favored due to its cost-effectiveness and ability to provide insights from diverse industry perspectives in the Colombian market. Despite challenges in survey design and data collection, surveys offered the most scalable and detailed information for research constructs, the defined proxy methodology for measuring the phenomena selected as the scope for this project.

The choice of an online survey as the data-gathering method was informed by its reach, speed, and cost-effective nature. However, bibliographic review related to online surveys revealed that this method presents limitations such as response and sampling biases, as well as privacy concerns. Considerations for cost, response rates, and data lifecycle management favored online surveys over paper-based or telephonic methods. Within online surveys, options include email, web-based, and application-based surveys, each with distinct advantages and drawbacks.

The online survey, designed for data collection, aimed to gather perceptions on technical, organizational, and relational factors, AI adoption, and competitiveness levels in Colombian organizations. The survey included sections on demographic data, technical, organizational, and relational factors, as well as AI adoption and perceived competitiveness. Control variables like organization age and size were considered. The Likert scale was used for measurement, with a 6-point scale chosen for its benefits in factor analysis. A branching methodology was implemented for clarity, and a "*Don't Know / No Reply*" option was included on the scale.

To maximize response rates, a user-friendly online survey platform was chosen to gather the information. While Google Forms was initially explored, its limitations led to the adoption of LimeSurvey, given its advanced features. The survey underwent expert validation and refinements to ensure clarity and relevance. The sample population consisted of professionals with expertise in functional and technical aspects relevant to the study. Invitation strategies included approaching alumni from relevant graduate programs and obtaining consent from the business school's ethics committee to ensure data security and compliance.

In terms of the sample, it was determined that researchers face multiple challenges in cost-efficient data gathering for quantitative studies, where methods such as targeted sampling using LinkedIn's snowballing had positive results for increasing the number of valid respondents, providing a replicable source for the gathering methodology of the project. In terms of sample size calculation, the "*Rule of 10*" for sample size estimation was identified as a commonly and highly criticized rule-of-thumb.

Therefore, after a detailed literature review, several articles recommending the inverse square root method for this estimation were identified. Monte Carlo simulations showed the 10-fold rule underestimated sample sizes compared to the inverse square root method for SEM-PLS models, making it a more robust method for sample estimation. Therefore, for this study, it was concluded that a minimum sample size of 69 complete observations was recommended to guarantee statistical significance given the PLS-SEM model developed.

The characteristics and considerations of the methods for this research project were carefully reviewed to ensure their most appropriate selection. Reflective and formative constructs were considered for the design of the survey questionnaire to measure the latent variables related to organizational, technical, and relational processes in AI technology adoption, as construct measurement is a valuable tool to indirectly assess non-observable phenomena and to provide sensitivity to changes in the variables. Therefore, construct indicators were defined to capture the essence of the phenomenon inquired about within the survey instrument.

Reliability of measurements was a crucial element in ensuring the accuracy of the data gathered. Structural equation modeling (SEM) based on partial least squares (PLS) was chosen as the method for data analysis. SEM allows for the analysis of complex causal relationships between latent variables and is particularly suitable for models involving non-directly measurable constructs. Once again, derived from a detailed bibliographic review, it was determined that PLS-SEM is a well-suited data analysis methodology for small sample sizes, non-normal distributions, and reflective constructs. It enables the testing of theoretical models, including mediation and moderation effects, and the development of predictive models based on the data obtained from the survey instrument.

Overall, the methodological design of the research project focused on selecting the most appropriate approaches for defining objectives, collecting data, and analyzing relationships between variables in the context of IA technology adoption in Colombian firms. The combination of quantitative research methods, online surveys, and PLS-SEM for data analysis ensures a comprehensive exploration of the factors influencing technology adoption and provides valuable insights for academia and industry stakeholders in emerging economies like Colombia. And while this project recognizes that surveys, especially online ones, present multiple challenges for data gathering for quantitative research, as respondents face distractions while completing surveys, the use of suitable techniques like PLS-SEM is crucial to account for and manage these shortcomings.

The PLS-SEM method is adept at handling non-normally distributed data, often seen in online surveys. It also offers the capacity to analyze various constructs effectively without the need for confirmatory factor analysis assumptions, unlike CB-SEM, making it more flexible for modeling. It has been widely used in fields such as IS, marketing, and management due to its reproducibility and advantages over CB-SEM, allowing for complex models and ordinal/nominal scaling of answers. CB-SEM has been typically used for testing relations between constructs, while PLS-SEM is more suited for predicting and developing theories based on empirical approaches, although they are both considered to be complementary methods.

PLS-SEM has also been identified to be an ideal method for handling formative and reflective measurement models, providing flexibility and exploration capabilities. In that sense, the SEM-PLS model developed as part of this project was defined to assess factors influencing Colombian organizations in adopting AI, focusing on technical, organizational, and relational aspects. The model included latent variables representing technical and digital maturity, organizational culture, and relational strategies. Formative indicators were defined for each variable.

In conclusion, the study focused on developing a comprehensive SEM-PLS model to understand factors influencing AI adoption in Colombian organizations. The online survey, designed for data collection, aimed to gather insights from professionals with relevant expertise. The chosen methodology, tools, and approach were carefully considered to ensure the study's validity and robustness, providing valuable insights into the adoption of AI technologies within the Colombian context.

4. RESULTS

The following sections present the results obtained from the analysis performed on the final dataset gathered using the online survey described in Chapter 3. A total of 90 complete responses (n=90) were obtained during a period of 10 months (from June 2023 to April 2024), through 3 different cycles of data collection. The data set was integrated, processed, and cleaned using Microsoft Excel and its Power Query tool, while analysis and data modeling were performed using the SmartPLS 4 software (Ringle et al., 2024), being recognized as one of the most comprehensive tools for SEM-PLS analysis in the academic field.

First, descriptive figures related to the demographic characteristics of the respondents and their organizations are presented, as well as those of each of the endogenous and exogenous variables that were defined in the SEM-PLS model as formative constructs. Afterwards, the hypotheses were tested with three SEM-PLS models (direct relations, mediation, and mediation with one control variable) based on the methodology proposed by J. F. Hair et al. (2019)

These models are shown in the next sections, including results for construct loadings, indicator reliability, construct internal consistency reliability, average variance extracted, and discriminant validity for each of the latent and manifest variables. For each of the models, the results show estimations using the bootstrapping routine (samples = 5,000) to assess for statistical significance at a 95% level for each of the variables and their relations (direct, mediation, and control).

4.1 Descriptive Results

The demographic features obtained from the online instrument show that most of the valid responses for this project (92.2%) were obtained from organizations based in

Colombia's capital city, Bogotá. This comes as no surprise, given that Bogotá is the largest urban center of the country with approximately 11.5 million inhabitants in its metropolitan area for 2023 (Naranjo, 2023), and as a region represents approximately 31% of the total Colombian GDP for 2023 (Sánchez, 2024).

Geographical location	# observations	Percentage
Bogotá - Cundinamarca - Boyacá	83	92.22%
Otro (Nacional)	5	5.56%
Eje Cafetero	1	1.11%
Barranquilla - Costa Atlántica	1	1.11%
Medellín - Antioquia	0	0.00%
Cali - Región Pacífico	0	0.00%
Bucaramanga - Cúcuta - Santanderes	0	0.00%
TOTAL	**90**	**100%**

Table 12 *- Survey respondent segmentation by geography*

In terms of the firm's characteristics, the results show that more than half of the respondents were employed in large organizations (more than 200 employees) at the time the online instrument was deployed, while micro (less than 10 employees), small (less than 50 employees) and medium (less than 200 employees) enterprises were less represented as part of the obtained sample.

This result could be paradoxical, as most Colombian organizations (close to 92%) were catalogued as microenterprises for 2022 (Bonilla González, 2023). With its industries, most of the respondents were part of information and technology organizations, while other fields were heterogeneously represented as part of the sample.

Firm's Size	# observations	Percentage
Large Enterprise	52	57.78%
Medium Enterprise	17	18.89%
Small Enterprise	11	12.22%
Micro Enterprise	10	11.11%
TOTAL	**90**	**100.00%**

Table 13 *- Survey respondent segmentation by firm size*

Firm's Industries	# observations	Percentage
Information technologies	22	24.44%
Financial or insurance services	11	12.22%
Other services	11	12.22%
Manufacturing	7	7.78%
Health services	6	6.67%
Professional services	6	6.67%
Transportation	5	5.56%
Public sector	5	5.56%
Mining or exploitation of natural resources	5	5.56%
Education services	3	3.33%
Other	2	2.22%
Mass consumption	2	2.22%
Construction	2	2.22%
Retail	1	1.11%
Wholesale trade	1	1.11%
Utilities	1	1.11%
Agricultural, livestock, or forestry production	0	0.00%
TOTAL	**90**	100.00%

Table 14 *- Survey respondent segmentation by type of industry*

In relation to the profiles of the respondents, most recognized themselves as having functional or business roles, while a minority declared themselves to have a technical role within their respective organizations. In terms of their experience, the sample includes a great range of variability, with certain outliers in terms of the maximum work experience. As a result, median and mode results were included as descriptive statistics to complement the values of the mean and standard deviation.

Respondents' type by role	# observations	Percentage
Functional / Business	69	76.67%
Technical	21	23.33%
TOTAL	**90**	**100%**

Table 15 *- Survey respondent segmentation by Role*

Respondents work Experience	Value (in years)
Mean	8.8
Median	5.0
Mode	1.0
Minimum	1.0
Maximum	50.0
Standard deviation	9.3

Table 16 *- Survey respondent work experience characteristics*

Regarding the assessed levels of AI, ML, and AA adoption at participant firms, the results are very interesting. Overall, the data gathered shows that the current levels of use of these technologies in the sample are moderate to high, considering results from organizations that range from experimentation to fully productive deployments and the fact that the levels of adoption of such technologies seem to decrease as their features and complexity increase, as seen in table 17.

As an example, highly sophisticated technologies such as image and video processing showed the lowest level of general adoption (close to 57%) with a lower percentage of fully productive projects deployed (close only to a 20%), while "*simpler*" technologies such as dashboards for visual representation of data have the highest levels of adoption (close to 76%) with a higher proportion of fully productive projects deployed (close to 42%).

AI / AA technology	Haven't used it	Analyzing its use (no definition)	Assessing Its use	At least 1 test project	At least 1 productive project	2 or more productive projects	Don't Know	TOTAL
Dashboards	16.67%	6.67%	8.89%	6.67%	8.89%	42.22%	10.00%	**100.00%**
Chatbots	24.44%	5.56%	8.89%	4.44%	14.44%	32.22%	10.00%	**100.00%**
Predictive Models	21.11%	6.67%	10.00%	5.56%	8.89%	30.00%	17.78%	**100.00%**
Natural Language Processing	23.33%	8.89%	11.11%	5.56%	8.89%	25.56%	16.67%	**100.00%**
Speech / Audio Processing	31.11%	6.67%	8.89%	7.78%	6.67%	17.78%	21.11%	**100.00%**
Image / Video processing	32.22%	10.00%	10.00%	8.89%	4.44%	20.00%	14.44%	**100.00%**

Table 17 *- Assessed levels of AI/ML/AA adoption at participant firms*

The online survey also gathered complementary information related to the motivations that Colombian companies had when adopting AI, AA, and ML technologies from a business point of view. As seen in figure 8, most of the assessed firms that had already started deploying these technologies, either for testing or production, mentioned that improving the strategic decision and supporting organizational processes with enhanced speed were the two main motivations to move forward, while cost reduction, reducing the use of personnel, and balancing or reducing workloads were among the lowest ranked in these aspects.

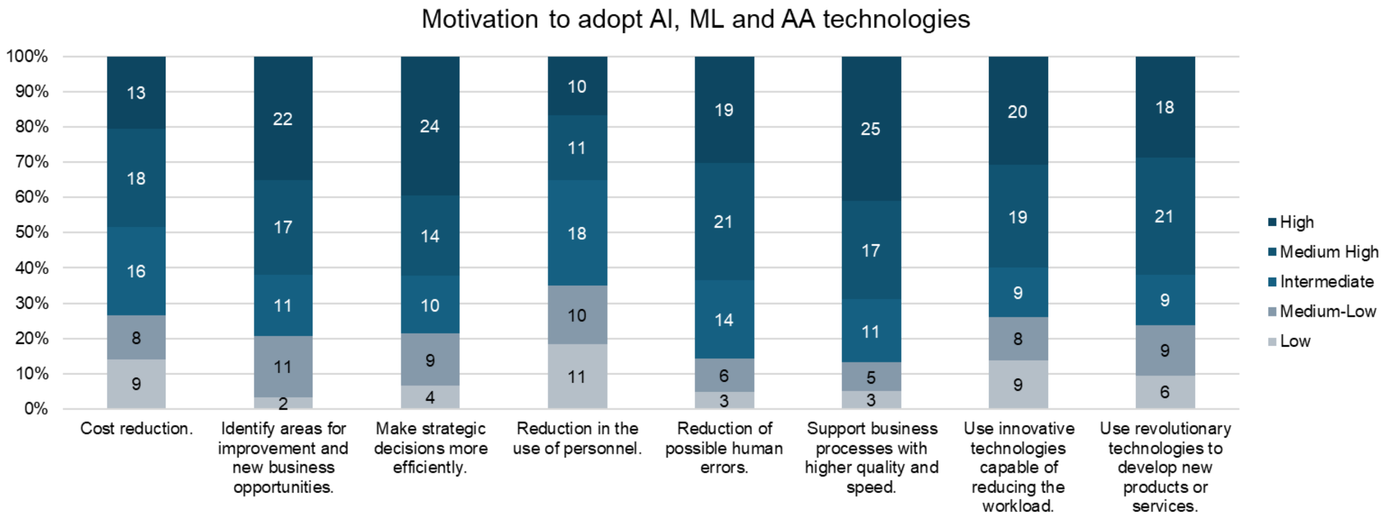

Figure 8 *- Distribution of motivations to adopt AI, LM, and AA technologies for active users*

At the same time, as seen in figure 9, while a high proportion of the assessed organizations seem to be using these technologies at least at a test level, a very low proportion (close to 50%) confirmed to have advanced in the definition of policies to control its use and key performance indicators (KPIs) to determine its impact at a business level, which emphasizes the importance of determining a potential relation between AI adoption and the level of organizational performance, one of the main objectives of this research project.

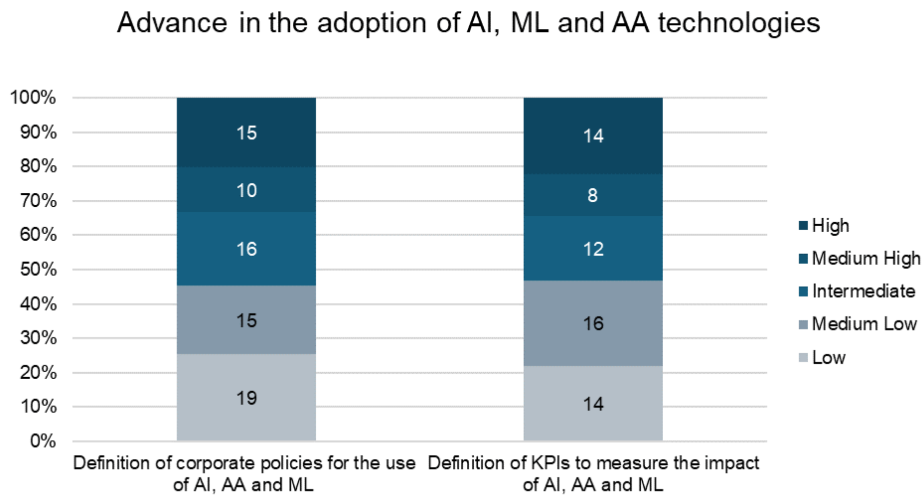

Figure 9 *- Distribution of the advancements of adoption of AI, LM, and AA technologies for active users*

For respondents who indicated that they had already started to measure some of the business outcomes obtained with the use of AI, AA, or ML technologies, a final question was posed, with the hope of determining which KPI was the most impacted. Out of 10 different options presented in the online survey instrument, Figure 10 shows that increased labor productivity, cost reductions, better knowledge and segmentation of customers, and improved customer satisfaction were the top-ranked business outcomes that assessed organizations have identified, while reduction in the use of personnel, improved time to

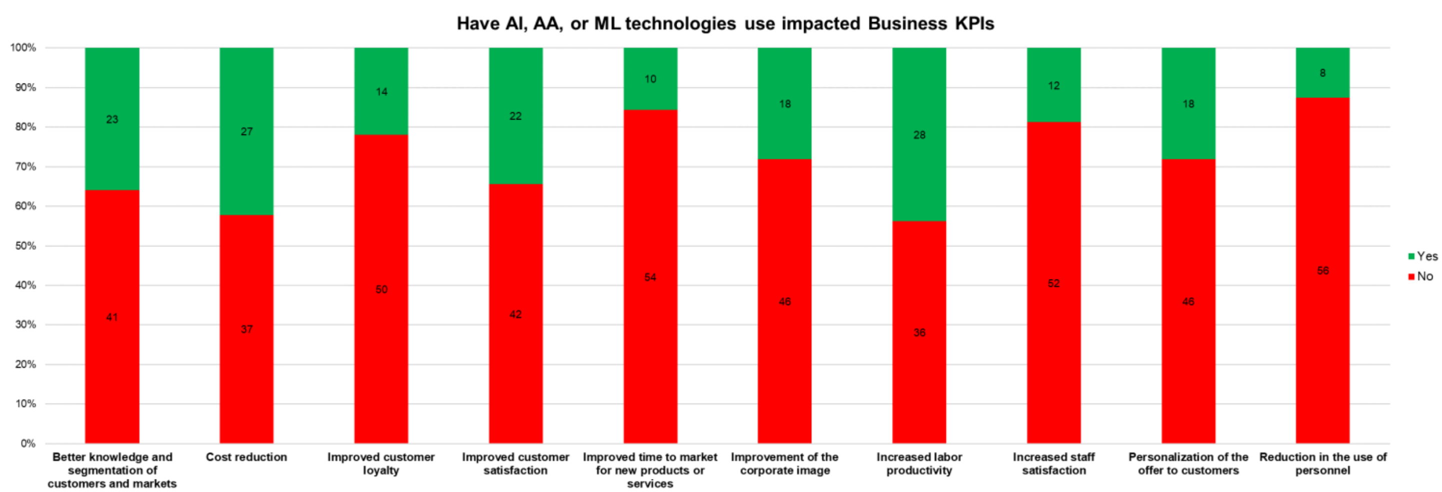

Figure 10 - Potential impacts for the adoption of AI, LM, and AA technologies at active users

market for new products and services, and increased staff satisfaction were among the lowest-ranked outcomes resulting from the use of AI technologies.

Concerning the endogenous and exogenous latent variables, SmartPLS delivers a series of descriptive statistics, based on the 90 observations and their defined indicators, including mean, median, minimum and maximum values, standard deviation, kurtosis, skewness, and statistics and p-values for the Cramer-von Mises test. In general, all results show rather normal results for each construct, displaying slightly lower levels of means when compared to medians and low figures of standard deviations (close to 1).

Regarding skewness, the data shows that for all latent variables (endogenous marked in blue), there is a tendency for longer left tails of each distribution curve, showing moderate levels of asymmetry towards maximum values. In terms of excess kurtosis, some latent variables show slightly leptokurtic distributions (positive excess kurtosis), which represent potential outliers in the distribution, while other latent variables show slightly platykurtic distributions (negative excess kurtosis), which means that most data points are in close proximity to the average.

Finally, in terms of normality, the Cramer-von Mises test shows that all latent variables' p-values are below the 0.05 threshold, confirming the assumption that the sample comes from a normal distribution. Further visual assessment of these results can be seen in Figure 11, represented on a comparative boxplot chart for all defined constructs (manifest and latent).

Latent variable	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises test statistic	Cramér-von Mises p value
DGSC	4.432	4.560	1.000	6.000	1.257	-0.315	-0.640	0.177	0.010
IDCI	4.626	4.740	1.000	6.000	1.174	0.547	-0.913	0.220	0.003
LAIA	3.595	3.664	1.000	6.000	1.576	-1.085	-0.175	0.136	0.036
LOC	4.536	4.800	1.193	6.000	1.253	-0.297	-0.729	0.265	0.001
LOI	4.288	4.581	1.000	6.000	1.344	-0.294	-0.764	0.314	0.000
LPP	4.505	4.627	1.000	6.000	1.072	1.318	-1.105	0.250	0.001
LRS	4.639	4.890	1.315	6.000	1.021	0.667	-0.957	0.301	0.000
TDCS	4.817	5.000	1.974	6.000	0.916	0.461	-0.935	0.279	0.001
TDM	4.577	4.717	1.264	6.000	1.174	-0.352	-0.672	0.242	0.002

Table 18 - *Descriptive statistics for defined formative (latent and manifest) constructs*

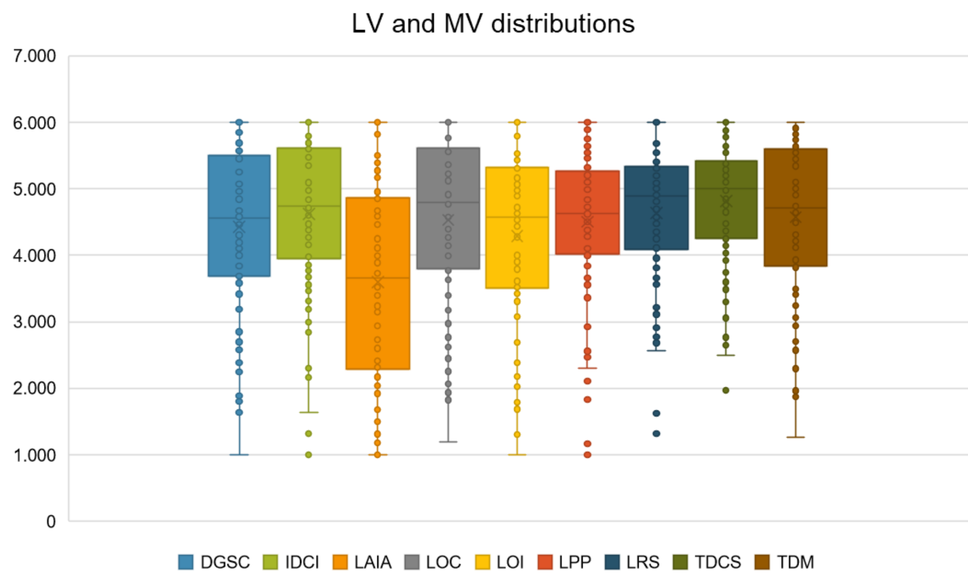

Figure 11 *- Boxplot figures describing the distribution of defined formative (latent and manifest) constructs*

Finally, as part of the descriptive analysis, SmartPLS V4 allowed the estimation of the correlation matrix for the latent and manifest constructs. As shown in Table 19, all constructs show high positive correlations, especially the latent ones, suggesting in some cases possible problems of multicollinearity among them (i.e., correlation between LOC and DGSC), while correlations between exogenous and endogenous ones are notably lower but still representative (marked in blue). The problem of multicollinearity is further explored and addressed in the following sections of this chapter.

LV	DGSC	IDCI	LAIA	LOC	LOI	LPP	LRS	TDCS	TDM
DGSC	1.000								
IDCI	0.800	1.000							
LAIA	0.710	0.658	1.000						
LOC	0.915	0.771	0.658	1.000					
LOI	0.796	0.687	0.700	0.707	1.000				
LPP	0.712	0.732	0.659	0.745	0.774	1.000			
LRS	0.779	0.673	0.653	0.676	0.864	0.733	1.000		
TDCS	0.778	0.820	0.672	0.789	0.680	0.723	0.715	1.000	
TDM	0.832	0.816	0.745	0.798	0.701	0.747	0.717	0.802	1.000

***Table 19** - Correlation levels for all formative (Latent and manifest) formative constructs*

The same analysis was performed using SmartPLS for all indicators considered as part of the outer structural model (n-indicators = 85), to assess their descriptive statistics and correlation matrix. However, due to the length of these results, they are offered for reference in Annex 7.1 at the end of this document.

4.2 Assessment of the outer models

Following the methodological approach provided by J. Hair & Alamer (2022) in their seminal paper to assess PLS-SEM models, the first step for the outer model assessment was to obtain critical indicators for the reflective constructs defined in the first two- developed models (direct relation for LAIA and LPP, represented in figures 12 and 13). Smart-PLS and its PLS-Algorithm module were used for this purpose. This process included the estimation of the outer loadings and their p-value, estimation of the indicators' reliability, examination of the internal consistency reliability, calculation of the average variance extracted (AVE), and analysis of the discriminant validity through the heterotrait-monotrait (HTMT) ratio.

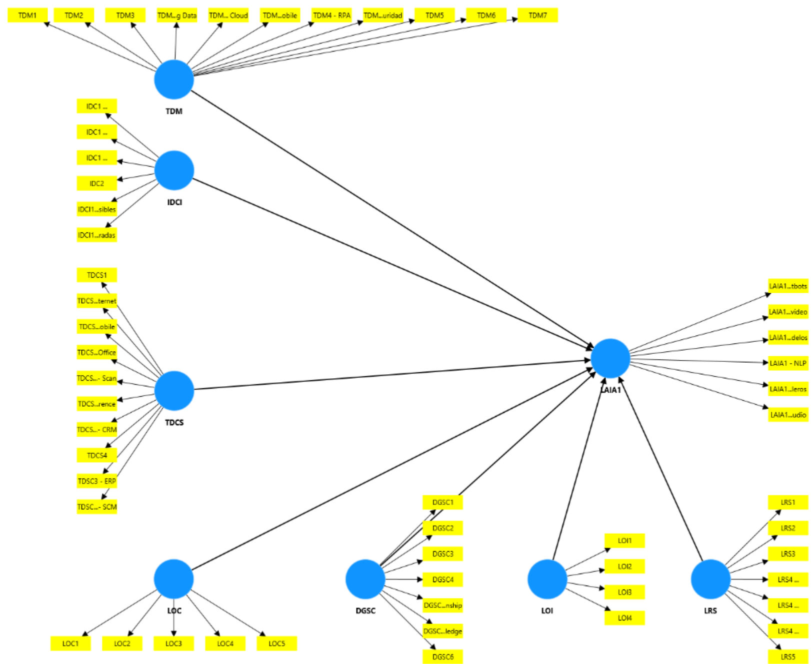

Figure 12 - *Visual representation of the proposed SEM-PLS model for direct relations between manifest variables and LAIA*

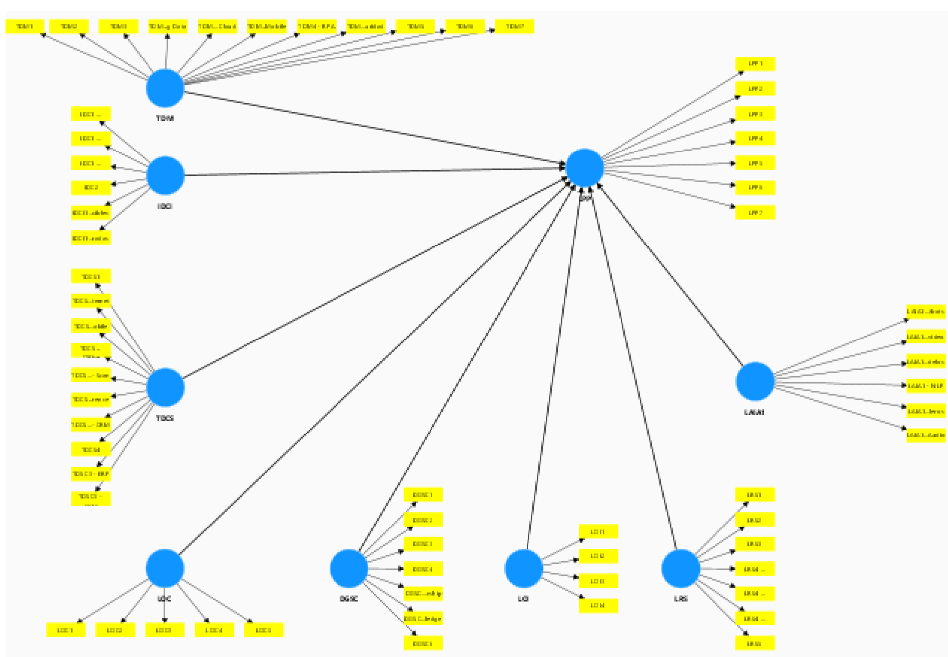

Figure 13 - *Visual representation of the proposed SEM-PLS model for direct relations between manifest variables and LPP*

For the first metric, outer loadings represent the correlations between them and each of their constructs. J. Hair & Alamer (2022) recommend that all selected indicators that are used as part of SEM models have a result equal to or greater than 0.7. However, they also define that values between 0.4 and 0.7 can be discretionally included where the indicators contribute to improving other metrics assessed as part of the outer model. Given the results obtained for this analysis (Table 20) and the following ones for other metrics, a decision to include all indicators as part of this first model (direct relation) was made.

The outer loadings correlate directly to a second metric (indicator reliability), defined as the squared value of each loading. A value above 0.5 for this metric is generally accepted, reflecting that each indicator shares at least 50% of the variance with its corresponding construct. For this model, indicators with a loading value lower than 0.7 (marked in red) are the same ones with a reliability metric below the threshold of 0.5. However, due to the results of additional metrics, all indicators were deemed appropriate to be included as part of the first model.

INDICATOR	DGSC	IDCI	LAIA	LOC	LOI	LPP	LRS	TDCS	TDM
DGSC1	0.886								
DGSC2	0.875								
DGSC3	0.773								
DGSC4	0.753								
DGSC5 - Championship	0.890								
DGSC5 - Knowledge	0.821								
DGSC6	0.870								
DGSC6									
IDC1 - Complete		0.895							
IDC1 - Trustworthy		0.857							
IDC1 - Known		0.856							
IDC2		0.766							
IDCI1 - Accesibles		0.867							
IDCI1 - Integrated		0.884							

LAIA - Chatbots			0.800						
LAIA - Image/video			0.853						
LAIA - Models			0.880						
LAIA - NLP			0.860						
LAIA - dashboards			0.849						
LAIA- Speech/Audio			0.777						
LOC1									
LOC1				0.847					
LOC2				0.894					
LOC3				0.898					
LOC4				0.841					
LOC5				0.857					
LOI1									
LOI1					0.857				
LOI2					0.838				
LOI3					0.883				
LOI4					0.791				
LOI4									
LPP1						0.791			
LPP2						0.770			
LPP3						0.840			
LPP4						0.840			
LPP5						0.780			
LPP6						0.781			
LPP7						0.762			
LRS1							0.786		
LRS2							0.836		
LRS3							0.604		
LRS4 - Consolidated							0.722		
LRS4 - Impacted							0.555		
LRS4 - Mature							0.630		
LRS5							0.786		
TDCS1								0.784	
TDCS2 - Internet								0.701	
TDCS2 - Mobile								0.480	
TDCS2 - Office								0.705	
TDCS2 - Scan								0.642	
TDCS2 - Videoconference								0.793	
TDCS3 - CRM								0.808	
TDCS4								0.704	

TDM1									0.790
TDM2									0.765
TDM3									0.796
TDM4 - Big Data									0.807
TDM4 - Cloud									0.616
TDM4 - Mobile									0.637
TDM4 - RPA									0.814
TDM4 - Security									0.824
TDM5									0.653
TDM6									0.803
TDM7									0.793
TDSC3 - ERP								0.747	
TDSC3 - SCM								0.705	

Table 20 *- Outer loadings of formative indicators for defined constructs*

The second step, suggested by J. Hair & Alamer (2022), is to validate construct reliability and validity. Reliability is a measurement that refers to the extent to which indicators and their constructs correlate and move together; in other words, the extent to which a variable is consistent in what it intends to measure and how its indicators act as a "*group*". Validity, on the other hand, refers to the extent to which a given construct, and therefore, its indicators, are measuring the right content and are a fit together to capture the essential concept of the whole construct. (Straub & Gefen, 2004).

To validate these concepts, three indicators are commonly used by researchers: Cronbach's alpha, composite reliability, and average variance extracted (AVE, for validity). The rule of thumb for the first two measurements is a result above 0.7 and below 0.95, as higher outcomes could reflect that indicators could be measuring the same dimensions of a given construct. For the last metric (AVE), generally accepted cutoffs are results above 0.5, which can be interpreted as the construct being able to capture a significant amount of variance from its indicators. For this first model (direct relations), results show that all constructs can be considered both reliable and valid, as seen in Table 21:

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
DGSC	0.930	0.932	0.943	0.705
IDCI	0.926	0.932	0.942	0.732
LAIA	0.914	0.917	0.933	0.701
LOC	0.918	0.919	0.938	0.753
LOI	0.864	0.866	0.907	0.710
LPP	0.903	0.908	0.923	0.633
LRS	0.833	0.867	0.873	0.501
TDCS	0.892	0.908	0.910	0.508
TDM	0.925	0.933	0.936	0.575

Table 21 *- Cronbach's alpha, composite reliability, and AVE results for defined constructs*

Finally, J. Hair & Alamer (2022) recommend as the last step of the outer model assessment, analyzing the discriminant validity of the constructs through the HTMT ratio. Discriminant validity in this context refers to the confirmation that all constructs within a model are conceptually different and therefore do not measure the same notion. In terms of HTMT, the recommended cutoff value to assess discriminant validity among constructs has been set below 0.85.

For this metric, results from the first proposed model obtained with SmartPLS show that two sets of constructs grouped under two global factors (DGSG/LOC - organizational factors and LRS/LOI - relational factors) show values above this threshold, suggesting high correlations between them that need to be assessed to move forward.

	DGSC	IDCI	LAIA	LOC	LOI	LPP	LRS	TDCS	TDM
DGSC									
IDCI	0.861								
LAIA	0.773	0.713							
LOC	0.986	0.832	0.717						
LOI	0.888	0.764	0.788	0.793					
LPP	0.767	0.783	0.716	0.807	0.866				
LRS	0.853	0.749	0.717	0.740	0.971	0.810			
TDCS	0.847	0.898	0.701	0.836	0.767	0.760	0.825		
TDM	0.893	0.878	0.795	0.858	0.774	0.803	0.802	0.866	

Table 22 *- HTMT ratio results for defined constructs*

According to Henseler et al. (2015), there are several approaches to treating issues of discriminant validity, including the possibility of merging highly correlated constructs, as long as it is logically supported by theory. A common procedure to methodologically perform this is to define a higher (second) order construct that combines those who present high levels of HTMT ratios, as their indicators should theoretically be measuring the same phenomenon.

For this model, the level of organizational culture (LOC) and the definition of IT and business strategies & alignment with levels of management support, knowledge, and IT championing (DGSG), both encompassed within organizational factors, exhibit high correlation. As observed in the literature review, these two constructs are strongly linked, enabling the formation of a general construct that encompasses multiple dimensions represented by all indicators assessed by the online instrument.

In the same manner, the level of relational strategy (LRS) and the level of open innovation (LOI), encompassed within relational factors, are highly interrelated, as many of their indicators are connected and could potentially be interchangeable. Therefore, to correct the discriminant validity between them, two higher-order constructs were defined (LOC&DS and LOI&RS). Figures 14 and 15 display a graphic representation of the adjusted models.

About discriminant validity, the results of this new model show that this approach improves the HTMT ratios to the desired metrics (above 0.7 and below 0.95), which allows us to move forward in the assessment of the inner model as the next step of the analysis.

	DGSC	IDCI	LAIA	LOC	LOC&DS	LOI	LOI&RS	LPP	LRS	TDCS	TDM
DGSC											
IDCI	0.861										
LAIA	0.773	0.713									
LOC	0.986	0.832	0.717								
LOC&DS	1.042	0.852	0.752	1.034							
LOI	0.888	0.764	0.788	0.793	0.851						
LOI&RS	0.874	0.761	0.752	0.768	0.832	1.056					
LPP	0.767	0.783	0.716	0.807	0.787	0.866	0.840				
LRS	0.853	0.749	0.717	0.740	0.808	0.971	1.115	0.810			
TDCS	0.850	0.898	0.720	0.863	0.859	0.770	0.801	0.783	0.811		
TDM	0.893	0.878	0.795	0.858	0.881	0.774	0.797	0.803	0.802	0.868	

***Table 23** - HTMT ratio results for adjusted defined constructs*

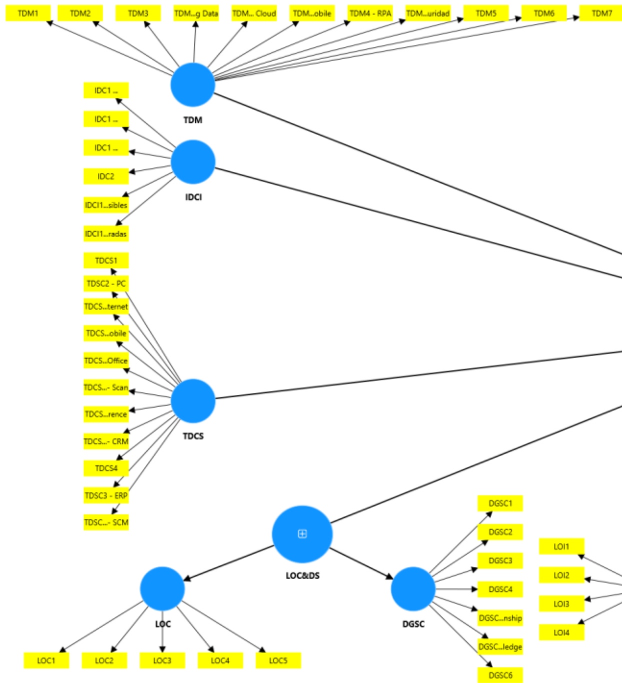

Figure 14 *- Visual representation of the adjusted SEM-PLS model for the first direct relations between manifest variables and LAIA*

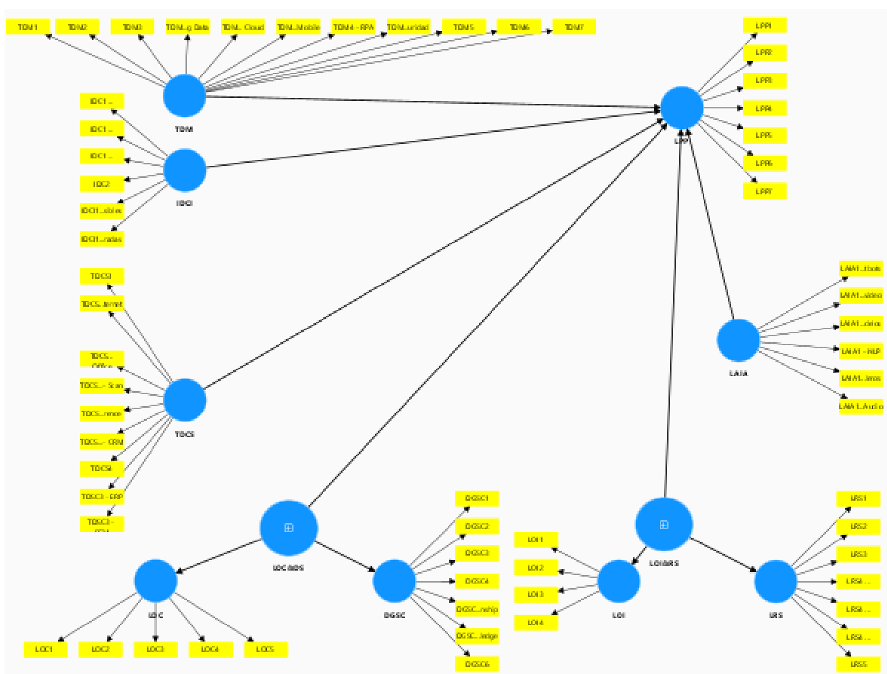

Figure 15 - *Visual representation of the adjusted SEM-PLS model for the second direct relations between manifest variables and LPP*

4.3 Assessment of the structural (inner) model

Following the proposed methodology by J. Hair & Alamer (2022), the following step for SEM-PLS analysis is to assess the inner model that defines the relation between the exogenous and endogenous constructs. The first recommended procedure to review the collinearity of the variables included in the model is to use a metric called the Variance Inflation Factor (VIF), which measures the levels of correlation between exogenous variables in an SEM model, and which ideally should be below a threshold of 5.

Once again, SmartPLS provides the results for this metric (VIF), as seen in Table 24. All exogenous constructs of the first proposed model show VIF values below the cut-off of 5 to the two endogenous constructs (LPP and LAIA), which allows us to move forward with the analysis.

	LAIA	LPP
IDCI	4.182	4.181
LOC&DS	4.845	4.845
LOI&RS	2.934	2.934
TDCS	4.058	4.058
TDM	4.432	4.432

Table 24 *- VIF results for defined constructs*

The next recommended step is to assess the size and significance of the path coefficients defined by the model. For this analysis, a level of significance of 95% was defined, and estimates were calculated using a Bias-corrected and accelerated (BCa) bootstrapping routine with 5,000 iterations, including a two-tailed significance test.

For the path coefficients, metrics between 0 and 0.1, 0.11 and 0.3, 0.3 to 0.5, and greater than 0.5 can be interpreted as weak, modest, moderate, and strong effects, respectively. As per the proposed model, figures 16 and 17 and tables 25 and 26 display the results of the bootstrapping routine, including the assessment of significance at 95% and the values for the resulting path coefficients.

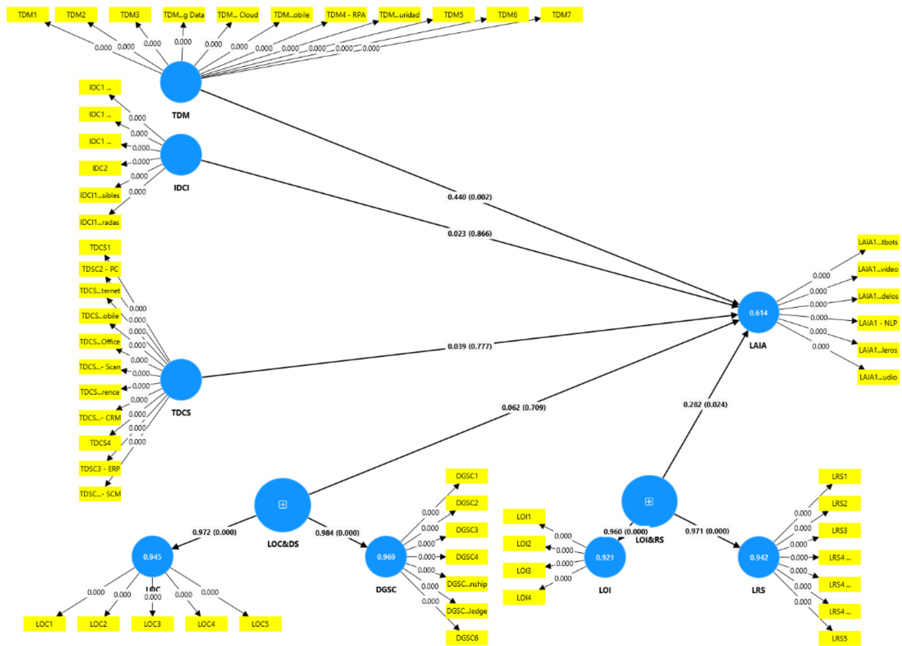

Figure 16 *- Visual representation of the adjusted SEM-PLS model for direct relations between manifest variables and LAIA, including resulting path coefficients*

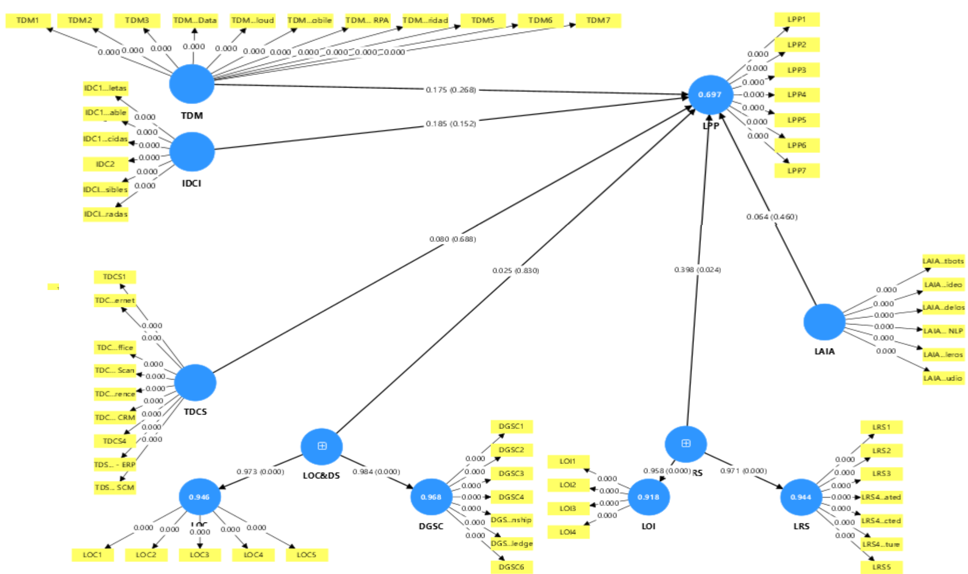

Figure 17 *- Visual representation of the adjusted SEM-PLS model for direct relations between manifest variables and LPP, including resulting path coefficients*

	LAIA	Effect size	LPP	Effect size
IDCI	0.030	Weak	0.185	Modest
LOC&DS	0.088	Weak	0.025	Weak
LOI&RS	0.297	Modest	0.398	Moderate
TDCS	0.000	Weak	0.080	Weak
TDM	0.426	Moderate	0.175	Modest
LAIA	N/A	N/A	0.064	Weak

Table 25 *- Resulting path coefficients and effects for the adjusted SEM-PLS models*

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IDCI -> LAIA	0.030	0.026	0.143	0.211	0.833
IDCI -> LPP	0.185	0.169	0.129	1431	0.152
LAIA -> LPP	0.064	0.063	0.087	0.739	0.460
LOC&DS -> DGSC	0.984	0.984	0.006	161.131	0.000
LOC&DS -> LAIA	0.088	0.081	0.174	0.507	0.612
LOC&DS -> LOC	0.972	0.973	0.007	129.879	0.000
LOC&DS -> LPP	0.025	0.007	0.119	0.214	0.830
LOI&RS -> LAIA	0.297	0.286	0.122	2.437	0.015
LOI&RS -> LOI	0.960	0.961	0.008	118.444	0.000
LOI&RS -> LPP	0.398	0.400	0.176	2.253	0.024
LOI&RS -> LRS	0.971	0.972	0.006	165.391	0.000
TDCS -> LAIA	0.000	0.010	0.175	0.003	0.998
TDCS -> LPP	0.080	0.082	0.198	0.401	0.688
TDM -> LAIA	0.426	0.444	0.148	2.888	0.004
TDM -> LPP	0.175	0.210	0.158	1.107	0.268

Table 26 *- Results from the bootstrapping routing for the adjusted direct relation SEM-PLS models*

Results from this analysis show that for the first endogenous variable (LAIA), only one construct (TDM) has a moderate path coefficient, another (LIO&RS) shows a modest one, while the rest display weak-sized effects. Regarding the other endogenous variable (LPP), the only two constructs that show a weak path coefficient are LOC&DS and TDS, while the rest of them range from modest to moderate size effects.

These results were contrasted with the ones obtained after the bootstrapping routine, resulting in only three statistically significant path coefficients. In particular, the path coefficient for TDM on LAIA is statistically significant, as well as the path coefficient of

LOI&RS on both LAIA and LPP. In all three cases, T-statistics are above the defined threshold for a 5% level of significance (1.96 for a two-tailed test), with corresponding p-values below the 0.05 level.

This assessment is confirmed with the information provided by SmartPLS on the confidence intervals for each exogenous construct on the endogenous variables, as seen in Table 27. In this table, the analysis shows that these two constructs were the only ones to have confidence intervals that do not include the value 0 within the minimum and maximum ranges, confirming their significance.

	Original sample (O)	Sample mean (M)	2.5%	97.5%
IDCI -> LAIA	0.030	0.026	-0.249	0.314
IDCI -> LPP	0.185	0.169	-0.105	0.241
LAIA -> LPP	0.064	0.063	-0.105	0.241
LOC&DS -> DGSC	0.984	0.984	0.969	0.992
LOC&DS -> LAIA	0.088	0.081	-0.246	0.436
LOC&DS -> LOC	0.972	0.973	0.957	0.985
LOC&DS -> LPP	0.025	0.007	-0.242	0.228
LOI&RS -> LAIA	0.297	0.286	0.031	0.512
LOI&RS -> LOI	0.960	0.961	0.943	0.975
LOI&RS -> LPP	0.398	0.400	0.062	0.719
LOI&RS -> LRS	0.971	0.972	0.958	0.981
TDCS -> LAIA	0.000	0.010	-0.346	0.341
TDCS -> LPP	0.080	0.082	-0.303	0.454
TDM -> LAIA	0.426	0.444	0.158	0.743
TDM -> LPP	0.175	0.210	-0.083	0.546

Table 27 *– Resulting confidence intervals for the adjusted direct relation SEM-PLS models*

The following step for the assessment of the structural (inner) model is to determine the coefficients of determination (or R^2), which represent the variance in the endogenous variables that are predicted by the exogenous ones. Once again, J. Hair & Alamer (2022) defined various ranges for this metric (between 0 and 0.1, 0.11 and 0.3, 0.3 to 0.5, and greater than 0.5) to be indicative of weak, modest, moderate, and strong explanatory power.

For the first proposed model, figures of R^2 and R^2 adjusted (corrected for potential overestimation) for the latent variables (LAIA and LPP) show strong explanatory power (above the 0.5 mark), revealing that the model could account for 59% in the level of AI adoption and 67.5% of the perceived competitiveness of assessed Colombian firms, while for the manifest ones, show that their indicators have a very strong explanatory power (above 0.9).

For LAIA	**R-square**	**R-square adjusted**
DGSC	0.96861839	0.968261781
LAIA	0.613757502	0.590766877
LOC	0.944913063	0.944287075
LOI	0.92076016	0.919859707
LRS	0.942082163	0.941424006

Table 28 *- R-square results for the adjusted SEM-PLS model (LAIA)*

For LPP	**R-square**	**R-square adjusted**
DGSC	0.967617038	0.96724905
LOC	0.946277021	0.945666532
LOI	0.917934234	0.917001668
LPP	0.693484026	0.675239028
LRS	0.943559339	0.942917968

Table 29 *- R-square results for the adjusted SEM-PLS model (LPP)*

About the effect size, the f^2 measurement is used in SEM-PLS to assess the impact of potentially removing a manifest construct on a latent one. For this metric, three different ranges represent the type of effect each exogenous variable has on the endogenous ones: Values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects. (Cohen, 1988). As seen in table 30, for this model, LOI&RS and TDM have medium effects on LAIA, while for LPP, IDCI and TDM show small effects, while LOI&RS show large ones.

	LAIA	Effect size (f^2)	LPP	Effect size (f^2)
IDCI	0.000	None	0.033	Small
LOC&DS	0.002	None	0.001	None
LOI&RS	0.070	Medium	0.199	Medium
TDCS	0.001	None	0.001	None
TDM	0.114	Medium	0.031	Small

Table 30 *- Effect size results for adjusted direct relation SEM-PLS models*

The final step in the analysis of the inner model is to assess the out-of-sample predictive power of the model, using a hold-out sample approach to assess its capabilities with data that the model has not yet seen or been trained with. SmartPLS V4 provides a very comprehensive and useful module defined as "*PLSpredict / CVPAT*", which uses a k-fold algorithm, randomly holds out a training sub-sample of the dataset to calculate the out-of-sample predictive power capability.

For the proposed model, a k-fold equal to 10 and several repetitions equal to 10 were used as the parameters for the prediction routine to obtain the out-of-sample performance when compared to the naïve linear regression model (LM) benchmark. This analysis was carried out by means of a linear regression for each of the exogenous indicators on the indicators of the endogenous variables of the structural equation model.

This comparison is made using three key metrics: Q^2 defined as a measure of predictive capacity or predictive relevance by assessing the model's ability to predict endogenous latent variables, root-mean-square error (RMSE), defined as the squared root of the averages of the squared differences between predictions and actual observations, and mean absolute error (MAE), defined as the average magnitude of the errors in a set of predictions without considering their direction (J. Hair & Alamer, 2022).

As a rule of thumb, if all its indicators of the latent (endogenous) variables show lower RMSE or MAE values when compared to the naïve LM model errors (RMSE or MAE), it can be interpreted that the model offers a high out-of-sample predictive capability.

	Q²predict	RMSE	MAE
LAIA	0.924	1.085	0.849
LPP	0.978	0.682	0.483

Table 31 *- Resulting predicted capacities for the adjusted direct relation SEM-PLS models.*

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
LAIA1 - Chatbots	0.373	1.592	1.331	3.001	2.283
LAIA1 - Image/video	0.404	1.450	1.168	2.412	1.793
LAIA1 - Modelos	0.412	1.455	1.148	2.528	1.900
LAIA1 - NLP	0.331	1.546	1.261	2.585	1.987
LAIA1 - tableros	0.442	1.431	1.139	2.179	1.700
LAIA1- Speech/Audio	0.280	1.549	1.250	2.680	2.040
LPP1	0.350	1.093	0.806	1.729	1.272
LPP2	0.245	1.269	0.989	2.108	1.574
LPP3	0.470	0.941	0.731	1.730	1.238
LPP4	0.498	1.000	0.771	1.469	1.075
LPP5	0.483	0.903	0.651	1.462	1.113
LPP6	0.301	1.338	1.076	1.819	1.389
LPP7	0.282	1.060	0.787	1.812	1.385

Table 32 *- Resulting predictive capabilities for direct indicators of latent constructs (LAIA and LPP)*

As seen in Tables 31 and 32 for the first proposed model (direct relation), the results show a high composite mark for the Q^2 metric for both latent variables (LAIA and LPP). Likewise, the results show lower RSME and MAE marks for all the indicators estimated with the PLS model when compared to those estimated with the LM.

4.4 Assessment of the structural (inner) model including mediation

As mentioned on the previous sections, the aim of this project is not only to assess the direct relation between technical, organizational, and relational factors on the perceived levels of AI adoption and competitiveness (performance) for Colombian organizations, but also to analyze if a mediation relation exists between the first (LAIA) and the second (LPP) endogenous variables concerning these three sets of factors.

With this research objective in mind, a third was defined in SmartPLS to measure mediation effects. More specifically, in this model all manifest constructs of technical, organizational, and relational factors were directly linked with the latent variable measuring the level of AI adoption (LAIA), and this in turn was then connected to the second latent variable of perceived performance (LPP) to assess potential mediation effects when compared with the first model. Figure 18 depicts the structure of this second model graphically.

Given the results of discriminant validity derived from the HTMT ratios obtained for the first model (direct relation), higher-order constructs (LOC&DS and LOI&RS) were directly used as part of the structure to avoid multicollinearity issues.

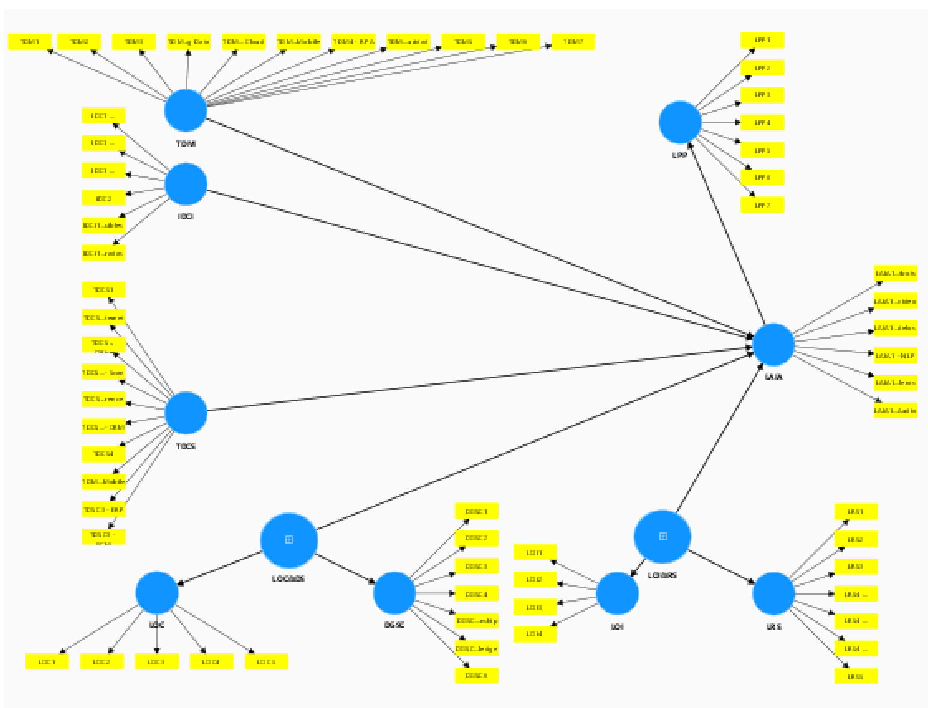

Figure 18 *- Visual representation of the adjusted SEM-PLS model including mediation through LAIA*

For the third (mediation) model, assessment for the bootstrapping routing was also performed, to be consistent with the validations for construct reliability, internal consistency, AVE, and discriminant validity that were already performed for the first model. In addition, no indicator changes were included for the manifest or latent variables. For the bootstrapping routine, the same parameters of the first model were used (95% level of significance, Bias-corrected and accelerated [BCa] bootstrapping routine with 5.000 iterations, and two-tailed test), allowing for comparison between its results and the ones obtained from the first one (direct relation).

Analysis shows that for the third model (mediation), only two manifest variables (LOI&RS and TDM) show statistically significant direct path coefficients at a 95% level to the first latent variable (LAIA), while only LOI&RS shows the same result as LPP. At the same time, the first latent variable (LAIA) shows a non-significant path coefficient at a 95% level to the second manifest variable (LPP). Bias-corrected confidence intervals obtained with SmartPLS confirms these results, as all three relations show intervals excluding 0 from their minimum and maximum ranges, as shown in Figure 19 and Tables 33 and 34.

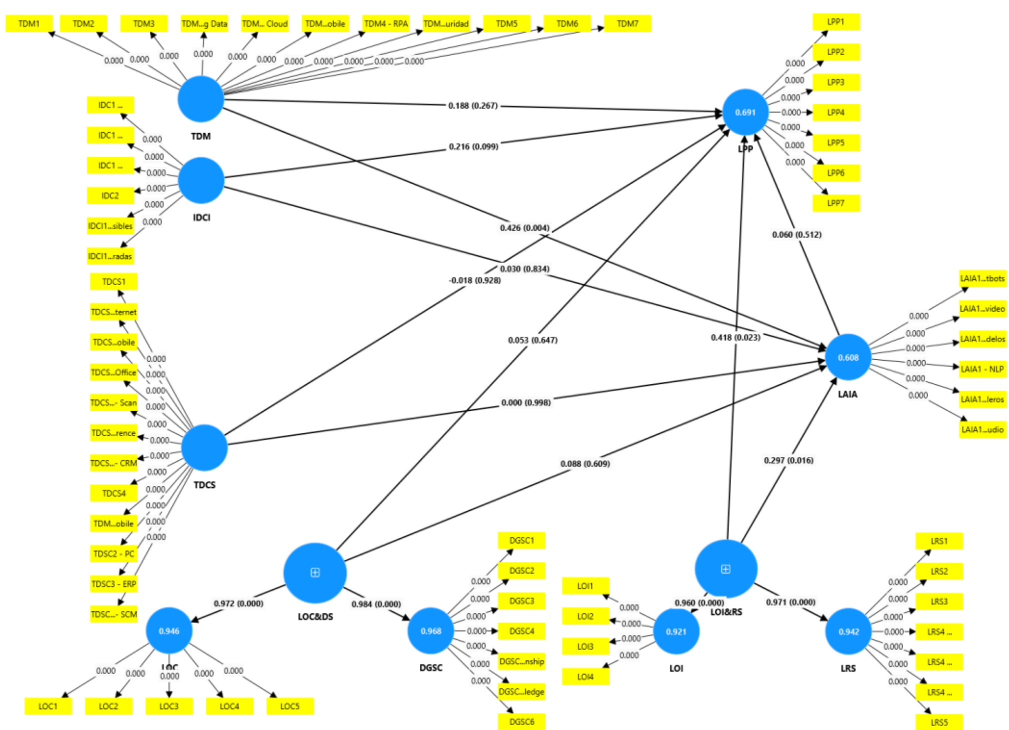

__Figure 19 -__ Visual representation of the adjusted SEM-PLS model including mediation through LAIA, and details of resulting path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IDCI -> LAIA	0.030077688	0.028338266	0.143269624	0.209937652	0.833724886
IDCI -> LPP	0.216128835	0.194883474	0,131158772	1.647841244	0.099448085
LAIA -> LPP	0.060333452	0.058941279	0.092035634	0.65554448	0.512147406
LOC&DS -> LAIA	0.088042225	0.079246314	0.171960788	0,511990124	0.608680525
LOC&DS -> LPP	0.053053139	0.042876149	0.115802922	0.458132988	0.646876803
LOI&RS -> LAIA	0.296978298	0.285881928	0.123810296	2.39865592	0.016491769
LOI&RS -> LPP	0.417795288	0.413846109	0.183534122	2.276390262	0.022864741
TDCS -> LAIA	0.000485438	0.008033712	0.173230856	0.002802258	0.997764236
TDCS -> LPP	-0.017796813	-0.007274887	0.196744845	0.090456311	0.927928232
TDM -> LAIA	0.426311395	0.445642067	0.1487888	2.8652116	0.00418468
TDM -> LPP	0.188086824	0.21630907	0.169402809	1.11029342	0.266925965

Table 33 *- Results from the bootstrapping routine for the adjusted mediated relation SEM-PLS model*

	Original sample (O)	Sample mean (M)	2.5%	97.5%
IDCI -> LAIA	0.030077688	0.028338266	-0.242194366	0.318760691
IDCI -> LPP	0.216128835	0.194883474	-0.095976291	0.424920125
LAIA -> LPP	0.060333452	0.058941279	-0.118138256	0.247939966
LOC&DS -> LAIA	0.088042225	0.079246314	-0.24226905	0.438038126
LOC&DS -> LPP	0.053053139	0.042876149	-0.194210861	0.258293624
LOI&RS -> LAIA	0.296978298	0.285881928	0.019214752	0.508596139
LOI&RS -> LPP	0.417795288	0.413846109	0.053488923	0.737551523
TDCS -> LAIA	0.000485438	0.008033712	-0.342783739	0.335358218
TDCS -> LPP	-0.017796813	-0.007274887	-0.379612741	0.386427677
TDM -> LAIA	0.426311395	0.445642067	0.1658386	0.759969913
TDM -> LPP	0.188086824	0.21630907	-0.099624893	0.572285658

Table 34 *- Resulting confidence intervals for the adjusted mediated relation SEM-PLS model*

As this third model aims to measure the possibility of a mediation relation between the manifest variables, the first latent variable (LAIA), and the second one (LPP), the most important information that can be extracted from the bootstrapping analysis is the special indirect effects assessment that SmartPLS calculates. These indirect effects allow us to estimate whether any statistically significant mediation effect exists.

As seen in Table 35, the results show that, in fact, LAIA shows no significant mediation relation between the LOI&RS, TDM, and the LPP of assessed Colombian firms at a 95% level. Once again, this can be confirmed using the results from the bias-corrected confidence intervals, as seen in Table 36.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IDCI -> LAIA -> LPP	0.001814691	0.000915642	0.015503062	0.117053699	0.9068222
LOC&DS -> LAIA -> LPP	0.005311891	0.002830182	0.019101667	0.278085223	0.780958434
LOI&RS -> LAIA -> LPP	0.017917726	0.017267557	0.030858425	0.58064292	0.561507297
TDCS -> LAIA -> LPP	2.92881E-05	0.000478697	0.017594088	0.001664657	0.998671863
TDM -> LAIA -> LPP	0.025720838	0.029145087	0.046425398	0.554025154	0.579586397

Table 35 *- Results from the bootstrapping routine for indirect effects of the adjusted mediated relation SEM-PLS model*

	Original sample (O)	Sample mean (M)	2.5%	97.5%
IDCI -> LAIA -> LPP	0.001814691	0.000915642	-0.032247537	0.035614627
LOC&DS -> LAIA -> LPP	0.005311891	0.002830182	-0.036551127	0.046883031
LOI&RS -> LAIA -> LPP	0.017917726	0.017267557	-0.036611164	0.086792697
TDCS -> LAIA -> LPP	2.92881E-05	0.000478697	-0.037814166	0.038562966
TDM -> LAIA -> LPP	0.025720838	0.029145087	-0.048102239	0.135433693

Table 36 *- Resulting confidence intervals for the indirect effect of the adjusted mediated relation SEM-PLS model*

In terms of the magnitude of the path coefficients, the results show that LOI&RS has a modest effect on LAIA and a moderate one on LPP, while TDM has a moderate effect on LAIA and a modest one on LPP. At the same time, the latent moderator, LAIA, shows a weak effect on the LPP of assessed Colombian firms.

As per the specific indirect effects, all factors show weak effects on LPP through LAIA mediation, as seen in Table 38.

	LAIA	Effect Size	LPP	Effect Size
IDCI	0.030	Weak	0,216	Weak
LAIA			0.060	Weak
LOC&DS	0.088	Weak	0,053	Weak
LOI&RS	0.297	Modest	0,418	Moderate
TDCS	0.000	Weak	-0,018	Weak
TDM	0.426	Moderate	0,188	Modest

Table 37 *– Resulting path coefficients and effect size for the mediated SEM-PLS model*

	Specific indirect effects	Effect Size
IDCI -> LAIA -> LPP	0.002	Weak
LOC&DS -> LAIA -> LPP	0.005	Weak
LOI&RS -> LAIA -> LPP	0.018	Weak
TDCS -> LAIA -> LPP	0.000	Weak
TDM -> LAIA -> LPP	0.026	Weak

Table 38 *- Specific indirect effect sizes for the mediated SEM-PLS model*

The coefficients of determination (or R^2) in this model for all the exogenous and first endogenous variable (LAIA) are the same as the ones obtained in the first model (direct relation without mediation), while the coefficient for the second exogenous variable shows a slight reduction for both base and adjusted results as a result of the mediation relationship. For the third model (mediation), a moderate explanatory power for LPP was observed, as shown in Table 39.

	R-square	R-square adjusted
DGSC	0.968	0.968
LAIA	0.608	0.584
LOC	0.946	0.945
LOI	0.921	0.920
LPP	0.691	0.668
LRS	0.942	0.941

Table 39 *- R-square results for adjusted mediated SEM-PLS model*

In relation to the effect size, or f^2 metric, the mediation model results show that only LOI&RS and TDM have visible effects on LAIA (medium), while LAIA has a large effect on LPP, as seen in Table 40.

	LAIA	Effect size (f^2)	LPP	Effect size (f^2)
IDCI	0.000	None	0.036	Small
LAIA	N/A		0.005	None
LOC&DS	0.004	None	0.002	None
LOI&RS	0.076	Small	0.178	Medium
TDCS	0.000	None	0.000	None
TDM	0.099	Small	0.022	Small

Table 40 *- Effect size results for the adjusted mediated relation SEM-PLS model*

Finally, the assessment for the out-of-sample predictive power for the mediation model was performed using k-folds equal to 10 and several repetitions equal to 10 as the parameters for the prediction routine. The results show a medium composite mark for the Q^2 metric for AI adoption (LAIA) and perceived performance (LPP), with high results for its indicators, as they displayed lower RSME and MAE marks for the structural model when compared to the naïve linear regression, as seen in Tables 41 and 42.

	Q²predict	RMSE	MAE
LAIA	0.545	0.687	0.537
LPP	0.555	0.692	0.491

Table 41 *- Resulting predicted capacities for the adjusted mediated SEM-PLS model.*

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
LAIA1 - Chatbots	0.379	1.584	1.327	3.001	2.283
LAIA1 - Image/video	0.409	1.445	1.160	2.412	1.793
LAIA1 - Modelos	0.418	1.447	1.138	2.528	1.900
LAIA1 - NLP	0.333	1.544	1.259	2.585	1.987
LAIA1 - tableros	0.447	1.424	1.133	2.179	1.700
LAIA1- Speech/Audio	0.278	1.550	1.250	2.680	2.040
LPP1	0.348	1.094	0.829	1.729	1.272
LPP2	0.264	1.252	0.988	2.108	1.574
LPP3	0.422	0.982	0.755	1.730	1.238
LPP4	0.405	1.089	0.859	1.469	1.075
LPP5	0.417	0.959	0.740	1.462	1.113
LPP6	0.307	1.333	1.120	1.819	1.389
LPP7	0.280	1.062	0.806	1.812	1.385

Table 42 *- Resulting predictive capabilities for the direct indicators of latent constructs (LAIA and LPP)*

4.5 Assessment of the structural (inner) model, including mediation and control

Given the demographic information that was gathered on the online instrument, a third model was developed to assess the possible effect of firm size in relation to the level of adoption of AI technologies and its mediation of the level of perceived performance.

With this in mind, a four-option (micro, small, medium, and large enterprise) categorical control variable (Firm type or FT) was added to the third (mediation) model. To include this variable in SmartPLS, four dummy indicators were defined in the data set (one for each of the categories defined for the FT variable). Afterwards, one of the categories was left out of the FT construct and analysis, being defined as the reference category (in this case, the category of micro-enterprises). Figure 20 graphically depicts the configuration for this third (mediation and control) model:

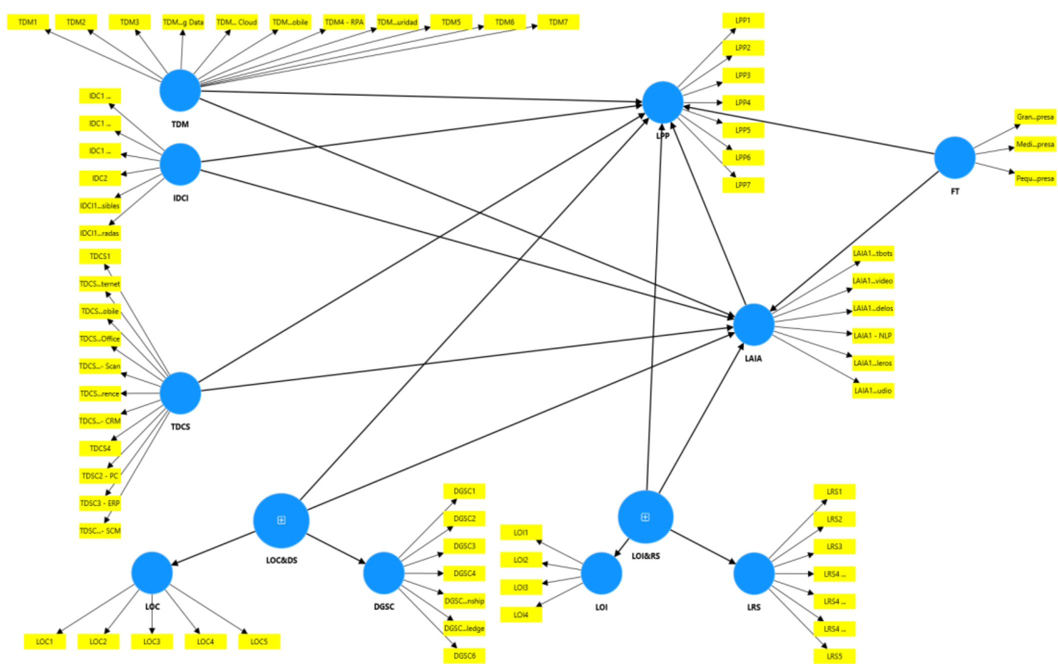

Figure 20 *- Visual representation of the adjusted SEM-PLS model, including mediation through LAIA and control*

This third proposed model, which incorporates both mediation and control variables, demonstrates substantial explanatory power, as indicated in the figures of R^2 and R^2 adjusted for the latent variables. Specifically, the model accounts for 63.1% of the variance in LAIA and 67.2% of the variance in LPP, exceeding the strong (0.5) and moderate (0.3) explanatory power thresholds, respectively. Furthermore, the model exhibits very strong explanatory power (above 0.9) for the manifest variables, indicating that their respective indicators are well explained.

	R-square	**R-square adjusted**
DGSC	0,968	0,968
LAIA	0,656	0,631
LOC	0,946	0,945
LOI	0,921	0,920
LPP	0,698	0,672
LRS	0,942	0,941

Table 43 *- R-square results for the adjusted mediated SEM-PLS model with control*

Regarding effect size (f^2), the specified metrics for the third adjusted model reveal notable effects. Specifically, a medium effect is observed on the manifest variable LOI&RS, and the control variable FT demonstrates a large effect on LAIA and LPP, respectively. Furthermore, LAIA exhibits a particularly low effect on LPP. The interpretation of this insubstantial effect from LAIA to LPP should, however, be contextualized by the significance of the control variable included in the model.

	LAIA	**Effect size (f^2)**	**LPP**	**Effect size (f^2)**
FT	0,139	Medium	0,023	Small
IDCI	0,013	None	0,043	Small
LAIA	N/A	N/A	0,000	None
LOC&DS	0,020	Small	0,005	None
LOI&RS	0,059	Small	0,170	Medium
TDCS	0,001	None	0,001	None
TDM	0,032	Small	0,009	None

Table 44 *- Effect size results for the adjusted mediated relation SEM-PLS model with control*

For this third adjusted model, which incorporates both mediation and a control variable, the bootstrapping routine was directly executed. This approach was feasible because the requisite validations for construct reliability, internal consistency, Average Variance Extracted (AVE), and discriminant validity were already established during the analysis of the first model (direct relation). Therefore, no changes were introduced to the indicators for either the manifest or latent variables in this subsequent model.

The bootstrapping parameters for this routine mirrored those employed in the first model: a 95% level of significance, a bias-corrected and accelerated (BCa) bootstrapping routine with 5,000 iterations, and a two-tailed test. Maintaining these consistent parameters across models ensures optimal comparability among the direct relation, mediation, and the current mediation-with-control-variable model.

The bootstrapping analysis for the third adjusted model (mediation with control variable) yielded specific insights into the statistical significance of the path coefficients. It was found that only the manifest variable LOI&RS exhibited statistically significant path coefficients (at a 95% confidence level) to both the first latent variable (LAIA) and the second latent variable (LPP).

Conversely, the first latent variable (LAIA) did not demonstrate a statistically significant path coefficient (at a 95% confidence level) to the second manifest variable (LPP). Furthermore, the control variable (FT) also showed non-significant path coefficients to both the first latent variable (LAIA) and LOI.

These findings are corroborated by the bias-corrected confidence intervals generated by SmartPLS, which indicate that the confidence intervals for all non-significant latent variable relationships include zero within their minimum and maximum ranges. Visual confirmation of these results can be observed in Figure 21, and further details are presented in Tables 45 and 46.

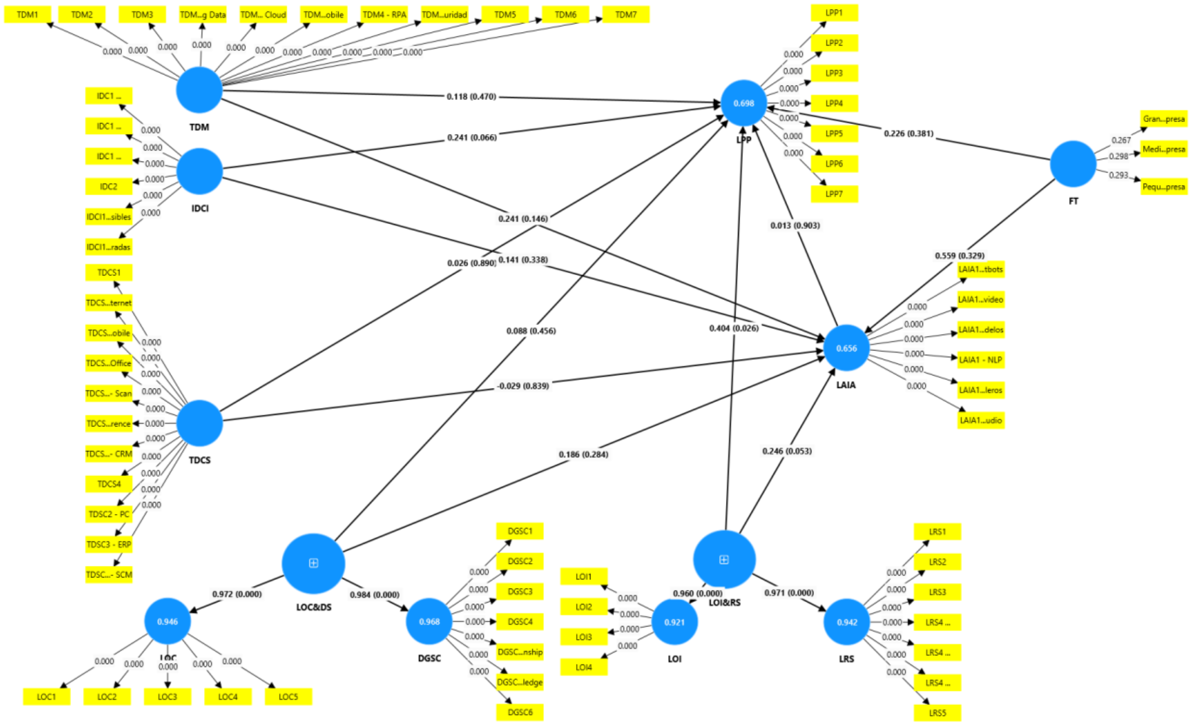

Figure 21 - *Visual representation of adjusted SEM-PLS model including mediation through LAIA and control, and details of resulting path coefficients*

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FT -> LAIA	0.559169277	0.210146829	0.580309135	0.963571386	0.335284133
FT -> LPP	0.225914582	0.066671004	0.257337932	0.877890717	0.380024099
IDCI -> LAIA	0.140507654	0.140041141	0.146492822	0.959143611	0.337509567
IDCI -> LPP	0.241391419	0.218015546	0.130427618	1.850769206	0.064232237
LAIA -> LPP	0.012718719	0.016906959	0.105485193	0.120573501	0.904031279
LOC&DS -> LAIA	0.185730168	0.177775375	0.174245689	1.065909688	0.286490173
LOC&DS -> LPP	0.087856948	0.075049303	0.11751652	0.747613594	0.454710828
LOI&RS -> LAIA	0.246153332	0.239395501	0.125368944	1.96343148	0.04962373
LOI&RS -> LPP	0.403524404	0.406248188	0.181123611	2.227895086	0.02590967
TDCS -> LAIA	-0.029070911	-0.01723464	0.145358772	0.199994198	0.841489182
TDCS -> LPP	0.025594966	0.029955781	0.182637516	0.140140792	0.888551571
TDM -> LAIA	0.241023793	0.248617715	0.166401525	1.448447023	0.147523433
TDM -> LPP	0.118266097	0.146104015	0.162374265	0.728354929	0.466413387

Table 45 - Results from the bootstrapping routine for the adjusted mediated relation SEM-PLS model with control

	Original sample (O)	Sample mean (M)	2.5%	97.5%
FT -> LAIA	0.559169277	0.210146829	-0.909829822	0.974734326
FT -> LPP	0.225914582	0.066671004	-0.449488329	0.487797823
IDCI -> LAIA	0.140507654	0.140041141	-0.127615432	0.446954936
IDCI -> LPP	0.241391419	0.218015546	-0.067581377	0.447747387
LAIA -> LPP	0.012718719	0.016906959	-0.184285406	0.23038119
LOC&DS -> LAIA	0.185730168	0.177775375	-0.149061493	0.541907364
LOC&DS -> LPP	0.087856948	0.075049303	-0.174155154	0.289866658
LOI&RS -> LAIA	0.246153332	0.239395501	-0.019865954	0.471878046
LOI&RS -> LPP	0.403524404	0.406248188	0.053921582	0.736991633
TDCS -> LAIA	-0.029070911	-0.01723464	-0.307532958	0.260705593
TDCS -> LPP	0.025594966	0.029955781	-0.317586722	0.388333123
TDM -> LAIA	0.241023793	0.248617715	-0.096597262	0.559928869
TDM -> LPP	0.118266097	0.146104015	-0.143493652	0.503857739

Table 46 - Resulting confidence intervals for the adjusted mediated relation SEM-PLS model with control

In the same manner as the third model, this adjusted model also investigates the potential for a mediation relationship among the manifest variables, the first latent variable (LAIA), and the second latent variable (LPP). Consequently, the most crucial data derived from the bootstrapping analysis is the specialized indirect effects assessment provided by SmartPLS, which determines the occurrence of any statistically significant mediations.

As presented in Table 47, the results for this model indicate that LAIA does not exhibit a mediation relationship between any of the latent variables, LAIA itself, and the LPP of the assessed Colombian firms, even when controlling for firm size at a 95% confidence level. Furthermore, the control variable (FT) also shows no significant path coefficients with LPP through LAIA. These findings are further substantiated by the bias-corrected confidence intervals, all of which encompass zero within their minimum and maximum ranges, as detailed in Table 48.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FT -> LAIA -> LPP	0.007111917	0.015773092	0.062493755	0.113802042	0.909397
IDCI -> LAIA -> LPP	0.001787077	0.001975153	0.020741727	0.08615856	0.9313421
LOC&DS -> LAIA -> LPP	0.00236225	0.000269678	0.02529688	0.093381072	0.9256027
LOI&RS -> LAIA -> LPP	0.003130755	0.004855707	0.029710068	0.105376907	0.9160789
TDCS -> LAIA -> LPP	-0.000369745	-0.002138106	0.015341007	0.024101727	0.9807719
TDM -> LAIA -> LPP	0.003065514	0.008870885	0.033624023	0.091170349	0.9273591

Table 47 *- Results from the bootstrapping routine for indirect effects of the adjusted mediated relation SEM-PLS model with control*

	Original sample (O)	Sample mean (M)	2.5%	97.5%
FT -> LAIA -> LPP	0.007111917	0.015773092	-0.111256695	0.146910772
IDCI -> LAIA -> LPP	0.001787077	0.001975153	-0.041592869	0.049482063
LOC&DS -> LAIA -> LPP	0.00236225	0.000269678	-0.054771037	0.05385293
LOI&RS -> LAIA -> LPP	0.003130755	0.004855707	-0.053478137	0.072951424
TDCS -> LAIA -> LPP	-0.000369745	-0.002138106	-0.039094608	0.026847
TDM -> LAIA -> LPP	0.003065514	0.008870885	-0.048138169	0.092412843

Table 48 - *Resulting confidence intervals for indirect effects of the adjusted mediated relation SEM-PLS model with control*

4.6 Summary

The results presented in this study provide valuable insights into the current state of adoption and use of AI, AA, and ML technologies among Colombian organizations. The data was collected through an online instrument over 10 months, yielding a total of 90 complete responses.

Demographic Characteristics: The majority of respondents (92.2%) were from organizations based in the Bogotá metropolitan area, which is the largest urban center in Colombia and accounts for approximately 31% of the country's GDP. In terms of firm size, over half of the participants were employed at large enterprises (>200 employees), while micro, small, and medium-sized firms were also well represented in the sample. This is somewhat surprising, as official statistics indicate that close to 92% of Colombian businesses are classified as micro-enterprises.

The respondents were predominantly from the information technology (24.4%) and financial/insurance services sectors (12.2%). Regarding the profiles of the survey participants, most self-identified as having functional or business roles (76.7%), while the remaining (23.3%) declared technical roles within their respective organizations. The sample exhibited a wide range of work experience, with a mean of 8.8 years, a median of 5.0 years, and a maximum of 50 years.

Levels of AI, ML, and AA Adoption: The data gathered provides a comprehensive overview of the current levels of adoption and use of AI, AA, and ML technologies among the assessed Colombian firms. The results indicate that the overall levels of adoption are moderate to high, with organizations ranging from experimentation to fully productive deployments of these technologies. Data shows that the levels of adoption tend to decrease as the complexity and sophistication of technologies increase. For example, highly advanced technologies such as image and video processing have the lowest overall adoption rate (close to 57%) and the smallest proportion of fully productive projects (around 20%). In contrast, simpler technologies like data visualization dashboards have the highest adoption rate (close to 76%) and the largest proportion of fully productive projects (around 42%).

Motivations for Adopting AI, ML, and AA: The survey also gathered information on the motivations that Colombian companies had when adopting AI, AA, and ML technologies from a business perspective. The top-ranked motivations were improving strategic decision-making processes and supporting organizational processes with enhanced speed, while cost reduction, reducing personnel, and balancing or reducing workloads were among the lowest-ranked factors.

However, the data also revealed that a relatively low proportion (close to 50%) of the assessed organizations have advanced in defining policies to control the use of these technologies and establishing key performance indicators (KPIs) to determine their business impact. This highlights the importance of determining the potential relationship between AI adoption and organizational performance, which is a key objective of this research project.

Structural Equation Modeling (SEM) Analysis: To further explore the relationships between the various factors influencing AI, ML, and AA adoption and organizational performance, a SEM analysis using the SmartPLS software was performed. Three different models were developed and assessed:

1. **Direct relations models:** These models examined the direct relationships between technical, organizational, and relational factors on the perceived levels of AI adoption (LAIA) and organizational competitiveness (LPP). The results showed that the indicators selected for each of the reflective constructs defined as manifest and latent variables showed high levels of consistency, validity, and reliability, allowing for good representability of the assessed phenomena. The model results showed that LOI&RS and TDM showed statistically significant paths to LAIA, while only LOI&RS did. The results for this model also showed strong explanatory power, accounting for 59.6% of the variance in LAIA and 67.2% of the variance in LPP. The out-of-sample predictive capabilities, performed using a hold-out sample approach, showed that this model had higher predictive relevance (Q^2) and lower root-mean-square error (RMSE) and mean

absolute error (MAE) compared to the benchmark linear regression models, suggesting strong out-of-sample predictive power.

2. **Mediation model:** This model incorporated a mediation effect using the constructs (endogenous and exogenous) previously defined for the first model, where the manifest variables were linked directly to LAIA, which in turn was connected to the LPP latent variable. The mediation analysis revealed that only two manifest variables (LOI&RS and TDM) had statistically significant path coefficients to LAIA, and one of them (LOI&RS) had a statistically significant path to LPP, while LAIA had an insignificant path coefficient to LPP, showing no significant mediated relationships between the organizational, technical, and relational factors and the main endogenous variable. For this model, the predictive power (Q^2) results showed once again lower root-mean-square error (RMSE) and mean absolute error (MAE) compared to the benchmark linear regression models, suggesting strong out-of-sample predictive power, although this metric was lower than the one obtained for the first models.

3. **Mediation model with control variable:** This third model included a control variable (firm type or FT) to assess the potential effect of firm size on the relationships between the variables. This model showed strong explanatory power for LAIA (63.1%) and LPP (67.2%), respectively. However, the control variable (FT) did not show a significant path coefficient either to LAIA or any potential effects on LPP through LAIA mediation.

5. DISCUSSION

This chapter presents a detailed analysis of the results obtained from the three PLS models developed as part of this research project. The analysis focuses on the significance of these findings regarding the research questions and hypotheses established in the introduction and literature review chapters, respectively. This chapter also examines the connection between the obtained results and the current academic discussion found in the IS and business management fields related to the adoption of digital ICTs at an organizational level.

As such, the primary objective for this section is to leverage the exploratory data analysis performed in the previous sections to gain insight into two key areas:

- **Unique AI Adoption Factors for Colombian Firms:** Does the data gathered as part of the project reveal any particular factors that may influence the dynamics of adoption of AI, AA, and ML technologies at assessed Colombian firms?
- **AI Adoption and Perceived Performance Link:** Is there a statistically significant relationship between the level of adoption of these technologies and the perceived level of performance of assessed Colombian firms? This specific question offers a novel approach to academia, based on the results obtained from the literature review.

Additional Considerations:

This section also critically evaluates the following elements:

- Implications for understanding ICT adoption from an organizational perspective, particularly in the context of Colombian firms when compared to other academic research performed from the perspective of organizations located in developed economies.

- Related relevant academic literature that can be used to contrast the obtained results and that can serve to interpret its validity in the context of IS and business management fields.

5.1 Factors influencing the adoption of AI technologies at Colombian firms

The primary research objective for this research was to determine whether sufficient evidence exists to explore a potential, significant, and independent influence of a specific set of technical, organizational, and relational factors on the levels of AI technology adoption and perceived competitiveness. In addition, another research objective was to determine whether the impact of these factors on the level of perceived competitiveness was mediated by the level of AI technology adoption. These direct and indirect relationships were analyzed using an SEM-PLS approach applied to the data collected with the use of an online survey instrument.

To address this research objective, four hypotheses were formulated as follows:

Hypothesis # 1

- ***Hypothesis 1A.*** Technical factors positively influence the levels of IA adoption of Colombian firms.
- ***Hypothesis 1B.*** Technical factors positively influence the levels of perceived competitiveness of Colombian firms.

Hypothesis # 2

- ***Hypothesis 2A.*** Organizational factors positively influence the levels of AI adoption of Colombian firms.
- ***Hypothesis 2B.*** Organizational factors positively influence the levels of perceived competitiveness of Colombian firms.

Hypothesis # 3

- ***Hypothesis 3A.*** Relational factors positively influence the levels of IA adoption of Colombian firms.
- ***Hypothesis 3B.*** Relational factors positively influence the levels of perceived competitiveness of Colombian firms.

Hypothesis # 4

- ***Hypothesis 4A.*** Levels of AI adoption positively influence the levels of perceived of competitiveness of Colombian firms.
- ***Hypothesis 4B*.** The relationship between technical, organizational, and relational factors and the level of perceived performance (as a proxy for competitiveness) at Colombian organizations is mediated by the level of adoption of AI technologies.

A series of PLS structural models was subsequently developed to examine potential relationships between the three sets of factors and the two dependent variables. The first category, technical variables, was operationalized into two reflective constructs: Technical Digital Maturity (TDM) and IT and Data Complexity and Integration (IDCI), based on relevant IS and business management literature on AI technologies.

TDM encompasses elements such as IT management and digital initiative departments, robust IT infrastructure, recent ICT investments, and the intensity and usability of deployed digital ICTs for business purposes. Previous research, including studies by such as Brătucu et al. (2024), Schuster et al. (2021), Saari et al. (2019) and Burguess (2018), highlighted TDM as a critical factor for organizational AI adoption.

These studies emphasize the importance of a strong technological foundation, including complementary digital technologies and cybersecurity protocols, to facilitate AI adoption. However, the relationship between TDM and AI adoption in developing countries, particularly Colombia, remains underexplored, as seen in the literature review conducted in Chapter 2.

The results obtained from the first PLS model indicate a strong, positive, and statistically significant relationship between TDM and LAIA for Colombian firms (path coefficient = 0.440, $t = 2.888$, $p < 0.05$). The path coefficient for this construct suggests that a one standard deviation increase in TDM is associated with a 0.440 standard deviation increase in LAIA, holding other variables constant. This represents a strong effect within the SEM-PLS framework.

This strong positive relationship between TDM and LAIA highlights the crucial role of technical and digital foundations for AI adoption among Colombian firms, as it presented the strongest impact within the first PLS model for direct relations.

Micro, small, and medium enterprises (MSMEs), which constitute most of the Colombian business fabric, face a series of obstacles to digital ICT adoption, given challenges such as cost, effort, and resource constraints. For these organizations, a thorough assessment of digital and technical maturity is essential to overcome low levels of

AI adoption, which is currently close to 77% below basic lines, according to Sosa et al. (2021).

Consistent with these conclusions, Verónica Alderete & Gutiérrez (2014) analyzed Colombian services firms and found a strong positive relationship between ICT investments and AI adoption. ICT investments can be considered as a proxy measurement of TDM, so that these authors' results are aligned with those obtained in the first PLS model of the present study.

Osorio-Gallego et al. (2016, p. 25) highlighted that technical complexity, including concerns about reliability, security, and cost-benefit ratios, represents a significant barrier to ICT adoption among Colombian MSMEs, as it connects to *"The fear of the vulnerability of the privacy of their information or the availability of their information"*. These challenges underscore the importance of developing a strong TDM, particularly for these organizations, to address vulnerabilities related to data privacy and availability that allow for rapid AI adoption.

Data complexity and integration (IDCI), defined as part of this research with indicators that measure dimensions such as accessibility, integration, dissemination, completeness, trustworthiness, and usability, has also been considered a critical technical factor for successful AI dissemination and deployment (Aldoseri et al., 2023). However, data quality, volume, and security usually pose significant challenges for MSMEs, underscoring the importance of robust data integration and governance strategies as foundational elements of broader digital and business strategies in general, and the adoption of AI technologies in particular.

Marr (2021) emphasizes the critical role of data integration in the context of a "*data infrastructure*" to support successful AI and data-driven initiatives. The exponential growth of data sources in recent years has made it evident that traditional data management tools have become inadequate for AI projects. Therefore, organizations must develop new technical capabilities to handle the volume, variety, veracity, and velocity of big data sources associated with AI tools. In this context, cloud-based solutions offer a viable option by providing flexible, on-demand resources at lower costs, thereby reducing barriers to entry for firms of all sizes and highlighting once again the importance of TDM as a prerequisite for AI adoption.

Similarly, Fu et al. (2023) identified three key data dimensions within the TOE framework for AI technology adoption: data acquisition (gathering and storage), usefulness, and complexity. The authors emphasize the critical role of data acquisition and its usefulness in enhancing AI capabilities while driving business value and organizational performance.

Well-known theoretical frameworks in the IS field generally identify a strong positive correlation between data integration and complexity and the adoption of AI, AA, and ML technologies. However, in the case of Colombian firms, the results of the first PLS model of the present study did not support the literature.

Although a strong positive correlation (0.658) was observed between these two constructs, their path coefficient between IDCI and AI adoption was negligible (0.030) and statistically insignificant ($t = 0.211$, $p > 0.05$). Consequently, the first hypothesis (H1A), related to the impact of technical factors on the levels of adoption of AI technologies, was only partially supported. Thus, this result seems to be counterintuitive; this may be attributed to the unique economic and organizational context of Colombian firms compared to those operating in advanced economies, where most of the current academic research has been performed.

Recent work by Abadía & Avila (2023) suggests that while cloud computing services have lowered entry barriers of basic IT capabilities for Colombian firms, developing specialized data analytics platforms requires substantial technical and financial investments. As a result, Colombian organizations may not follow a linear path between the definition of data integration and advancements in AI technological adoption because of financial restrictions that can result in individual data repositories (silos) integrated through basic analytics, BI tools, or even manual structures, to provide distinct data perspectives. This reality reduces the potential direct impact of IDCI on LAIA.

In the same line, Grimaldi et al. (2019) studied the relationship between data maturity (a proxy for IDCI) and business performance in terms of customer experience and operational efficiency. They found that while data-driven conditions are essential for the successful AI implementation among Colombian organizations, they are not a sufficient condition to guarantee it.

These elements are consistent with the findings of Rojas-Berrio et al. (2022), who observed that Colombian SMEs acknowledge the importance of a strong technological infrastructure for enhanced data management and improved business outcomes. While these principles appear to support the conclusions of traditional ICT adoption models, they also underscore the challenges arising from limited financial resources and access to specialized support. These financial limitations among Colombian firms significantly impede the development of advanced data platforms and other Industry 4.0 and digital ICTs, which, in turn, may hinder their ability to negatively impact exploration and use of AI technologies, partially explaining the research results.

Organizational factors, the second category of exogenous variables in the first PLS model, comprised three initial reflective constructs: Technical and Digital Competence and

Skills (TDCS), Level of Organizational Culture (LOC), and Definition of Global Digital Strategy and IT Championing (DGSC). However, during the initial SEM analysis, it was identified that LOC and DGSC presented multicollinearity issues, suggesting that their indicators could be measuring similar dimensions of the same phenomenon.

Consequently, a formative higher-order construct was created, combining the individual indicators of Level of Organizational Culture and Digital Strategy (LOC&DS). This decision was theoretically supported based on results from Duerr et al. (2018) and Zhen et al. (2021) that identified the importance of the so-called “*Digital organizational culture*”, a concept that encompasses a joint understanding of organizational practices in a digital context as a motivation to digitalize.

Multiple studies have identified the significance of TDCS and LOC&DS in the adoption and use of digital ICTs, including AI. Bettoni et al. (2021) emphasizes, on the one hand, the role of digital skills in understanding the use of data-driven applications to obtain competitive advantages from various sources and, on the other hand, the role of organizational culture in providing flexibility for experimentation and agility in reorganizing processes around digital ICTs. Both of them jointly facilitate AI adoption among firms.

Bley et al. (2022) extended this view by incorporating TDCS (divided into technical and business skills) as a component of the human resource dimension influencing AI implementation. They identify as key cultural factors different organizational artifacts, values, and assumptions, including manager support for AI technologies, which was proxied by IT championing within TDCS in the PLS model of this research.

The first PLS model, however, showed surprising results for organizational factors with AI adoption. These results challenge some of the existing findings at an organizational level in the literature. While TDCS and LOC&DS initially exhibited strong correlations with

LAIA (0.720 and 0.752, respectively), the SEM analysis revealed modest and statistically insignificant path coefficients (TDCS: 0.039, $t = 0.777$, $p > 0.05$; LOC&DS: 0.062, $t = 0.709$, $p > 0.05$), leading to the rejection of the second hypothesis. Although both constructs demonstrate positive relationships with the observed levels of AI adoption, their influence among Colombian firms appears to be negligible.

Literature suggests potential explanations for the unexpected findings regarding TDCS in the Colombian context. Shakina et al. (2021) identified the occurrence of a "*corporate divide*" among firms, represented by a scarcity of skilled labor that limits a proactive approach to digital ICT adoption. This circumstance forces smaller organizations to rely on external expertise instead of forming their criteria to take advantage of these advancements and to avoid being left behind in terms of competitiveness and positioning. This behavior could partially explain the results of the present study, as Colombian firms may have a lower dependency on internal formation of technical and digital skills, as they initially are forced to procure them from external experts.

Aldoseri et al. (2023) support these findings by demonstrating that due to a shortage of high-skilled talent, firms interested in digital ICTs (such as AI) often tend to outsource critical ICT adoption phases such as development, deployment, and management to highly skilled independent contractors or IT consultants, reducing the potential impact of the lack of personnel and, therefore, reducing the dependence on internal skill formation.

While the existing literature emphasizes the importance of organizational culture and data strategy in fostering intrafirm innovation, risk-taking, experimentation, and agility for digital ICT adoption, previously used definitions of the LOC&DS construct are usually defined with broader dimensions than the one that was used in this research. As a result, some indicators that have been used by other authors as part of the organizational culture construct are aligned in the case of this project with the third factor (relational).

For example, Chang Muñoz et al. (2022) identified a link between organizational culture, represented in internal and external cooperation mechanisms, and the use of computerized tools for business optimization. This dimension aligns with the concept of open innovation, included within relational factors for the PLS models of this study.

In a study of AI readiness, Jöhnk et al. (2021) also identified organizational culture as a critical factor for the adoption of AI technologies, alongside strategic alignment, resources, knowledge, and data. In particular, these authors concluded that while these factors are generally applicable among firms, a context-specific analysis is essential to determine if any of them have a higher prevalence over the others. In the case of Colombian firms, financial and technical resource importance might overshadow the influence of organizational culture and human resources when considering AI adoption at a business level, which could explain the results of the present study.

Rowland & Carroll (2022) examined organizational motivations related to the definition of a digital strategy for AI adoption through the lens of exploration and exploitation theory, identifying four stages: exploration, exploitation, embedment, and emergence. They argue that rather than a prerequisite for AI adoption, a well-defined digital strategy often emerges because of AI implementation.

By emphasizing the concept of organizational ambidexterity, the authors propose a circular feedback relationship between AI dissemination and the definition of a digital strategy rather than a causal one. According to this proposal, AI integration drives strategy refinement and evolution, allowing for a series of possibilities and value paths, which accordingly result in a more robust digital strategy. This could potentially explain the results obtained in the first model, as Colombian firms might be leveraging AI use to strengthen their digital strategy.

Relational factors for the first PLS model included Level of Open Innovation (LOI) and Level of Relationship Strategies and Competitive Pressure (LRS). However, exploratory analysis also revealed multicollinearity issues between these constructs, suggesting that these indicators might be measuring similar phenomena. To address this, once again, a higher-order construct that combined the indicators was defined. Similarly, as with the organizational factors, this approach was based on relevant theoretical frameworks that could support the combination of these first-order constructs.

Lenart-Gansiniec (2016) explored the possibility of interconnections between relational capital and open innovation at an organizational level. They conclude that communication with the environment provides paths for robust relational capital, resulting in improved organizational innovations, especially based on open standards.

D. Ryu et al. (2021) expanded this view from the context of technological innovation capital, demonstrating that strong relational capital at SMEs allows for increased technological innovation capabilities, leading to enhanced international performance based on open innovations. Based on these findings, a higher-order construct (LOI&RS) was defined for the first model.

The SEM-PLS results revealed that this construct presented a high correlation with the LAIA (0.761). Bootstrapping analysis showed a modest path coefficient (0.297) with a statistically significant effect ($t=2,437$, $p<0,05$), which fully confirms the third proposed hypothesis. This result reflected that a variation in 1 standard deviation in LOI&RS is associated with a 0.297 standard deviation increase in the LAIA.

The levels of open innovation have been recognized as a critical factor driving the adoption of AI technologies at an organizational level, confirming the results obtained from this first model. Messeni Petruzzelli et al. (2022) performed an empirical study on a sample of 107 Italian SMEs to assess the impact of LOI on the adoption of Industry 4.0 digital technologies, including big data and analytics technologies. Their results showed a positive relation between LOI and the level of adoption of analytics technologies, especially with its breadth (ability to collaborate with external actors to promote adoption) and depth (intensity of these collaborations, represented in access to different types of resources to support adoption).

Dudnik et al. (2021) delved into the Russian energy industry, finding that AI tools positively impact business outcomes such as process optimization, grid management, and remote monitoring based on large amounts of information derived from Internet of Things (IoT) devices. The study revealed a strong correlation between AI readiness and LOI, emphasizing the importance of open innovation strategies. However, resistance to innovation due to fear, mental unreadiness, and learning aversion shows limitations for AI organizational adoption.

Horani et al. (2023) examined the determinants of AI adoption among 512 IT/IS senior managers, identifying competitive pressure and external vendor support as significant factors within the TOE framework. These factors are proxies and indicators used in the construct of LOI&RS. Accordingly, their findings align with the first PLS model of this study, supporting a positive and statistically significant impact of LOI&RS on AI adoption intensity.

The findings of the first model also aligned with the study performed by Arias-Pérez et al. (2023), who analyzed the effect of competitive pressure on the intention to adopt AI technologies for information services, computer programming, wholesale and retail trade, and financial and insurance services in Colombian firms.

This study concluded that competitive pressure, as part of a relational strategy, has a positive moderating effect aligned with the opportunity to adopt digital ICTs (such as AI) on higher organizational impact. This study also identified that higher levels of technical and digital maturity (related to TDM) are obtained by relational capital, allowing to tackle issues of incompatibility between digital resources and technological capabilities in a more effective manner.

Table 49 summarizes the findings for the first component of the first PLS model, including their alignment with the proposed hypothesis and related relevant literature:

Hypothesis	Result	Supporting literature
H1A (Technical factors on LAIA)	Partially supported. TDM has a statistically significant impact (positive) on LAIA. ($p < 0.05$) IDCI does not show any statistically significant impact on LAIA. ($p > 0.05$)	(Sosa et al., 2021). (Verónica Alderete & Gutiérrez, 2014) (Osorio-Gallego et al., 2016) (Abadía & Avila, 2023) (Grimaldi et al., 2019)
H2A (Organizational factors on LAIA)	Rejected. TDS and LOC&DS do not show any statistically significant impact on LAIA. ($p > 0.05$)	(Shakina et al., 2021) (Aldoseri et al., 2023) (Chang Muñoz et al., 2022) (Jöhnk et al., 2021) (Rowland & Carroll, 2022)
H3A (Relational factors on LAIA)	Fully supported. LOI&RS has a statistically significant impact (positive) on LAIA. ($p < 0.05$)	(Lenart-Gansiniec, 2016) (Messeni Petruzzelli et al., 2022) (Dudnik et al., 2021) (Horani et al., 2023) (Arias-Pérez et al., 2023),

Table 49 *- Summary of results and findings for the first component of the SEM-PLS models*

5.2 Factors influencing the perceived level of performance at Colombian firms

As mentioned in the introduction section of this document, this research project aims to identify factors influencing AI technology adoption among Colombian firms. However, the

IS and business management fields have increasingly recognized the broader organizational and business implications of AI beyond its clear technical capabilities.

In today's competitive global landscape, characterized by increased organizational competitiveness, academia has focused on defining the role of digital ICTs in enhancing organizational functionalities and explored the potential relationship between AI adoption and the formation of dynamic capabilities to improve organizational performance and intra-firm value generation.

As a result, the second PLS model for this research project explored whether the three defined factor categories (technical, organizational, and relational) and the level of AI adoption had a direct impact on the levels of perceived performance for Colombian organizations. To assess perceived performance, a formative construct (level of perceived performance, or LPP) was defined, including indicators that serve as proxy measurements, such as comparative income levels and market share growth, human resource productivity and innovation capabilities, labor attractiveness, product/service suitability, and customer loyalty.

The first part of the inner model examined direct relationships between the two technical constructs (TDM and IDCI) to assess statistical significance. While both TDM and IDCI presented strong positive correlations with LPP (0.803 and 0.783, respectively), the resulting path coefficients from TDM and IDCI to LPP were modest and statistically insignificant (TDM: 0.188, $t = 1.386$, $p > 0.05$; IDCI: 0.216, $t = 1.688$, $p > 0.05$, respectively).

The relationship between these variables has been previously explored in the IS and business management literature. He et al. (2023) examined the link between digital maturity (a proxy used for TDM), organizational resilience, and enhanced organizational capabilities among SMEs, finding that digital maturity and digital transformation enable SMEs to build the necessary capacities to navigate adversity and achieve enhanced organizational performance.

Aguilar-Rodríguez et al. (2021) defined the relationship between digital 4.0 technologies and organizational performance in Latin American economies. They found that a strong technical base (a proxy used for TDM) is a contributing factor for enhanced digital transformation and the formation of capabilities such as customer relations, adaptability to international standards, and new market access.

However, the study also concludes that sociocultural factors have a profound influence on these relations. Using a sample of Peruvian firms, they found stronger connections between Industry 4.0 technology adoption and organizational performance when comparing the results with those found in Colombian firms. This highlights the importance of subtle cultural differences in apparent comparative organizations based on factors such as size or sales.

In relation to data integration and IT complexity, there are varying perspectives among scholars. Ghasemaghaei (2020) utilized the Resource-based value (RBV) framework to examine the relationship between big data processing and organizational performance from the perspective of relevant specific resources for value generation.

Ghasemaghaei's study found that big data technologies, which are related to advanced analytics, can benefit firms' performance, but it also emphasized the need for highly specialized technical tools and sufficient analytical skills that not all firms can afford or rapidly build. Given the financial and human resource constraints of many Colombian firms, once again, it could be argued that the results of the first model reflect a limitation on their ability to implement effective data strategies, reducing the impact data integration may have on organizational performance.

Felipe et al. (2020) explored the relation between IT complexity and perceived performance through the lens of IS capabilities. Their innovative approach revealed that robust technical capabilities mediate the impact of IT complexity on organizational performance by fostering organizational agility. This agility enables organizations to dynamically reconfigure resources, particularly those related to data collection and processing. This effect is especially pronounced in high-tech markets due to their unique demands compared to low- and mid-tech markets.

Hou (2020) provides a complementary perspective, suggesting that IT infrastructure flexibility and integration mediate the relationship between organizational performance and supply chain capabilities for Taiwanese electronic firms. While no direct relationship was found between IT infrastructure and organizational performance, the study highlights the mediating role of organizational capabilities.

These findings could partially explain the results obtained for assessed Colombian firms, which are predominantly low- and mid-tech and characterized by a less pronounced impact of organizational agility through the extensive use of IT platforms. At the same time, the potential mediating role of organizational capabilities is not assessed in this second PLS model, explaining the lack of a significant direct relationship between IDCI and LPP.

The second part of the inner model examined relationships between the three organizational factors defined as part of the model and perceived performance. Due to the previously identified multicollinearity issues between LOC and DGSC described in the previous section, the analysis focused on assessing the higher-order construct LOC&DS.

As a result, the relationships between TDCS, LOC&DS, and LPP were analyzed**.** While both TDCS and LOC&DS exhibited strong positive correlations with LPP (0.783 and 0.787, respectively), the path coefficients were negative, weak, and statistically insignificant for TDCS and positive, weak, and statistically insignificant for LOC&DS, respectively (TDCS: -0.018, $t = 0.092$, $p > 0.05$; LOC&DS: 0.060, $t = 0.514$, $p > 0.05$).

In terms of technical and digital skills, authors such as Tulungen et al. (2022) examined the relationship between digital leadership, digital skills, and organizational performance using a sample of Indonesian firms and an exploratory analysis methodology. Their PLS analysis revealed a positive and significant direct impact of digital leadership on performance. However, the indirect relationship through digital skills was weak and non-significant, potentially due to the time and effort that is required by firms to build a strong digital knowledge base and digital literacy before acquiring internal digital skills.

Shin et al. (2023) conducted a similar study on Korean firms using SEM-PLS derived from the RVB framework. Their work confirmed a significant direct relationship between digital leadership, human resource digital capabilities, and organizational performance. While human resource digital capabilities played a mediating role, they emphasized the importance of the findings in the context of Korea's advanced digital landscape and the necessity to evaluate its applicability in other latitudes.

Given these findings, it could be inferred that the impact of human resource digital capabilities on firm performance may be less pronounced compared to organizations placed on more advanced economies as a result of technical talent scarcity and challenges for internal skill development in Colombian firms.

Shahzad & Luqman (2012) studied the relation between organizational culture and digital strategies on LPP. Their review of over 60 studies performed on organizations of all industries and sizes revealed four types of LOC: counter, sub, strong, and weak. This analysis showed that a positive relation between LOC and LPP exists, emphasizing that the impact of organizational culture on job performance, competitive advantages, and ultimately, organizational performance is clear.

Martinez Avella (2010) explored the relationship between organizational culture and organizational performance using the Denison model (Denison & Janovics, 2000), based on dimensions such as involvement, consistency, adaptability, and organizational mission for selected Colombian firms. While the study identified potential associations between both constructs, it also concluded that determining causality may require the consideration of additional factors beyond those explored within the Denison model, such as regional or country cultural context.

This may suggest that theoretical models developed in other economic contexts, such as the TOE and DOI, may need a profound level of adaptation to account for subtle organizational and cultural differences in emerging countries, such as Colombia, which partially explains the results obtained in the second PLS model of this study.

Leischnig et al. (2016) examined the relationship between digital strategy and organizational performance within 121 European firms, with interesting results. Their study found that the presence or absence of a clearly defined digitalization strategy could influence market performance, depending on the combination of various organizational and environmental factors. The results showed that industries with high dependency on individual consumers for revenue generation (e.g., online retailers) are more likely to benefit from digital ICT adoption, as these technologies allow firms to gain flexibility and adaptability in responding to changes in demand. In contrast, industries with more stable demand (e.g., manufacturing) may focus on leveraging traditional ICTs for efficiency and operational improvements rather than adopting emerging ICTs.

Given the rapid evolution and novelty of disruptive digital technologies such as generative AI or deep learning, it could be possible that the result of this study reflects that Colombian firms may not be considering their use in the immediate future due to technical and human resource limitations, scarce IT budgets, and limited in-house skills, among other constraints that might hinder their ability to fully embrace these technologies. As a result, Colombian firms might not see the link between AI adoption and the potential organizational impacts, which explains in part the results obtained.

Regarding the relational factors, the second PLS model focused on the higher-order construct LOI&RS due to the multicollinearity of the individual constructs initially defined. The analysis revealed a strong positive correlation (0.840) and a significant positive path coefficient (0.418, $t = 2.530$, $p < 0.05$) between LOI&RS and LPP, making it the only factor with a fully statistically significant relationship, similar to that with LAIA.

Cuevas-Vargas et al. (2022) explored the relationship between open innovation, ICT adoption, organizational performance, and absorptive capacity using a sample of 145 small firms located in Bogotá (Colombia's capital city). Absorptive capacity is a measurement of how well organizations integrate new external knowledge and capabilities and turn them into tangible assets to enhance their competitiveness. The integration of new external knowledge requires interacting with other organizations under an open innovation approach.

This study found that firms foster open innovation to enhance organizational performance, including strengthening their ability to identify, process, store, analyze, and share information both internally and externally. In this regard, their findings demonstrate that this principle holds across various industries, revealing that micro-sized firms derive significant benefits from rapid information flows, which facilitate expedited decision-making processes and accelerate new product development.

A limited number of studies have explored the relationship between relational strategy and organizational performance in the Colombian context. Aramburu et al. (2015) examined the connection between structured capital, innovation capabilities, and organizational performance for Colombian technology-based firms.

This study theorized that a strong relational strategy with external actors can foster innovation, leading to enhanced organizational performance. The results obtained for relational strategy in the first PLS model of this study are in line with Aramburu et al. (2015) findings, as collaboration with professional networks seems to be crucial for fostering organizational innovation. However, it is important to keep in mind that while relational strategy can certainly enhance innovation, it does not guarantee a direct impact on financial performance on its own.

Finally, the second PLS model also assessed the potential impact of the level of AI adoption on perceived organizational performance at the assessed Colombian firms. Agarwall et al. (2022) studied a sample of Indian companies operating across different industries to assess their financial performance before and after the AI era. The analysis was based on two indicators: operating cost and profit.

The results of their analysis showed that AI has a direct positive impact on organizational performance, increasing in most cases the observed levels of operating profit while maintaining average operating costs, especially for firms located in the IT industry. This finding recognizes that AI adoption requires high levels of capital investments, skilled human talent, and IT infrastructure, which can in turn initially affect financial indicators, and thus, organizational performance.

Iwuanyanwu (2021) conducted a comprehensive study involving 330 American firms to investigate the relationship between AI adoption and organizational competitiveness. This study revealed a direct and statistically significant positive relation between these two variables. The observed benefits extended beyond financial gains, encompassing improvements in efficiency, turnaround times, customer satisfaction, and the quality of service, which are metrics that align with the indicators used for the LPP variable in our second PLS model.

However, the authors also highlighted the substantial capital investments required for successful AI deployment within organizations. The study emphasized that these investments may not yield significant returns on capital (ROC) in the short term. Instead, a medium-to-long-term perspective is crucial. The authors recommend that organizations manage their expectations accordingly, recognizing that the initial phases of AI adoption may involve substantial negative cash flows before yielding visible financial returns.

Although the results for the second PLS model showed a strong positive correlation (0.659) between LAIA (Level of AI Adoption) and LPP (Level of Perceived Performance), the path coefficient was found to be positive but also weak, and statistically insignificant (LAIA: 0.064, $t = 0.460$, $p > 0.05$). This finding appears to contradict the results of the aforementioned previous studies, which have identified AI adoption as a key driver of enhanced competitiveness and organizational performance.

However, this discrepancy may be attributed to the fact that most of the firms participating in the study are in the early stages of AI experimentation. They may not have yet fully realized the potential benefits of AI adoption. This interpretation is further supported by the finding that a significant proportion of firms with AI test or productive projects in place had not defined specific key performance indicators (KPIs) or specialized measurements to evaluate the potential impact of their current AI initiatives.

Table 50 summarizes the findings for the second component of the first PLS model, including their alignment with the proposed hypothesis and related relevant literature:

Hypothesis	Result	Related existing literature
H1B (Technical factors on LPP)	Rejected. Neither TDM nor IDCI shows a statistically significant impact on LPP. ($p > 0.05$)	(He et al., 2023) (Aguilar-Rodríguez et al., 2021) (Ghasemaghaei, 2020)(Felipe et al., 2020)(Hou, 2020)
H2B (Organizational factors on LPP)	Rejected. Neither TDS nor LOC&DS shows any statistically significant impact on LPP. ($p > 0.05$)	(Tulungen et al., 2022) (Shin et al., 2023) (Shahzad & Luqman, 2012) (Martinez Avella, 2010) (Leischnig et al., 2016)
H3B (Relational factors on LPP)	Fully supported. LOI&RS has a statistically significant impact (positive) on LPP. ($p < 0.05$)	(Cuevas-Vargas et al., 2022) (Aramburu et al., 2015)
H4A	Rejected. LAIA does not have a statistically significant impact on LPP. ($p > 0.05$)	(Iwuanyanwu, 2021) (Agarwall et al., 2022)

Table 50 *- Summary of results and findings for the second component of the SEM-PLS models*

5.3 Mediating role of AI adoption for technical, organizational, and relational factors on the perceived level of performance at Colombian firms

The final hypothesis of this research aimed to define a potential mediating role of the levels of AI adoption between the three categories of factors (technical, organizational, and relational) and the levels of perceived performance for Colombian firms. As highlighted by the resource-based view (RBV) and dynamic capabilities frameworks, the value of digital ICTs extends beyond their inherent technical capabilities. These frameworks emphasize that the true value of emerging technologies lies in a firm's ability to leverage them to create a sustainable competitive advantage by effectively integrating them into their core operations and adapting to the evolving business landscape.

As a result, a third SEM-PLS model was designed to examine the mediating role of LAIA (Level of AI Adoption) between the exogenous constructs (technical, organizational, and relational factors) and the endogenous construct (LPP - Level of Perceived Performance). For this model, all exogenous constructs were directly connected to LAIA, which in turn was directly connected to LPP.

As mentioned in previous sections of this chapter, the first and second PLS models revealed significant relationships between TDM (technical and digital maturity), LOI&RS (level of open innovation and & relational strategy), and LAIA (level of AI adoption) (partially supporting H1A and fully supporting H3A), as well as between LOI&RS and LPP (level of perceived performance - fully supporting H3B). However, the results of the third model measuring the mediation effects show significantly different findings.

The mediation analysis surprisingly revealed that none of the exogenous factors (TDM, IDCI, TDCS, LOC&DS, or LOI&RS) exhibited a statistically significant relationship with LPP through LAIA. All resulting path coefficients for specific indirect effects were positive but weak (lower than 0.1 in all cases), and all t-statistics and p-values indicated non-significant impacts (all greater than 0.05). This suggests that LAIA does not have a discernible mediating effect on the relationship between technical, organizational, or relational factors and the level of perceived performance at assessed Colombian organizations when compared to their direct relationships.

In terms of the potential mediating role of AI adoption on the impact of TDM on organizational performance, insights can be drawn from the work of Bati Almasradi et al. (2022). Their study, conducted on Pakistani firms, examined the relationship between electronic HR management capabilities (communication, training, recruitment, compensation, and performance appraisal), ICT adoption, and organizational performance within the framework of the Resource-Based View (RBV).

This study found that ICT adoption mediates the relationship between HR management capabilities and perceived performance, as ICTs enhance organizational capabilities and streamline processes, allowing for higher agility, automation, and simplicity. However, this mediating relation requires a series of technical capabilities that are gradually built over time as these technical innovations are explored, tested, fully adopted, and deployed.

In the case of AI technologies, it is evident that the results show that most of the assessed Colombian organizations are primarily in the early stages of experimentation. This suggests that these firms have not yet reached a point where they can significantly improve business results by automating manual and repetitive tasks, thereby preventing them from achieving stronger technical maturity, enhanced capabilities, and, ultimately, improved organizational performance solely by employing AI technologies.

Fonseka et al. (2022) also examined the impact of e-commerce platform adoption and AI on organizational performance in Sri Lanka. Their study found that AI acts as a mediator, enhancing the relationship between e-commerce adoption and performance by providing valuable features like increased efficiency, customer segmentation, improved shopping experiences, and overall customer satisfaction– all business outcomes defined within the context of digital and technical maturity. However, the study emphasizes that these technologies must be fully deployed and integrated within productive projects to benefit from these advantages.

Thus, given that most Colombian firms assessed in this study are still in the early stages of AI adoption, they may not have yet reached the level of AI integration observed in the Sri Lankan context. This suggests that, despite the significant potential for AI to enhance organizational performance, achieving this potential requires a more advanced level of AI implementation and integration that is not captured with the data gathered in this research.

While Colombian firms might benefit from the use of AI technologies to enhance the effectiveness of other digital ICTs that are signals of TDM (e.g., CRM, ERP, cloud computing, IoT, and big data), the findings of the present study also suggest that there is a learning curve that must be overcome to fully realize the advantages of AI adoption. By automating and optimizing repetitive processes and providing improved inputs, AI has the potential to significantly amplify the impact and capabilities of these technologies on organizational productivity and performance, which is in line with the Resource-Based View (RBV) perspective. However, it is crucial to acknowledge that these benefits may not materialize immediately and may require a significant investment of time and resources to be explicit.

This interpretation finds support in the work of Wamba-Taguimdje et al. (2020). An in-depth analysis of over 500 IT industry-specific case studies revealed that 179, 379, and 455 cases, respectively, demonstrated that infrastructure flexibility, automation, and information effects– proxy measurements for TDM, have significant positive impacts on AI capabilities. Furthermore, this study showed that enhanced AI capabilities subsequently positively influence its reach within the context of organizational processes and overall agility, which can ultimately influence organizational performance.

While the third model in this study aimed to assess the potential mediation of LAIA (Level of AI Adoption) between TDM and LPP, it may not fully account for the dynamic nature of process-oriented capabilities that evolve in the context of AI adoption. This limitation could partially explain the unexpected results of the mediation analysis, where no significant mediating effect of LAIA was observed.

While TDS (technical and digital skills) and LOC&DS (level of organizational culture & data strategy) may appear directly related to the process of AI adoption and its impact on perceived organizational performance (LPP), the findings of the third model, which revealed a non-statistically significant mediation effect of LAIA (level of AI adoption), may not be entirely surprising.

Yu et al. (2023) highlighted that while AI adoption has a direct relationship with performance at individual, organizational, and employment levels, it also interacts with various organizational factors. These factors include organizational structures (where organizational culture is embedded) and technical subsystems (which encompass practices and knowledge). However, they also emphasized that the impact of AI adoption can be significantly influenced by external environmental factors such as competitive pressure and government regulations, which are partially captured within the LOI&RS (level of organizational innovation & relational strategy) construct in this study.

Concerning the set of relational factors, Alhosani & Safian (2024) further explored the mediating role of AI between innovation (marketing, management, and process) and organizational performance with the definition of an adapted framework. Their findings suggest that AI fully mediates the specific relationship between management innovation and observed performance and partially mediates the specific relationship between process innovation and performance.

The study concluded that AI could enhance organizational capabilities, leading to increased competitiveness and performance. However, it does so from the perspective of a very specific set of innovation factors (management and process) that differ from the ones that were defined for the level of open innovation (LOI) construct in this third model.

At the same time, while the first and second models of the present study provided evidence that, in Colombian firms, LAIA and LPP are positively influenced by relational and innovation capabilities (represented in LOI&RS), the results of the mediation model could be non-significant due to the lack of distinction between the separate components of the construct LOI&RS. Chen et al. (2022) explored the impact of AI on creativity within the Chinese e-commerce industry and found that the former can positively influence the latter by automating repetitive tasks, which allows for greater focus on innovation. They also found that AI can enhance market and customer assessment capabilities, supporting strategic decision-making and enhanced performance.

In this case, rather than having a mediation relation between LOI and LPP through LAIA or a direct relation between LAIA and LPP, their study found that the LAIA and LPP relation is mediated by LOI.

Olan et al. (2022) explored the relationship between AI use, knowledge sharing, and organizational performance. Their study found that AI capabilities can positively moderate the relationship between knowledge sharing and performance. AI technologies enhance employee interaction, which fosters knowledge sharing and ultimately improves organizational efficiency. However, AI technologies themselves do not guarantee improved performance. They must be combined with other IT and AI initiatives to drive results based on a combined approach between knowledge sharing and technical capabilities. This is a possible explanation of the results obtained in this research.

Surprisingly, firm size, included as a control variable, did not exhibit significant effects on the endogenous variables in this study, neither in the models measuring direct relationships nor in the one measuring mediation. While previous research by Alekseeva et al. (2020) or Cho et al. (2022) suggests that firm size influences AI adoption and performance, the results of the third model in the present study indicate that firm size is not a significant predictor of these endogenous variables.

One possible explanation for this result lies in the composition of the sample, which consists primarily of large enterprises (approximately 58%). The relatively small proportion of micro, small, and medium-sized enterprises may have limited the ability of the models to detect a significant effect of firm size.

Table 51 summarizes the findings for the mediation component for the second PLS model, including their alignment with the proposed hypothesis and related relevant literature:

Hypothesis	Result	Related existing literature
H4B (LAIA mediation for technical factors on LPP)	Rejected LAIA does not show a statistically significant mediation impact, neither for TDM nor ICDI on LPP ($p > 0.05$)	(Bati Almasradi et al., 2022) (Fonseka et al., 2022) (Wamba-Taguimdje et al., 2020)
H4B (LAIA mediation for organizational factors on LPP)	Rejected. LAIA does not show a statistically significant mediation impact, neither for TDS nor for LOC&DS on LPP ($p > 0.05$)	(Yu et al., 2023)
H4B (LAIA mediation for relational factors on LPP)	Rejected LAIA does not show a statistically significant mediation impact for LOI&RS on LPP ($p > 0.05$)	(Ebraheem Esmaeel Saleh Alhosani & Ezwan Mohd Safian, 2024) (D. Chen et al., 2022) (Olan et al., 2022)

Table 51 *- Summary of results and findings for the third component of the SEM-PLS models*

6. CONCLUSIONS, IMPLICATIONS, AND POTENTIAL LIMITATIONS

AI has emerged as a transformative force, reshaping industries and driving economic growth. In the past decade, technologies such as advanced analytics (AA), machine learning (ML), and deep learning (DL) have become indispensable tools for organizations seeking sustainable competitive advantage and value creation. While previous digital technologies were often viewed as enablers of strategic capabilities, AI has emerged as a necessity for organizations seeking to achieve market competitiveness. In other words, it has become a critical factor to maintain a strong market position and drive sustainable growth.

Despite the surge in academic interest in AI technologies, there is still a significant gap in research examining the factors that enable or hinder AI adoption, as well as in research examining the impact that AI has on organizational performance.

In fact, while numerous studies have explored AI's potential impact at an organizational level, there is still a scarcity of research examining the relationship between AI adoption and organizational performance, particularly in emerging markets such as Colombia. Understanding this relationship is crucial for policymakers, practitioners, and organizations to develop effective and adaptive AI deployment strategies that can improve the economic growth of emerging countries.

Although existing methodological and theoretical frameworks developed over the last years have been used independently to study ICT adoption and organizational performance (i.e., the technology, organization, and environmental and diffusion of innovations models along with the dynamic capabilities theory), this research aimed to define a novel framework adapted to simultaneously explore in a sample of Colombian organizations the relationships between technical, organizational, and relational factors, on the one hand, and AI adoption and perceived performance, on the other hand. By combining different approaches, this research hopes to generate valuable insights.

Using a quantitative approach and a comprehensive online survey, this study analyzed responses from 90 Colombian business and technical leaders across various industries and regions. The results of this instrument were used to define a series of structural equation models based on partial least squares (SEM-PLS). These models include technical, organizational, and relational factors as explanatory variables of both AI adoption levels (LAIA) and perceived performance levels (LPP), and they are tested in a sample of Colombian firms.

In terms of the level of AI adoption (LAIA), only technical factors, specifically technical and digital maturity (TDM), demonstrated a significant positive relationship. This finding aligns with previous academic research that has highlighted the importance of technical capabilities in driving intrafirm AI adoption.

In particular, the results suggest that factors such as investments in other digital technologies (e.g., cloud computing, big data), open and user-friendly technical platforms, dedicated organizational units for platform management, and robust data security protocols are crucial for successful intra-firm AI adoption. These findings provide valuable insights for organizations seeking to advance their AI initiatives and could serve as an indicator of potential initiatives that new firms should prioritize to successfully advance in the deployment of AI.

Surprisingly, the results from the model indicated that IT and Data Complexity & Integration (IDCI) did not have a significant impact on AI adoption. While previous studies have defined data integration as a crucial factor for AI success, the specific context of Colombian firms, particularly MSMEs, may be unable to invest in robust data management practices due to financial and technical restrictions. These firms may prioritize AI adoption over data quality and governance with the hope of maintaining a competitive edge, which potentially forces them to use data sources in as-is formats.

Although data integration and complexity are essential for optimal AI implementation, the findings of this research suggest that Colombian firms may be prioritizing AI adoption while addressing data challenges as a secondary objective. This highlights the importance of simultaneous efforts in data quality and experimentation to maximize the potential benefits of using AI, rather than making these efforts sequential steps. The simultaneous combination provides a flexible approach for firms seeking to rapidly adopt AI technologies.

Regarding organizational factors, based on the results of the present study, neither Technical and Digital Skills and Competence (TDCS) nor Level of Organizational Culture and Digital Strategy and Governance (LOC&DS) displayed statistically significant impacts on AI adoption in Colombian firms. While these factors are often considered crucial for AI implementation, the specific context of Colombian organizations may influence their relative importance.

Previous studies have shown that digital literacy and data management skills are critical elements for AI adoption, but Colombian firms may face challenges in acquiring and retaining skilled talent. This limitation may lead organizations to rely on external consultants or vendors for AI implementation, reducing the potential impact of this factor.

In other words, while technical and digital skills are of high importance for AI adoption, a potential explanation of the results in this regard is that Colombian firms may prioritize external collaboration and open innovation to overcome internal skill limitations, dynamics that are assessed in the relational component of the models tested in the present study. This approach allows for the acquisition of expertise and the gradual development of internal capabilities with knowledge-transfer flows, which enables firms to progress in their AI adoption journey with the use of external support.

Similarly, neither the Level of Organizational Culture nor the Digital Strategy definition (LOC&DS) displayed a statistically significant impact on AI adoption. While these factors are often considered key elements for AI implementation in previous studies, the findings of the first model in this study suggest that they may not be critical for Colombian firms.

The lack of significant impact of organizational culture and digital strategy may be attributed to the specific context of the Colombian market and its organizations. These factors may be intertwined with dimensions measured by relational factors on the model, such as industry dynamics and regulatory environments, which could influence AI adoption. Additionally, organizational culture may require factoring not only intra-firm elements defined in the scope of this project but also the external organizational context that, in the case of Colombian firms, is represented by extreme restrictions and frugality when compared with firms placed in developed economies.

The alignment between digital strategy and business strategy has been identified in IS literature as an imperative for successful AI adoption. However, the results of this research suggest that this may not be a prerequisite for Colombian firms, as has been observed with other disruptive technologies in other emerging markets. A circular relationship between business strategy, digital strategy, and AI adoption, rather than a linear one, may be more prevalent in the Colombian market. This is because firms may have been prioritizing AI implementation to drive digital transformation and enhance their strategic capabilities instead of developing a defined digital strategy to provide a baseline for AI implementation.

Finally, the results of this research also indicate that the Level of Open Innovation and Relationship Strategy (LOI&RS) shows a statistically significant positive impact on the levels of AI adoption. This finding aligns with existing research suggesting that collaboration with external partners can facilitate AI adoption, particularly in emerging markets like Colombia, which is characterized by high resource limitations.

This research considered LOI as the organizational ability to develop collaborations with external actors to enable transformational capabilities. This concept aligns with existing research that highlights the importance of external collaboration for AI adoption. Small organizations with limited resources, such as Colombian ones, may be leveraging partnerships with external experts to acquire necessary skills and capabilities to accelerate their AI initiatives and drive positive business outcomes. This stresses the importance of fostering extended ecosystems and external integration to leverage effective AI use.

The significant impact of RS on LAIA can be attributed to the intense competitive pressure and fear of missing out (FOMO), which drives organizations to adopt AI technologies. As the global market becomes increasingly digital and integrated, Colombian firms may be compelled to embrace AI to remain competitive against native-digital players. This aligns with the global trend of organizations leveraging AI to maintain their market position.

The result from the structural model also sheds light on the relationship between the three explanatory factors analyzed, the level of AI adoption, and the level of perceived performance. Interestingly, among the explanatory factors, only the relational one showed a significant impact on LPP, while technical and organizational factors did not.

While research suggests a positive relationship between technical factors (TDM and IDCI) and organizational performance, studies on emerging markets, including Colombia, indicate that this relationship may be less critical. Contextual factors, such as resource constraints and market dynamics, can influence the impact of technical capabilities on performance.

Colombian firms may face limitations in developing strong technical capabilities and data governance due to resource constraints (human and financial) and a challenging business environment. To overcome these challenges, they may adopt adaptive and flexible strategies, leveraging frugal innovations to maximize the impact of their AI initiatives with lower levels of technical investments, since most of them are not categorized as high-tech firms.

This suggests that Colombian firms may not rely solely on technological factors such as technological platforms and data integration to achieve high performance. Instead, a combination of technological capabilities, organizational agility, and strategic partnerships may be essential for driving business success.

The structural model also revealed that neither technical and digital skills (TDCS) nor organizational culture and digital strategy (LOC&DS) had a statistically significant impact on perceived performance. Although previous research suggests a positive link between these factors and organizational performance, the specific context of Colombian firms, including resource constraints and skill shortages, may once again mitigate their influence.

Previous research also suggests a positive link between digital skills and leadership with organizational performance, as it allows for improved use of digital ICTs to improve business processes, agility, and flexibility. However, the specific context of emerging markets like Colombia may reduce the influence of these relationships. Factors such as limited access to skilled talent and high training costs may limit the impact of digital capabilities on performance, which partially explains the results obtained in this research.

Moreover, the basic assumptions of previous research in other geographical locations may be different, especially in developed economies.

Regarding LOC&DS, while previously developed frameworks have shown a positive link between organizational culture and digital strategy with performance, the specific context of emerging economies, such as Colombia, may influence these relationships. Factors such as economic constraints and cultural nuances may limit the extent to which Colombian firms can invest in developing strong organizational cultures and digital strategies. Prioritizing other areas, such as operational efficiency and cost reductions, may take precedence over long-term strategic initiatives regarding these elements, requiring that current theories, such as the RVB model, need profound adaptations to be correctly applied in our geographies.

Current research also suggests a potential link between digital strategy definition and organizational performance, although the impact may be contingent on various factors, including industry characteristics and organizational context. In the case of low-tech industries, the influence of digital strategies on performance may be less pronounced. Firms in these industries may prioritize leveraging existing digital technologies to improve efficiency and productivity rather than investing in complex digital transformations that may also require higher learning curves and the formation of technical-specific skills.

Similarly to LAIA, relational factors (LOI&RS) were the only ones with a significant relationship with perceived performance. This finding underscores the importance of open innovation and external collaboration for Colombian firms, especially MSMEs. By leveraging external knowledge and resources, these firms can overcome internal limitations and enhance their overall performance. This positive impact of external collaboration can be attributed to the benefits of open innovation ecosystems, which provide access to knowledge, skilled talent, and technical support. By leveraging these resources, firms can enhance their decision-making capabilities and overall performance.

Although research assessing relational strategy and its influence on organizational performance is limited, particularly in the context of Colombian firms, the findings of this study align with the few existing studies in the literature, suggesting that external collaboration can significantly impact organizational performance.

By leveraging professional networks and strategic partnerships, Colombian firms can access valuable knowledge, resources, and opportunities to enhance their competitive position. This is particularly evident in the role of professional networks and relationships among first-line and second-line managers, as these connections can facilitate knowledge sharing, collaboration, and access to resources, markets, and clients.

One surprising finding of the second PLS model in this study was the statistically nonsignificant direct relation between levels of AI adoption and perceived performance at assessed Colombian firms. Even if this result may appear counterintuitive, it suggests that AI adoption is a dynamic process that unfolds over time if one considers the conclusions from other studies on this topic.

Firms need to navigate a learning curve that encompasses various stages, including prospection, assessment, testing, deployment, and the productive use of these technologies to achieve tangible business outcomes. Given that most of the organizations participating in this study were in the early stages of this learning curve, it's plausible that they have not yet reached a point where AI adoption has translated into measurable improvements in key performance indicators (KPIs) related to competitiveness, operational efficiency, or financial performance.

This may explain the lack of a statistically significant direct relationship between AI adoption and perceived performance. As these firms move up in the AI adoption curve, they will continue to integrate AI into their operations and refine their AI strategies. In such a case, they are likely to experience more significant and measurable performance improvements over time.

Finally, the model did not reveal a significant mediation effect of AI adoption (LAIA) on the relationship between independent variables (technical, organizational, and relational factors) and perceived performance (LPP). This suggests that, regardless of its direct influence on organizational performance, AI adoption may not necessarily mediate the impact of explaining factors on perceived performance.

The lack of a significant mediation effect between AI adoption and organizational performance may seem counterintuitive. However, it is important to consider the potential time lag between AI implementation and observable performance outcomes. The survey captured a snapshot in time, which may not fully reflect the long-term impacts of AI adoption. As organizations move beyond the experimental phase and integrate AI into their core operations, its impact on performance is likely to become more pronounced, with direct and measurable business impacts represented by either KPI or OKR improvements.

Surprisingly, firm size did not have a significant impact on the direct and indirect relationships between the defined variables of the model. While firm size has often been considered a factor influencing AI adoption and performance among scholars, the results suggest that other factors may play a more dominant role in the Colombian context.

This may be due to the specific challenges and opportunities faced by Colombian firms, regardless of their size. In fact, smaller and medium-sized enterprises (SMEs) may exhibit greater agility and adaptability, allowing them to leverage AI technologies effectively, despite resource constraints. This suggests that firm size may not be a decisive factor in AI adoption and performance in the Colombian context.

6.1 Implications for Practitioners

This study offers several actionable insights for business leaders and managers seeking to leverage AI for enhanced organizational performance, particularly within emerging markets using Colombian firms as a reference.

1. The significant impact of technical and digital maturity on AI adoption highlights the importance of strategic investments to define a robust digital infrastructure. Therefore, organizations should make it a priority to upgrade their IT systems, focusing on elements such as data quality and digital-ready applications. Potential investments to foster AI adoption should include elements such as cloud computing, big data analytics, and user-friendly technical platforms.
2. The strong positive relationship between open innovation, relationship strategy, and both AI adoption and perceived performance underscores the value of external collaboration. Organizations should actively seek partnerships with external experts, research institutions, and technology providers to acquire the necessary skills and resources for successful AI implementation. This collaborative approach may prove useful to overcome internal limitations, accelerate AI initiatives, and drive technology-based innovation.
3. The results of this project also show that IT and data complexity & integration did not significantly impact AI adoption. This suggests that some Colombian firms may be prioritizing AI adoption over data management initiatives, possibly as a result of competitive pressure. Despite this strategy, which may offer short-term gains to accelerate AI usage, it is crucial to address data challenges, which are still a critical issue for AI dissemination and application. Organizations should

invest in data governance, integration, and quality management to ensure the long-term success and scalability of their AI initiatives, prioritizing a flexible approach that defines data quality efforts with AI experimentation.

4. Given the unique context of emerging markets and their cultural and social differences with first-world economies, practitioners should develop AI strategies that are adaptable, flexible, and customizable. This includes being open to frugal innovations and focusing on solutions that maximize impact with limited financial, organizational, and technical resources.

6.2 Implications for Policymakers

The findings of this research project also offer valuable guidance for policymakers in emerging economies seeking to foster AI adoption and drive economic growth.

1. Governments could prioritize investments in developing robust digital infrastructure, including high-speed internet access, cloud computing facilities, and data centers. This may foster an enabling environment for AI adoption across various industries.
2. Policies should also encourage collaboration between local firms and international technology providers, research institutions, and universities. This open-collaborative model could facilitate the transfer of knowledge and best practices, accelerating AI adoption and innovation. Incentives for open innovation and public-private partnerships could be particularly effective, especially in emerging countries with high levels of MSMEs characterized by frugality and technical and financial limitations. This could include providing financial assistance, technical support, and access to training programs.
3. Recognizing the importance of technical and digital skills, policymakers could invest in public education and training programs to develop a skilled workforce

capable of implementing and managing AI technologies. This may include promoting general STEM education, providing vocational training, and supporting lifelong learning initiatives to keep up with continuous technical developments.

4. As AI adoption increases, policymakers could also develop clear regulatory frameworks and ethical guidelines to ensure the responsible and equitable use of these technologies. This includes addressing issues related to data privacy, security, and algorithmic bias.

6.3 Implications for Academics

While the scope of this research is exploratory, its results and conclusions contribute to the growing body of academic literature on AI adoption and offer guidelines for future research.

1. The results of the different models highlight the importance of contextualizing existing theoretical frameworks, such as the TOE framework and Dynamic Capabilities Theory, to account for the specific characteristics of emerging markets in relation to AI adoption and its impact on organizational performance. Future research should explore how these theories can be adapted and extended to better explain AI adoption in different contexts.
2. This project also reflects the complex interplay between organizational culture, digital strategy, and AI adoption in emerging markets, such as Colombia. And while there are several well-known frameworks to study the dynamics of ICT adoption and their potential impact on value creation and competitiveness, most of them lack specificity to examine the specific cultural factors that enable or hinder AI implementation and how organizations can foster a culture of innovation and digital transformation.

3. The result of this research also establishes the importance of longitudinal studies to examine the long-term impacts of AI adoption on organizational performance, recognizing the dynamics of these processes. Future research should use methodologies that address the time lag between AI implementation and observable outcomes, providing a more comprehensive understanding of the relationship between AI and organizational performance.
4. Finally, the results of the present study suggest that future studies could expand the geographical scope to include a wider range of emerging economies, allowing for cross-country comparisons and a more nuanced understanding of the factors influencing AI adoption.

6.4 Limitations and future directions

It is important to note that while developing the methodology and analyzing the results of the online survey, potential limitations of the study were identified that could restrain its generalization. The first limitation relates to sample size. With only 90 valid responses, this study adopts an exploratory approach rather than a confirmatory one. The complexity of the online survey and the number of indicators defined for all PLS models limited the sample size, focusing the analysis on identifying potential relationships between variables rather than establishing definitive causal links.

Given the limited sample size, future research derived from this project should focus on either increasing the sample size through collaborations with external institutions or simplifying the model by reducing the number of indicators and constructs, focusing on those that display the most important relations. These approaches would enhance the generalizability of the findings, allowing for more robust statistical analyses.

A second limitation of the study is the geographical scope. By focusing solely on Colombian organizations, the generalizability of the findings may be limited. Future research could expand the sample to include organizations from other Latin American countries to enhance the validity and generalizability of the results and contrast potential context-specific elements that have been identified as critical in the discussion part of this document.

A third and final limitation relates to the methodological approach. While SEM-PLS is a powerful quantitative and analytic technique, a mixed-methods approach, combining quantitative and qualitative methods, could provide deeper insights. For instance, a multiple-case study design could be employed to explore the findings of the quantitative analysis in more detail and identify additional contextual factors that were potentially overlooked by the definition of the structural model, with the hope of enhanced validity and extendibility.

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8. ANNEXES

a. Online instrument questionnaire (original in Spanish):

https://drive.google.com/drive/u/1/folders/1QTNULEfbCep0a7SCo8iARMaQOvru7ZTK

b. Correlation matrix for SEM-PLS model indicators:

https://docs.google.com/spreadsheets/d/1pWJTRugUmFKsbrt_bAqk3i6dUMzhaFD7/edit?usp=drive_link&ouid=117251528109032770769&rtpof=true&sd=true

c. Results of test sessions for online instrument assessment (In Spanish):

Session # 1 – Experienced Full time Engineering faculty member - Commentaries:

- Revisar la pregunta B7 (sección demográfica), para ofrecer una escala más flexible y menos restrictiva a la inicialmente establecida.
- El alcance de la primera pregunta del cuestionario (D1) es demasiado técnico, revisar su formulación para que sea más digerible.
- Reducir las dimensiones que se evalúan como parte de cada pregunta, ya que puede influir negativamente en la calidad de las respuestas. En este punto, se sugiere que abran en elementos separados para ofrecer elecciones independientes que reduzcan el sesgo en las respuestas que se obtengan.
- Se recomiendo revisar la sección de preguntas de la sección técnica para validar la claridad de su formulación y su entendimiento por parte del personal de negocio.
- De igual forma, revisar si es factible ofrecer un glosario de términos en la sección organizacional para facilitar la respuesta de los participantes con un perfil con conocimiento técnico.

- Validar si es posible consolidar ciertas preguntas que parecen apuntar a recoger percepciones sobre un mismo grupo de conceptos, para facilitar su entendimiento.
- Revisar la redacción de algunas preguntas para que sean más concisas y de fácil comprensión.
- Para el componente de uso de otras tecnologías de información, se sugeriría incluir una pregunta que valide los niveles actuales de inversión como un proxy sobre su adopción.
- Se sugiere validar la escala que se ofrece para cada una de las preguntas del instrumento ofrezcan una ordenación de mayor a menor valoración, y que este esquema se mantenga a lo largo del instrumento.
- Se sugiere que para los participantes que confirmen que sus compañías han empezado a realizar inversiones en tecnologías de IA se validen los potenciales impactos que han tenido, y potenciales uso de métricas (KPIs) que se han definido.

Session # 2 – Experienced Full time Business faculty member - Commentaries:

- Se recomienda para la pregunta D7 (inversiones en otras ICT) se realice validaciones por cada una de ellas de forma independiente.
- Se recomienda revisar la definición de la pregunta D10 para que la métrica de uso de ICTs a nivel de negocio se exprese en una proporción numérica en vez de solo un adjetivo (mayoría).
- Se recomienda segmentar las preguntas relacionadas con el uso de ICTs en herramientas tecnológicas básicas y avanzadas.
- Para las preguntas técnicas y organizaciones se recomienda validar la posibilidad de usar esquemas anidados que permitan ofrecer la opción de No sabe/ No

responde en las secciones técnicas y organizacionales dependiendo del perfil del respondiente.

- Es importante revisar el banco de preguntas diseñado, ya que algunas son repetitivas o muy similares.
- Es importante validar la distribución de la encuesta para garantizar que el diseño facilite el entendimiento y garantice tasas mas altas de participación y compleción.
- Formular las preguntas de uso de ICTs más específicas para poder capturar su aplicación a nivel de negocio y revisar la terminología usada para que se mas entendible.
- En relación con la sección de competitividad, es importante validar la forma como se mide este constructo y los indicadores que se han definido, ya que aparentemente puede existir una tendencia a responder positivamente y a tener una tendencia a sobreestimar la competitividad de la compañía por la que está respondiendo.
- Revisar los perfiles que van a responder la encuesta para ofrecer diferenciación dependiendo del conocimiento i línea de negocio donde realiza sus actividades (técnico, de negocio, directivo).
- Es importante validar la longitud de la encuesta, ya que puede afectar las tasas de respuesta.

Session # 3 – Experienced Full time economy faculty member - Commentaries:

- Validar tema de protección de datos e implicaciones en ética de la investigación para garantizar que el proceso de captura de datos siga las mejores prácticas definidas a nivel académico.
- Validar la redacción de la pregunta D8, acotando cuales serían estas tecnologías.
- Precisar a qué se hace referencia con procesos digitales y procesos manuales en el marco de la pregunta D9, ofreciendo la respuesta la escala de porcentaje.
- Se recomienda que la para pregunta D16 se ofrezcan escalas de medición separadas para cada una de las dimensiones que se esperan validar.
- El validar elementos como la autosuficiencia y el conocimiento de herramientas tecnológicas en el personal puede ser complejo, por lo que se recomienda validar las escalas que se definieron en este apartado y separarlas entre conocimientos básicos y avanzados.
- Revisar la redacción de la pregunta de clima laboral (E6) para validar la relación que se busca medir.
- Ofrecer una última alternativa que diga “No sé, no conozco” para personas que definitivamente pueden no tener el conocimiento sobre ciertas preguntas técnicas u organizacionales.
- Revisar la formulación de las preguntas de la sección organizacional, ya que algunas de ellas se pueden solapar.
- Definir un potencial glosario de términos que pueda ser ofrecido a los participantes con el fin de facilitar responder preguntas muy específicas.
- Se recomienda dividir las dimensiones usadas en la pregunta F16 para obtener mediciones independientes de cada una de ellas.
- Se recomienda revisar la redacción de las preguntas de la sección de competitividad para facilitar la medición de estas capacidades.

- Se recomienda incluir el concepto de Analitica avanzada en el cuadro de medición de adopción de tecnologías de IA (pregunta H1).
- En la sección de motivaciones para adopción e IA, se recomienda incluir en el listado elemento como reducción de carga laboral y motivaciones de uso de personal.

Session # 4 – Industry expert # 1 – Education Sector – Commentaries:

- Se recomienda establecer que las preguntas demográficas sean completamente opcionales para aumentar las tasas de participación.
- En la pregunta D7 la formulación de las ICTs para ofrecer su significado en español e inglés.
- Tener en cuenta en el diseño de la encuesta diferentes botones de avance y limpieza de las respuestas para que no se confundan al final de la encuesta
- Adicionar la opción de No sabe / No responde, especialmente en la parte de percepción de competitividad y en el uso de analítica de datos e IA.
- En la parte sección de medición de impacto, ajustar las escalas intermedias de medición a “Medio bajo” y “Medio alto”.

Session # 5 – Industry expert # 1 – CIO of public entity – Commentaries:

- Se recomienda validar las escalas de ponderación de las preguntas para que sean pares obligando a los participantes a dar una respuesta concreta.
- Se recomienda validar la terminología usada en las preguntas para diferencias conceptos que se formulan desde el punto de vista administrativo y otro desde el componente técnico.
- Sería conveniente separar las diversas dimensiones de la pregunta E3 para obtener resultados por cada tecnología avanzada que se quiere analizar.

- Para la pregunta E7 se recomienda revisar la potencial alineación de las dimensiones que la componen con los que están contenidos en la pregunta número E8 para asegurar que no se sobrepongan.
- Revisar el detalle ortográfico de las preguntas para garantizar que no existan errores.
- Revisar la redacción de la pregunta F3 para garantizar que sea correcto.
- Se recomienda que la sección de impactos y métricas sea anidada respecto a la respuesta que se obtengan en la sección de uso de tecnologías de IA.
- Revisar la totalidad de las preguntas para poder ofrecer opciones de “No Sabe / No Responde” con branching dependiendo del tipo de rol que responda la encuesta.
- Se recomienda incluir una pregunta de tipo de rol para correlacionarla con la anterior.

Session # 5 – Industry expert # 1 – CMO of retail company – Commentaries:

- Se recomienda incluir en las opciones de industria de la información demográficas las opciones de consumo masivo y e-commerce.
- Establecer con mucha claridad las diferentes partes de la encuesta que son obligatorias y cuales son opcionales.
- Incluir las opciones de No sabe/No responde en las preguntas de la sección técnica.
- Aclarar el concepto de gestión documental ofreciendo ejemplos para facilitar las respuestas de esta sección.

- Revisar la redacción de las preguntas de la sección de competitividad, especialmente las que hacen referencia a la medición de recursos físicos y humanos.
- Incluir un glosario en relación con las definiciones de políticas de Inteligencia artificial y analítica avanzada
- Se recomienda definir de manera muy cuidadosa la base de datos de potenciales participantes en el estudio ya que es probable que personas jóvenes o personas con alto conocimiento de negocios tenga mayor probabilidad de responder el instrumento de forma más sencilla.