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# Radical Change and Dominant Character of Digital Transformation in Artificial Intelligence Entrepreneurship in Less Innovative Economies

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**Abstract**
The company's rapid adaptation to digital transformation (DT) both in the most innovative economies and in the less innovative economies is one of the topics that keeps the field of innovation studies very busy but also governments. The artificial intelligence (AI) sector is one of the areas that is having the greatest degree of influence due to the effects of DT. While it is true that with DT these companies have a high potential for innovation, it is also true that their business models require a permanent readaptation process with the dynamics and complexity of technological changes. This research contributes to help companies to understand the complexity and dynamics of DT. Through a set of configurations based on the qualitative comparative analysis (QCA) method, it is possible to identify the positioning of the companies in the artificial intelligence sector in relation to this technological pattern. One of the most relevant conclusions is that the construction of configurations related to radical changes allows companies to observe the complexity and dynamics of these changes.

**Keywords** Digital transformation · Artificial intelligence · Entrepreneurship · Innovation capacity

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## Introduction

COVID-19 has caused a digital disruption of historic proportions both in the most innovative economies and in the less innovative economies (Eberly et al., 2021; Blackburn et al., 2020). Brusoni et al. (2020) state that companies developing complex technologies like DT strive to create more value through radical innovations. This work is based in a set of previous scientific reports that highlight the group of actions that companies have taken globally during the COVID-19 pandemic to take advantage of the opportunities offered by digital transformation (DT), be able to stay competitive and innovate (Zimmermann, 2020; Harms et al., 2021) also shows that within them, there is a collection of innovation capabilities that can be used in times of uncertainty and high turbulence (Strielkowski, 2020).

For many authors, these types of actions have been classified as “agile” (Doz & Guadalupe, 2019). However, the question arises, whether these companies can remain competitive after overcoming the pandemic crisis. However, the question that comes up is, whether these companies can remain competitive after overcoming the pandemic crisis. It cannot be based on the fact that the actions taken by companies during the pandemic remain stable or are sufficient to sustain themselves in the market, at the same time that the dynamics of DT becomes more complex (Brusoni, et al., 2020). The research question of this work is about how to characterize the positioning of the innovation management of companies in the face of the current dynamics of DT. It is based on the hypothesis that the accumulation of innovation capacities of companies allows developing agile strategies in situations of uncertainty that can be used for their adaptation in DT, but their permanence and success are conditioned on the ability to understand the dynamics of the DT (Kayal, 2008; Godinho et al., 2006; Harms et al., 2021).

The theoretical framework of this work addresses DT not only as an expression of current technological change but also positions it as a dominant technological pattern (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021) capable of transforming the economic structure of companies (Westerman et al., 2014), consequently this implies radical changes in the way they act and react in the context of innovation (Sarasvathy, 2001; McKelvie et al., 2020; Harms et al., 2021). Digital transformation for this paper is defined as a multidisciplinary and structural process in which an organization incorporates digital technologies to develop a digital business model. This comprehensive approach involves profound changes in various areas, including technological, organizational, and cultural aspects, with the central goal of creating and capturing greater value. Digital transformation goes beyond the mere adoption of digital tools; it entails a profound reconfiguration of the organization’s operation, its interaction with customers, the management of internal processes, and the formulation of value propositions. This process aims to position the organization in a digital environment, facilitating effective adaptation and generating substantial benefits (Tabrizi et al., 2019; Tang, 2021).

The dynamics in which DT develops is highly complex, and such complexity is characterized, among other things, by the constant recombination of information technologies, communication, and also by its high resistance to not disappear as a technological pattern. From this, it is inferred that the exhaustion of DT as a techno-economic paradigm even in the maturity stage of the technology is unpredictable (Escott Mota, 2020; Palacios & Escott, 2021). This statement could expand the findings in the field of innovation studies on the behavior of DT as a techno-economic paradigm, since it broadens the approach of Pérez (1983, 2004), but also raises relevant differences.

The general objective of this work is to characterize the main configurations that describe the innovation management of companies in the artificial intelligence (AI) sector in Mexico compared to the dynamics of DT in Mexico. For this, reports are used that have characterized the dynamics of DT through a set of variables produced by the use of theoretical contrasting methods (Hart, 2018). These variables are defined here as integrated components and also as adaptive conditioning variables of DT (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021). The approach with which these variables are used bears some similarity to the position of Werhahn et al. (2015) when he analyzes the innovation strength of entrepreneurs, beginning to maximize their returns with the help of variables and indicators that characterize the existing innovation capacities.

Additionally, and based on the set of identified variables (integrated components), the analysis of DT dynamics is expanded through the identification of two operational logics: (a) transmission and (b) reflection. With them, an attempt is made to characterize the dynamic and effect of DT in companies to give DT the attribute of a dominant technological pattern (Escott Mota, 2020; Palacios & Escott, 2021).

The second methodological moment is made up of the use of the Comparative Qualitative Analysis (QCA) (Ragin, 2006, 2009), with which it is possible—even with small samples—to generate the configurations that characterize the innovation management of the companies of the AI sector versus DT dynamics. Research works in the field of innovation and entrepreneurship that have used QCA (Harms et al., 2021) confirm the usefulness of this method to analyze elements related to the complexity and uncertainty of DT (Sarasvathy, 2001). The QCA analysis has focused on ventures in the AI sector in Mexico; this area has also shown, like many companies in the high-tech sector, an ambivalent behavior, in the sense that many have been able to adapt organizationally to the DT and others do not (Zimmermann, 2020). Mexican companies have been no exception in manifesting this behavior (Albrieu et al., 2019).

Based on the contributions of Schumpeter (1911, 1942, 1939) who stated that the introduction of a new technology brings with it the disappearance of the previous ones (creative destruction) and emphasized the role of entrepreneurs in this process, is that it is used in this work the figure of entrepreneurial AI companies (Unger et al., 2017). Schumpeter (1942) emphasized the role of entrepreneurs in coping with complex dynamics, which is directly perceived by them. They are the ones who must react to reorganize and readapt their capacities for innovation Schumpeter (1942). Entrepreneurs must, therefore, manage their own evolution, develop the capacity to adapt and co-participate in the creation of an environment favorable to innovation (Kane et al., 2015; Doz and Guadalupe, 2019). For the purposes of this work, entrepreneurial companies in AI are those that have the capacity and agility to lead the business in times of uncertainty and in the midst of exponential technological changes (Kallmuenzer et al., 2019).

This research offers several contributions. One of them is that it constitutes a rapid response study to produce evidence on the perception and positioning of the innovation management of entrepreneurial companies in advanced economies in the AI sector against the dynamics of DT (Werhahn et al., 2015). This not only enriches the scientific discussion in the field of innovation studies, but also offers companies methodological tools to understand the dynamics and complexity of DT and consequently develop agile actions to redirect their current strategies.

## Theoretical Background

### Radical Change and Digital Transformation as Dominant Technological Pattern

The notion of radical change that emerges from the contributions of Schumpeter (1934, 1942) has a greater significance with the current dynamics that DT experiences. In modern capitalism, the force acquired by the production and development of technological knowledge is observable, taking advantage of digitization from industries to generate incremental and radical changes (Anderson & Tushman, 1990). Thus, radical change can be considered as a discontinuous change (Anderson & Tushman, 1990) that involves radical changes capable of transforming the economic structure. This creates the challenge for companies to adapt to a new competitive dynamic (Benner, 2016; Jenkins, 2010; Morro, 2019).

The advent of the COVID-19 pandemic has accelerated the process of adaptation to digitalization and with it the use of companies' innovation capabilities (Benner, 2016; Escott & Palacios, 2020; Portuese, 2021). In this way, it is possible to observe an exponential growth rate of companies in sectors using DT (Statista Research Department, 2021). Souto (2015) argues this: "Specifically, the keys to successful radical innovations lie in adopting a new contextual and conceptual framework through which innovations can occur and customer needs can be met, thereby giving rise to new competitive advantages." Also, the permanent change in the approach to business models within companies has been part of this process of adapting to digitalization.

Taking as a starting point the notion of "creative destruction" (Schumpeter, 1961) and with them the subsequent set of research reports (Barr et al., 1992; Dosi & Cimoli, 1994; Luján and Moreno, 1996; Zeppini, 2011; Estrada et al., 2016; Jiménez-Barrera, 2018; Valenduc, 2018; Cantner, 2017), it can be stated that the dynamics that technological change has been experiencing has not only accelerated, but is also highly complex (Blackburn et al., 2020; Kurzweil, 2012). Such complexity is not only reduced at this level of analysis of technological change, but also, which is observable in companies that are impacted by the dynamics of these changes (Jenkins, 2010). The power achieved by DT as a technological pattern within the economic structure provides companies with resources to innovate, as Schumpeter (1942) conceived when referring to the power of the market to generate, promote and generate conditions for innovation (Portuese, 2021).

Based on the contributions of Uşaklıoğlu (2020), Katz et al. (2020), Kurzweil (2012), Brynjolfsson and McAfee, (2015), Agudelo et al. (2020), Escott Mota (2020), Escott et al. (2020), and Palacios and Escott (2021), some aspects can be identified that allow a first approach to the characterization of DT as a dominant technological pattern: (a) fuller acceleration, (b) higher resilience intensity, (c) new sources of information, (d) permanence, (e) recombination of information technologies, (f) acceleration of innovation diffusion, and (g) regeneration. From this, it follows that DT has unique elements (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020) markedly different from previous technological paradigms (Pérez, 2004). Although it is true that technological change has historically been approached from the theoretical approach of innovation due to its endogenous and exogenous nature (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020), due to its geographical effect (Pérez, 2004), due to its impact on social, institutional, economic, and political actors (Estrada et al., 2016; Valenduc, 2018; Cantner, 2017; Cantner & Vannuccini, 2018 and Valenduc & Vendramin, 2017), for its linear, dynamic, and exponential state (Kurzweil, 2012), for the challenges it poses (Benner, 2016), and for its technological manifestations (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020; Pérez, 2018a, b, c), so is the fact that in the current stage of capitalism (Mazzucato, 2018; Schumpeter, 1942), this approach broadens the degree of complexity in which the dynamics of these changes develop.

The contributions of Pérez (2001, 2004) linked to the techno-economic paradigm and technological revolutions and financial capital allow them to be used as referential theoretical reports to characterize and identify alterations in DT behavior. We start from the set of phases identified for each technological revolution: Phase 1 Irruption, Phase 2 Frenzy, Phase 3 Synergy, and Phase 4 Maturity (Pérez, 2004) and then proceed to buy it with the dynamics that DT currently experiences (see Fig. 1).

The previous figure shows the behavior of the techno-economic paradigm until reaching a point of maturity of the technology and the market that causes the birth of a new technological revolution (Pérez, 2001). According to the figure, the dynamics acquired by DT is highly complex and the effect of digital technologies on the entire economic structure is observed. Although it is true according to Pérez (2001, 2004) that this technological pattern would preserve the elements and phases in which the techno-economic paradigm develops (irruption, frenzy, synergy, and maturity), so is the fact that the nature of this technology allows a recombination of different technological sectors (artificial intelligence, digitization, big data and analytics, autonomous robots, simulation, horizontal and vertical integration systems, internet of things industry, cyber security, the cloud, additive manufacturing, augmented reality) that give greater strength to the technological pattern, thereby extending its permanence and permanently transforming the technological knowledge base generated in industries (Jenkins, 2010; Benner, 2016; Anderson & Tushman, 1990; Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021).

According to this, the technological maturity phase (Pérez, 2004) in the case of DT would be occurring to regenerate the same existing digital technological pattern (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020) referred to the fact that the technology maturity phase is expressed as a restriction phase of the existing techno-economic paradigm, where the productivity and profits

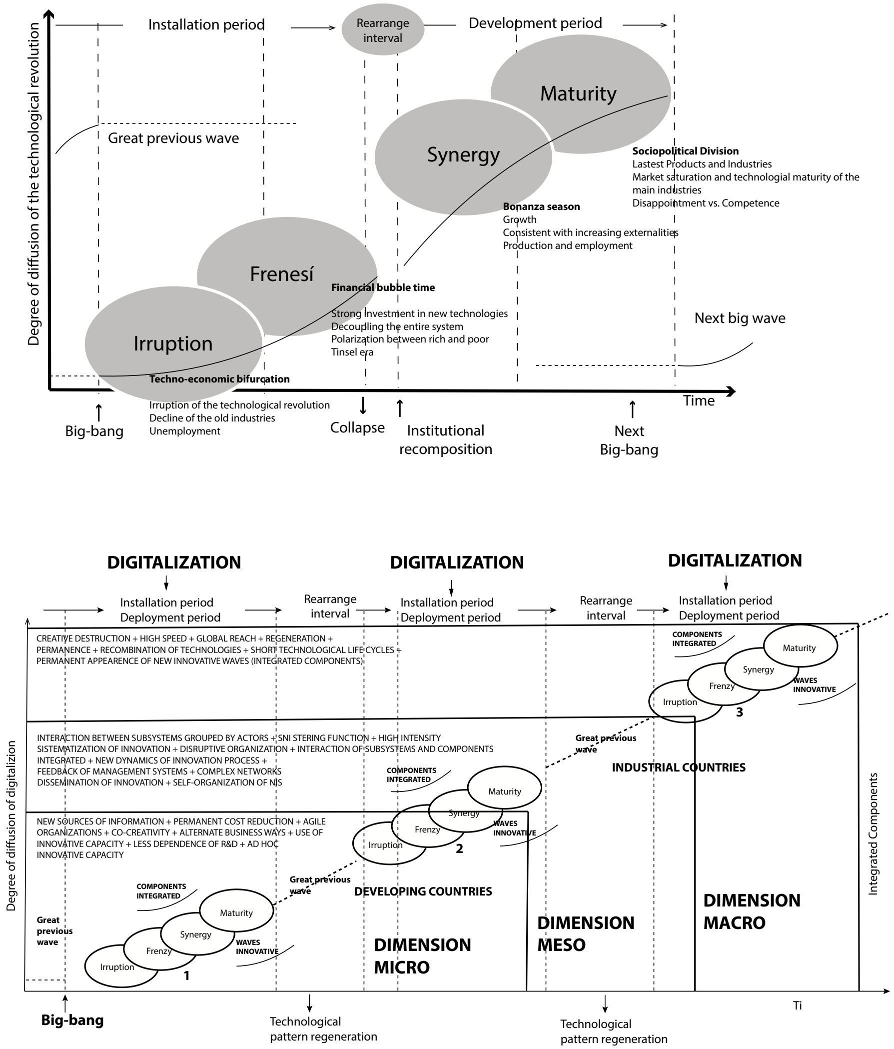


**Fig. 1** Behavior of technological paradigms. Source: own elaboration, taking as a reference the reports of (Pérez, 2004, 2010; Escott Mota, 2020; Palacios & Escott, 2021)

of companies are threatened and it is precisely at this time that it would be necessary to generate an effective demand (Pérez, 2001, 2004) through new radical innovations (Anderson & Tushman, 1990), which could generate a new technological revolution.

In the case of DT, such depletion of the techno-economic paradigm would not take place in what refers to the very existence of the techno-economic paradigm (digital transformation) since it would not disappear, but it would be generating the conditions for new digital technologies to appear as radical innovations (Palacios & Escott, 2021). In this context, the innovative attitude of entrepreneurs creates the basis for the generation of radical changes, revolutionizing the way of production of a new or existing product, new production methods, generating new sources of supply of raw materials or markets and reorganizing the company (Blackburn et al., 2020; Schumpeter, 1942), since they are the first to seek combinations of knowledge and technology to obtain greater economic benefits (Schumpeter, 1963).

Another important aspect to highlight in Fig. 1 is that the "integrated components" identified maintain a consistent appearance in the dimension in which they have been identified (macro dimension, meso dimension, and micro dimension). The interrelation of these dimensions and integrated components occurs when in the macroeconomic dimension, which has a direct relationship with the radical changes, new signals or changes appear for the companies. This results in a process of adaptation and activation of the integrated components in the meso and micro dimensions. This means that from the perspective of the companies, the relevance and consistency of the components integrated in the macro dimension are fundamental to redirect the innovation strategy that was being executed.

## Transmission and Reflection as Operational Logics of Digital Transformation

Recent reports (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020) provide important information about the characteristics related to the dominant character of DT. There, it is possible to observe approaches to understand the direction or behavior of DT within the National Innovation System (NIS). That is, it is possible from a NIS performance perspective (Palacios & Escott, 2021) to identify the positioning and effect of the elements that make up the DT (see Fig. 2).

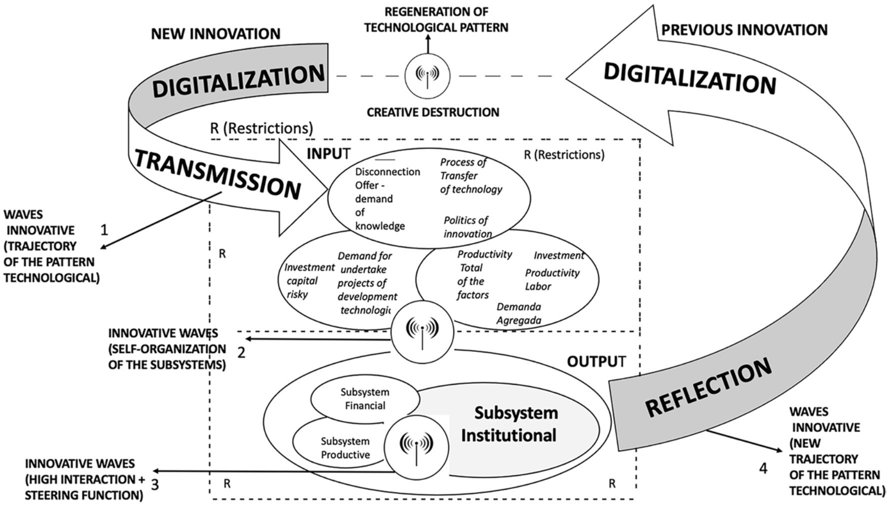


**Fig. 2** High performance of the NIS (Few restrictions). Source: Escott Mota, 2020; Palacios & Escott, 2021

Based on the contributions of Estrada et al. (2016), it is possible to identify and analyze more rigorously the exogenous elements that influence the NIS, when it is analyzed in the form of sub-systems (productive, institutional, and financial) instead of making an individual categorization by innovation actors (entrepreneurs, academics, financiers, among many others). Analyzing the effects of exogenous aspects of the NIS, such as: technological development, venture capital investment, total factor productivity, aggregate demand, and labor productivity implies a configuration that simplifies and allows such effects to be observed more directly, and these are subsystems (Alvarez-Castañón et al., 2018).

It is important to highlight that this approach adopted by Estrada et al. (2016) starts from the assumption of the high complexity observed in the NIS when adapting to new technological changes (Morin, 1998, 2013; Freeman, 1987; Freeman, 1982; Dosi, 1982; Lundvall, 1992; Nelson, 1993; Kayal, 2008 and Godinho et al., 2006). According to Estrada et al. (2016), this complexity cannot only be addressed from within companies as a condition to be overcome with the increase in innovation capacity, but, rather, they are a condition that is presented as restrictive to innovation and is from this perspective, it is possible to develop radical changes within companies (Alvarez-Castañón et al., 2018).

The previous figure forms the basis of this research to position the theoretical and operational value of the integrated components (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021) within the dynamics developed by DT and that logically it develops differently according to the innovation capacity possessed by the innovation actors (Palacios & Escott, 2021). This means that a differentiation is possible regarding the behavior of the technological pattern according to geographical aspects and level of economic development (Álvarez-Castañón et al., 2016; 2018; Escott Mota, 2020; Palacios & Escott, 2021). Based on the previous contributions (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021; Escott & Palacios, 2020), the "integrated components" (IC) are structurally the set of variables related to the dynamics of DT in the economy, which behave as "innovative waves" (information) and which determine the type of actions that companies develop to adapt to technological changes (Benner, 2016; Jenkins, 2010). ICs are, therefore, constitutive elements of the dominant technological pattern (Escott et al., 2020).

The identification of these variables is possible by the application of theoretical contrasting processes that involve the crossing of relevant approaches and analysis on the behavior of the technological pattern in the global economic structure (Marquina et al., 2013; Escott Mota, 2020; Escott et al., 2020). This was achieved in the first instance by selecting a set of theoretical perspectives linked to the analysis of innovation and technological change selected longitudinally, which had the ability to have incorporated previous theoretical perspectives, such as Zeppini (2011), Pérez (2001, 2010, 2018a, 2018b, 2018c), Schot (1992), Fatás-Villafranca et al. (2012), Choi et al. (2018), Valenduc (2018), Cantner and Vannuccini (2018), and Mazzucatto (2015, 2018). Starting from an in-depth analysis regarding the theoretical contributions related to the characterization of DT (Escott et al., 2020), this research interprets ICs as adaptive conditioning variables of digital transformation.

The understanding of how integrated components operate in the context of companies or enterprises is based on the identification of two logical operational processes: transmission and reflection (Escott Mota, 2020; Palacios & Escott, 2021). These processes are made up here and are an approximation to characterize the beginning and end of

DT behavior as a dominant technological pattern (see previous Fig. 2). The transmission provides information in the form of innovative waves, about the new technological and innovation trajectories that are generated by radical changes (Anderson & Tushman, 1990) within the same techno-economic paradigm of DT; and this determines the actions that companies would develop to adapt to this paradigm, depending on the level of their innovation capabilities (Escott Mota, 2020; Escott et al., 2020; Palacios & Escott, 2021).

For its part, reflection refers to the discontinuous changes (Anderson & Tushman, 1990) that are generated from the dynamics of the technological pattern capable of transforming the economic structure (Benner, 2016; Jenkins, 2010; Morro, 2019; Schumpeter, 1934, 1942) and finally signify the beginning of a new stage of the dominant technological pattern (Escott Mota, 2020). On reflection, the interaction of the actors for the development of greater capacities for knowledge and innovations is observed as the most relevant condition to generate radical changes within DT. Thus, both reflection and transmission configure the input and output dynamics of both information and innovation capacity on the part of the actors (Escott Mota, 2020; Palacios & Escott, 2021).

In practical terms and with the support of recent studies on the dynamics and effects of DT during the COVID-19 crisis in companies and enterprises (Blackburn et al., 2020), some levels of DT behavior can be interpreted through transmission and reflection. It starts from the fact that COVID-19 has caused years of changes in the way companies do business in all sectors and regions; companies have accelerated actions in approximately three to four years primarily through digitization and AI to develop interactions with their partners and customers in the supply chain and internal operations, including the proportion of digital products (Blackburn et al., 2020).

From this it can be inferred that companies have implemented a set of technological capabilities that others do not have (Kallmuenzer et al., 2019), for example: technological talent, use of more advanced technologies, speed in experimentation and innovation. According to these studies, an approximation to how reflection operates could be interpreted as the speed with which new digital offers or digitally enhanced have been created in all regions globally. It is inferred, therefore, that some companies managed to commercialize new innovations during the crisis by experimenting with combinations of digital technologies (Janice et al., 2021) but they have also developed organizational strategies linked to innovation management (Khoshlahn & Ardabili, 2016; Cantner & Vannuccini, 2018; Guertler et al., 2020; Alofan et al., 2020). The innovation strategies developed in small companies during the pandemic are very likely to be difficult to imitate (Rivkin, 2000). In this way, companies are innovating in the way things are done, toward a transversal, collaborative, intuitive, democratic and highly technological and intelligent way (Santos & Massó, 2016).

## Method

### Population and Statistical Sample

The acceleration of AI, like other expressions of the current dynamics of technological change, is changing the global economic structure (Nambisan, 2017; Von Briel et al., 2018), particularly in economic sectors such as finance, industry, home automation, autonomous vehicle driving, marketing, resource distribution, facial recognition, medicine, and teaching (Ávila-Tomás et al., 2021; Baumgartner et al., 2016). According to reports by Rao and Verweij (2017), AI will generate a massive disruption in the global population, due to its technological composition will be able to promote innovation more quickly and consequently increase the current rate of entrepreneurship. One of the challenges of the current economy is reducing costs while increasing productivity and precisely AI is a technology that allows us to process large sets of unstructured data and perform tasks that usually require human intelligence, at the same time as reduces costs and increases the rate of productivity and innovation (Choudhury et al., 2018; Cockburn et al., 2018; Stone et al., 2022).

This dynamism that AI develops so much is one of the reasons why a very important number of startups are being generated globally that are promoting an artificial intelligence ecosystem (Montes et al., 2021), and it is also one of the arguments to think that AI could impact 14.5% on the global GDP increase in 2030 in North America and up to 26.1% in China (Rao & Verweij, 2017; Fernández et al., 2020). According to Statista (2021), the public and personal services sector represents the area with the highest increase in profits. The increase in patents in AI has had a growth pattern that has increased fivefold worldwide from 2016 to 2019. AI startups are characterized by constant technological innovation, offering specific solutions to certain sectors or in a transversal way and their innovation is associated with the ability to combine knowledge resources, a critical process for the competitiveness of a country and a company. (Cantner, 2017). According to Statista (2021), the highest percentage of startups as of May 2021 belongs to the software, data, and fintech sector.

This research was carried out through data analysis in eight (8) companies located in the State of Querétaro[1]: (1) Company A[2], (2) Company B[3], (3) Company C[4], (4) Company D[5], (5) Company E, (6) Company G[6], (7) Company H[7], and (8) Company AU[8]. The sample is represented by the selection of Mexican entrepreneurial

[1] It is important to note that these companies not only have a presence in the State of Querétaro but in more States of the Country: Company A (Baja California), Company B (Aguascalientes), Company C (All the Mexican Republic), Company D (North of the Country), Company H (All the Mexican Republic), and Company AU (State of Mexico and Mexico City).

[2] Company dedicated to the development of scientific software with the use of AI.

[3] After modifying his business scheme, he has managed to increase his income fivefold in just 3 years.

[4] Since 2011, it has been awarded the Great Place to Work distinction based on the change in the labor ecosystem, impacting internal justice, skills, leadership, and innovative thinking.

[5] Academy focused on data science and machine learning.

[6] It defines an economic bag of more than 21.2 million pesos in support of research, technology and innovation centers, and is the state with the highest number of patent applications in Mexico. In 2020, in conjunction with Zoho, entrepreneurs were trained to improve processes and automation through AI.

[7] In 2018, it obtained the ESX Innovation award where the most impactful and innovative technologies in the electronics and life safety industry are recognized.

[8] Awarded with the business merit award in 2019 according to its activity, job creation, and competitiveness.

companies in the AI area in the economic sectors classified by the National Institute of Statistics and Geography (INEGI) (2021a, b). The profiles to which the questionnaire was directed were exclusively positions related to the implementation of AI linked to the innovation management of companies located in states such as Querétaro, Jalisco, Baja California, Mexico City, State of Mexico, and Aguascalientes. These states show an increase in GDP that is higher than the national average. The selected States obtained competitiveness medals (Centro de Investigación en Política Pública, 2020), and are in the top positions of the Sustainable Competitiveness Index of Mexican States[9] (Tecnológico de Monterrey, 2017). Segmented companies were chosen mainly in the tertiary sector since in the first quarter of fiscal year 2021, they represent 64% of the gross domestic product in Mexico. One of the companies belongs to the secondary sector with the highest participation in the National GDP: Manufacturing Industries.

The works of Escott Mota, 2020, Escott et al. (2020), and Palacios and Escott (2021), which characterize the dominant character of DT in the economy and in the different actors, organizations, served the elaboration of a questionnaire with closed questions (Fassio, 2018). This questionnaire was available online and was developed with strict control and monitoring guidelines and definition of concepts. Then, with the information obtained, the data was analyzed through the method: Comparative Qualitative Analysis (QCA) (Ragin, 1987). With the application of the QCA, logical configurations are elaborated (Ragin, 1987), with which it is not only possible to observe the composition of the complex causality manifested by DT as the dominant technological pattern, but also with the results produced by the method. It is possible to identify and analyze the positioning of companies' innovation management in the context of DT during the COVID-19 pandemic (Harms et al., 2021; Xu et al., 2007; Khoshlahn & Ardabili, 2016; Guertler et al., 2020; Alofan et al., 2020; Cantner, 2017).

## Operationalization of the Dominant Nature of Digital Transformation in Companies in the Artificial Intelligence Sector

Theoretical relationships and combinations to understand complex theoretical aspects in the field of innovation studies are being increasingly used (Harms et al., 2021; Kraus, Ribeiro-Soriano & Schüssler, 2018; Escott Mota, 2020). The dynamics and complexity of digital transformation is an expression of current technological change (Palacios & Escott, 2021). Its analysis would not be possible without a selection of variables from different theoretical and conceptual approaches to innovation (integrated components) (Escott et al., 2020). With the QCA, it is not only possible to test the relevance of the conceptual and theoretical approaches linked to the phenomenon studied in this work (Kraus et al., 2018), but, it is possible, to also identify probable solutions through the resulting configurations (Ragin et al., 2011), which for the purposes of this work would be aimed at providing companies with information to readjust their

[9] The first 6 places are occupied by: CDMX, Nuevo León, Querétaro, Jalisco, Baja California, and the State of Mexico. The index assesses: government performance, productive infrastructure and human capital, innovation and entrepreneurship, economic performance, business efficiency, and resilience.

strategies in two directions: (1) on the innovation management of companies to adapt more dynamically and quickly to the DT; and (2) on the internal organizational management of companies in the face of the dynamics and complexity of DT.

The operationalization of the QCA consists of three phases[10]: (I) selection and description of the cases; (II) analytical moment, and (III) interpretation of the results. Phase I constitutes the methodological design of the research, here the eight (8) companies of the AI sector in Mexico were chosen and the empirical information from them was collected to finally set causal conditions associated with the dynamics of digital transformation (Ariza and Gandini, 2012). Phase II comprises the in-depth analysis of the probable compositions of causal conditions that generate the dynamics of DT in entrepreneurial companies in the AI area in Mexico through the following processes: (1) dichotomization; (2) truth table; (3) minimization; and (4) minimum formula (Ariza & Gandini, 2012). With phase III, the results are interpreted through the following steps: (1) factoring, (2) interpretation, and (3) generalization (Ragin, 2006; Ariza & Gandini, 2012).

## Selection of Cases and Description

One of the salient features to use the QCA is that it allows the analysis of small samples (Ragin & Rihoux; 2004; Ragin, 2006), which is ideal in a case study approach. This enables the phenomenon to be analyzed in its natural context, observing the interactions of the actors directly (Yin, 2009). The research uses eight (8) case studies of companies in the AI sector in the city of Querétaro. The selected companies are the following: (1) Company A, (2) Company B, (3) Company C, (4) Company D, (5) Company E, (6) Company G, (7) Company H, and (8) Company AU (see Table 1).

The group of companies permanently develops new technologies in AI through new business models and undertakings and executing actions within innovation management to adapt to DT. All this in the conditions and circumstances of innovation that Mexico presents (Albrieu et al., 2019). The economic activity of these companies through the development of AI indicates the nature and therefore the relevance of these case studies to analyze their positioning within the current dynamics of DT (Cohron et al., 2020).

## Information Gathering

The research tool chosen to collect the data that would later be used in the QCA analysis consists of an online questionnaire of closed questions sent to four people or actors with relevant and binding positions in the AI area in each of the companies selected. The selection of the companies was made through direct contacts and through the support of AI Mexico,[11] who supported the management of contact with

[10] To replicate the methodology, it is recommended to consult Escott, M. (2018). Introduction to comparative qualitative analysis as a research technique. Digital magazine CIENCIA@UAQRO, 11(1), 56–66.

[11] AI México has a strong global presence and sphere of influence. In the first year, the organization established a community of over 600 members in 8 countries and partnerships with businesses around the world according to their website.

**Table 1** Description of selected study cases

| Company | Foundation year | Employee range | Industrial sector | Type of technology applied in the AI sector | Level of competitiveness in the national market |
|---|---|---|---|---|---|
| Company A | 2018 | From 100 to 250 | 5411 professional, scientific, and technical services | Machine learning, virtual reality, big data | Medium |
| Company C | 1984 | More than 250 | 5110 publishing of newspapers, magazines, books, software and other materials, and publishing of these publications integrated with printing | Virtual agents,<br>Employee assistants,<br>Marketing strategies | High |
| Company D | 2018 | From 11 to 50 | 5411 professional, scientific, and technical services | Machine learning | Medium |
| Company E | 2002 | More than 250 | 5614 investigation, protection, and security services | Machine learning | Medium |
| Company G | 1979 | More than 250 | 9313 state public administration | Virtual reality, big data, cyber defense | High |
| Company H | 2001 | More than 250 | 5614 investigation, protection, and security services | Biometrics, image recognition | High |
| Company AU | 1997 | More than 250 | 3360 manufacture of transport equipment and parts for motor vehicles | Virtual reality, robotics, hardware optimized for artificial intelligence | High |
| Company B | 2001 | From 11 to 50 | 4340 wholesale trade of agricultural and forestry raw materials, for industry, and waste materials | Machine learning, employee assistants, marketing strategies | Medium |

Source: Own elaboration

According to Porter (1990); Krugman (1994) are the companies that compete, not the nations. For Rubio and Arargón (2006), competitiveness is the ability of a company to compete with others, having a favorable position that allows a superior performance to competing companies. Lall et al. (2005) measure competition according to market capture and/or profitability, that is, the average cost does not exceed the market price of their product or that of their competitors (Solleiro & Castañón, 2005)

**Table 2** Integrated components or adaptive conditioning variables to digital transformation

| Integrated components or conditional variables adaptive to DT | Characteristics that identify the integrated component | Nomenclature |
|---|---|---|
| • Heterogeneity of the actors—homo agents | • Invention<br>• Innovation<br>• Adoption of technology<br>• Heterogeneous networks | hactor |
| • Interaction of the actors—competition and cooperation<br>• Technological competence | • Transactions and external relations to the market<br>• Emerging variable of economic actors | iactor |
| • Technological diversity<br>• Technological convergence<br>• Technological niche | • Recombinant technological innovation<br>• Innovation through technological fusion<br>• Business investment generated by key technologies produced by fusion of technologies | diversidadt |
| • Network externalities | • Decision feedback loops<br>• Technological value measured by users | externaidadr |
| • Social interactions<br>• Technological assimilation<br>• Government action | • Decision feedback<br>• Adoption of technology for the formation of new social habits<br>• Deployment of industries based on the socio-economic and institutional context<br>• Social effects as a result of the new technological deployment<br>• Transformative potential of the paradigm due to the socio-institutional context<br>• Innovations generated by dynamic demands | interaccions |
| • Environmental policy<br>• Sustainable development | • Flexible technology standards<br>• Alternative technological trajectories determine patterns of production and consumption<br>• Technological regime | dsostenible |
| • Endogenous investment in R&D | • Operating routines determine investment in R&D | inversionend |
| • Knowledge threshold | • Accumulated knowledge<br>• Technological potential generated by cumulative knowledge<br>• New technological paradigm driven by cumulative knowledge | uconocimiento |
| • Technological transition<br>• Inflection point | • Technological maturation by input of technologies<br>• Technological transition (Installation and deployment of technology)<br>• New economic take-off | puntoinf |

**Table 2** (continued)

| Integrated components or conditional variables adaptive to DT | Characteristics that identify the integrated component | Nomenclature |
|---|---|---|
| • Technological paradigm<br>• Technological pattern | • Paradigm as a technological pattern<br>• Differentiated technological revolutions | patront |
| • Links between institutions | • Coalition and coordination between actors<br>• Stakeholder information to define forms of action | nexoinst |
| • Technological direction | • Profitable propagation of the technological paradigm | direcciont |
| • Technological diffusion | • Technological propagation in user groups<br>• Gradual technological diffusion as a result of organizational and technical changes | difusiont |
| • Scientific policy | • Technology as an instrument of political power<br>• Institutions<br>• Scientific policy generated by the parallel evolution of technologies and institutions<br>• Steering function | Steeringf |
| • Technological exponential behavior | • Exponential acceleration of technology | exponencialt |

Source: Own elaboration based on research by Escott Mota (2020), Escott et al. (2020), and Palacios and Escott (2021) directors of entrepreneurial organizations in the field of AI. A personal conversation was held with each contact to ensure understanding of the importance of their collaboration. These actors provided the data of 3 additional employees who are within the organization and who have a key position in the development of entrepreneurship and innovation management strategies. The questionnaire consists of 16 questions; the respondents had to answer from the perspective of the innovation management of each of their companies. In this way, it was possible to operationalize the integrated components, based on the works of Escott Mota, 2020, Escott et al. (2020), and Palacios and Escott (2021). Table 2 shows the description of the selected variables, the nomenclature of the variable to be operationalized in the QCA, and the set of questions formulated in the questionnaire related to each variable.

The empirical data of the cases were validated considering the principles of Silverman (2001): (a) contrast, (b) triangulation, and (c) comparison. The companies are subject to contrast since in them, different turns, sizes, and creation dates are observed (Silverman, 2001). The information from the questionnaires can be triangulated since there is sufficient information on each company, as well as the case studies They were subjected to constant comparison through the fsQCA analysis that allows to analyze dynamics of digital transformation in entrepreneurial companies in the area of artificial intelligence in Mexico.

## Establish Cause Conditions

The variables included in the study are of two types: causal and independent or dependent and outcome; the combinations of the causal variables will provide the result (Ragin, 2009). For the purposes of this research, the dependent variables are the integrated components. They are associated with the presence of a result—dependent variable—which refers to the strategic orientation of innovation management in the field of AI in entrepreneurial companies in Mexico. The variables—dependent and result—must be transformed from binary variables to fuzzy sets—fuse categories—this transformation is known as calibration (Ragin, 2006).

## Analytical Moment

This phase of the research refers to the exhaustive analysis of causal conditions and possible combinations through a computer package. This phase is made up of three sub-phases: (1) calibration; (2) handling of variables; and (3) analysis of conditions through Tosmana fsQCA (Ariza & Gandini, 2012).

The calibration causes the value of the variables to be interpreted in intervals (from 0 to 1); this is important when a certain variable conditions the environment for the action of another variable (Byrne, 2002; Vidal-Súarezet al., 2013), since it will allow: (1) to know from which interval of the variable a feasible environment is developed for the causal relationship between two variables; (2) which intervals change the direction of such correspondence, or according to which interval the variation in the first variable becomes irrelevant for the existing correspondence between the two variables. For the calibration of the variables in this research, the

Likert scale was used at five points—1 being totally in disagreement and 5 totally agreeing—this type of scale turns out to be one of the most used in various fields of research and particularly in the field of research, social sciences area (Carifio & Perla, 2007). The Likert scale when calibrated in the Tosmana software in its fsQCA mode takes values of the following: 0, 0.4, 0.75, and 1 (Misangyi et al., 2017).

## Analysis and Results of the fsQCA

With the application of the QCA, logical configurations were created to track the behavior of the integrated components in entrepreneurial companies in the AI sector (see Table 3).

Table 3 is made up of two sections. The first section establishes the configuration of categories (Model M1), represented by the conditioning and adaptive variables of the digital transformation that are essential for identifying the strategic orientation of the current innovation management that companies develop in the face of the dynamism of the digital transformation as the dominant technological pattern. This is a solution with a high theoretical relevance (Duşa, 2018), able to explain the cases studied: (1) Company A, (2) Company B, (3) Company C, (4) Company D, (5) Company E, (6) Company G, (7) Company H, and (8) Autoliv. Likewise, the symbol → at the end of the M1 model can be seen; this represents that the minimization algorithm has established the "sufficiency condition," that is, the conditioning and adaptive variables of the DT through their individual configurations separated by the + sign show the strategic orientation of the current innovation management that companies develop in the face of the dynamism of DT as the dominant technological pattern.

Model M1 is shown with the fsQCA's own language, where the + sign represents the Ó used in logical operations, symbolizing the existence of more than one sufficiency condition (Wagemann, 2012). The sign * represents conjunction or the logical "AND" (Wagemann, 2012). The sign ~ represents disjunction or condition

**Table 3** Configuration model

| | | *Configuration model* |
|---|---|---|
| *1* | M1 | ~HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * INVERSIONEND * UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * DIFUSIONT * EXPONENCIALT+<br>HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * INVERSIONEND * UCONOCIMIENTO * PUNTOINF * PATRONT * ~NEXOINST * DIRECCIONT * DIFUSIONT * ~EXPONENCIALT+<br>HACTOR * ~IACTOR * ~DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT+<br>~HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * PUNTOINF * PATRONT * NEXOINST * DIRECCIONT * DIFUSIONT * ~EXPONENCIALT+<br>~HACTOR * ~IACTOR * ~DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT+<br>~HACTOR * ~IACTOR * DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * DSOSTENIBLE * INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT+<br>~HACTOR * ~IACTOR * ~DIVERSIDADT * EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT+<br>"=>IA |

| | | Tasa de cobertura | Índice de concistencia |
|---|---|---|---|
| 1 | ~HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * INVERSIONEND * UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * DIFUSIONT * EXPONENCIALT | 0.3738 | 0.9090 |
| 2 | HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * INVERSIONEND * UCONOCIMIENTO * PUNTOINF * PATRONT * ~NEXOINST * DIRECCIONT * DIFUSIONT * ~EXPONENCIALT | 0.6089 | 0.8207 |
| 3 | HACTOR * ~IACTOR * ~DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT | 0.3145 | 0.9750 |
| 4 | ~HACTOR * IACTOR * DIVERSIDADT * EXTERNAIDADR * INTERACCIONS * DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * PUNTOINF * PATRONT * NEXOINST * DIRECCIONT * DIFUSIONT * ~EXPONENCIALT | 0.3364 | 0.8690 |
| 5 | ~HACTOR * ~IACTOR * ~DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT | 0.2984 | 1.0000 |
| 6 | ~HACTOR * ~IACTOR * DIVERSIDADT * ~EXTERNAIDADR * ~INTERACCIONS * DSOSTENIBLE * INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * ~DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT | 0.3548 | 0.9362 |
| 7 | ~HACTOR * ~IACTOR * ~DIVERSIDADT * EXTERNAIDADR * ~INTERACCIONS * ~DSOSTENIBLE * ~INVERSIONEND * ~UCONOCIMIENTO * ~PUNTOINF * ~PATRONT * ~NEXOINST * DIRECCIONT * ~DIFUSIONT * ~EXPONENCIALT | 0.3135 | 0.9750 |
| MI | | 0.7650 | 0.7528 |

Source: Own elaboration from Tosmana

**Table 4** Positioning of innovation management in the AI sector

| Presence | Variables | Key code | Innovation management strategic in the field of artificial intelligence in enterprises in Mexico through |
|---|---|---|---|
| Yes | Heterogeneity of the actors—homo agents - | hactor | Development of heterogeneous internal and external innovation networks with other actors for the development of technological adaptation activities in artificial intelligence |
| Yes | Interaction of the actors—competition and cooperation<br>Technological competence | iactor | Definition of digital strategies to maintain competition and their products in the market through interaction with external actors |
| Yes | Technological diversity<br>Technological convergence<br>Technology niche | diversidadt | Development of an R&D strategy that connects the intern to the different organizational and operational areas to enhance their innovative capacity |
| Yes | Network externalities | externaidadr | Choice and implementation of the innovation strategy based on user needs |
| Yes | Social interactions<br>Technological assimilation<br>Government action | interaccions | Promotion of interaction mechanisms between internal and external actors (government, society, industry) to obtain information and use it in the design of the innovation strategy |
| Yes | Environmental policy<br>Sustainable development | dsostenible | Placement of environmental sustainability among the top three innovation priorities of the company |
| Yes | Endogenous investment in R&D | inversionend | Determination of expenses and investment expenses and investment in R&D of the company are also due to the internal dynamics generated by the organizational and operational processes |
| Yes | • Knowledge threshold | uconocimiento | Product development is decisively related to the use and accumulation of knowledge generated within the company |
| Yes | Technological transition<br>Inflection point | puntoinf | Formulation of innovation strategies based on the monitoring of maturity, obsolescence, and new deployment of digital technologies |
| Yes | Paradigm as a technological pattern<br>Differentiated technological revolutions | patront | Differentiation of the work of coordination and collaboration between innovation actors to generate innovation |
| Yes | Links between institutions (networks) | nexoinst | Development of economic analysis and projections on the benefit generated by digitization in the short and medium term |

**Table 4** (continued)

| Presence | Variables | Key code | Innovation management strategic in the field of artificial intelligence in enterprises in Mexico through |
|---|---|---|---|
| Yes | Technological management | direcciont | Conformation of the diffusion of technology in the business strategy to implement new organizational and product innovation strategies |
| Yes | Technological diffusion | difusiont | Conception of the preponderant performance of a specific innovation actor to impact the artificial intelligence market |
| Yes | Scientific policy | Steeringf | Identification of an innovation actor |
| Yes but at a low level | Exponential technological behavior | exponencialt | An organizational unit is partially consolidated to monitor the exponential development that artificial intelligence is experiencing and uses the information to implement new innovation strategies |

Own elaboration

necessary but not sufficient to produce the result (Wagemann, 2012). When reviewing the M1 model, 7 individual ways—configurations—of the conditioning and adaptive variables of the digital transformation are seen separated by the + sign, which show the strategic orientation of the current innovation management that companies develop in the face of the dynamism of the digital transformation as the dominant technological pattern (see previous Table 4).

In the second section of the previous table, you can see each individual configuration—listed from 1 to 7—that is, each conditioning and adaptive variable of the DT individually generates the strategic orientation of the current innovation management that companies develop against the dynamism of the DT together with its indicators: (a) sufficiency inclusion score, inclS; (b) proportional reduction in inconsistency, PRI; (c) raw coverage, covS; and (d) unique coverage, covU. It is important to define the above indicators when interpreting the results. Wagemann (2012) defines the PRI as an adjustment measure proposed by Ragin (2009) to calculate the degree to which a minimum term is as sufficient for a result as it is for the negation of this result. Ragin (2006) mentions that a value equal to 0.8 or greater is sufficient to generate a result. For his part, Duşa (2018) mentions that sufficiency inclusion score is based on the sufficiency inclusion score, returning a truth value that indicates the degree to which the evidence is consistent with the hypothesis that there is a sufficiency relationship between a configuration and the set of results. Raw coverage indicates the total percentage of cases that explain the result from a configuration (Ragin, 2006). Unique coverage refers to the percentage of cases exclusively explained by a certain configuration (Ragin, 2006).

In this sense, the (see Table 3) exhibits in detail the individual configurations of the integrated components that identify the strategic orientation of the current innovation management that companies develop against the dynamism of DT as the dominant technological pattern, as well as their corresponding indicators which will be analyzed from now on. Within these 7 configurations, configuration No. 2 appears as the most representative (Ragin, 2009). There, a total coverage rate of 0.6089 is observed, which means that 60% of the surveys carried out show that companies focus more on the innovation strategy compared to DT in correspondence with a specific group of variables (see Table 4).

According to the previous table, it can be seen that of the 15 operationalized DT conditioning and adaptive variables, all of them are present in all configurations; however, it is worth noting that the variable "technological exponential behavior" (see Table 3 of configurations, configuration 1 where a disjunction of the exponential variable is appreciated t) is present but at a lower level of belonging, that is, within the strategic orientation of current innovation management developed by companies, an organizational unit is partially consolidated to monitor the exponential development that AI is undergoing and the information is used to implement new innovation strategies.

The second most relevant configuration is No. 1; here a total coverage rate of 0.3738 is presented, which means that 37% of the companies interviewed validate that the conditioning and adaptive variables of the specific DT of this configuration show the orientation strategy of the current innovation management that companies develop against the dynamism of DT in a very specific way. It should be noted that in this configuration, there are five variables with a low level of belonging to the strategic orientation of innovation management: ~ hactor * uknowledge * ~ pointinf * ~ patront * ~ nexoinst * ~ direcciont * diffusiont * exponentialt. This means that strategies to address DT are incipient.

The third most relevant configuration is No. 6; here a total coverage rate of 0.3738 is presented, which means that 37% of the companies interviewed validate that the conditioning and adaptive variables of the specific DT of this configuration show an orientation very specific innovation management strategy. It should be noted that in this configuration, there are eleven variables with a low level of belonging to the strategic orientation of innovation management: ~ factor * ~ actor * ~ externality * ~ interactions * ~ uknowledge * ~ pointinf * ~ patront * ~ nexoinst * ~ direccíont * ~ diffusiont * ~ exponentialt. This allows us to interpret that the strategies to address these variables are also incipient.

Analyzing the 7 configuration pathways, 2 is more closely related to the variables that characterize the dominant character of DT and consequently show potential strategic elements that can be used by companies to quickly adapt to the dynamics that the pattern develops, but this does not mean that the other configurations are not relevant, since they show other ways by which other alternatives of strategic orientation of the current innovation management can be generated that companies develop in the face of the dynamism of DT as the dominant technological pattern (Ragin, 2006).

## Conclusions

The seven configurations identified in the QCA have a coverage of 0.7650, indicating that 70% of the companies in the AI sector analyzed in this study are represented by the set of variables (integrated components) that characterize the TD as the dominant technological pattern. This initially allows identifying the positioning of these companies' innovation management in the face of the dynamics and complexity of the TD. Subsequently, it would enable these companies to readjust their innovation strategies during and after COVID-19. Based on these results, it can be asserted that the contributions of Schumpeter (1942) and subsequent ones from neoschumpeterian economics (Jenkins, 2010; Benner, 2016; Morro, 2019; Estrada et al., 2016) continue to hold significant theoretical value for understanding technology sectors highly shaped by technological change. However, it is crucial to recognize that the application of these theories may depend on the context, and their explanatory power could vary among different industries or regions.

Identifying configurations that allow observing the efforts of these companies to adapt to the TD is relevant, particularly in less advanced economies. In contrast to industrialized economies where the dynamism of the technological pattern generates radical innovations (Benner, 2016; Jenkins, 2010; Palacios & Escott, 2021). Nevertheless, although the configurations provide a comprehensive view of innovation management, the lack of specific information on how companies learned and adapted during the COVID-19 pandemic limits the depth of understanding. Future research incorporating empirical data from this critical period could enhance the study's robustness.

While it is true that for companies in the AI sector in Mexico, discontinuous changes capable of transforming the local, regional, or national economic structure cannot be clearly identified (Anderson & Tushman, 1990), it is significant to note that through innovation management, these companies mobilize innovation capacities for the adaptation and sustainability of competitiveness (Schumpeter, 1942). However, it is fundamental to recognize that policy effectiveness may vary depending on factors not explored in this research, such as regulatory environments, political climates, or international collaborations.

According to this work, adapting to the dynamics of the dominant technological pattern does not necessarily mean being able to innovate but also creating conditions for innovation. This materializes in the development of organizational innovation capabilities. This clarifies an issue in innovation studies when formulating public policies linked to the TD (Escott, 2020): policies are formulated either for radical innovations or incremental innovations, depending on the specific innovation capacity existing in geographical contexts (Escott Mota, 2020, and Palacios & Escott, 2021).

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## Declarations

**Ethics Approval** This article does not contain any studies with human participants or animals performed by any of the authors.

**Consent to Participate** Not applicable.

**Consent for Publication** The authors approved the publication of the final manuscript.

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