eman ta zabal zazu

Universidad del País Vasco
Euskal Herriko Unibertsitatea

Rudy Fernández Escobedo

The Industrial Cluster in the Digital Era

Unleashing the economic development synergies of industrial agglomeration and digital transformation in Spain

2024

eman ta zabal zazu

Universidad del País Vasco
Euskal Herriko Unibertsitatea

Rudy Fernández Escobedo

The Industrial Cluster in the Digital Era

Unleashing the economic development synergies of industrial agglomeration and digital transformation in Spain

Supervisors:
Begoña Eguía Peña, PhD
Leire Aldaz Odriozola, PhD

2024

The Industrial Cluster in the Digital Era:
Unleashing the economic development synergies of industrial agglomeration and digital transformation in Spain

Universidad del Pais Vasco / Euskal Herriko Unibertsitatea (UPV/EHU)
Faculty of Economics and Business (Sarriko)
Department of Public Policy and Economic History
Lehendakari Agirre, 83
48015 Bilbao (Bizkaia), Spain

Suggested citation:
Fernández-Escobedo, R. (2024). The Industrial Cluster in the Digital Era: Unleashing the economic development synergies of industrial agglomeration and digital transformation in Spain. Universidad del País Vasco / Euskal Herriko Unibertsitatea (UPV/EHU).

Executive summary (Spanish)

La investigación sobre el desarrollo económico ha sido una preocupación fundamental desde que Adam Smith escribió su libro "La Riqueza de las Naciones" en 1776. Desde entonces, se han llevado a cabo múltiples esfuerzos para comprender este fenómeno y utilizar tal comprensión en la promoción del desarrollo económico de las naciones.

La Teoría de la Aglomeración, uno de los resultados de estos esfuerzos, pone énfasis en las aglomeraciones industriales, sus causas y efectos en la economía. Dicha teoría, enmarcada en el conocimiento de la geografía económica, destaca la relevancia de la geografía y el papel de las ciudades y regiones como elementos clave para el desarrollo económico de las naciones a largo plazo.

Investigadores y académicos han conceptualizado múltiples modelos de aglomeración basados en la urbanización y la localización. Entre estos modelos han destacado el *clúster industrial* y *el distrito industrial*, siendo el primero el más influyente de los últimos treinta años debido al alcance de su instrumentalización, principalmente en los EE.UU. y Europa.

Sin embargo, la aglomeración industrial se encuentra ante desafíos contemporáneos relacionados con la transformación digital y el desarrollo tecnológico, y se ha convertido en un actor importante en términos de competitividad y desarrollo económico. Además, la falta de un entendimiento amplio sobre el fenómeno de la aglomeración en entornos más complejos e interconectados genera una importante brecha de conocimiento para la investigación.

Esta tesis tiene como objetivo contribuir al avance en el campo de la geografía económica, el desarrollo regional y la economía digital, respondiendo a las siguientes tres preguntas dentro del marco conceptual de la Teoría de la Aglomeración y los clústers industriales:

1. ¿Es teóricamente factible desarrollar un instrumento de política industrial basado en clústers y transformación digital?
2. ¿Es posible adaptar e implementar una metodología integral para identificar clústers en territorios fuera de los EE.UU., basada en procedimientos de vanguardia?
3. ¿Existe una relación positiva entre los clústers y la adopción de tecnología con el desarrollo económico, y cuál es el papel de la competitividad en dicha relación?

Esta tesis aborda las preguntas de investigación mediante un enfoque conceptual y empírico, que incluye una revisión de la literatura junto con un análisis de datos económicos. La elección del ámbito geográfico, España, se debe a su historia de políticas basadas en aglomeración industrial. Además, como miembro de la Unión Europea, España proporciona un marco de datos estandarizados que pueden facilitar la aplicabilidad de las metodologías desarrolladas en esta tesis en otras economías europeas. La tesis consta de tres capítulos y cada capítulo aborda las preguntas generales de investigación.

El Capítulo I propone el concepto de *Clúster Industrial Digital* (CID) como un instrumento de política industrial para el desarrollo económico en el contexto de la digitalización y la Industria 4.0. Se basa en los cimientos de los clústers industriales tradicionales y tiene como objetivo integrar tecnologías digitales y espacios virtuales en el marco de los clústers.

El concepto de CID reconcilia los desafíos planteados por la globalización y la deslocalización con la importancia de la proximidad geográfica y las economías basadas en el conocimiento. El capítulo revisa la literatura relevante sobre clústers industriales, aglomeración digital, tecnologías de la información y comunicación (TIC) e Industria 4.0, así como el impacto de la pandemia de COVID-19 en estos fenómenos.

El estudio compara el CID con otros instrumentos de política industrial y presenta su implementación potencial, requisitos estructurales, externalidades y desafíos. Se espera que el CID facilite la integración digital, la descentralización y la colaboración entre organizaciones geográficamente dispersas dentro de los clústers. Además, el CID ofrece beneficios como la integración multirregional, la gestión del conocimiento, la diversidad industrial y la co-creación de valor.

Este capítulo pone de manifiesto que el CID puede ser especialmente relevante tanto para economías desarrolladas como en desarrollo, en particular en clústers de manufactura de alto valor agregado, ayudándolos a superar las disparidades regionales en infraestructura digital. El capítulo ofrece perspectivas para responsables políticos, organizaciones de clústers e investigadores, y además presenta un modelo de implementación para el CID.

Por otro lado, el capítulo también aborda desafíos relacionados con la digitalización y el desarrollo regional para que el CID tenga éxito, incluida la modernización de la infraestructura, la innovación en modelos de negocio, la evaluación de tecnologías, la ciberseguridad y las regulaciones.

Sin embargo, más allá de los desafíos de la transformación digital, persisten retos con respecto a la identificación empírica de aglomeraciones industriales.

La aglomeración industrial juega un papel vital en fomentar la productividad y la innovación en una economía competitiva. Los modelos de distrito industrial y de clúster industrial han ganado una significativa popularidad en las últimas décadas, siendo el primero altamente institucionalizado en Europa y los EE.UU. Los esfuerzos para identificar y mapear aglomeraciones industriales han resultado en el desarrollo de herramientas de mapeo como el *U.S. Cluster Mapping Project* y la *European Cluster Collaboration Platform*. Sin embargo, existe una brecha en la literatura respecto a una iniciativa integral de mapeo de clústers para Europa que utilice datos, metodología y literatura estandarizados.

El Capítulo II tiene como objetivo abordar esta brecha mediante la implementación de una metodología cuantitativa que utiliza datos locales para complementar los esfuerzos de mapeo de clústers existentes a nivel nacional. La metodología se aplica en España, un país con características geográficas e industriales únicas, y se centra en crear *Definiciones de Categoría de Clústers* (CCD) domésticas, así como un mapa de clústers.

Además, el estudio explora la correlación entre la presencia de clústers y diversas variables económicas, al mismo tiempo que construye índices de adopción regional de TIC e Industria 4.0.

Los hallazgos contribuyen a la literatura al resaltar las adaptaciones metodológicas necesarias para diferentes economías, cuestionar el supuesto de representatividad de los vínculos interindustriales estadounidenses y demostrar la correlación entre la presencia de clústers y otras variables como la educación, la adopción tecnológica y la competitividad. El estudio ofrece perspectivas prácticas para investigadores, responsables políticos y profesionales.

Finalmente, el Capítulo III explora las complejas relaciones entre los clústers industriales, la adopción de tecnología, la competitividad y el desarrollo económico. Su objetivo es contribuir a la literatura mediante la investigación sobre el papel de los clústers en la promoción del desarrollo económico en España. El estudio utiliza una metodología detallada de mapeo de clústers, así como un enfoque de multi-mediación basado en un *Modelo de Ecuaciones Estructurales por el Método de Mínimos Cuadrados Parciales* (PLS-SEM) para analizar las relaciones entre la aglomeración industrial, la adopción tecnológica, la competitividad y el desarrollo económico, expresado este último en dos dimensiones: el PIB *per cápita* y las ganancias *por trabajador*.

Los hallazgos demuestran que la aglomeración industrial, la digitalización y la competitividad influyen significativamente en el desarrollo económico. Los clústers actúan como promotores de la adopción de tecnología, lo que a su vez afecta a la competitividad y estimula la innovación, el apoyo institucional y la productividad. El estudio revela que la relación entre los clústers y el desarrollo económico está mediada por la adopción de tecnología y la competitividad.

Este último estudio proporciona conocimientos valiosos sobre las dinámicas complejas de los clústers y su influencia en los resultados económicos, contribuyendo a la búsqueda de un desarrollo económico sostenible e inclusivo.

A continuación, y con base en los hallazgos de la tesis, se presentan las respuestas a las preguntas de investigación y los principales argumentos que las respaldan.

1. Es teóricamente factible desarrollar una herramienta de política basada en clústeres industriales y transformación digital. Los argumentos presentados en el Capítulo I resaltan la compatibilidad y la sinergia potencial entre la aglomeración industrial y la transformación digital, introduciendo el concepto del Clúster Industrial Digital (CID) como un nuevo instrumento de política industrial basado en un modelo de aglomeración digital.

2. Es posible adaptar e implementar una metodología de extremo a extremo para identificar clústeres industriales en territorios fuera de los EE. UU. El Capítulo II aplica con éxito dicha metodología al contexto español, utilizando datos locales a nivel NUTS-2. Este esfuerzo parte de iniciativas previas de mapeo de clústeres, demostrando la viabilidad de aplicar esta metodología a países europeos y desafiando el supuesto de representatividad, que establece que los patrones de localización encontrados en los EE. UU. son representativos de aquellos en Europa.

3. Los clústeres industriales y la adopción de la tecnología tienen una relación positiva y significativa con el desarrollo económico; sin embargo, el papel de la competitividad emerge como un factor influyente en esta relación compleja. En el Capítulo III, la aglomeración industrial demuestra su impacto positivo en la adopción tecnológica. Además, la relación positiva entre los clústeres industriales y la adopción de tecnología es crucial para impulsar el desarrollo económico, el cual también se ve influido por el nivel de competitividad.

La tesis tiene implicaciones para la política, la academia y la industria. Los responsables de políticas industriales pueden desarrollar el concepto de CID, adaptar metodologías de mapeo de clústers y promover la adopción de tecnología y competitividad en el marco de la aglomeración industrial, como promotores del desarrollo económico. Los investigadores pueden beneficiarse de los enfoques metodológicos y las perspectivas dinámicas presentadas, las cuales les brindan una comprensión ampliada de las relaciones entre clústers industriales, tecnología, competitividad y su impacto en el desarrollo económico. Los industriales pueden utilizar los conocimientos para desarrollar estrategias de desarrollo regional y de localización industrial, así como de asignación de recursos y adopción de tecnología.

Sin embargo, se deben reconocer las limitaciones de esta investigación, como la falta de evaluación empírica del CID y aquellas relacionadas al tamaño de la muestra, la disponibilidad de datos y la inferencia causal. Dichas limitaciones podrían condicionar la generalización de los hallazgos.

Las recomendaciones para futuras investigaciones incluyen, por un lado, la realización de estudios empíricos y de caso sobre el CID, y por otro, la ampliación de los ejercicios de mapeo de clústers en diferentes países de Europa. También es recomendable ejecutar análisis longitudinales sobre el impacto de la aglomeración industrial que consideren mejoras metodológicas relacionadas a variables de desarrollo económico, así como partir de una muestra más grande (ampliar el alcance geográfico) que soporte la validez de los resultados. Además, se sugiere incorporar a futuros análisis perspectivas que sean de interés para responsables políticos e industriales.

Esta tesis amplía el conocimiento en geografía económica y contribuye al desarrollo de la teoría de la aglomeración al considerar los efectos disruptivos de la transformación digital. Aporta metodologías sólidas, perspectivas dinámicas y soluciones teórico-prácticas a los desafíos de los clústers industriales y la transformación digital. Contribuye al desarrollo de un enfoque más integral y aporta elementos valiosos para el diseño de políticas efectivas para el crecimiento económico sostenible, la innovación y el desarrollo regional.

A mi madre, por su cariño y apoyo incondicional.

A Prisci, por su amor y comprensión.

A mi padre, por estar siempre ahí.

A mi hermano y a mi hermana, por creer en mí.

A mi gran amigo Mota, por ser mí compañero de lucha.

Ubi concordia, ibi victoria – Publius Syrus

Acknowledgements

I extend my sincere gratitude to my esteemed supervisors, Professor Begoña Eguía Peña and Professor Leire Aldaz Odriozola. Their wealth of experience and knowledge played a pivotal role in shaping this project, and their guidance has been instrumental in bringing me to this point.

Furthermore, I want to express my special thanks to Dr. Hector Cuevas Vargas, whose mentorship has provided me with invaluable insights along this journey.

I am deeply appreciative of the University of the Basque Country for furnishing the essential resources and support needed for the development of my research project. My thanks extend to the Department of Public Policy and Economic History and the Doctoral Programme in Economic Integration.

Lastly, my heartfelt gratitude goes to Euskadi and its resilient people for their warm welcome. It is their industrious spirit that served as a profound inspiration for this research.

Eskerrik asko!

Contents

Introduction

Background

Economic development is probably the main matter of economic concern since Adam Smith wrote his book *The Wealth of Nations* back in 1776.

Thenceforth, industrialist, policymakers, and researchers have led multiple efforts to understand this phenomenon and use such understanding in the promotion of economic development among nations.

The theory of agglomeration, one of the results of the aforementioned efforts, was founded by Marshall (1920) and placed emphasis on industrial agglomerations, its causes, and its effects on economy. This theory, framed under the economic geography's body of knowledge, stressed the relevance of geography and the role of cities and regions as key elements for economic development of nations in the long term. Under its approach, macroeconomics is not able to fully understand economic development by itself and must be complemented by regional and local approaches, as proximity and agglomeration are sources of competitive advantages (Leamer & Storper, 2001).

Researchers conceptualized two models of agglomeration based on industrial agglomeration: the urbanization and the localization (Feser, 1998; Jofre-Monseny et al., 2014; Scott & Storper, 2007). The first was concerned about cities and the second one about larger regions, and both provided economist and geographers with foundations for conceptual developments and models concerning industrial agglomeration as source of economic prosperity (Becattini, 1990; Hoover, 1948; Krugman, 1991; Porter, 1990; Slaper et al., 2018).

Academics have made significant efforts to synthesize the existing theoretical and empirical literature to better comprehend and elucidate the causes and consequences of agglomeration (Cruz & Teixeira, 2010; Duranton & Puga, 2004; Fujita & Mori, 2005; Hoover, 1948; Krugman, 1991; Romanelli & Khessina, 2005; Skokan & Zotyková, 2014; Zeibote & Muravska, 2018). The main challenge in these endeavors lies in the conceptual heterogeneity inherent to the agglomeration theory, as similar phenomena are described using different concepts (Duranton, 2011; Storper, 2009).

Tecnopolis, *millieux innovateur*, regional innovation system, industrial district, and industrial cluster. These are some of the most transcendental concepts developed around the industrial agglomeration phenomenon; all of them share foundations and expect to have similar effects over economy (Bayliss, 2007; Ortega-Colomer et al., 2016). However, as foundations remain consistent among concepts, the situation is different for the externalities.

There is a substantial body of literature that delves into the motives, drivers, and barriers behind the emergence of industrial agglomeration. These diverse scholarly works often serve to complement and reinforce one another, proposing historic, sociologic, economic, and competitive drivers of agglomeration (Babkin et al., 2018; Bayliss, 2007; Becattini, 1990; Cortright, 2006; Delgado, Porter, et al., 2014; Duranton & Puga, 2004; Jasinska & Jasinski, 2019; Johansson et al., 2006; Ketels, 2004; Ketels & Memedovic, 2008; Krugman, 1991; Leamer & Storper, 2001; Marshall, 1920; Ortega-Colomer et al., 2016; Porter, 1990; Romanelli & Khessina, 2005; Rosenthal & Strange, 2001; Schumpeter, 1934; Scott & Storper, 2007; Vlaisavljevic et al., 2020). Nevertheless, all those proposals fit in the theoretical framework of regional development and rely over a common factor: geographic proximity.

In contrast, the research about industrial agglomeration's externalities, either positives or negatives, is abundant but less conclusive. The existence of conceptual heterogeneity has posed significant challenges for academics when attempting to assess the effects of this phenomenon. The challenges rest in the lack of consensus on the geographic delimitation of the phenomenon and the definition of its actors, resulting in methodological shortcomings concerning to the identification of industrial agglomerations and the nature of their externalities (Delgado et al., 2016; Ortega-Colomer et al., 2016; Rocha, 2004).

However, two models of industrial agglomeration have stood out in the discussion among researchers, industrialist, and policymakers: the industrial cluster and the industrial district. The industrial district concept was born in Italy, in the northern region, where was widely studied and exported to the world, portraying agglomeration as an urbanization phenomenon (Becattini, 1990; Sforzi, 2015). In contrast, the industrial cluster was framed in the American context, such as Silicon Valley, and views industrial agglomeration as a localization phenomenon (Porter, 1990; Slaper et al., 2018). Both concepts were first observed and described as a real-world phenomenon, and later they were instrumentalized as policy tools as an intent to achieve industrial policy goals of nations and regions.

Although the industrial district approach initially gained popularity, the industrial cluster ended up prevailing over other models of industrial agglomerations, gaining significant popularity among policymakers and industrials owing to its straightforward approach and its relative ease of implementation (Delgado, Porter, et al., 2014; Porter, 2000; Porter et al., 2007).

Nonetheless, researchers criticize the Porterian industrial cluster for several reasons: its oversimplification, static view, limited applicability, and potential negative consequences on regional development (Duranton, 2011; Feser, 1998; Grashof & Fornahl, 2021; Molina-Morales et al., 2017; Rocha, 2004; Sforzi, 2015; Skokan & Zotyková, 2014). One of the main criticisms is that the model tends to oversimplify the complexities of industrial development and competitiveness, arguing that the model focuses too heavily on geographic proximity and inter-firm collaboration, while neglecting other crucial factors such as institutional support, access to resources, and global value chains, underestimating studies made under different approaches as the industrial district. Another criticism is that this model assumes a static view of industrial agglomeration treating it as a self-contained entity, whereas industries and clusters are constantly evolving, influenced by global forces in today's dynamic and interconnected global economy. Critics argue that the model fails to account for the dynamic nature of agglomeration and their interactions with the broader economic environment. Additionally, academics question the generalizability of the industrial cluster as a one-fits-all model across different industries and regions, as it may not be applicable or effective in diverse contexts. And finally, there are concerns that the Porterian cluster model may lead to a concentration of resources and opportunities in already established clusters, exacerbating regional inequalities, and hindering the development of emerging industries and regions.

Despite its flaws, the industrial cluster concept succeeded in taking the industrial agglomeration at the center of the conversation for industrial policymakers, achieving large levels of institutionalization all around the world (Ortega-Colomer et al., 2016). Furthermore, the concept has evolved embracing different approaches introduced from other models of agglomeration (Caloffi et al., 2018).

Challenges

The industrial cluster as phenomenon and policy tool has built bridges among policymakers, industrials, and researchers, creating a common language to discuss industrial policy based on agglomeration. Unfortunately, the enthusiasm for implementing the model has surpassed the efforts to deeply understand and solve contemporaneous challenges concerning industrial agglomeration, which this thesis introduces and summarizes in three general research questions.

The first challenge concerns to digitalization and globalization. Globalization and advancements in Information and Communication Technologies (ICT) have led to the dispersal of economic activity and the rise of digital economies, transforming the traditional role of geography and face-to-face interactions (Alcacer et al., 2016; Almeida et al., 2020; Knell, 2021). The development of ICT has facilitated globalization and the adoption of innovative industrial technologies associated with Industry 4.0 (Maresova et al., 2018; Muller et al., 2018; Schwab, 2016). Moreover, the COVID-19 pandemic introduced contrasting forces (Guo et al., 2020). On one hand, it exerted immense pressure on globalization while highlighting the importance of regional economies. On the other hand, it accelerated digitalization efforts in both the public and private sectors, empowering the delocalization of specific activities. This challenge lead to the first research question*: is it theoretically feasible to develop a policy tool founded on industrial clusters and digital transformation?*

The second challenge has a methodological nature. As mentioned earlier, there is not a consensus among researchers about how to identify industrial agglomeration under a quantitative and empirical approach (Delgado et al., 2016; Lorenzini & Lombardi, 2018).

This lack of consensus daunts the empirical assessment of the agglomeration's externalities and the feasibility of novel policy tools based on such agglomeration. The situation has led to researcher to opt for the *representativeness assumption*, which assumes that the cross-industry linkages found in US are representative for those found in other countries and, thus, are useful to identify industrial clusters over them (Ketels & Protsiv, 2021; Szanyi et al., 2010). Such assumption has discouraged the empirical assessment of the industrial cluster presence along economies, resulting in the second research question*: is it possible to adapt and implement an end-to-end methodology to identify industrial clusters over territories outside US, according to state-of-the-art methodologies?*

The third and last challenge encompass the two aforementioned plus the externalities issue. The development of innovative policy tools founded on agglomeration and digitalization demands a deeper understanding of the relationship between these phenomena. Although there are previous efforts to comprehend such relation, the rapid advances in ICT and the emergence of novel ideas as Industry 4.0 have left research behind with important gaps about how these phenomena interact in real world (Corradini et al., 2021; Cuevas-Vargas & Fernández-Escobedo, 2022; Grashof et al., 2021; Yudina, 2019). Additionally, while the final purpose of the mentioned policy tools is contributing to economic development through the improvement of elements as the productivity and the innovation, the intricate nature of the economy and agglomerations presents significant challenges in comprehending these phenomena and their mutual dynamics (Delgado, Porter, et al., 2014; Slaper & Ortuzar, 2015; Storper, 2009). The thorough understanding of all those relations calls for novel research techniques capable to seed light over the phenomena, helping to develop more comprehensive and effective policy for economic development. Therefore, the final research question is*: are industrial clusters and technology positively related to economic development and what is the role of competitiveness in such relation?*

Those research questions serve as a foundation for this thesis, which delves into the complexities of the topic at hand, aiming to advance our understanding and inform strategic decision-making.

Rationale

The rationale behind this research is to address several key challenges in the field of industrial agglomeration while answering the general research questions. Such challenges are previously presented as well-stablished criticism to a wide spectrum of industrial agglomeration models.

Firstly, the static view of industrial clusters limits the understanding of its dynamic nature, particularly in a digital context. By adopting a more dynamic perspective of industrial agglomeration based on digital transformation, this research seeks to capture the evolving aspects of the phenomenon and offer insights into how novel policy tools could establish a path for adaptation.

Additionally, there is a lack of methodological application for cluster mapping, where existing approaches may not be effectively or straightforwardly applied to other economic realities or contexts. This research is tailored to address this gap through the assessment of the replicability of state-of-the-art methodologies, thus providing methodological insights and practical implications for future research.

Furthermore, the oversimplification of the agglomeration phenomenon is another issue that needs to be tackled. Many current approaches tend to overlook the intricacies and nuances involved in industrial clusters, leading to incomplete or inadequate reasoning. This research aims to delve deeper into the complexities of the phenomenon at hand and provide a more comprehensive analysis, involving digitalization and multiple economic and sociodemographic variables, adopting novel approaches to assess their complex dynamics.

In addition to the challenges mentioned, another crucial issue that this research aims to tackle is the limited applicability of previous methodological and conceptual models, hindering their practical implementation. This research aims to develop practical and applicable solutions that can be implemented in various contexts, expanding the scope of their utilization.

Lastly, this research aims to tackle the lack of a comprehensive understanding of the relationships among involved variables. Many existing studies may only examine isolated aspects without considering the interdependencies and interactions among variables. This research seeks to bridge this gap by conducting a thorough analysis of the complex relationships among clusters, digitalization, competitiveness, and economic development. By employing advanced analytical techniques and considering the intricate connections between different factors, a more holistic and nuanced understanding of the problem can be achieved. Therefore, this research aims to contribute to the development of more accurate models and theories that capture the multidimensional nature and effects of the industrial agglomeration phenomenon.

By addressing these challenges, this research aims to contribute to the advancement of the economic geography by providing more robust methodologies, capturing the complexity of the problem, adopting a dynamic viewpoint, enhancing the applicability of solutions, and leading to more effective strategies, interventions, and policies to address the challenges of industrial clusters and digital transformation.

Structure

This thesis addresses the previously raised research questions through a conceptual and empirical approach, conducting an in-depth literature review and the analysis of economic and sociodemographic data. This is accomplished through the application of first-and-second generation statistical techniques.

The object of study is the impact of industrial clusters and digitalization levels on competitiveness and economic development in the Spanish economy. The election of Spain obeys practical and conceptual rationales. The country has a contemporaneous history implementing policy tools based on industrial agglomeration, mainly under the approach of industrial clusters and industrial districts, which ensures the existence of the phenomenon over territory. Besides, the existing body of literature of the Spanish case guarantee the availability of public data to conduct the research. Ultimately, as member of the European Union, Spain provides a framework of standardized data that may ease the applicability of the methodologies developed in this thesis over other European economies.

The thesis is structured by three chapters and a last section including general conclusions and remarks. Each chapter is organized following a *research paper* structure, and they aim to address and answer the general research questions presented.

Chapter I proposes the concept of the Digital Industrial Cluster (DIC) as a policy tool for economic development in the context of digitalization and Industry 4.0. It builds upon the foundations of traditional industrial clusters and aims to integrate digital technologies and virtual spaces into the cluster framework. The DIC concept reconciles the challenges posed by globalization and delocalization with the importance of geographic proximity and knowledge-based economies. The chapter reviews relevant literature on industrial clusters, digital agglomeration, ICT, and Industry 4.0, as well as the impact of the COVID-19 pandemic on these phenomena. It compares the DIC with other policy tools and presents its potential implementation, structural requirements, externalities, and challenges. The DIC is expected to facilitate digital integration, decentralization, and collaboration among geographically dispersed organizations within clusters. It offers benefits such as multi-regional integration, knowledge management, industrial diversity, and value co-creation. The DIC can be particularly relevant for both developed and developing economies, supporting high-value-added manufacturing clusters and addressing regional disparities in digital infrastructure. The chapter provides insights for policymakers, cluster organizations, and researchers, and offers a deployment model for the DIC. However, challenges related to digitalization and regional development must be addressed for the DIC to succeed, including infrastructure modernization, business model innovation, technology assessment, cybersecurity, and regulations.

However, beyond the challenges of digital transformation, there are still issues concerning the empirical identification of industrial agglomerations.

Industrial agglomeration plays a vital role in fostering productivity and innovation in a competitive economy. The industrial district and industrial cluster models have gained significant popularity in recent decades, with the former being highly institutionalized in Europe and the US. Efforts to identify and map industrial agglomerations have resulted in the development of mapping tools such as the Cluster Mapping Project in the US and the European Cluster Collaboration Platform in Europe. However, there is a gap in the literature regarding a comprehensive cluster mapping initiative for Europe that uses common data, methodology, and literature. Chapter II aims to address this gap by implementing a quantitative methodology using domestic raw data to complement existing national-level cluster mapping efforts. The methodology is tested on Spain, a country with unique geographic and industrial characteristics, and focuses on creating domestic Cluster Category Definitions (CCD) and a cluster map. The study explores the correlation between cluster presence and various economic variables, while also constructing indexes for regional ICT adoption and Industry 4.0 technologies. The findings contribute to the literature by highlighting methodological modifications necessary for different economies, questioning the representativeness assumption of American cross-industry linkages, and demonstrating the impact of cluster presence on education, technology adoption, and competitiveness. The study provides practical insights for researchers, policymakers, and practitioners, while acknowledging limitations related to data aggregation and availability.

Finally, Chapter III explores the intricate relationships between industrial clusters, technology adoption, competitiveness, and economic development. It aims to contribute to the existing body of knowledge by investigating the role of industrial clusters in promoting economic development in Spain. The study utilizes a granular mapping methodology and a structural equation modeling approach to analyze the relationships between industrial clusters, technology adoption, competitiveness, and two dimensions of economic development: GDP per capita and earnings per worker. The findings demonstrate that industrial clusters, digitalization, and competitiveness significantly influence economic development. Industrial clusters serve as promoters of technology adoption, which in turn impacts competitiveness and drives innovation, institutional support, and productivity. The study reveals that the relationship between industrial clusters and economic development is mediated by technology adoption and competitiveness. The research findings offer valuable insights for policymakers, industrials, and academics. Policymakers can formulate effective strategies and policies to develop industrial clusters and enhance competitiveness. Industrial stakeholders can make informed decisions regarding business location, resource allocation, and technology adoption. Academics benefit from an expanded understanding of the relationships between industrial clusters, technology, competitiveness, and their impact on economic development. However, the research has limitations in terms of sample size, data availability, causal inference, and generalizability. Despite these limitations, the study provides valuable insights into the complex dynamics of industrial clusters and their influence on economic outcomes, aiding in the pursuit of sustainable and inclusive economic development.

The thesis concludes with a summary of the key findings, their implications, and the significance of this research for the field of industrial agglomeration. By examining these chapters, readers will gain a comprehensive understanding of the interaction between industrial clusters and digitalization, and its broader implications, providing valuable insights for policy and advice for future research.

References

Alcacer, J., Cantwell, J., & Piscitello, L. (2016). Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies*, *47*(5), 499–512. https://doi.org/10.1057/jibs.2016.22

Almeida, F., Duarte, J., & Monteiro, J. (2020). The challenges and opportunities in the digitalization of companies in a post-COVID-19 world. *IEEE Engineering Management Review*, *48*(3), 97–103. https://doi.org/10.1109/EMR.2020.3013206

Babkin, A., Plotnikov, V., & Vertakova, Y. (2018). The analysis of industrial cooperation models in the context of forming digital economy. *SHS Web of Conferences*, *44*, 12. https://doi.org/10.1051/shsconf/20184400012

Bayliss, D. (2007). Dublin's digital hubris: Lessons from an attempt to develop a creative industrial cluster. *European Planning Studies*, *15*(9), 1261–1271. https://doi.org/10.1080/09654310701529268

Becattini, G. (1990). The Marshallian industrial district as a socio-economic concept. In F. Pike, G. Becattini, & W. Sengenberger (Eds.), *Industrial Districts and Inter-Firm Cooperation in Italy* (pp. 37–51). ILO.

Caloffi, A., Lazzeretti, L., & Sedita, S. R. (2018). The story of cluster as a cross-boundary concept: From local development to management studies. In F. Belussi & J. L. Hervas-Oliver (Eds.), *Agglomeration and Firm Performance. Advances in Spatial*

Science (pp. 123–137). Springer. https://doi.org/10.1007/978-3-319-90575-4_8

Corradini, C., Santini, E., & Vecciolini, C. (2021). The geography of Industry 4.0 technologies across European regions. *Regional Studies*, *55*(10–11), 1667–1680. https://doi.org/10.1080/00343404.2021.1884216

Cortright, J. (2006). *Making Sense of Clusters: Regional Competitiveness and Economic Development* (p. 66). The Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/wp-content/uploads/2016/06/20060313_Clusters.pdf

Cruz, S. C. S., & Teixeira, A. A. C. (2010). The evolution of the cluster literature: Shedding light on the regional studies-Regional science debate. *Regional Studies*, *44*(9), 1263–1288. https://doi.org/10.1080/00343400903234670

Cuevas-Vargas, H., & Fernández-Escobedo, R. (2022). How strategic opportunities enhance the tendency to implement Industry 4.0 in Mexican SMEs. A multiple mediation approach. *Procedia Computer Science*, *214*(C), 636–643. https://doi.org/10.1016/j.procs.2022.11.222

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38. https://doi.org/10.1093/jeg/lbv017

Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, *3*(1), 3–45. https://repository.upenn.edu/real-estate_papers/2

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J. F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (pp. 2063–2117). Elsevier.

Feser, E. J. (1998). Old and new theories of industry clusters. In M. Steiner (Ed.), *Clusters and Regional Specialisation. European Research in Regional Science* (Vol. 8, pp. 18–40). Pion.

Fujita, M., & Mori, T. (2005). Frontiers of the new economic geography. *Papers in Regional Science*, *84*(3), 377–405. https://doi.org/10.1111/j.1435-5957.2005.00021.x

Grashof, N., & Fornahl, D. (2021). “To be or not to be” located in a cluster?—A descriptive meta-analysis of the firm-specific cluster effect. In *Annals of Regional Science* (Vol. 67, Issue 3). Springer Berlin Heidelberg. https://doi.org/10.1007/s00168-021-01057-y

Grashof, N., Kopka, A., Wessendorf, C., & Fornahl, D. (2021). Industry 4.0 and clusters: Complementaries or substitutes in firm’s knowledge creation? *Competitiveness Review*, *31*(1), 83–105. https://doi.org/10.1108/CR-12-2019-0162

Guo, H., Yang, Z., Huang, R., & Guo, A. Q. (2020). The digitalization and public crisis responses of small and medium enterprises: Implications from a COVID-19 survey. *Frontiers of Business Research in China*, *14*(1), 25. https://doi.org/10.1186/s11782-020-00087-1

Hoover, E. M. (1948). *The location of economic activity* (p. 310). McGraw-Hill.

Jasinska, K., & Jasinski, B. (2019). Clusters under industry 4.0 conditions - Case study: the concept of Industry 4.0 cluster in Poland. *Transformations in Business & Economics*, *18*(2B), 802–823. http://www.transformations.knf.vu.lt/47b/article/clus

Jofre-Monseny, J., Marin-Lopez, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: evidence from the location of new firms in Spain. *Journal of Regional Science*, *54*(2), 313–337. https://doi.org/10.1111/jors.12076

Johansson, B., Karlsson, C., & Stough, R. R. (2006). The emerging digital economy: Conclusions. In B. Johansson, C. Karlsson, & R. R. Stough (Eds.), *The Emerging Digital Economy. Advances in Spatial Science* (5th ed., pp. 331–339). Springer.

Ketels, C. (2004). *Cluster-based economic development: What have we learned.* Department of Trade and Industry, London, March 17, 2004. https://www.hbs.edu/faculty/Pages/item.aspx?num=47012

Ketels, C., & Memedovic, O. (2008). From clusters to cluster-based economic development. *International Journal of Technological Learning, Innovation and Development*, *1*(3), 375–392. https://doi.org/10.1504/IJTLID.2008.019979

Ketels, C., & Protsiv, S. (2021). Cluster presence and economic performance: a new look based on European data. *Regional Studies*, *55*(2), 208–220.

https://doi.org/10.1080/00343404.2020.1792435

Knell, M. (2021). The digital revolution and digitalized network society. *Review of Evolutionary Political Economy*, *2*(1), 9–25. https://doi.org/10.1007/s43253-021-00037-4

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Leamer, E. E., & Storper, M. (2001). The economic geography of the Internet age. *Journal of International Business Studies*, *32*(4), 641–665. https://doi.org/10.1057/palgrave.jibs.84909988

Lorenzini, F., & Lombardi, S. (2018). L’identificazione dei distretti industriali: una rassegna metodologica [Mapping industrial districts: A methodological review]. *Scienze Regionali, Italian Journal of Regional Science*, *17*(2), 225–260. https://doi.org/10.14650/90223

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., & Krejcar, O. (2018). Consequences of Industry 4.0 in business and economics. *Economies*, *6*(3), 14. https://doi.org/10.3390/economies6030046

Marshall, A. (1920). *Principles of economics* (8th ed., p. 69). Macmillan (original work published 1890).

Molina-Morales, F. X., Martinez-Chafer, L., & Valiente-Bordanova, D. (2017). Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones Regionales-Journal of Regional Research*, *39*, 39–57. https://investigacionesregionales.org/es/article/disruptive-technological-innovations-as-new-opportunities-for-mature-industrial-clusters-the-case-of-digital-printing-innovation-in-the-spanish-ceramic-tile-cluster/

Muller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247. https://doi.org/10.3390/su10010247

Ortega-Colomer, F. J., Molina-Morales, F. X., & Fernández-de-Lucio, I. (2016). Discussing the concepts of cluster and industrial district. *Journal of Technology*

Management & Innovation, *11*(2), 139–147. https://doi.org/10.4067/S0718-27242016000200014

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *62*(2), 73–93. https://www.hbs.edu/faculty/Pages/item.aspx?num=6105

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15–34. https://doi.org/10.1177/089124240001400105

Porter, M. E., Ketels, C., & Delgado, M. (2007). The microeconomic foundations of prosperity: Findings from the Business Competitiveness Index. In A. Lopez-Claros (Ed.), *The Global Competitiveness Report 2006–2007* (Vol. 2006, pp. 51–80). World Economic Forum.

Rocha, H. O. (2004). Entrepreneurship and development: The role of clusters. *Small Business Economics*, *23*(5), 363–400. https://doi.org/10.1007/s11187-004-3991-8

Romanelli, E., & Khessina, O. M. (2005). Regional industrial identity: Cluster configurations and economic development. *Organization Science*, *16*(4), 344–358. https://doi.org/10.1287/orsc.1050.0131

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191–229. https://doi.org/10.1006/juec.2001.2230

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest and the business cycle* (1th ed., p. 255). Transaction Publishers.

Schwab, K. (2016). *The fourth industrial revolution* (1th ed., p. 192). World Economic Forum.

Scott, A. J., & Storper, M. (2007). Regions, globalization, development. *Regional Studies*, *41*(1), 191–205. https://doi.org/10.1080/0034340032000108697

Sforzi, F. (2015). Rethinking the industrial district: 35 years later. *Investigaciones Regionales*, *32*(2015), 11–29. http://www.aecr.org/images/ImatgesArticles/2015/11/2_Sforzi.pdf?_ga=2.131452296.680042952.1678926565-1405984931.1678409478

Skokan, K., & Zotyková, L. (2014). Evaluation of business cluster performance during its lifecycle. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *62*(6), 1395–1405. https://doi.org/10.11118/actaun201462061395

Slaper, T., Harmon, K., & Rubin, B. (2018). Industry clusters and regional economic performance: A study across US Metropolitan Statistical Areas. *Economic Development Quarterly*, *32*(1), 44–59. https://doi.org/10.1177/0891242417752248

Slaper, T., & Ortuzar, G. (2015). Industry clusters and economic development. *Indiana Business Review*, *90*(1), 7–9. https://www.ibrc.indiana.edu/ibr/2015/spring/pdfs/article2.pdf

Storper, M. (2009). Roepke lecture in economic geography - Regional context and global trade. *Economic Geography*, *85*(1), 1–21. https://doi.org/10.1111/j.1944-8287.2008.01001.x

Szanyi, M., Iwasaki, I., Csizmadia, P., Illésy, M., & Makó, C. (2010). Cluster development in Hungary: searching for a 'critical mass' of business via cluster mapping. In B. Dallago & C. Guglielmetti (Eds.), *Local economies and global competitiveness* (pp. 113–133).

Vlaisavljevic, V., Cabello-Medina, C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting and Social Change*, *155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Yudina, T. (2019). Digital segment of the real economy: digital economy in the context of analog economy. *St. Petersburg State Polytechnical University Journal. Economics*, *12*(2), 7–18. https://doi.org/10.18721/JE.12201

Zeibote, Z., & Muravska, T. (2018). Promoting the regional competitiveness through clusters' approach: Case of the Latvian information technology cluster. *European Integration Studies*, *12*, 77–91. https://doi.org/10.5755/j01.eis.0.12.20846

CHAPTER I

The Digital Industrial Cluster: A paradigm shift for economic development in the Digital Era

I.1 Introduction

Economic development is one of the central purposes of the economic study and one of the most studied phenomena in this field. Marshall (1920) developed the foundations of the theory of agglomeration to tackle such topic, and for the last century economists and geographers have developed different models of agglomeration as a source of economic prosperity (Becattini, 1990; Hoover, 1948; Krugman, 1991; Porter, 1990; Slaper et al., 2018).

Scholars have endeavored to consolidate the theoretical and empirical literature to understand and explain the causes and effects of agglomeration (Babkin et al., 2017; Bayliss, 2007; Cruz & Teixeira, 2010; Duranton & Puga, 2004; Fujita & Mori, 2005; Hoover, 1948; Krugman, 1991; Malmberg & Maskell, 2002; Romanelli & Khessina, 2005; Skokan & Zotyková, 2014; Wixted, 2009; Zeibote & Muravska, 2018). However, these efforts found their main challenge in the conceptual heterogeneity embedded in the theory of agglomeration, which describes similar phenomena using different concepts (Duranton, 2011; Ortega-Colomer et al., 2016; Storper, 2009). Despite this, there have been two concepts especially successful in the theory of agglomeration: the industrial district as an urbanization phenomenon (Becattini, 1990), and the industrial cluster as a localization phenomenon (Porter, 1990). The latter has become specifically popular among policymakers, scholars and practitioners, due to its approach on competitiveness and regional development based on value systems (Delgado et al., 2016; Delgado, Porter, et al., 2014; Porter, 1990, 2000); anyhow, traditional agglomeration still relies on geography independently of the concept, model, or idea.

Nevertheless, the globalization and advances in Information and Communication Technologies (ICT) have been a powerful delocalization force, dispersing economic activity and boosting digital economies, changing the traditional role of geography and interactions (Alcacer et al., 2016; Almeida et al., 2020; Knell, 2021). The development of ICT has made it possible to tackle contemporary business challenges, boosting globalization and novel industrial technologies associated with Industry 4.0 (Alcacer et al., 2016; Almeida et al., 2020; Knell, 2021). Industry 4.0, which surfaced a decade ago, aims to overcome challenges linked to globalization and delocalization (Maresova et al., 2018; Muller et al., 2018; Schwab, 2016).

Additionally, the COVID-19 pandemic emerged and placed firms and economies all around the world under enormous pressure to adopt digitalization as a survival strategy (Guo et al., 2020). Besides, the COVID-19 pandemic detonated two paradoxical forces: (1) placed globalization under huge pressure and stressed the relevance of regions, and (2) simultaneously boosted digitalization forces in both public and private sector, empowering delocalization for particular activities (Guo et al., 2020).

All those disrupting forces have made it necessary to rethink the relevance of geographical proximity and the foundations of new models of digital agglomeration in a technological transformation context. Particularly, in a world changed by the pandemic where the digital was adopted at a rapid pace with more optimism than a deep understanding of the phenomenon (Lember et al., 2019). Furthermore, even when the digital transformation has defied traditional ideas about economy and locational competitive advantage (Muller et al., 2018; Yudina, 2019), elements like knowledge spillovers, entrepreneurship, and culture are still well embedded in regions and cities. Also, they have been growing in importance in a complex and dynamic economy based on knowledge (Bathelt & Li, 2014; Jofre-Monseny et al., 2014).

Therefore, it is relevant that notions and ideas around industrial clusters -one of the most relevant concepts for regional development policy based on industrial agglomeration- evolve toward a digital context amid the development of Industry 4.0, particularly with a multiregional perspective. Besides, the realities of the knowledge-based economy demand the creation and implementation of innovative models for economic development that fuse technology with society (Almeida et al., 2020; Fuks & Kawa, 2013; Jasinska & Jasinski, 2019; Malmberg & Maskell, 2002).

Accordingly, the main purpose of this chapter is to propose the theoretical foundations of a new policy tool called the Digital Industrial Cluster (DIC), a new concept developed and discussed in this research to contribute to filling such theoretical gap with a normative approach. This novel idea reconciles industrial clusters and digitalization under the future conditions of Industry 4.0 through a new model of digital clustering.

Therefore, the chapter contributes to literature in three ways: (1) developing the vision of the DIC as a novel policy tool founded on traditional industrial clusters and thought for a future world shaped by digitalization and Industry 4.0; (2) comparing the DIC and other policy tools based on digital agglomeration to understand similarities, differences and advantages of the former; and (3) presenting where the DIC could find its way toward implementations and what externalities could be expected from doing so. Furthermore, the chapter addresses two questions placed in a post-pandemic context: how a DIC could function in a real-world scenario?, and how a DIC can be deployed taking advantage of agglomeration and digital transformation? In the discussion, innovation and Industry 4.0 occupy a special place since both topics are relevant for answering the questions raised. Additionally, main challenges for the deployment of the DIC and its expected externalities are presented.

This conceptual chapter aims to set the foundations and extend the theoretical discussion about the DIC, to provide valuable guide for researchers, industrials, and policymakers about how such model could be implemented and whether it is a feasible option for digital integration in its regions/industries or not.

For this, the chapter comprises a review of the most relevant and influential literature about the industrial cluster phenomenon, focusing on works that explore the agglomeration from a technological perspective and a digital context. Moreover, the chapter also examines the literature about the impact of ICT and Industry 4.0 on the foundations of agglomeration, including a review of previous policy tools developed to support the digital agglomeration phenomenon. Additionally, with the purpose of reinforcing the context of the development of the DIC proposal, the chapter also addresses literature related to the impact of COVID-19 on industrial agglomeration, the role of the digital phenomenon in the pandemic and the deconstruction of some basic assumptions about digitalization.

This chapter is structured as follows. First, it presents a literature review on the industrial cluster as an agglomeration phenomenon and as a policy tool, the impact of ICT and Industry 4.0 on industrial clusters, previous policy tools based on digital agglomeration, and the relationship among pandemic, digitalization, and industrial agglomeration. Second, it contributes to literature developing the DIC concept as a policy tool, comparing it with other similar tools and presenting a way toward its implementation; additionally, this section also discusses the structural needs for the deployment of a DIC, and its expected externalities and challenges. Finally, the main conclusions are presented together with DIC's limitations and implications for policymakers and cluster organizations, along with future lines of research.

I.2 Literature review

I.2.1 The industrial cluster: the phenomenon and the policy tool

The *industrial cluster* concept does not have a universally accepted definition, but the main ideas about this real-world regional phenomenon fit the framework of regional development (Charykova & Markova, 2019; Delgado, Porter, et al., 2014; Götz & Jankowska, 2017; Ketels & Memedovic, 2008). Moreover, many of the most popular cluster concepts share their fundamental ideas with the theory of agglomeration, namely: geography, social proximity, technology, goods & services flows and exchange, interrelations, networking, cooperation, competition, knowledge, learning, trust relationships, and structural and institutional strength (Bathelt & Taylor, 2002; Cortright, 2006; Jofre-Monseny et al., 2014; Maskell & Malmberg, 1999; Titze et al., 2011).

An industrial cluster, as an agglomeration phenomenon, can be defined as a group of organizations geographically concentrated and interconnected as value systems, with strong social, productive, and intellectual links, that either compete or cooperate, taking advantage of the region where they are located and improving its business climate and innovation capabilities.

As the definition implies, there are certain conditions or foundations for an industrial cluster to exist. These foundations reach three perspectives: a competitiveness perspective, a sociological/historical perspective, and an economic perspective.

The competitiveness perspective points out not only the value system that shapes the integration but also the cost of economic factors, demand conditions, strategy/rivalry in the industry, and supporting organizations for the core sector (Delgado et al., 2016;

Delgado, Porter, et al., 2014; Elola et al., 2012; Jasinska & Jasinski, 2019; Johansson et al., 2006; Porter, 1990, 2000; Porter & Ketels, 2007).

From the sociological/historical perspective, multiple elements play a central role in the agglomeration phenomenon in general and in the industrial clustering in particular, including the historical path, social context, legal framework, economic policy, mutual confidence, reciprocity, and even luck (Bathelt, 2008; Bathelt & Boggs, 2003; Bathelt & Li, 2014; Bathelt & Taylor, 2002; Bayliss, 2007; Becattini, 1990; Leamer & Storper, 2001; Ortega-Colomer et al., 2016; Romanelli & Khessina, 2005; Storper, 2009; Vlaisavljevic et al., 2020).

Finally, from the economic perspective, the input-output linkages, labor market pooling, and knowledge spillovers look like the primary seeds to start an agglomeration phenomenon (Babkin et al., 2018; Cortright, 2006; Duranton, 2011; Duranton & Puga, 2004; Ketels, 2004; Ketels & Memedovic, 2008; Krugman, 1991; Marshall, 1920; Rosenthal & Strange, 2001; Schumpeter, 1934).

But beyond the agglomeration phenomenon itself, the impact of industrial clusters on development has attracted the attention of researchers and policymakers. Despite the challenges found by researchers when assessing the effects of industrial clusters at micro, meso, and macroeconomic level -due mainly to the difficulty to understand a complex and multidimensional phenomenon-, the empirical evidence about positive externalities is consistent (Bayliss, 2007; Delgado, Porter, et al., 2014; Duranton, 2011; Feser, 1998; Jofre-Monseny et al., 2014; Ketels, 2004; Ketels & Memedovic, 2008; Porter, 2000; Rocha, 2004; Scott & Storper, 2007; Skokan & Zotyková, 2014; Slaper et al., 2018; Storper, 2009).

Researchers have identified multiple industrial cluster's externalities, but there are few that are worth of highlighting because of their relevance for regional development agenda: increasing productivity, boosting competitiveness, improvement of innovation capabilities, raising salaries, and GDP growth.

Porter and Ketels (2007) point out that such externalities tend to be stronger in traded clusters, boosting foreign direct investing and trading (Babkin et al., 2013; Bathelt & Li, 2014). Moreover, Lines and Monypenny (2006) also note that industrial clusters strengthen linkages among government, industry and institutions, improving the business climate and even the sociocultural standards of the region, making it possible to land better policies and private initiatives aimed at boosting economic growth.

In highly dynamic economies and regions, those externalities -productivity, competitiveness, and innovation- are central for development (Yelkikalan et al., 2012). Additionally, researchers support the role of regions as development engines for entire countries, even when globalization became the new normal (Bathelt et al., 2004; Feser, 1998; Jofre-Monseny et al., 2014; Leamer & Storper, 2001; Scott & Storper, 2007; Storper, 2009).

These ideas have been influencing public and private initiatives to develop policy tools based on this agglomeration phenomenon. The industrial cluster as a policy tool aims to coordinate formal efforts to build regional networks of interrelated industries, with the intention of developing innovation capabilities, specialization, vertical and horizontal integration, and mobility of factors (Bathelt & Taylor, 2002; Fernandez et al., 2018; Storper, 2009; Vlaisavljevic et al., 2020).

Those policy tools -also called industrial clusters- rely on the idea of building *cluster organizations* that are defined as "*legal entities that support the strengthening of collaboration, networking and learning in innovation clusters and function as innovation support providers by providing or channeling specialized and customized business support services to stimulate innovation activities*" (European Cluster Collaboration Platform, n.d.). It is a paradigm of economic development based on knowledge and collaboration at a regional level.

The industrial cluster as policy tool has taken advantage of this paradigm, mainly because any sector of the economy can implement it even whether the sector is knowledge-intensive or not, and whether it is in a developed country or not (Ketels & Memedovic, 2008; Lines & Monypenny, 2006; Temouri et al., 2021).

Therefore governments and industry leaders around the world have made big efforts to create industrial clusters from scratch and develop the preexisting ones, favoring traded-and-preexisting clusters over local-and-new ones, due to former ones have a larger positive impact on economic development and better chances to succeed in the long term (Bathelt & Li, 2014; Elola et al., 2012; Slaper et al., 2018; Slaper & Ortuzar, 2015). The Cluster Mapping Project in the US and the European Cluster Collaboration Platform in Europe are the epitome of those efforts, although the first approaches the industrial cluster as a real-world phenomenon whilst the second approaches it as a policy tool.

Even if there is still a long way to completely understand the industrial cluster phenomenon and its potential as a policy tool, industrial clusters have been effective in boosting key elements for development (Babkin et al., 2017; Delgado, Porter, et al., 2014; Duranton, 2011; Portugal et al., 2012; Zeibote & Muravska, 2018).

I.2.2 The industrial cluster phenomenon in the context of ICT and Industry 4.0

Economists recognize the central role of technology in globalization processes, reducing transaction costs and digitalizing multiple economic and social dynamics, improving communication and enhancing information-flow capabilities (Alcacer et al., 2016; Almeida et al., 2020; Angehrn, 1997; Johansson et al., 2006; Scott & Storper, 2007). Likewise, technology has strengthened the trans-local relationships, suggesting that such relationships become increasingly relevant for regional competitiveness and success.

Currently, developed and developing countries aim to technological leadership (Babkin et al., 2018; Fernandez et al., 2018), due to its positive impact on production, distribution, communication, and innovation (Almeida et al., 2020; Bathelt & Turi, 2011; Del Chiappa & Baggio, 2015).

At this point, the ICT infrastructure has made possible the creation of an entire new virtual and digital economy (Lehdonvirta & Ernkvist, 2011), based on innovation, creativity, and knowledge, disrupting the strategy and operation of firms (Afonasova et al., 2019). On the one hand, the virtual economy is the pinnacle of ICT development, reaching cryptocurrencies, virtual jobs, virtual goods and services, virtual assets, and virtual markets. Furthermore, after a wide literature review Popescu and Popescu (2011) concluded that even when virtual economies are particularly linked to videogames, their impact will be more and more noticeable in the real-world as ICT infrastructure increases its scope and processing power. On the other hand, the digital economy departs from digital representations of real goods and services produced in the real-world (it includes on-line services, on-line communities, e-Commerce and e-Government); such economy finds its way between the real and the virtual one, and it is traceable, connected, shared, personalized and direct (Baggio & Del Chiappa, 2014; Richter et al., 2017; Yudina, 2019).

Recently, the digital economy has had a protagonist role in economic development, shaping new ideas as Industry 4.0 (Afonasova et al., 2019; Yudina, 2019). This term was coined in Germany in 2011 (Schwab, 2016) to describe a novel tendency in the industry, shaped by digitalization, automation and big data. Maresova et al. (2018) says that Industry 4.0 refers to the integration of machinery and devices in a network of sensors and software to predict, control, and plan an industrial processes.

Although the concept of Industry 4.0 is still fuzzy according to academics, it has become a common term among industrials, practitioners, and policymakers to refer to the adoption and implementation of state-of-the-art technologies, namely, cyber-physical systems, Internet of things, Internet of services, smart factories, advanced manufacturing, robotics, 3D printing, blockchain, and artificial intelligence (Atik & Ünlü, 2019; Park, 2018; Zezulka et al., 2016). This research adopts the term Industry 4.0 under this approach.

Owing to its flexibility and decentralization, Industry 4.0 could contribute to overcome contemporary challenges related to global competition, volatile markets, customization, and products with shorter life-cycle (Maresova et al., 2018; Muller et al., 2018). Moreover, global value chains demand a decentralized approach, which Industry 4.0 could provide through real-time communication between people, machines and processes (Brettel et al., 2014; Erboz, 2017; Hermann et al., 2016). Therefore, industries around the world are looking for competitive advantage through the implementation of technologies associated with Industry 4.0 (Crabtree et al., 2016; Karnitis & Karnitis, 2017).

In summary, virtualization and digitalization, which include Industry 4.0, are natural tendencies in a globalized society shaped by information. These new forces could seem disruptive for the evolution of industrial clusters, a real-world phenomenon that relies intensely on geographical proximity and face-to-face interactions, two elements challenged by the virtual and digital economy perspective.

However, the disappearance of industrial clusters because of ICT is far from reality. Virtualization, digitalization, and Industry 4.0 still require people and their communication, social and organizational skills (Maresova et al., 2018). Besides, taking traditional face-to-face interactions into digital environments has made it possible for industrial clusters to break traditional frontiers and build new and highly dynamic value-systems based on knowledge (Fuks & Kawa, 2013; Götz, 2019a). Moreover, the industrial clusters' wide geographical distribution is a direct effect of the improvement on communications (Jasinska & Jasinski, 2019).

Furthermore, Götz (2021) highlighted that industrial clusters are not only compatible with ICT and Industry 4.0 but also fertile ground for them. Industrial clusters are the epitome of interconnection between people, technology and organizations, so they can be used as *laboratories* to prove and experiment novel technologies, boosting the development of digital ecosystems, improving cooperation, innovation and development (Almeida et al., 2020; Delgado, Porter, et al., 2014; Jasinska & Jasinski, 2019).

Industrial clusters have proven to encourage open innovation and collaboration inside regions, which in turn ease digital transformation. Owing to a more stable and less uncertain environment, industrial clusters can adopt new approaches based on multisectoral and multiregional integration in the form of "innovation networks" supported by Industry 4.0 and digital technologies (Almeida et al., 2020; Babkin et al., 2018; Bathelt & Turi, 2011; Gagnidze, 2022; Götz & Jankowska, 2017; Jasinska & Jasinski, 2019; Vlaisavljevic et al., 2020).

Hermann et al. (2016), Muller et al. (2018) and Maresova et al. (2018) have mentioned the need to strengthen the theoretical foundations of the effects of ICT and Industry 4.0 on industrial clusters, to make possible a better empirical understanding of the phenomenon. As fast as technology evolves, economists should move in this promising field, as the quick integration of these technologies in certain forms of industrial organizations such as clusters could have positive and significant effects in the economic development of regions (Senyo et al., 2019). After all, the regional dimension remains relevant in the context of the scientific, technological and social change (Ortega-Colomer et al., 2016).

I.2.3 The digital agglomeration as emulator of the industrial cluster

The popularization of the industrial clusters as a policy tool and the advances on ICT gave rise to the digital agglomeration phenomenon (Charykova & Markova, 2019). In the context of the digital economy, firms expect to agglomerate in digital environments where they can improve their cooperation and interaction (Babkin et al., 2018). If firms and economies wish to maintain their competitive position in global markets, they must stimulate innovation through interactive learning and external networking (Cuevas-Vargas et al., 2022; Della et al., 2018). Besides, the need of combining close and strong bonds found inside of the clusters with distant and out-of-the-cluster relationships, is a invaluable opportunity to access global sources of knowledge (Molina-Morales et al., 2017).

Three models of digital agglomeration have found their way into research through either empirical or theoretical constructs, and they can be understood not only as policy tools but also as a project or even a technology (Della et al., 2018; Jasinska & Jasinski, 2019; Senyo et al., 2019). They intend to emulate the dynamics of industrial agglomerations into digital environments, expecting to obtain similar externalities as those found in industrial clusters (Charykova & Markova, 2019; Popescu & Popescu, 2011; Porter, 2000; Ratten, 2016).

The first model developed was the Virtual Industry Cluster (VIC). A VIC is a complex construct built and studied in the late 90's based on the idea of creating a global digital hub of firms belonging to interrelated sectors, coordinated by Virtual Enterprise Brokers to exploit market opportunities through the organization of temporary-and-project-focused Virtual Enterprises (Flores & Molina, 2000). No new VIC projects were run after the first empirical evaluation of the model under the name VIRPLAS; however, the concept remains in theoretical discussions about digital agglomeration (Anthony Jnr & Abbas Petersen, 2020).

The second model presented was the Digital Business Ecosystem (DBE), which is a digital environment for collaboration and value-creation that challenges the traditional frontiers of industry through flexibility and openness (Senyo et al., 2019). Digital entities from multiple sectors populate the DBE aiming to digital integration (Baggio & Del Chiappa, 2014; Sarkar et al., 2007). The European Union made serious efforts to develop a DBE, starting in 2003 and shutting down the project in 2007; however, since DBE's scope is wide, it has made difficult to deepen the study of the phenomenon, causing the loss of interest from researchers in the last decade (Senyo et al., 2019).

The third and last model was the e-Sourcing Cluster (eSoC), also called *electronic cluster* or *e-cluster,* that aims to build a digital space for grouping interrelated organizations with a single-sectorial approach and a global scope; the eSoC's main purpose is to connect enterprises that are looking to collaborate to acquire the same type of resources under better conditions (Adebanjo, 2010; Fuks & Kawa, 2013). Researchers only have discussed the electronic cluster theoretically.

All three models intend to highlight the relevance of networking, competition, and cooperation (Almeida et al., 2020; Bayliss, 2007; Charykova & Markova, 2019; Delgado, Porter, et al., 2014; Duranton, 2011; Jofre-Monseny et al., 2014; Ketels & Memedovic, 2008; Porter, 2000; Rocha, 2004; Scott & Storper, 2007; Skokan & Zotyková, 2014; Slaper et al., 2018; Storper, 2009); nevertheless, they ignore the contribution of geographical proximity, which is at the core of traditional industrial clusters and its externalities. This makes it necessary to develop new policy tools to reconcile digital agglomeration and geographic concentration (Golov et al., 2021).

I.2.4 Pandemic, digitalization, and industrial agglomeration

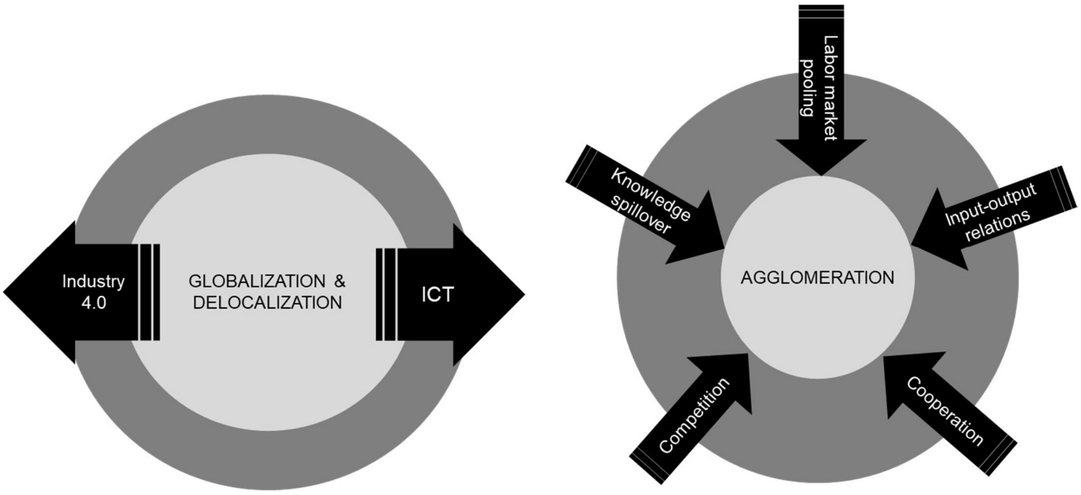
The COVID-19 pandemic challenged all sectors of the economy, and forced companies and governments all around the world to adopt not only new technologies, but also different processes and whole new business models (Guo et al., 2020). Therefore, one of the obvious answers in a world of social distancing and closed borders was digitalization (Grover & Sabherwal, 2020), boosting two paradoxical forces: the delocalization of economic activity and the need for regional synergies (Almeida et al., 2020). In a post-pandemic world, countries and businesses are still struggling to go back to normal, but those paradoxical forces remain active, looking for new economic models capable of conciliating them both.

On the one hand, there are the delocalization forces of ICT and Industry 4.0. Economists recognize the central role of technology in globalization processes, improving communication, trans-local relationships and information-flow capabilities (Alcacer et al., 2016; Almeida et al., 2020); furthermore, Industry 4.0 -thanks to its decentralized approach- improves global value chains through real-time communication among people, machines and systems (Brettel et al., 2014; Erboz, 2017; Hermann et al., 2016).

On the other hand, the agglomeration forces shape regions as centers of prosperity and as engines of growth for countries. Digitalization has made it possible for industrial agglomerations to build new value systems, that are more multiregional, more multisectoral and more multidisciplinary (Fuks & Kawa, 2013; Götz & Jankowska, 2017; Jasinska & Jasinski, 2019). This form of industrial organization has developed an important synergy with ICT and Industry 4.0, giving those technologies a fertile ground for development getting in return more competitive industries and regions (Almeida et al., 2020; Delgado et al., 2016).

The COVID-19 pandemic strengthened both forces (**Figure I.1**), pushing governments and industries to look for innovative models of business and economic development, capable of conciliating both approaches. Many of those innovations were already underway before the COVID-19, but they were accelerated by the pandemic, particularly the migration from analog to digital (Grover & Sabherwal, 2020; Ricarte, 2020). In the field of digital economy, the pandemic introduced novel practices, and even when life returned to normal after the emergency, digital trends will continue to significantly influence global development from now on (Lanshina et al., 2020).

Figure I.1. Delocalization forces vs industrial agglomeration forces.



SOURCE: Author's elaboration.

In this context, digitalization made it possible not only to mitigate the impacts of the pandemic on the economy but also to enhance the impact of ICT on people and organizations (Grover & Sabherwal, 2020). Technology changed business processes, business relationships, communication, and distribution, bringing renewed attention to the digital agglomeration phenomenon (Knell, 2021).

Disruptive technologies employed in digitalization during the pandemic include (Anthony Jnr & Abbas Petersen, 2020): Big Data analytics, cloud computing, smartphone/mobile, social media analytics, chatbots, artificial intelligence, machine learning, blockchain, additive 3D printers, augmented reality, robotics/automatization and Internet of Things (IoT). Many of those technologies are traditionally associated with Industry 4.0 (Atik & Ünlü, 2019; Zezulka et al., 2016), hence it is not possible to analyze digitalization without including the Industry 4.0 approach.

However, the COVID-19 emergency also laid bare fundamental challenges related to digitalization and Industry 4.0, part of the main foundations of the DIC. The pandemic deconstructed basic assumptions about technology adoption in organizations and countries, bringing to the surface issues such as (Anthony Jnr & Abbas Petersen, 2020; Faraj et al., 2021):

- Uneven access to digital infrastructures.
- Organizational structures unfriendly to digital transformation.
- The persistence of analog and rigid business processes.
- Panoptical surveillance and privacy concerns.
- Inadequate sense of urgency, poor management dedication and inadequate strategic alignment.
- Inadequate industrial guidelines, and limited skills and knowledge.

Furthermore, the optimist shown by the industry about accelerated digitalization during the pandemic has overlooked the impact of this phenomenon over innovation, which is at the core of economic development. Such an impact has been heterogeneous depending on the kind of technologies implemented and the purpose of its implementation.

Usai et al. (2021) assessed the impact of digitalization on innovation, and found that even when the adoption of digital technologies improves business performance, supporting previous findings (Afonasova et al., 2019), its impact on innovation is less clear; except for 3D printing, robotics, and Big Data analytics, other technologies proved to have little relevance to a firm's innovation performance. These authors argument that the loss of relational and human capital play a significant role in this phenomenon since digitalization relays more strongly on explicit knowledge than on unique knowledge. However, results are not conclusive since they depends on the kind of technology analyzed, the kind of effects tested, and the approach of the assessment made over digitalization (Lember et al., 2019): for example, online social networks have shown to have a direct and positive impact on knowledge transfer, which finally impacts on innovation capabilities (Palacios-Marqués et al., 2016).

Theoretical and empirical discussion about the impact of digitalization on innovation still has a long way to go. However it is clear among researchers that the digital advance have multifaceted implications on organizations (Palacios-Marqués et al., 2016), and academics agrees on the relevance of face-to-face interaction even in the middle of the digital era (Leamer & Storper, 2001; Usai et al., 2021; Yoo et al., 2012).

Finally, at this point the next question raises: *how could digitalization and localization forces be conciliated into a single model after pandemic?* Particularly since digitalization appears to be an unstoppable delocalization force, despite its challenges related to infrastructure and its impact on innovation.

I.3 The Digital Industrial Cluster

I.3.1 The vision of the Digital Industrial Cluster (DIC)

The industrial cluster as a policy tool has failed to adopt the central ideas of digitalization and virtualization, especially those about the diminished relevance of geographical proximity. The opposite happened with other policy tools based on digital agglomerations, which have overlooked the relevance of geography.

This chapter proposes a novel policy tool. This policy tool finds its foundations not only in traditional industrial clusters but also in the digitalization/virtualization phenomenon, making a theoretical contribution that expects to find its way through the future world shaped by Industry 4.0. This policy tool seizes the benefits of geographical proximity and uses technology to leverage the positive externalities of interrelatedness, with a multiregional approach.

This policy tool is named the *Digital Industrial Cluster (DIC),* a normative and multifaceted concept that revolves around five main ideas.

First, the DIC needs a technological platform with a multidimensional architecture network: the virtual space where interaction occurs. This network should be able to support a multiplicity of dynamic and amorphous interactions among different organizations and their processes; ICT, software applications, hardware, and devices will play a central role for this purpose (Senyo et al., 2019). In the DIC, Industry 4.0 occupies a privileged position because of its capabilities to automate, decentralize, and interconnect, since the integration of people, processes, and real-world information into business functions could be impossible without technologies associated to Industry 4.0 (Götz & Jankowska, 2017; Jasinska & Jasinski, 2019; Maresova et al., 2018).

Second, the DIC should integrate digitalized organizations, which are the digital representation of participants and their products, services, relations, and interactions. Such organizations must belong to real and interrelated industrial clusters because the DIC tries to emulate interrelations that exist in a real-world industrial agglomeration. Therefore, the term "digital" was preferred over "virtual" when the concept was created.

Third, the DIC should empathize the multiregional character: the virtual space groups organizations from interrelated and dispersed industrial clusters. The DIC goes toward a more inclusive and multiregional interconnectivity among clusters and their members; for the DIC the geographical proximity is less relevant as enterprises do not have to be in one place because they cooperate using state-of-the-art ICT.

Fourth, the DIC expects to have technology capable of supporting and even replacing multiple organizational functions through a process of digital transformation, for example: communicating, innovating, networking, selling, buying, marketing, procuring, acquiring, biding, tracking, financing, ranking, sharing, learning, and teaching. The main goal of this digitalization process is to improve interactions among participants, enhancing the networking (Palacios-Marqués et al., 2016; Park, 2018).

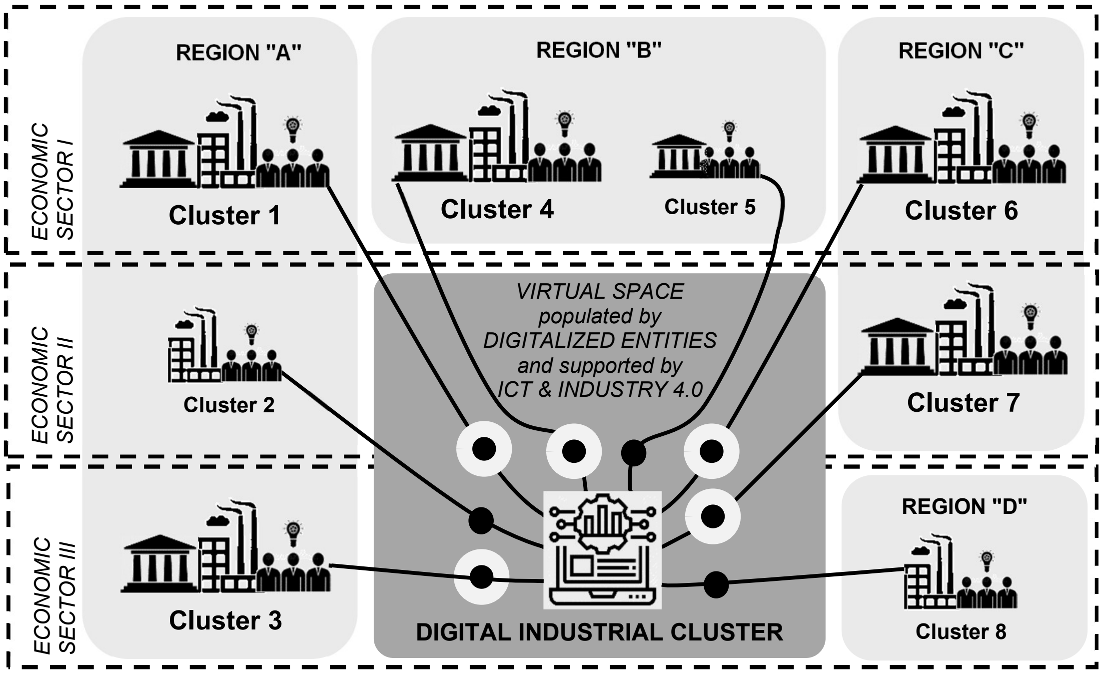
Fifth and final, organizations in the DIC are expected to compete and collaborate, as it happens in the industrial cluster to which they belong. Since those organizations are expected to belong to interconnected traditional industrial clusters, they should be more open and more used to collaboration and competition as long as they possess infrastructure -both analog and digital- to support such interactions beforehand (Alcacer et al., 2016; Delgado, Porter, et al., 2014; Jofre-Monseny et al., 2014; Wixted, 2009).

In conclusion, the DIC could be defined as a *virtual space where digitalized organizations compete and cooperate; these organizations belong to interrelated and geographically dispersed industrial clusters, and they take advantage of technological infrastructure hosted in the virtual space that supports or even replaces any organizational function capable of being digitalized*.

The DIC visualizes the construction of a virtual space where multiple interrelated and geographically dispersed industrial clusters interact through their members. The DIC will support itself in the power of networking as any other policy tool based on industrial agglomeration does, and it could even be understood as a network in the same sense that an industrial cluster does; however, the DIC does not intend to become a global interfirm network because of its cluster character, which pretends to develop such digital and virtual infrastructure after real regional clusters to enhance their externalities.

Figure I.2 illustrates how the DIC would be capable of integrating multiple clusters and their members into a single virtual space under the value system approach. The dotted boxes group clusters from the same sector; those clusters exist in different regions and are expected to be interrelated through competition, cooperation, or both. The light-grey boxes group clusters from different sectors; such clusters are established in the same region and are expected to be interrelated mainly through buyer-supplier relations. The dark-grey box represents the virtual space integrated by cluster members where digitalized organizations and functions interact among them, supported by ICT and Industry 4.0.

Figure I.2. The vision of the Digital Industrial Cluster (DIC) as a policy-tool.



SOURCE: Author's elaboration.

The figure shows how the DIC effort should be capable of bringing together mature clusters (Cluster 1, 3, 4, 6 and 7) and growing ones (Cluster 2, 5 and 8); likewise, the DIC should be capable of integrating diversified and developed regions (Region A and Region C, respectively) with less diversified and developing ones (Region B and Region D, respectively).

A DIC should be capable of meeting industrial clusters' participants (e.g. suppliers, buyers, clients, partners, entrepreneurs, SMEs, universities, research centers, NGOs, business associations, and governments) into a single virtual space that must be scalable, adaptive, symbiotic, self-organized and self-sustained (Baggio & Del Chiappa, 2014; Senyo et al., 2019).

Developing a DIC could be the next step to lead the evolution of industrial clusters thanks to its main strengths centered on multiregional synergy and technological leverage, strengths that the COVID-19 pandemic of 2020 made more relevant than ever before (Almeida et al., 2020; Guo et al., 2020).

The DIC not only looks to exploit assets settled in traditional industrial clusters, like knowledge, expertise, resources, structures, and social networks, but it also aims to end-to-end digitalization, enhancing interdisciplinarity and interconnection among geographically distant organizations, creating innovation networks and reinforcing global value chains (Mostafa et al., 2019).

I.3.2 Comparing the DIC with similar policy tools

Even as a novel concept, the DIC departs from state-of-the-art ideas of agglomeration, digitalization, and virtualization. Therefore, it is necessary to discuss the comparison between the DIC and other similar concepts and make it clear how this policy tool takes further previous approaches (**Table I.1** presents a summarized comparison).

Before starting, it is relevant to highlight that the term digital cluster is commonly found in the literature referring to policy tools aimed to cluster ICT industries (Bayliss, 2007; De Waele & De Cleyn, 2014; Evans, 2019; Feferman, 2014; Kayley, 2017). Therefore, since the *digital cluster* is a category of traditional industrial clusters -as could be an automotive cluster or a biotechnology cluster-, it is conceptually different from the DIC.

The DIC concept borrows notions from the DBE, the eSoC and the VIC, so it retains similarities but also core differences with those, enriching the literature about industrial policy, development, and technology. The DIC also brings a more realistic and practical approach, leveraged by Industry 4.0.

The DIC may be understood as a special kind of DBE because both are multi-sectorial concepts leveraged on technology to overcome traditional challenges imposed by geographically dispersed firms. Also, both policy tools aim at digital integration of firms to compete and cooperate (Baggio & Del Chiappa, 2014); furthermore, the virtual environment, which must be created to support digital interactions under the umbrella of a DIC, is equivalent to the concept of Digital Ecosystem (DE) as both refer to a virtual space populated by digital entities.

Table I.1. Comparison between the Digital Industrial Concept (DIC) and similar policy tools that emulate industrial agglomeration.

Elements	Digital industrial Cluster (DIC)	Digital Business Ecosystem (DBE)	e-Sourcing Cluster (eSoC)	Virtual Industry Cluster (VIC)
Scope	Multi-regional	Global	Global	Global
Main foundations	Geographical proximity, digitalization, and interrelatedness	Digitalization	Digitalization and interrelatedness	Virtualization and interrelatedness
Genesis & nature	Planned & Formal	Planned & Formal	Planned & Formal	Planned & Formal
Sectorial approach	Multi-sectorial	Multi-sectorial	Single-sectorial	Multi-sectorial
Members	Interrelated organizations belonging to interrelated clusters	Any organization	Interrelated organizations	Any organization integrated as Virtual Enterprise
Digital agglomeration forces	Yes	None	Yes	None
Intermediation between members	None	None	None	Virtual Enterprise Broker
Expected interactions between members	Competition and cooperation	Competition and cooperation	Cooperation	Cooperation
Organizational functions supported by ICT	Any able to be digitalized	Any able to be digitalized	Selling & purchasing	Selling & purchasing
Basic ICT needs	-Virtual environment to support digital interactions -Capabilities to deploy Industry 40 associated technologies	-Virtual environment to support digital interactions	-Virtual environment to support digital interactions	-Virtual environment to support digital interactions

SOURCE: Author's elaboration.

However, the DIC points to multiregional and interrelated clusters, because these organizations are integrated beforehand and are more used to cooperate and compete (Charykova & Markova, 2019; Delgado, Porter, et al., 2014). By contrast, DBE's scope is global and overlooks interrelatedness and geographical proximity, making it more difficult to involve participants into the network (Senyo et al., 2019).

Other similar model to the DIC is the eSoC, which is close to DBE and can be part of one. The eSoC detonates agglomeration forces through cooperation, making procurement its core foundation and oversighting other organizational functions; therefore, the eSoC adopts a single-sectorial approach that differs from the multi-sectorial approach of the DIC.

The DIC could also be compared or even confused with another term: the VIC. Although the name suggests wide commonalities between them, the differences between the DIC and the VIC are significant. The VIC possesses a global scope and expects the creation of temporary Virtual Enterprises to intermediate relations among interrelated participants, aiming to only-cooperation projects; in a separate way, the DIC proposes interaction among real organizations without the need of using intermediaries. In a nutshell, the VIC is a model that needs intermediaries and complex relationships to function (Babkin et al., 2013).

While all policy tools aim at digital agglomerations through planned and formal platforms, the DIC is the only one thought to rise from a real-world industrial agglomeration. This is relevant because any digital platform involving interrelated firms will trigger more powerful agglomeration forces, being capable to success even with a reduced number of participants. Differently, digital platforms involving any organization from multiple sectors and with no previous interrelations among them will rely strongly on the volume of participants to succeed (Alcacer et al., 2016; Babkin et al., 2018; Cortright, 2006; Delgado et al., 2016; Delgado, Porter, et al., 2014; Duranton, 2011; Duranton & Puga, 2004; Fuks & Kawa, 2013; Hoover, 1948; Jasinska & Jasinski, 2019; Johansson et al., 2006; Ketels, 2004; Ketels & Memedovic, 2008; Krugman, 1991; Lehdonvirta & Ernkvist, 2011; Marshall, 1920; Porter, 2000; Porter & Ketels, 2007; Rosenthal & Strange, 2001; Schumpeter, 1934; Zeibote & Muravska, 2018).

Finally, the DIC is the only policy tool to highlight the relevance of Industry 4.0 and the synergy between them (Götz, 2019b; Park, 2018; Tsakalerou & Akhmadi, 2021). The DIC expects to bring substantial amounts of data from real-world processes -including manufacturing, provisioning and transportation- to a virtual environment, where it can be processed to digitally support other processes. Therefore, Industry 4.0 represents the most appropriate approach to make such an idea possible, introducing the digitalization and decentralization of traditional in-place activities (Almeida et al., 2020; Götz & Jankowska, 2017; Jasinska & Jasinski, 2019; Maresova et al., 2018).

I.3.3 Toward the implementation of the DIC

The DIC is a new policy tool introduced in this thesis to build theoretical foundations that could lead to empirical identification and assessment of early manifestations of this phenomenon, which could be found first in developed and developing countries as they show favorable conditions for the creating of proto-DIC.

Economies where industrial clusters exist and interrelate should be able to implement the DIC. Developed and well-integrated macro-regions such as North America and Europe have adopted for decades now industrial cluster policies, and interconnectivity among clusters and their members is a reality that has been leveraging on technology for years (Bathelt & Li, 2014; Della et al., 2018; Götz & Jankowska, 2017; Jasinska & Jasinski, 2019). Moreover, organizations as the Cluster Mapping Project have designed empirical methodologies to identify cross-industry linkages across large and diversified economies (industry-approach) (Delgado et al., 2016); such methodologies together with the *cluster organizations'* expertise (firm-approach) could be used to identify cross-cluster linkages.

However, the readiness of the industries to deploy Industry 4.0 will determine the potential for geographical dispersion of the DIC and the kind of clusters involved in its development. Clusters with high rates of Industry 4.0 adoption are better prepared to deal with geographical dispersion, interdisciplinarity, flexibility, and decentralization; moreover, literature shows that high-value-added manufacturing clusters appear to be better prepared to embrace the approach of extended cluster based on digital platforms and Industry 4.0, particularly in industrialized countries like Germany and others on its way to industrialization as Poland (Götz, 2019b, 2021; Götz & Jankowska, 2017).

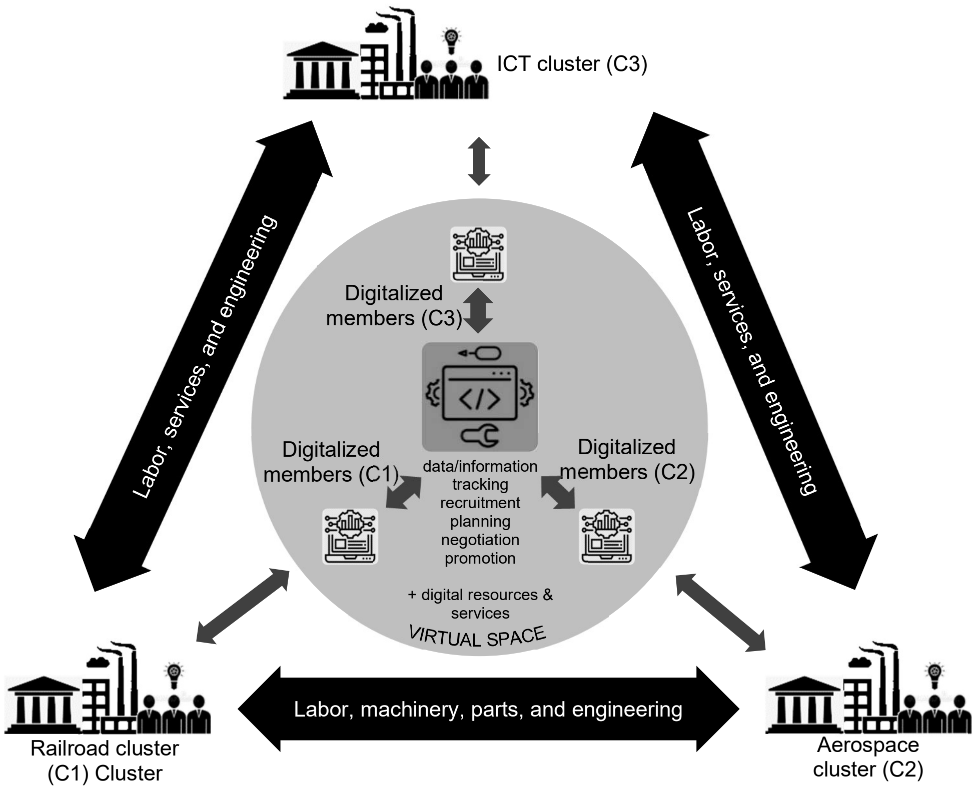
For example, the integration of multiple clusters into cluster-hybrid solutions was already documented in Poland, under the umbrella of *cluster organizations* created for transferring knowledge and organizing business (Jankowska et al., 2021; Jasinska & Jasinski, 2019). Such project comprised high-value-added clusters but do not involve a virtual space that hosts and manages digital interactions among digitalized organizations, therefore they cannot be understood as DIC.

However, to gain further understanding of the DIC, **Figure I.3** illustrates -from a theoretical viewpoint- how a real case could be integrated, departing from this Polish case. For this straightforward example, there are three clusters: railroad cluster (C1), the aerospace cluster (C2), and the ICT cluster (C3). Electronic, plastic, and metal-mechanic companies in C1 and C2 use to share labor, machinery, parts, and engineering due to similarities in productive processes. Those cluster members also interact with C3 that provides them with services (like cyber-security, software, and digital insurance), engineering and labor for specific projects. Such interactions occur mainly through individual industries with no formal mediation of *cluster organizations* (those interactions are represented outside the gray circle). Nonetheless, the project *Demonstrator*+ of the National Center for Research and Development was capable to formally integrate those clusters into a single temporary initiative to develop a state-of-the-art driving simulator based on virtual reality. That project additionally involved the Department of Research and Development, the Military University of Technology, and the Railway Institute.

Should the DIC be developed in this context, it would offer a virtual space for digitalized cluster members to support complex interactions and offer to participants digital resources and services. The DIC would make possible not only the coordination of R&D but also the management of other complex interactions, for example: the tracking of purchase and production orders, the management of customer-supplier relations, the sharing of data and information in real-time, and the co-creation and promotion of products and services. The gray circle in **Figure I.3** represents the core of the DIC**.**

However, before the implementation of a DIC, organizations and clusters must develop multiple layers and phases of digital transformation, which the next section discusses and presents to deepen the understanding of this novel model.

Figure I.3. The vision of a DIC for the integration of three industrial clusters in Poland; the interactions outside of the gray circle happen out of the DIC but still are influenced by it.



SOURCE: Author's elaboration.

I.3.4 Deployment model of the DIC: digitalization and agglomeration at the same place

The DIC concept is designed to differentiate itself from other models of digital agglomeration, such as the Digital Business Ecosystem, e-Sourcing Cluster, and the Virtual Industry Cluster. With a multiregional approach based on interrelatedness, the DIC expects to improve the engagement among participants of traditional industrial clusters and to detonate digital agglomeration; moreover, this model expects to conciliate digitalization and localization forces for the new post-pandemic reality.

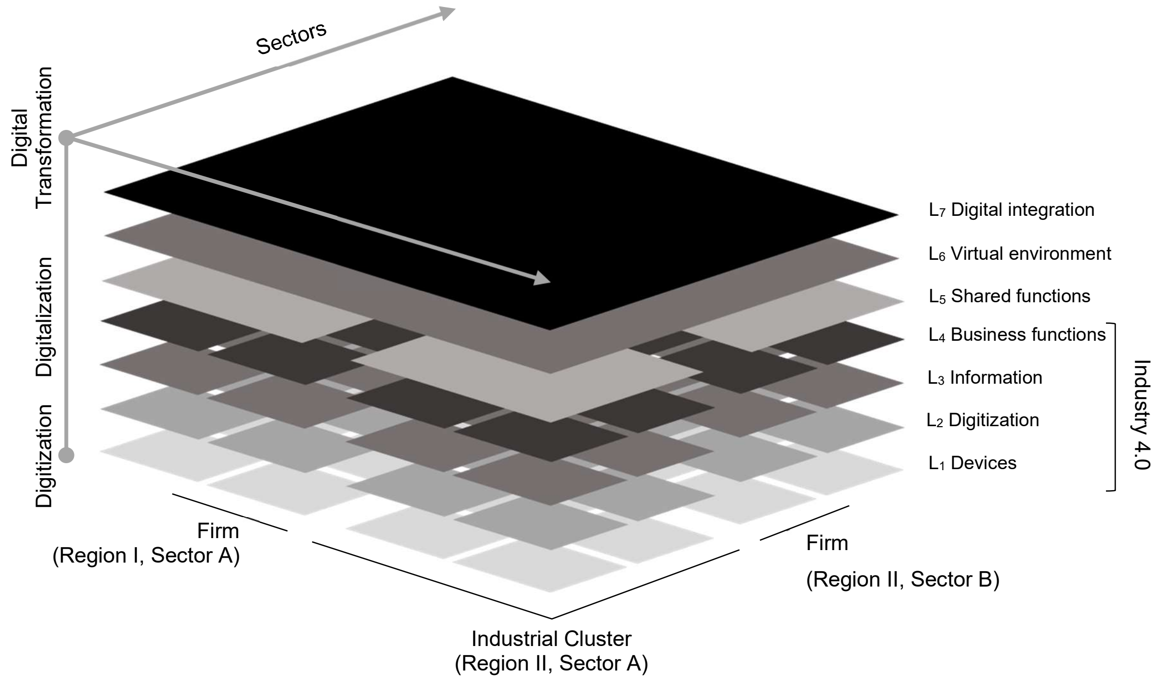
According to the definition of the DIC, two core elements need to be present: a virtual environment where the digitalized version of organizations, processes and people can interact, cooperate, and even compete; and multiple interrelated and interconnected industrial clusters which are expected to be dispersed in geography. Comparing with other models of digital agglomeration, the DIC does not expect geographical dispersion among all its individual members since they belong to actual industrial clusters. This provides multiple advantages to this novel model, discussed later in this chapter.

For this model, it is assumed that the DIC members are ready to support or even replace their shared business process by digital versions of them. However, since industrial clusters and their interrelations are expected to exist beforehand, the following discussion revolves around the digital transformation that the DIC involves.

To succeed the DIC must enable multiple functional layers capable of integrating people, organizations, and technologies; the main purpose is to digitalize and manage multiple organizational functions among participants to replicate cooperation and competition dynamics that are found in traditional industrial agglomerations. Therefore, the main challenge for digital integration among multiple organizations is the need to transfer real facts to digital data, and then create massing amounts of information which must be managed among cluster participants inside a virtual environment. As a result, Industry 4.0 plays a significant role in the DIC, since technologies like IoT and Big Data make possible the migration from analog data to digital data and the management of such amounts of information.

Zezulka et al. (2016) presented a model of all the different interconnected features of the technical–economical properties for the Industry 4.0 applications. This model showed the multiple layers needed to deploy Industry 4.0 technologies in business, inspiring the deployment model presented in **Figure I.4.** It represents different interconnected features, organizations and regions needed to deploy a DIC. The figure also shows, through a 3D model, how two regions (x-axis) and two sectors (z-axis) can be integrated into a single DIC. The model presents four traditional industrial clusters integrated by four individual firms: (1) Region I, Sector A, (2) Region I, Sector B, (3) Region II, Sector A and (4) Region II, Sector B. The model also presents over the y-axis seven layers of integration (L), going from individual firms (small squares) to industrial clusters (medium squares), to finally a DIC (big square).

Figure I.4. Deployment model of the Digital Industrial Cluster (DIC) from a multilayer/multidimensional perspective.



SOURCE: Author's elaboration.

The relevance of Industry 4.0 lies at the foundations of the model (from L_1 to L_4) since the integration of people, processes, and information into business functions supported by digital platforms could be impossible without Industry 4.0 associated technologies. At L_5, it is expected that individual industrial clusters are interconnected at the local level, after each member has undergone its individual process of digitalization and integration with other cluster members. It is relevant to mention how the top four levels go from individual business functions (L_4) to full digital integration (L_7), with intermediate layers related to: the shared functions among organizations (L_5) for which the preexistent relationships inside of the traditional industrial clusters become relevant, and the virtual environment (L_6) where clusters and individual firms coexist thanks to shared platforms and homogeneous data structure.

One of the main strengths of this deployment model is that it comprises the three phases of digital transformation (Anthony Jnr & Abbas Petersen, 2020; Verhoef et al., 2021). In the first phase, the digitization (from L_1 to L_2), analog data is transformed into a digital format through devices like sensors, robots, and cyber-physical systems. In the second phase, the digitalization (from L_3 to L_5), technology platforms use data to transform it into new information aimed to support -and even replace if possible-organizational processes and functions which can be fully internal or shared with other organizations. Finally, in the third phase -digital transformation (from L_6 to L_7)- firms and industrial clusters experience deep transformations in their way of doing business, thanks to the emergence of unexpected patterns and new knowledge recombination supported by technology, all inside a well-established environment of interrelatedness (Bathelt & Turi, 2011; Buteau, 2021; Cuevas-Vargas et al., 2022; Knell, 2021). It is at the third phase where multiregional and multisectoral integration through digital platforms has been reached.

The presented model shows the path toward digital transformation in a world chaotically pushed toward digitalization under the misleading assumption that digital will replace face-to-face interaction (Usai et al., 2021); furthermore, even when multiple organizations have adopted a digital approach at this time as a practical answer to contingency (Guo et al., 2020), the DIC and its deployment model is a fresh proposition since there is still a lack of models of industrial organization that have managed to conciliate analog with digital because the traditional models are looking more for substitution than for synergies.

The DIC is a complex model that is leveraged on ICT, Industry 4.0 and industrial cluster synergies to support and to facilitate interactions among organizations to boost development, in a world where geographical proximity and the role of face-to-face between individuals are still relevant after pandemic (Bathelt & Turi, 2011; Götz & Jankowska, 2017; Junge et al., 2016; Kayley, 2017; Leamer & Storper, 2001; Usai et al., 2021). Industry leaders and policymakers could find useful the deployment model presented either to develop plans of digital integration among interrelated industrial clusters or also to assess the level of digital integration for currently developed projects of digital transformation among agglomerated industries.

I.3.5 The DIC externalities: tackling concerns about digitalization and innovation

But why implement a DIC? As previously mentioned, researchers still must assess empirically the DIC to find evidence about its externalities on industry and economy - either positive or negative-. Similarly, a large part of the literature related to DBE, VIC and eSoC is theoretical, but there are empirical studies worthy of mention: the European Union's DBE project[1] and VIRPLAS, a VIC project developed by the COSME network[2].

Both projects were shut down before 2008 and used to be hosted on their own websites (currently unavailable). Research centers and universities designed and led those projects from scratch as policy tools aimed to integrate SMEs from multiple sectors. Even though both projects were born and died before the boom of social networks, smartphones, and Industry 4.0, they laid the groundwork for future understanding of the phenomenon and for future projects of digital/virtual integration.

This background and subsequent research about digital agglomeration, which this chapter has presented and discussed, have made possible to reach some suggestions about how the implementation of a DIC could lead to positive externalities at micro, meso and macro levels of the economy. In the next paragraphs, this research discusses the expected positive impacts of the DIC and also presents the foundations of those impacts, and their relations with other variables and phenomena; furthermore, it is addressed how the DIC is expected to tackle multiple concerns related to digitalization and innovation, a complex relationship presented in the literature review which has been under revision after COVID-19 pandemic.

The most evident and expected externality of the DIC is **the strengthening and promotion of multi-regional interactions and integration**. The DIC could overcome one of the main limitations of traditional industrial clusters development: the geographical proximity (Fuks & Kawa, 2013). The development of a DIC will contribute to boost connectivity and relatedness between regions and companies, in spite of their geographical dispersion or their apparently unrelated disciplines, thanks to ICT capabilities to orchestrate activities through virtual and physical space (Alcacer et al., 2016; Almeida et al., 2020; Bathelt & Turi, 2011; Schwarzer et al., 2019). Furthermore,

---

[1] The European Commission provides public information about this project: Community Research and Development Information Service (CORDIS). (2007). DBE – Digital Business Ecosystem. *EU Research Results*. Retrieved from: https://cordis.europa.eu/project/id/507953/es

[2] COSME stands for *Cooperation for Small and Medium Enterprises*, a research group performed by Latin-American and European universities during the late 90's.

multi-regional integration has a significant impact on economic growth (Alcacer et al., 2016; Della et al., 2018).

The second expected externality is **the improvement of the knowledge creation and its management**. The information flow is expected to become easier and more traceable in a DIC, strengthening global pipelines as multiple interactions from multiple actors will occur in the same virtual space, which is intended not only as a means of communication but also as a repository for knowledge (Aleksandrovich, 2019; Bathelt et al., 2004; Cuevas-Vargas et al., 2021; Gertler & Wolfe, 2006; Owen-Smith & Powell, 2004; Scarle et al., 2012; Schwarzer et al., 2019).

The third expected externality is **the stimulation of competition and industrial diversity**. The openness and flexibility of the DIC pursue to make it easy and cheap for firms to take part in it, especially for SMEs and entrepreneurs capable to offer relevant products and services to other members on the platform (Alcacer et al., 2016; Fuks & Kawa, 2013; Richter et al., 2017). Additionally, with the reinforcement of economic integration, the participants of digital environments have access to various resources to achieve results in a more effective and efficient way, reducing costs and increasing returns (Babkin et al., 2013; Mostafa et al., 2019); furthermore, the digitalization improves cooperation and competition, and helps organizations to develop their fundamental expertise (Babkin et al., 2018; Della et al., 2018; Muller et al., 2018).

The fourth expected externality is **the enhancement of agility and value co-creation**. The technological approach of co-creation and co-production in a DIC will take participants toward more agile value chains, enhancing their capabilities to compete in new markets and improving competitiveness for clusters, regions and entire countries (Almeida et al., 2020; Baggio & Del Chiappa, 2014; Buteau, 2021; Lember et al., 2019; Sarkar et al., 2007).

The fifth externality is **the reduction of the organizational friction toward digital transformation**. Pandemic made evident the uneven access to digital infrastructure and the persistence of the analog in rigid business processes, which raised concerns about the potential success of the process of digital transformation. However, since the DIC aims to be founded on traditional industrial clusters, it expects to create ideal conditions and positive drivers for digitalization and Industry 4.0, making easier and cheaper for SMEs and entrepreneurs the digitalization process, particularly after pandemic (Götz & Jankowska, 2017; Guo et al., 2020; Jasinska & Jasinski, 2019; Karnitis & Karnitis, 2017; Maresova et al., 2018; Temouri et al., 2021). Industrial clusters tend to homogenize digital penetration among members; furthermore, the adoption of technology has a positive effect in the development of new one since knowledge spill overs provides adequate industrial guidelines and skills, required to support the digital transformation (Alcacer et al., 2016; Almeida et al., 2020; Watanabe et al., 2018).

It is important to highlight the externalities presented are related to each other and feed themselves; besides, the DIC aims to boost anticipated externalities from traditional industrial clusters, like innovation and economic development (Watanabe et al., 2018).

However, questions rise about how the externalities of the DIC will deal with innovation, due to the complex digitalization-innovation relationship. The discussion about negative effects of digitalization over innovation turns around the replacement of face-to-face interactions for homogeneous-and-standardized digital platforms (Usai et al., 2021), but the DIC does not pretend to fully replace analog by digital but only those processes where human interventions lack of substantial value. For those processes where human direct and face-to-face intervention is relevant for creation and production (Lember et al., 2019), the digital environment is expected to bring support and enhance interconnectivity, leveraging well-established qualities of industrial clusters like knowledge, learning, trust and relationships (Bathelt & Turi, 2011; Jofre-Monseny et al., 2014; Palacios-Marqués et al., 2016; Titze et al., 2011). Moreover, multi-regional and external networks, especially those supported by technology, provide means to access different sets of capabilities, skills, expertise and resources, enhancing the potential for innovation (Della et al., 2018; Knell, 2021; Senyo et al., 2019). The information flow -both formal and informal- is expected to become easier in a DIC context, leading to unexpected patterns, knowledge recombination and creation of new ideas, products, technologies and processes (Alcacer et al., 2016; Aleksandrovich, 2019; Buteau, 2021; Cuevas-Vargas et al., 2021; Jasinska & Jasinski, 2019; Scarle et al., 2012; Schwarzer et al., 2019; Senyo et al., 2019). Furthermore, digital economy tends to lower barriers of entry, making it easier for companies to become new players in new markets, changing the way of doing business (Verhoef et al., 2021; Watanabe et al., 2018).

Finally, the combination of all externalities presented expects to drive to economic growth. Since DIC aims to strength digital multi-regional integration and develop regionally integrated networks, a significant impact on economic growth is expected. Besides, a DIC makes easier for participants to catch new market opportunities and makes easier for entrepreneurs and SMEs to be part of the network (Fuks & Kawa, 2013; Lehdonvirta & Ernkvist, 2011; Temouri et al., 2021). All these factors incentivize innovation and competitiveness, both powerful drivers of economic growth (Almeida et al., 2020; Babkin et al., 2017; Delgado, Porter, et al., 2014; Duranton, 2011; Portugal et al., 2012; Zeibote & Muravska, 2018). Furthermore, the systematic digitalization of relationships among clusters and their members should serve to reduce regional asymmetries and to develop territories lagging behind, phenomena widely observed during the pandemic (Afonasova et al., 2019; Almeida et al., 2020).

The DIC has in mind that the most advanced regions are those that are more open and connected (Alcacer et al., 2016; Della et al., 2018), and it does not pretend to replace neither traditional industrial clusters, the relevance of geographical proximity, nor face-to-face interactions between individuals. Rather, the DIC as a policy tool means to build technological infrastructure to support and facilitate interactions among cluster-member organizations to boost development; besides, economies still need a combination of analog and digital interactions to succeed.

To conclude, even when literature supports the externalities presented, it is important to point out that further theoretical and empirical research is needed, because of existing gaps in the literature related to digital transformation and its relationship with models of digital integrations based on industrial clusters. In this sense, this chapter contributes to fill this gap.

I.3.6 The expected challenges for the deployment of the DIC

To be deployed and to spill its benefits into the involved regions, the DIC needs that companies and regions overcome relevant challenges. Those challenges are not new, but health emergency exposed them particularly among not digitalized people and firms (Almeida et al., 2020; Anthony Jnr & Abbas Petersen, 2020; Faraj et al., 2021); such challenges right now are in hands of academics, practitioners, industry leaders and policymakers.

In the first place, there is the need for companies and regions to construct new infrastructure and knowledge -more flexible, more agile and more interconnected-, in order to be capable of becoming a proficient player in the digital economy (Alcacer et al., 2016; Almeida et al., 2020; Bathelt & Turi, 2011). This challenge reaches also the traditional clusters, which must become more cross-sectorial, horizontal and geographically dispersed (Götz & Jankowska, 2017; Schwarzer et al., 2019). Similarly, the lack of infrastructure and human capital is one of the main barriers for the advance of digitalization (Leamer & Storper, 2001; Maresova et al., 2018).

The second challenge -capable to reduce the positive impact of the DIC over innovation if left unaddressed- is related to business models and value creation. Companies embedded in digital economies struggle with the creation of new business models capable of capturing value. Even for scholars, this is a fertile ground for research: how do firms create and capture value in a less decentralized and modular environment? (Alcacer et al., 2016; Maresova et al., 2018; Usai et al., 2021). The success of the DIC will depend strongly on the capacity of organizations to create new types of products and services, and the redesign of the production system (Ahmad & Schreyer, 2016; Almeida et al., 2020); however, the development of all those products and services must be motivated by market realities, and not only for initiatives disconnected from market needs, otherwise their destiny will be failure (Jasinska & Jasinski, 2019).

The third challenge is remarkably close to the second one: the difficulties for assessing the positive impact of digitalization on economy affects the willingness of participants to support a digital agglomeration initiative, especially in the public sector. ICT and Industry 4.0, as factors of growth, still have impacts difficult to assess from the traditional GDP structure which measures revenue; the added value found in digital economies -as utility, collaboration and even happiness-, remains uncaptured by GDP (Carson, 2012; Maresova et al., 2018). Furthermore, industrialized -and usually more digitalized- countries face an apparent decline in productivity, a paradox in the digital economy age (Afonasova et al., 2019; Ahmad & Schreyer, 2016; Watanabe et al., 2018).

Fourth, there are justified concerns about cyber security and privacy. The participants of digital environments achieve better reciprocal understanding and develop a base for mutual trust, resulting in more transparent business ecosystems (Fuks & Kawa, 2013); however, high level of transparency could expose participants to cyber security risks and privacy issues (Mostafa et al., 2019; Schwarzer et al., 2019). These situations could drive participants to be more reluctant in being part of the DIC initiatives, encouraging the creation of new barriers to information access and discouraging the implementation of Industry 4.0 (Buteau, 2021; Muller et al., 2018).

Finally, and closely related to the previous one, there is the challenge of regulation, law, and ethics. Any digital or virtual environment is capable of trespassing traditional borders, reshaping their role and importance (Berman et al., 2020); this makes necessary to develop an appropriate legal and ethical framework, flexible enough to be useful in multiple regions but also clear enough to close doors to illegality and unethical behavior, especially in topics related to data protection, intellectual property and platform governance (Scarle et al., 2012; Senyo et al., 2019).

The whole five challenges presented are not exclusive for digital clusters, but also for developing digital and virtual economies. To overcome these challenges, deepening research into the development of clusters and Industry 4.0 in the context of digital economy and multiregional integration is needed (Jasinska & Jasinski, 2019; Maresova et al., 2018).

I.4 Conclusions

The industrial cluster phenomenon was first studied to know its genesis and effects, and later it was applied around the world as a policy tool for economic development, becoming widely recognized in developed and developing countries. Such a policy tool relies on the foundations of agglomeration: geographical proximity, interrelatedness, innovation, competitiveness, and resources transfer.

However, in the age of Industry 4.0 and digital economies, technology has defied geography and challenged traditional value chains. Furthermore, the COVID-19 pandemic changed the world for people and organizations, disrupting not only the way of life of billions of people but also the traditional ways of doing business. Besides, lockdown made relevant the need of synergies among regions -once again- and challenged globalization as never before.

In this chaotic and post-pandemic environment, governments and firms found on digitalization a way to boost the economy. ICT and Industry 4.0 have a great delocalization power, but -paradoxically- they also found in the localization phenomenon the more fertile ground for their development and success. Such events encouraged scholars, practitioners, and policymakers to create novel concepts and models for economic progress, capable to take advantage of geographic proximity but also of the state-of-the-art ICT and Industry 4.0's associated technologies.

The industrial cluster as an industrial agglomeration phenomenon remains as a relevant approach for economic development, being resilient to pandemic, digitalization, and globalization. This chapter departs from such models of digital agglomeration and proposes a new one named the Digital Industrial Cluster (DIC) as a new policy tool, which fits industrial agglomeration in a future context shaped by digital economies and Industry 4.0. The DIC as a normative concept could be defined as a virtual space where digitalized organizations take advantage of technological infrastructures aimed to support or even to replace any organizational function capable of being digitalized. It is expected that those organizations belong to interrelated and geographically dispersed clusters, to replicate the cooperation and competition dynamics founded in traditional industrial clusters.

This policy tool aims to support the evolution of traditional industrial clusters through ICT and Industry 4.0, making possible the digital integration of economic entities that belong to clusters into a virtual space, facilitating digitalization and decentralization of analog interactions found in clusters. Besides, the implementation of the DIC expects positive externalities, including multi-regional integration, knowledge management, industrial diversity, and value co-creation. The DIC also expects to improve economic development and innovation in regions where it could be implemented, taking advantage of networks and infrastructure currently developed by traditional industrial clusters. Furthermore, the DIC could be a flexible alternative to integrate lagging-behind regions to improve their economy and their digital infrastructure since health emergency proved that digital capabilities around the world and among industries still have a high level of heterogeneity.

The DIC could find its way in developed and developing economies where industrial cluster policies are common, favoring high-value-added manufacturing clusters as they could be better prepared to embrace the approach of extended clusters based on digital platforms and Industry 4.0. Thus, this research could be useful for policymakers and *cluster organizations* since they usually are the main actors in the visualization, design, and implementation of such kinds of policy tools; moreover, *cluster organizations* have developed governance structures that could be adapted to the DIC for optimal governance, management, and operation. Additionally, a 3D model of seven layers was presented as a deployment model of the DIC, comprising the three phases of digital transformation and highlighting the relevance of Industry 4.0 for this model of digital agglomeration. The deployment models expect to make clearer for industrials, researchers, and policymakers how industries and industrial clusters are expected to be integrated into a single virtual space, where digital processes will support and even replace organizational functions and processes.

The DIC aims to deal with post-pandemic obstacles related to digitalization -such as the complex relationship among digitalization and innovation-, since this model aims to replace analog processes by digital ones only where human interventions lack of substantial value. Those processes where human direct and face-to-face intervention is transcendental are expected to be supported and enhanced by digital transformation. However, the DIC -as any other model of development based on digital transformation- needs regions to overcome regional challenges to succeed. COVID-19 pandemic made more evident such challenges that involve governments, firms, and academics, as they are related to infrastructure modernization, development of new business models, economic assessment of technology, cybersecurity, and regulations. The relevance of addressing those challenges lies in the fact that they can reduce or even cancel the externalities of the DIC, particularly those related to innovation.

This research expects to become a useful instrument for policymakers and *cluster organizations* to help them visualizing the organization and development of a real-world DIC, particularly in economies and regions capable to deploy such complex projects. The understanding of the theoretical foundations of this model will allow practitioners to decide: (1) whether this model fits their industrial policy, (2) whether their regions and clusters are ready for a DIC, and (3) whether the DIC is the right way to take their industrial clusters to the next level of integration and development. Furthermore, since the DIC aims to become a complex network to support economic integration, this chapter aims to be a valuable theoretical foundation for industry leaders, researchers, and policymakers not only for the future deployment of a DIC but also for its early identification in real-world.

Finally, more theoretical advancements could lead to the empirical identification and assessment of early manifestations of this phenomenon, especially after the COVID-19 pandemic pushed the need for novel models of digital integration. Additionally, further empirical research is needed to assess the potential benefit of the deployment of a DIC, and to identify regions and actors capable to participate on such project; collection and analysis of data related to the penetration of ICT and Industry 4.0 on regions with prevalence of traditional industrial clusters would make easier for researchers and policymakers to overcome the current challenges faced by the deployment model of the DIC.

References

Adebanjo, D. (2010). The complexities of e-reverse-auction-facilitated aggregated procurement in digitally clustered organisations. *Supply Chain Management-an International Journal*, *15*(1), 69–79. https://doi.org/10.1108/13598541011018139

Afonasova, M. A., Panfilova, E. E., Galichkina, M. A., & Slusarczyk, B. (2019). Digitalization in economy and innovation: The effect on social and economic processes. *Polish Journal of Management Studies*, *19*(2), 22–32. https://doi.org/10.17512/pjms.2019.19.2.02

Ahmad, N., & Schreyer, P. (2016). Are GDP and productivity measures up to the challenges of the digital economy? *International Productivity Monitor*, *30*, 4–27.

Alcacer, J., Cantwell, J., & Piscitello, L. (2016). Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies*, *47*(5), 499–512. https://doi.org/10.1057/jibs.2016.22

Aleksandrovich, S. K. (2019). Цифровая экономика и ее роль в управлении современными социально-экономическими отношениями [Digital Economy and Its Role in Management of Modern Social and Economic Relations]. *State and Municipal Management Scholar Notes*, *1*(4), 102–105. https://doi.org/10.22394/2079-1690-2019-1-4-102-105

Almeida, F., Duarte, J., & Monteiro, J. (2020). The challenges and opportunities in the digitalization of companies in a post-COVID-19 world. *IEEE Engineering Management Review*, *48*(3), 97–103. https://doi.org/10.1109/EMR.2020.3013206

Angehrn, A. (1997). Designing mature internet business strategies: The ICDT model. *European Management Journal*, *15*(4), 361–369. https://ideas.repec.org/a/eee/eurman/v15y1997i4p361-369.html

Anthony Jnr, B., & Abbas Petersen, S. (2020). Examining the digitalisation of virtual enterprises amidst the COVID-19 pandemic: A systematic and meta-analysis. *Enterprise Information Systems*, *15*(5), 617–650. https://doi.org/10.1080/17517575.2020.1829075

Atik, H., & Ünlü, F. (2019). The measurement of Industry 4.0 performance through Industry 4.0 Index: An empirical investigation for Turkey and European countries. *Procedia Computer Science*, *158*, 852–860. https://doi.org/10.1016/j.procs.2019.09.123

Babkin, A., Kudryavtseva, T., & Utkina, S. (2013). Formation of industrial clusters using method of virtual enterprises. *International Conference on Applied Economics (Icoae)*, 68–72. https://doi.org/10.1016/s2212-5671(13)00011-7

Babkin, A., Plotnikov, V., & Vertakova, Y. (2018). The analysis of industrial cooperation models in the context of forming digital economy. *SHS Web of Conferences*, *44*, 12. https://doi.org/10.1051/shsconf/20184400012

Babkin, A., Vertakova, Y., & Plotnikov, V. (2017). Study and assessment of clusters activity effect on regional economy. *SHS Web of Conferences*, *35*, 63. https://doi.org/10.1051/shsconf/20173501063

Baggio, R., & Del Chiappa, G. (2014). Real and virtual relationships in tourism digital ecosystems. *Information Technology & Tourism*, *14*(1), 3–19. https://doi.org/10.1007/s40558-013-0001-5

Bathelt, H. (2008). Clusters and regional development: Critical reflections and explorations. *Economic Geography*, *84*(1), 109–112. https://doi.org/10.1111/j.1944-8287.2008.tb00394.x

Bathelt, H., & Boggs, J. S. (2003). Toward a reconceptualization of regional development paths: Is Leipzig's media cluster a continuation of or a rupture with the past? *Economic Geography*, *79*(3), 265–293. https://doi.org/10.1111/j.1944-8287.2003.tb00212.x

Bathelt, H., & Li, P. F. (2014). Global cluster networks-foreign direct investment flows from Canada to China. *Journal of Economic Geography*, *14*(1), 45–71. https://doi.org/10.1093/jeg/lbt005

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Bathelt, H., & Taylor, M. (2002). Clusters, power and place: inequality and local growth in time–space. *Geografiska Annaler: Series B, Human Geography*, *84*(2), 93–109. https://doi.org/10.1111/j.0435-3684.2002.00116.x

Bathelt, H., & Turi, P. (2011). Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. *Geoforum*, *42*(5), 520–529. https://doi.org/10.1016/j.geoforum.2011.04.007

Bayliss, D. (2007). Dublin's digital hubris: Lessons from an attempt to develop a creative industrial cluster. *European Planning Studies*, *15*(9), 1261–1271. https://doi.org/10.1080/09654310701529268

Becattini, G. (1990). The Marshallian industrial district as a socio-economic concept. In F. Pike, G. Becattini, & W. Sengenberger (Eds.), *Industrial Districts and Inter-Firm Cooperation in Italy* (pp. 37–51). ILO.

Berman, A., Marino, A., & Mudambi, R. (2020). The global connectivity of regional innovation systems in Italy: a core–periphery perspective. *Regional Studies*, *54*(5), 677–691. https://doi.org/10.1080/00343404.2019.1672865

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 perspective. *World Academy of Science, Engineering and Technology. International Journal of Information and Communication Engineering*, *8*(1), 37–44. https://doi.org/10.5281/zenodo.1336426

Buteau, S. (2021). Roadmap for digital technology to foster India's MSME ecosystem—

opportunities and challenges. *CSI Transactions on ICT*, *9*(4), 233–244. https://doi.org/10.1007/s40012-021-00345-4

Carson, K. A. (2012). [Review of the book The great stagnation: How America ate all the low-hanging fruit of modern history, got sick, and will (eventually) feel better, by T. Cowen]. In *Freeman* (Vol. 62, Issue 5).

Charykova, O. G., & Markova, E. S. (2019). Региональная кластеризация в цифровой экономике [Regional clustering in the digital economy]. *Economy of Region*, *15*(2), 409–419. https://doi.org/10.17059/2019-2-8

Cortright, J. (2006). *Making Sense of Clusters: Regional Competitiveness and Economic Development* (p. 66). The Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/wp-content/uploads/2016/06/20060313_Clusters.pdf

Crabtree, A., Lodge, T., Colley, J., Greenhalgh, C., Mortier, R., & Haddadi, H. (2016). Enabling the new economic actor: Data protection, the digital economy, and the databox. *Personal and Ubiquitous Computing*, *20*(6), 947–957. https://doi.org/10.1007/s00779-016-0939-3

Cruz, S. C. S., & Teixeira, A. A. C. (2010). The evolution of the cluster literature: Shedding light on the regional studies-Regional science debate. *Regional Studies*, *44*(9), 1263–1288. https://doi.org/10.1080/00343400903234670

Cuevas-Vargas, H., Fernandez-Escobedo, R., Cortes-Palacios, H. A., & Ramirez-Lemus, L. (2021). The relation between adoption of information and communication technologies and marketing innovation as a key strategy to improve business performance. *Journal of Competitiveness*, *13*(2), 23–40. https://doi.org/10.7441/joc.2021.02.02

Cuevas-Vargas, H., Parga-Montoya, N., & Fernandez-Escobedo, R. (2022). The adoption of ICT as an enabler of frugal innovation to achieve customer satisfaction. The mediating effect of frugal innovation. *Procedia Computer Science*, *199*, 198–206. https://doi.org/10.1016/j.procs.2022.01.025

De Waele, W., & De Cleyn, S. H. (2014). Belgium: Building a digital cluster of innovation in the heart of Europe. In J. S. Engel (Ed.), *Global Clusters of Innovation: Entrepreneurial Engines of Economic Growth around the World* (pp. 120–140). Edward Elgar Publishing Ltd.

Del Chiappa, G., & Baggio, R. (2015). Knowledge transfer in smart tourism destinations: Analyzing the effects of a network structure. *Journal of Destination Marketing & Management*, *4*(3), 145–150. https://doi.org/10.1016/j.jdmm.2015.02.001

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38. https://doi.org/10.1093/jeg/lbv017

Della, M. R., Del Giudice, M., Lombardi, R., & Soto-Acosta, P. (2018). Open innovation, product development, and inter-company relationships within regional knowledge clusters. *Journal of the Knowledge Economy*, *9*(2), 680–693. https://doi.org/10.1007/s13132-016-0356-x

Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, *3*(1), 3–45. https://repository.upenn.edu/real-estate_papers/2

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J. F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (pp. 2063–2117). Elsevier.

Elola, A., Valdaliso, J., Lopez, S. M., & Aranguren, M. J. (2012). Cluster life cycles, path dependency and regional economic development: Insights from a meta-study on Basque clusters. *European Planning Studies*, *20*(2), 257–279. https://doi.org/10.1080/09654313.2012.650902

Erboz, G. (2017). How to define Industry4.0: The main pillars of Industry 4.0. *Managerial Trends in the Development of Enterprises in Globalization Era*, 761–767. https://www.researchgate.net/publication/326557388_How_To_Define_Industry_40_Main_Pillars_Of_Industry_40

European Cluster Collaboration Platform. (n.d.). *Cluster definitions*. Retrieved April 1, 2022, from https://clustercollaboration.eu/cluster-definitions#:~:text=Cluster organisations are the legal,activities%2C especially in SMEs2.

Evans, G. L. (2019). Emergence of a digital cluster in east London: Birth of a new hybrid firm. *Competitiveness Review*, *29*(3), 253–266. https://doi.org/10.1108/cr-08-2018-

0047

Faraj, S., Renno, W., & Bhardwaj, A. (2021). Unto the breach: What the COVID-19 pandemic exposes about digitalization. *Information and Organization*, *31*(1), 100337. https://doi.org/10.1016/j.infoandorg.2021.100337

Feferman, F. (2014). Brazil: Good governance in the tropics - The rise of the Porto digital cluster of innovation. In J. S. Engel (Ed.), *Global Clusters of Innovation: Entrepreneurial Engines of Economic Growth around the World* (pp. 296–337). Edward Elgar Publishing Ltd.

Fernandez, S. R., Castillo, D., & Martinez, L. A. (2018). Clúster virtual: Nueva alternativa a la competitividad eficaz en las empresas [Virtual cluster: New alternative to effective competitiveness in enterprises]. *Tendencias*, *19*(1), 164–186. https://doi.org/10.22267/rtend.181901.92

Feser, E. J. (1998). Old and new theories of industry clusters. In M. Steiner (Ed.), *Clusters and Regional Specialisation. European Research in Regional Science* (Vol. 8, pp. 18–40). Pion.

Flores, M., & Molina, A. (2000). Virtual industry clusters: Foundation to create virtual enterprises. In L. M. Camarinha-Matos, H. Afsarmanesh, & H. Erbe (Eds.), *Advances in networked enterprises: Virtual organizations, balanced automation and system integration* (pp. 111–120). Springer Science+Business Media.

Fujita, M., & Mori, T. (2005). Frontiers of the new economic geography. *Papers in Regional Science*, *84*(3), 377–405. https://doi.org/10.1111/j.1435-5957.2005.00021.x

Fuks, K., & Kawa, A. (2013). e-Sourcing clusters in network economy. In A. Hakansson & R. Hartung (Eds.), *Agent and Multi-Agent Systems in Distributed Systems - Digital Economy and E-Commerce. Studies in Computational Intelligence* (pp. 33–51). Springer.

Gagnidze, I. (2022). Industry 4.0 and industry 5.0: can clusters deal with the challenges? (A systemic approach). *Kybernetes*. https://doi.org/10.1108/K-07-2022-1005

Gertler, M. S., & Wolfe, D. A. (2006). Spaces of knowledge flows: Clusters in a global context. In R. Martin, B. Asheim, & P. Cooke (Eds.), *Clusters and Regional*

Development: Critical Reflections and Explorations (Vol. 29, pp. 218–235). Routledge.

Golov, R. S., Palamarchuk, A. G., Anisimov, K. V., & Andrianov, A. M. (2021). Cluster Policy in a Digital Economy. *Russian Engineering Research*, *41*(7), 631–633. https://doi.org/10.3103/S1068798X21070108

Götz, M. (2019a). The industry 4.0 induced agility and new skills in clusters. *Foresight and STI Governance*, *13*(2), 72–83. https://doi.org/10.17323/2500-2597.2019.2.72.83

Götz, M. (2019b). Unpacking the provision of the industrial commons in Industry 4.0 cluster. *Economics and Business Review*, *5*(4), 23–48. https://doi.org/10.18559/ebr.2019.4.2

Götz, M. (2021). Cluster role in industry 4.0 – a pilot study from Germany. *Competitiveness Review*, *31*(1), 54–82. https://doi.org/10.1108/CR-10-2019-0091

Götz, M., & Jankowska, B. (2017). Clusters and Industry 4.0 - Do they fit together? *European Planning Studies*, *25*(9), 1633–1653. https://doi.org/10.1080/09654313.2017.1327037

Grover, V., & Sabherwal, R. (2020). Making sense of the confusing mix of digitalization, pandemics and economics. *International Journal of Information Management*, *55*(September), 102234. https://doi.org/10.1016/j.ijinfomgt.2020.102234

Guo, H., Yang, Z., Huang, R., & Guo, A. Q. (2020). The digitalization and public crisis responses of small and medium enterprises: Implications from a COVID-19 survey. *Frontiers of Business Research in China*, *14*(1), 25. https://doi.org/10.1186/s11782-020-00087-1

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industry 4.0 scenarios. *49th Hawaii International Conference on System Sciences (HICSS)*, 3928–3937. https://doi.org/10.1109/hicss.2016.488

Hoover, E. M. (1948). *The location of economic activity* (p. 310). McGraw-Hill.

Jankowska, B., Maria, E. D., & Cygler, J. (2021). Do clusters matter for foreign subsidiaries in the Era of industry 4.0? The case of the aviation valley in Poland. *European Research on Management and Business Economics*, *27*(2).

https://doi.org/10.1016/j.iedeen.2021.100150

Jasinska, K., & Jasinski, B. (2019). Clusters under industry 4.0 conditions - Case study: the concept of Industry 4.0 cluster in Poland. *Transformations in Business & Economics*, *18*(2B), 802–823. http://www.transformations.knf.vu.lt/47b/article/clus

Jofre-Monseny, J., Marin-Lopez, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: evidence from the location of new firms in Spain. *Journal of Regional Science*, *54*(2), 313–337. https://doi.org/10.1111/jors.12076

Johansson, B., Karlsson, C., & Stough, R. R. (2006). The emerging digital economy: Conclusions. In B. Johansson, C. Karlsson, & R. R. Stough (Eds.), *The Emerging Digital Economy. Advances in Spatial Science* (5th ed., pp. 331–339). Springer.

Junge, M., Severgnini, B., & Sorensen, A. (2016). Product-marketing innovation, skills, and firm productivity growth. *Review of Income and Wealth*, *62*(4), 724–757. https://doi.org/10.1111/roiw.12192

Karnitis, G., & Karnitis, E. (2017). Sustainable growth of EU economies and Baltic context: Characteristics and modelling. *Journal of International Studies*, *10*(1), 209–224. https://doi.org/10.14254/2071-8330.2017/10-1/15

Kayley, P. (2017). Interpersonal relationships as key drivers of cluster performance. *12th European Conference on Innovation and Entrepreneurship (ECIE)*, 362–367. https://www.researchgate.net/publication/321185237_Interpersonal_Relationships_as_key_Drivers_of_Cluster_Performance/citations

Ketels, C. (2004). *Cluster-based economic development: What have we learned*. Department of Trade and Industry, London, March 17, 2004. https://www.hbs.edu/faculty/Pages/item.aspx?num=47012

Ketels, C., & Memedovic, O. (2008). From clusters to cluster-based economic development. *International Journal of Technological Learning, Innovation and Development*, *1*(3), 375–392. https://doi.org/10.1504/IJTLID.2008.019979

Knell, M. (2021). The digital revolution and digitalized network society. *Review of Evolutionary Political Economy*, *2*(1), 9–25. https://doi.org/10.1007/s43253-021-00037-4

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Lanshina, T., Barinova, V., Kondratyev, A., & Romantsov, M. (2020). Sustainable development and digitalization: The unusual COVID-19 crisis requires original solutions. *International Organisations Research Journal*, *15*(4), 91–114. https://doi.org/10.17323/1996-7845-2020-04-05

Leamer, E. E., & Storper, M. (2001). The economic geography of the Internet age. *Journal of International Business Studies*, *32*(4), 641–665. https://doi.org/10.1057/palgrave.jibs.84909988

Lehdonvirta, V., & Ernkvist, M. (2011). *Knowledge map of the virtual economy* (p. 59). infoDev/World Bank. https://doi.org/10.1596/27361

Lember, V., Brandsen, T., & Tõnurist, P. (2019). The potential impacts of digital technologies on co-production and co-creation. *Public Management Review*, *21*(11), 1665–1686. https://doi.org/10.1080/14719037.2019.1619807

Lines, T., & Monypenny, R. (2006). *Industrial clustering*. Proceedings of the Sustainable Economic Growth for Regional Australia National Conference - SEGRA, August 28-30, 2006. https://www.researchgate.net/profile/Richard-Monypenny/publication/238712690_Industrial_Clustering/links/5bd8fe6c4585150b2b934b96/Industrial-Clustering.pdf

Malmberg, A., & Maskell, P. (2002). The elusive concept of localization economies: Towards a knowledge-based theory of spatial clustering. *Environment and Planning A*, *34*(3), 429–449. https://doi.org/10.1068/a3457

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., & Krejcar, O. (2018). Consequences of Industry 4.0 in business and economics. *Economies*, *6*(3), 14. https://doi.org/10.3390/economies6030046

Marshall, A. (1920). *Principles of economics* (8th ed., p. 69). Macmillan (original work published 1890).

Maskell, P., & Malmberg, A. (1999). The competitiveness of firms and regions - “Ubiquitification” and the importance of localized learning. *European Urban and Regional Studies*, *6*(1), 9–25. https://doi.org/10.1177/096977649900600102

Molina-Morales, F. X., Martinez-Chafer, L., & Valiente-Bordanova, D. (2017). Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones Regionales-Journal of Regional Research*, *39*, 39–57. https://investigacionesregionales.org/es/article/disruptive-technological-innovations-as-new-opportunities-for-mature-industrial-clusters-the-case-of-digital-printing-innovation-in-the-spanish-ceramic-tile-cluster/

Mostafa, N., Hamdy, W., & Alawady, H. (2019). Impacts of internet of things on supply chains: A framework for warehousing. *Social Sciences*, *8*(3). https://doi.org/10.3390/socsci8030084

Muller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247. https://doi.org/10.3390/su10010247

Ortega-Colomer, F. J., Molina-Morales, F. X., & Fernández-de-Lucio, I. (2016). Discussing the concepts of cluster and industrial district. *Journal of Technology Management & Innovation*, *11*(2), 139–147. https://doi.org/10.4067/S0718-27242016000200014

Owen-Smith, J., & Powell, W. W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, *15*(1), 5–21. https://doi.org/10.1287/orsc.1030.0054

Palacios-Marqués, D., Popa, S., & Pilar Alguacil Mari, M. (2016). The effect of online social networks and competency-based management on innovation capability. *Journal of Knowledge Management*, *20*(3), 499–511. https://doi.org/10.1108/JKM-05-2015-0175

Park, S. C. (2018). The Fourth Industrial Revolution and implications for innovative cluster policies. *AI and Society*, *33*(3), 433–445. https://doi.org/10.1007/s00146-017-0777-5

Popescu, V. A., & Popescu, C. R. (2011). Real economy versus virtual economy - New challenges for nowadays society. *Manager*, *13*(1), 7–15. https://manager.faa.ro/archive/manager_13/articles/1303.pdf

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *62*(2), 73–93. https://www.hbs.edu/faculty/Pages/item.aspx?num=6105

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15–34. https://doi.org/10.1177/089124240001400105

Porter, M. E., & Ketels, C. (2007). *Competitiveness in the global economy: Sweden's position*. Globaliseringsrådet, Stockholm, April 27, 2007. https://www.hbs.edu/faculty/Pages/item.aspx?num=46514

Portugal, M., Ribeiro, F., Kramer, B., Maccari, E. A., & Ritor, H. (2012). Impact of the types of clusters on the innovation output and the appropriation of rents from innovation. *Journal of Technology Management & Innovation*, *7*, 70–80. http://doi.org/10.4067/S0718-27242012000400006

Ratten, V. (2016). International collaboration and knowledge transfer among universities and firms affecting regional competitiveness. *Thunderbird International Business Review*, *58*(1), 91–93. https://doi.org/10.1002/tie.21724

Ricarte, É. (2020). Digitalization process expansion during the COVID-19 pandemic. *Finisterra*, *55*(115), 53–60. https://doi.org/10.18055/Finis20350

Richter, C., Kraus, S., Brem, A., Durst, S., & Giselbrecht, C. (2017). Digital entrepreneurship: Innovative business models for the sharing economy. *Creativity and Innovation Management*, *26*(3), 300–310. https://doi.org/10.1111/caim.12227

Rocha, H. O. (2004). Entrepreneurship and development: The role of clusters. *Small Business Economics*, *23*(5), 363–400. https://doi.org/10.1007/s11187-004-3991-8

Romanelli, E., & Khessina, O. M. (2005). Regional industrial identity: Cluster configurations and economic development. *Organization Science*, *16*(4), 344–358. https://doi.org/10.1287/orsc.1050.0131

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191–229. https://doi.org/10.1006/juec.2001.2230

Sarkar, R., Prabhakar, T. V, & Chatterjee, J. (2007). Towards digital ecosystems for skill based industrial clusters: Lessons from the "Digital Mandi" project. *IEEE International Conference on Digital Ecosystems and Technologies*, 128–133. https://doi.org/10.1109/DEST.2007.371958

Scarle, S., Arnab, S., Dunwell, I., Petridis, P., Protopsaltis, A., & de Freitas, S. (2012). E-commerce transactions in a virtual environment: Virtual transactions. *Electronic Commerce Research*, *12*(3), 379–407. https://doi.org/10.1007/s10660-012-9098-4

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest and the business cycle* (1th ed., p. 255). Transaction Publishers.

Schwab, K. (2016). *The fourth industrial revolution* (1th ed., p. 192). World Economic Forum.

Schwarzer, J., Chen, L., Cheng, W., Ciuriak, D., Kimura, F., Nakagawa, J., Pomfret, R., & Rigoni, G. (2019). The digital economy for economic development: Free flow of data and supporting policies. *Proceedings of the T20 Japan Task Force 8: Trade, Investment and Globalization*, 20. https://t20japan.org/policy-brief-digital-economy-economic-development/

Scott, A. J., & Storper, M. (2007). Regions, globalization, development. *Regional Studies*, *41*(1), 191–205. https://doi.org/10.1080/0034340032000108697

Senyo, P. K., Liu, K., & Effah, J. (2019). Digital business ecosystem: Literature review and a framework for future research. *International Journal of Innovation Management*, *47*, 52–64. https://doi.org/10.1016/j.ijinfomgt.2019.01.002

Skokan, K., & Zotyková, L. (2014). Evaluation of business cluster performance during its lifecycle. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *62*(6), 1395–1405. https://doi.org/10.11118/actaun201462061395

Slaper, T., Harmon, K., & Rubin, B. (2018). Industry clusters and regional economic performance: A study across US Metropolitan Statistical Areas. *Economic Development Quarterly*, *32*(1), 44–59. https://doi.org/10.1177/0891242417752248

Slaper, T., & Ortuzar, G. (2015). Industry clusters and economic development. *Indiana Business Review*, *90*(1), 7–9. https://www.ibrc.indiana.edu/ibr/2015/spring/pdfs/article2.pdf

Storper, M. (2009). Roepke lecture in economic geography - Regional context and global trade. *Economic Geography*, *85*(1), 1–21. https://doi.org/10.1111/j.1944-8287.2008.01001.x

Temouri, Y., Pereira, V., Muschert, G. W., Ramiah, V., & Babula, M. (2021). How does cluster location and intellectual capital impact entrepreneurial success within high-growth firms? *Journal of Intellectual Capital*, *22*(1), 171–189. https://doi.org/10.1108/JIC-02-2020-0066

Titze, M., Brachert, M., & Kubis, A. (2011). The identification of regional industrial clusters using qualitative input-output analysis (QIOA). *Regional Studies*, *45*(1), 89–102. https://doi.org/10.1080/00343400903234688

Tsakalerou, M., & Akhmadi, S. (2021). Agents of innovation: Clusters in industry 4.0. *Procedia Manufacturing*, *55*(C), 319–327. https://doi.org/10.1016/j.promfg.2021.10.045

Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*(May), 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*(July 2018), 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vlaisavljevic, V., Cabello-Medina, C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting and Social Change*, *155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Watanabe, C., Naveed, K., Tou, Y., & Neittaanmaki, P. (2018). Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technological Forecasting and Social Change*, *137*, 226–240. https://doi.org/10.1016/j.techfore.2018.07.053

Wixted, B. (2009). *Innovation system frontiers: Cluster networks and global value* (p. 226). Springer. https://doi.org/10.1007/978-3-540-92786-0

Yelkikalan, N., Soylemezoglu, E., Kiray, A., Sonmez, R., Ezilmez, B., & Altun, M. (2012). Clustering approach as a regional development tool. *8th International Strategic Management Conference*, *58*, 503–513.

https://doi.org/10.1016/j.sbspro.2012.09.1027

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the Digitized World. *Organization Science*, *23*(5), 1398–1408. http://www.jstor.org/stable/23252314

Yudina, T. (2019). Digital segment of the real economy: digital economy in the context of analog economy. *St. Petersburg State Polytechnical University Journal. Economics*, *12*(2), 7–18. https://doi.org/10.18721/JE.12201

Zeibote, Z., & Muravska, T. (2018). Promoting the regional competitiveness through clusters' approach: Case of the Latvian information technology cluster. *European Integration Studies*, *12*, 77–91. https://doi.org/10.5755/j01.eis.0.12.20846

Zezulka, F., Marcon, P., Vesely, I., & Sajdl, O. (2016). Industry 4.0 - An introduction in the phenomenon. *IFAC PapersOnLine*, *49*(25), 8–12. https://doi.org/10.1016/j.ifacol.2016.12.002

CHAPTER II

Unveiling industrial clusters in Spain: Methodological insights, conceptual challenges, and practical implications

II.1 Introduction

The relevance of industrial agglomeration is undeniable in a highly competitive and complex economy, in which productivity and innovation are key elements looking constantly for fertile ground to flourish (Yelkikalan et al., 2012); besides, urbanization and localization have proven to be an essential condition for economic development in the long term (Jofre-Monseny et al., 2014). There are multiple models of industrial agglomeration; however, the industrial district (Becattini, 1990) and the industrial cluster (Porter, 1990) have been particularly popular for the last three decades and the former has reached high levels of institutionalization in Europe and the US (Ortega-Colomer et al., 2016).

The efforts for empirically identifying such agglomerations over territory have led to the development of mapping tools, as an effort to help policymakers, industrials, and practitioners to understand and capitalize the industrial agglomeration phenomenon. The largest institutional efforts in this matter are the Cluster Mapping Project directed by the Institute of Competitiveness (in the US), and the European Cluster Collaboration Platform sponsored by the European Observatory for Clusters and Industrial Change (in Europe). There are also national efforts for mapping industrial districts departing from manufacturing industries (Lorenzini & Lombardi, 2018).

However, while the Cluster Mapping Project departs from Cluster Category Definitions (CCD)[3] derived from an empirical methodology designed to identify cross-industry linkages across the US economy, the European Observatory for Clusters departs from the homologation of US cluster definitions for the European context (Ketels & Protsiv, 2021; Szanyi et al., 2010), assuming industrial and environmental homogeneity between EU countries and the US (Brodzicki, 2010). Moreover, the mapping of industrial districts relies on Local Labor Markets as territorial units (Boix & Trullén, 2010), which are not harmonized for all European countries.

This represents a relevant gap in the literature for Europe, since a comprehensive cluster mapping initiative should develop a quantitative methodology based on common data, methodology, and literature, capable of being implemented in a comprehensive way across any particular economy to identify specific CCD for the geographic region being analyzed (Ketels, 2017).

Is it possible to complement the existing efforts of cluster mapping at a national level through the implementation of a comprehensive and quantitative methodology using domestic raw data? This chapter pretends to tackle that research question testing the methodology of Delgado et al. (2016) over Spain, not only because such country has been object of multiple institutional efforts to implement industrial agglomeration policies (Ortega-Colomer et al., 2016), but also because there are previous exercises of industrial agglomeration mapping that suggest sufficient data for the analysis (Boix & Galletto, 2009); furthermore, Spain brings the opportunity to test the methodology in a country with different geographical and industrial structure when compared to other advanced economies like the US and Germany (ICEX España Exportación e Inversiones, n.d.)

Since this is the first time such methodology is fully applied using domestic raw data outside the US, the study aims to: (I) present a robust cluster analysis methodology for the Spanish context to create domestic CCD and a cluster map; (II) discuss the methodological implications of the research and its differences with other exercises of cluster identification; and (III) explore the correlation between the existence of clusters and multiple economic variables. Besides, two indexes are built to summarize the

[3] In the context of cluster mapping initiatives, a Cluster Category Definition is a brief description of a group of industries that share different linkages related to employment, know-how, and value-chain, among others.

regional adoption of ICT (ICT index) and the regional adoption of technologies associated to Industry 4.0 (Industry 4.0 index); this is the first time such regional analysis is made for Spain, helping to fill another gap in literature.

The remainder of the chapter is structured as follows. The first section presents a theoretical background for the industrial cluster concept, common methodologies for cluster mapping, and externalities of this phenomenon. The second section of the chapter presents the quantitative methodology implemented for the cluster mapping exercise. The third and fourth parts present results and discuss them in the frame of previous research, respectively. Finally, main conclusions and limitations are presented, together with implications for cluster scholars and policymakers.

II.2 Theoretical background

Academics make broad efforts to consolidate empirical and theoretical literature about industrial agglomeration, its identification, causes, and effects. However, for the last thirty years, the concept of industrial cluster has reached a high level of popularity and institucionalization around the world, becoming a central element for industrial policy and creating a common language for regional development that could not be matched by other related concepts (Babkin et al., 2017; Hermans, 2021; Ortega-Colomer et al., 2016; Skokan & Zotyková, 2014).

This section presents literature framed by previous research about the industrial cluster, its externalities, and mapping methodologies.

II.2.1 The industrial cluster concept

Although the seminal work of Marshall (1920) laid the foundations of the cluster concept, it did not reached relevance among researchers and policymakers until the 90's, influenced mainly by the research of Becattini (1990), Krugman (1991), and Porter (1990).

Since then, this idea has been evolving from the basic viewpoints of networking and competitiveness to most complex and multidisciplinary approaches like knowledge management and the triple helix of innovation (Caloffi et al., 2018). Moreover, the cluster has adopted ideas or even competed with other models of industrial agglomeration; such is the case of the industrial district concept, from which the industrial cluster adopted its socio-economic-and-geographical notion (Sforzi, 2015).

In its current form, the industrial cluster concept rests on geographical, economic, competitive, and sociologic foundations (Jofre-Monseny et al., 2014) (**Figure II.1**). Furthermore, literature reveals that also the historical foundations play a relevant role in the cluster genesis and evolution when studied under the path-dependence model (Elola et al., 2012; Zhu & Pickles, 2016).

Figure II.1. Foundations of industrial clusters.

Geographic closeness		
Economics	Competitiveness	Sociology/History
• Input-output linkages • Labor market pooling • Knowledge spillovers	• Cost of economic factors • Demand conditions • Strategy and rivalry in the industry • Support organizations	• Historical path • Social context • Legal framework • Economic policy • Luck • Mutual confidence and reciprocity

SOURCE: Author’s elaboration based on the work of Babkin et al. (2018), Bathelt and Li (2014), Becattini (1990), Delgado et al. (2014, 2016), Duranton (2011), Duranton and Puga (2004), Elola et al. (2012), Jasinska and Jasinski (2019), Krugman (1991), Leamer and Storper (2001), Marshall (1920), Romanelli and Khessina (2005), Rosenthal and Strange (2001), Schumpeter (1934), and Vlaisavljevic et al. (2020)

Therefore, the industrial clusters can be defined as “*a group of companies and institutions geographically concentrated, whose relationships have as main characteristics the collaboration and exchange of resources, which implies a high cognitive proximity among actors*” (Tavares et al., 2021, p. 193).

Finally, although there are multiple definitions for the cluster, all of them fit the idea of a geographic space where economics of agglomeration manifest themselves among related organizations (Delgado et al., 2016).

II.2.2 The externalities of industrial clusters

The conceptual heterogeneity of clusters, added to the difficulty to establish their geographic delimitations and fully identity valuable networks and participants, makes difficult for researchers to generalize empirical findings about the impact of clusters on economic development. Skokan and Zotyková (2014) raise the next question as one of the most important for the study of clusters: how to measure the benefits of clusters on economy?

The most influential studies about the positive impact of clusters on economy are focused on innovation, showing that the access of cluster members to specialized inputs, skilled labor, market intelligence, and supportive infrastructure has a positive effect on it (Delgado, Porter, et al., 2014; Tavares et al., 2021; Ybarra & Domenech-Sanchez, 2012).

Likewise, there are empirical evidence about positive externalities related to the improvement of competitiveness, productivity, salaries, unemployment, and GDP. Slaper et al. (2018) found that regions with high prevalence of industrial clusters outperformed regions with low prevalence of them in variables like GDP per capita, wage level and total income per worker. Similarly, Babkin et al. (2018) observed a positive and significant relation between the existence of industrial agglomeration phenomena and competitiveness.

Empirical studies also show that clusters, as innovation networks, enhance collaboration among government, industry, and research centers, creating more stable and less uncertain business environments in which digital transformation and Industry 4.0 have better probabilities to evolve and improve the innovation capabilities (Babkin et al., 2018; Götz & Jankowska, 2017; Grashof et al., 2021; Jasinska & Jasinski, 2019; Vlaisavljevic et al., 2020). Furthermore, research made on different models of industrial agglomeration has reached similar results (Hervás-Oliver, 2021).

However, the conclusions about cluster externalities are far for being definitive. Literature shows that the life-cycle stage of clusters moderates the externalities of such agglomeration phenomenon (Elola et al., 2017; Skokan & Zotyková, 2014). Additionally, studies have shown that clusters can fall into technological lock-in, affecting the competitiveness of regions and industries (Elola et al., 2012; Zhu & Pickles, 2016). In addition, the best-known negative externality is what some authors call congestion costs, which implies the cost increase of key resources for cluster members, provoking diminishing returns and hurting entrepreneurship, competitiveness, and firm performance (Delgado, Porter, et al., 2014; Grashof & Fornahl, 2021; Slaper et al., 2018).

To conclude, it is important to mention that despite the challenges found by researchers to assess the effects of industrial clusters on economy and their actors, the findings about the positive effect on innovation and productivity tend to be more consistent in clusters that involve high-tech and traded industries, compared with low-tech and local industries (Bathelt & Li, 2014; Grashof & Fornahl, 2021; Slaper & Ortuzar, 2015; Tavares et al., 2021).

II.2.3 Methodologies for identification of industrial clusters

Researchers have developed multiple tools and approaches to build methodologies for clusters identification. Between the top-down methods and the bottom-up methods, the former fit better the needs of cluster mapping initiatives (Hermans, 2021; Ketels, 2017) as those methods have a quantitative approach based on statistical modeling, and are broadly applicable with nationwide/multi-industry scope.

The top-down methods depend on the definition of specific territories (spatial units for study); once studies define such units, the methodologies aim to analyze data in search of geographical concentration of industries and cross-industry linkages.

The main tools for identifying industrial agglomeration are the indexes and the location quotients (LQ). Ellison et al. (2010) proposed an index of industry concentration that has suffered from multiple revisions and adaptations for cluster mapping projects. Additionally, the Gini coefficient is another index adapted to measure industrial agglomeration (Burki & Khan, 2011). The LQ is also a popular measure to explore agglomeration; this one revolves around the employment specialization of regions when compared with others (Slaper et al., 2018). The central limitation of all those tools is that they only can be used on well specified industries or group of industries, which make them useless to find cross-industry linkages.

In the case of cross-industry linkages identification, there are tools and methodologies that depart from Marshallian micro-foundations of agglomeration; among them, it is worth mentioning the next ones.

The quantitative input-output analysis (QIOA) was developed to capture linkages related to flow of goods and services, departing from the study of Input-Output matrices (Oosterhaven et al., 2001; Titze et al., 2011). Similarly, the cross-industry patent citations measures and technology-flow matrices were developed to identify agglomeration patterns for knowledge linkages among industries (Ellison et al., 2010; Scherer, 1984). These tools are commonly limited for the availability of the data and the disaggregation level of it.

Most robust methodologies include the locational correlation (LC) analysis and the Sforzi-ISTAT methodology. The first one is capable of combining multiple approaches and capturing cross-industry linkages related to co-location, labor market pooling input-output relations and knowledge-flow, and it is the base of contemporaneous cluster mapping efforts (Diodato et al., 2018). However, it is limited for the quality/quantity of the data and is not capable of finding agglomeration patterns by itself. The second one is based on industrial district's literature and departs of the identification of Local Labor Markets and the definition of the groups of economic activities, which should be made previous to the analysis (Boix & Galletto, 2009). Nevertheless, while the methodology can find agglomeration patterns, it is limited by the need of a harmonized Local Labor Market structure for different countries and the *ex ante* aggregation of industries, which reduces its flexibility and its capacity to find complex cross-industry linkages, respectively.

Finally, state-of-the-art methodologies combine multiple of these methods with algorithms of cluster analysis based on Ward's linkage, finding agglomeration patterns and cross-industry linkages at the same time, providing the needed data to create appropriate CCD for specific territories (Delgado et al., 2016). Unfortunately, such methodologies tend to use administrative divisions as spatial units for study, missing the rationale of community that shapes the concept of Local Labor Markets, which is at the heart of the industrial district mapping (Canello & Pavone, 2016).

Although the presented tools and methods have the mentioned limitations, researchers recognize their valuable potential for cluster mapping, particularly when they are combined, and their results are used for comparison purposes.

II.3 Methodology

This empirical research has an exploratory, descriptive, non-experimental, and cross-sectional design with a quantitative approach, using the statistical technique known as cluster analysis. The research also uses the Pearson correlation coefficient to explore correlation between pairwise industries and among CCD and multiple macroeconomic variables.

The presented methodology is focused on traded industries (Delgado, Bryden, et al., 2014) and based on the work of Delgado et al. (2016) which describes the current algorithm used by the Cluster Mapping Project to establish CCD in the US.

The analysis is based on the National Classification of Economic Activities for Spain (CNAE-2009) at 2-digits level and uses autonomous communities as spatial units to analyze data (NUTS-2), excluding Ceuta and Melilla. These decisions are made for two reasons: first, to ensure sufficient data from the Spanish Statistical Office; and second, to avoid finding artificially high LC across many industries if small regions with low industrial representations are used (Porter, 2003).

The method follows multiple steps: to build the datasets which are arranged as similarity matrices (step one); to build and assess the groups of clusters (steps second to fourth); and to choose the highest quality group of clusters and project it over Spanish territory (steps five and six).

A total of 47 out of 88 2-digits codes for CNAE-2009 are analyzed[4]. The research uses multiple open databases from the Spanish Statistical Office, the Spanish Patent and Trademark Office, and the European Commission[5]. The baseline of the analysis is

[4] Information for 21 codes was not available by the Spanish Statistical Office; another 31 codes were grouped into 11 provisional codes to homologize the CNAE-2009 with the industrial classification of the input-output matrix. Due to statistical confidentiality, there is incomplete information for specific industries in particular regions; this data was disregarded.

[5] Data were retrieved from https://www.ine.es for economy, labor market and ICT; http://consultas2.oepm.es/ipstat/faces/IpsBusqueda.xhtml for industrial property; and https://ec.europa.eu/regional_policy/es/information/maps/regional_competitiveness/ for competitiveness.

2019 to avoid the economic shock of COVID19 pandemic. However, for data not available in 2019 the most recent information is used instead.

The first group of data used for cluster analysis includes:

- Statistical structure for business – commerce, industry, and services (year 2019, CNAE-2009 2-digits, NUTS-2).
- Annual national accounting – input-output matrix (year 2016 – rev. 2019).
- Annual national accounting – origin-destination matrices (years 2010 to 2018).
- The labor force survey (year 2011, CNO-2011 2-digits[6], CNAE-2009 2-digits).

The second group of data is used to explore the correlation between CCD and macroeconomic variables, and includes:

- For economics:
    - The regional accounting for the real GDP per capita (year 2019).
- For population and employment:
    - The labor force survey for regional active population and for regional unemployment rate (average for all four quarters of 2019).
    - The wage structure survey for total income per worker (year 2019).
    - The educational attainment survey for adults with professional education or more (year 2016).
- For innovation:
    - The regional patent application per million inhabitants as innovative activity (average 2018-2019).
- For competitiveness:
    - The Regional Competitiveness Index (RCI) for sub-index *basic* (year 2019).
- For ICT and Industry 4.0:
    - The regional survey on ICT usage and e-commence in enterprises.
    - eCommerce in enterprises with more than ten employees (years 2017, 2019, 2020 and 2021, depending on the specific item since different data is collected each year).

[6] CNO stands for the National Classification of Occupations, and its most recent edition was published in 2011. The research used the 2-digit classification of occupations.

II.3.1 Step one: Building the similarity matrices

Similarity matrices (M_{ij}) provide information about the relatedness between pairs of industries *i* and *j*. To build a unidimensional matrix, it is required to transform one or more indicators into a single similarity measure; multidimensional matrices are built combining similarity measures from unidimensional matrices.

The indicators and measures used in this research are chosen to capture as many cross-industry linkages as possible (e.g., knowledge, skills, supply, or demand links). **Table II.1** shows the specifications of each matrix built.

II.3.2 Step two: Identifying traded industries and adjusting similarity matrices

While local industries serve local markets, traded industries are those that produce goods and services that are either exported or sold across regions. As Delgado et al. (2016) points out, distribution of local industries is related to regional population whereas distribution of traded industries is a more complex phenomenon.

Since this research is focused on traded industries (both natural-resource-based and not), it is necessary to identify them and remove local ones from the similarity matrices. Five methodologies are tested to assess the 47 CNAE 2-digit industries and find traded industries:

- The three-criteria methodology of Delgado, Bryden, et al. (2014), based on cutoffs set by literature, using location quotient measures computed with 2019 data.
- The three-criteria methodology of Porter (2003), based on cutoffs set literature, using both location quotient measures and locational Gini Coefficient measures computed with 2019 data[7].

[7] The first and second methodology were adjusted for the Spanish case (CNAE 2-digit & NUTS-2). The set of traded industries obtained with the methodology of Delgado, Bryden, et al. (2014) was used as the comparable base for the other four.

Table II.1. Similarity matrices used to generate sets of Cluster Category Definitions.

Similarity matrix	Indicators used	Measure computed	Theoretical foundation
Unidimensional matrices			
Co-location pattern for employment (LC_Emp)	Employment size of industry *i* and *j* in region *r*	Locational Correlation of employment [-1, 1]	Delgado et al.(2016) Diodato et al.(2018) Porter(2003)
Co-location pattern for establishments (LC_Est)	No. of establishments of industry *i* and *j* in region *r*	Locational Correlation of establishments [-1, 1]	Delgado et al.(2016) Diodato et al.(2018) Porter(2003)
Geographic concentration of employment (COI)	Employment size of industry *i* and *j* in region *r*	Co-agglomeration Index	Delgado et al.(2016) Diodato et al.(2018) Ellison et al.(2010)
Input-Output Links (IO)	Inputs of industry *i* coming from *j*, and outputs of industry *i* going to *j*	Average share of inputs of industry *i* coming from *j*, outputs of industry *i* going to *j,* and vice versa [0, 1]	Delgado et al.(2016) Ellison et al.(2010)
Labor Occupation Links (Occ)	Employment size of industry *i* and *j* related to occupation *k*	Occupational correlation [-1, 1]	Delgado et al.(2016) Glaeser & Kerr(2009)
Multidimensional matrices			
Co-location pattern (LC)	Locational correlation of employment, and locational correlation of establishments	Average of LC_Emp and LC_Est	Delgado et al.(2016)
Co-location pattern and Geographic concentration of employment (LC_COI)	Locational correlation of employment, locational correlation of establishments, and Co-agglomeration Index	Average of (standardized) LC_Emp, LC_Est, and COI	Author
Geographic concentration of employment, Input-Output Links, and Labor Occupation Links (COI_IO_Occ)	Co-agglomeration Index, average share of input-output links, and occupational correlation	Average of (standardized) COI, IO, and Occ	Delgado et al.(2016)
All unidimensional measures (ALL)	All unidimensional measures	Average of (standardized) LC_Emp, LC_Est, COI, IO, and Occ	Delgado et al.(2016)

SOURCE: Author's elaboration.

- The export to gross value-added ratio (Mano & Castillo, 2015), based on a single cutoff set by literature, using 2010-to-2018 ratios average to reduce overrepresentation of external shocks[8].

---

[8] Original data showed important variation in ratios from one year to another, therefore average is used.

- The locational Gini Coefficient (Carlino & Kerr, 2015), based on a single cutoff set by the author[9].
- The multi-criterion based on export to gross value-added ratio and the locational Gini Coefficient[10].

II.3.3 Step three: Setting parameters and running clustering functions

In this step, the following parameters (ρ) are used: clustering functions are run over raw data as each similarity matrix is built with a common internal scale; starting values for clustering functions are chosen at random; and multiple number of clusters (*numc*) are set, going from seven to 13[11], when functions are run.

Two clustering functions (*F*) for continuous data are used in this research (Delgado et al., 2016; Everitt et al., 2011; Grimmer & King, 2011): the hierarchical function of Ward's minimum variance (squared Euclidean distance) (*H*), and the centroid based function (kmean) (*K*).

Before running clustering functions over the similarity matrices, the algorithm is tested and validated following the method of Delgado et al. (2016), using an artificial similarity matrix based on the first digit of the CNAE-2009 2-digits code for the traded industries.

---

[9] The cutoff was set at 0.01, as multiple cutoffs were tested in incremental ranges of 0.01 looking for the set of traded industries with the maximum overlap with the set defined by the three-criteria methodology of Delgado, Bryden, et al. (2014). The geometric mean was used to measure the industry overlap in each direction.

[10] For this multi-criterion methodology, the set of traded industries included all those industries classified as traded by both the gross value-added ratio methodology and the locational Gini Coefficient methodology.

[11] As the analysis is based on CNAE-2009 2-digits codes with 27 traded industries determined in step two, working with numbers of clusters greater than 13 would have increased the chances for the appearance of multiple one-industry groups; the minimum number of clusters is set following to Delgado et al. (2016) who set the minimum number of clusters as the half of the maximum number chosen.

Let C be a single group of clusters given F and ρ, then:

$$C = F\left(M_{ij}, \rho\right) \quad \text{(II.1)}$$

The clustering algorithm is run over all nine similarity matrices, using all possible combinations of parameters.

II.3.4 Step four: Assessing quality of the groups of clusters through Validation Scores

Validation Scores (*VS*) are computed for each group of clusters (*C*), following Delgado et al. (2016) methodology; *VS* are the average of two partial validations scores*: VS-Cluster* and *VS-Industry*. All five unidimensional matrices *(M)* are used to build the validation scores, since the capture of different industry interdependencies is assumed for each of them; a single similarity measure between *i* and *j* represents a relatedness measure.

On the one side, *VS-Cluster* measures whether individual clusters (*c*) in *C* are meaningfully different from each other, and it is made up of two averaged sub-scores. These sub-scores depart from the Within Cluster Relatedness for *c* (WCR_c) measure (as the average relatedness between pairs of industries within a *c*), and the Between Cluster Relatedness for *c* (BCR_c) measure (as the average relatedness between industries in *c* and those in another cluster). *VS-Cluster*'s sub-scores are expressed as follows:

$$VS - Cluster\ Average_C^M = \frac{\sum_c I\left[WCR_c\left(M_{ij}\right) > AvgBCR_c\left(M_{ij}\right)\right]}{N_c} * 100 \quad \text{(II.2)}$$

$$VS - Cluster\ Percentile95_C^M = \frac{\sum_c I\left[WCR_c\left(M_{ij}\right) > Pctile95BCR_c\left(M_{ij}\right)\right]}{N_c} * 100 \quad \text{(II.3)}$$

where N_c is the number of individual clusters in *C,* and *I* is an indicator function equal to 1 for a given cluster *c* which met the condition expressed inside brackets.

On the other hand, *VS-Industry* measures whether individual industries (*i*) in the group of clusters are more related to the industries within its own cluster than to industries outside its cluster, and it is also made up of two averaged sub-scores. These sub-scores depart from the Within Cluster Relatedness for *i* in *c* (WCR_{ic}) measure (as the average relatedness between *i* and other industries within a *c*), and the Between Cluster

Relatedness for *i* in *c* (BCR_{ic}) measure (as the average relatedness between *i* and those in another cluster). *VS-Cluster*'s sub-scores are expressed as follows:

$$VS - Industry\ Average_C^M = \frac{\sum_i I[WCR_{ic}(M_{ij}) > AvgB\quad {}_i(M_{ij})]}{N_i} * 100 \qquad \text{(II.4)}$$

$$VS - Industry\ Percentile95_C^M = \frac{\sum_i I[WCR_{ic}(M_{ij}) > Pctile95BCR_i(M_{ij})]}{N_i} * 100 \qquad \text{(II.5)}$$

where N_i is the number of individual industries in *C*.

II.3.5 Step five: Choosing the groups of clusters with higher quality and setting Cluster Category Definitions

The *C* with the highest position in the *VS* rank (let's call it *C**) is elected to create CCD at the regional level (NUTS-2). Also, for comparison purposes a different *C* is selected based on specific criteria (let's call it *C***): it must hold the second-highest position in the *VS* rank and must be built with a different similarity matrix than *C**.

Also, an Overlap Score for *C** is computed following Delgado et al. (2016). First, for each individual cluster (*c*) in *C** an equivalent individual cluster (*b*) from *C*** is assigned. Second, the overlap between pairs of clusters is computed using the geometric mean:

$$overlap_{cb} = \frac{Shared\ Industries_{cb}}{\sqrt{Industries_c * Industries_b}} * 100 \qquad \text{(II.6)}$$

Third and last, the Overlap Score averages all overlaps for each *c* in *C** (a higher score means more consistent and well-defined clusters):

$$Overlap\ Score_C = \frac{\sum_{c \in C} overlap_{cb}}{N_c} \qquad \text{(II.7)}$$

Names are defined arbitrarily for each individual cluster looking at the industries that configured each cluster and aiming to suggest names easy to assimilate for researchers, policymakers, and development practitioners. These names are Cluster Category Definitions (CCD).

II.3.6 Step six: Finding the territorial presence of clusters over Spain

Since each group of clusters is configured by a set of individual clusters, this step is about finding the presence of each individual cluster over the analyzed regions (spatial units of study).

The US's Cluster Mapping Project recognizes three types of clusters presence over territory based on employment share and location quotients (Delgado et al., 2016; Ketels, 2017): clusters by top employment specialization (TESp), clusters by top employment share (TESh), and clusters by top employment specialization & share (TESS). The results of the analysis of territorial presence are presented in the Results and Discussion section.

II.3.7 The correlation analysis

Finally, after exploring the territorial presence of *c*, correlation analysis is made among cluster presence and multiple variables.

The presence of each individual cluster over regions is arranged as a discrete dichotomous variable (1-0, the cluster is present or not). Also, the total count of *c* (by TESp, TESh, and TESS) in each territory is considered.

Multiple variables are selected to run the Pearson's correlation analysis against the presence of clusters. Variables election is based on the work of Delgado et al. (2014) and Slaper et al. (2018): GDP per capita, earning per worker, natural resources dependency[12], population, percentage of the population with a university degree or more, unemployment rate, patent application to million inhabitants ratio, and RCI basic sub-index. The calculation and introduction of ICT and Industry 4.0 indexes is a novelty

[12] The natural resources dependency is a ratio that measures the proportion of employees working on traded industries dependent on natural resources in function of the total number of employees working on traded industries.

introduced in this research. To build these indexes, multiple measures are considered following literature about ICT and Industry 4.0 impact on business (Almeida et al., 2020; Atik & Ünlü, 2019; Maresova et al., 2018).

On the one hand, the ICT index groups ten different measures related to the use of computers, Internet connection, webpage, social networks, Enterprise Resource Planning, Customer Relationship Management, electronic communications, eGovernment, eSignature, and cybersecurity. On the other hand, the Industry 4.0 index groups six different measures related to the use of: industrial robots, big data, cloud computing, 3D printing, Internet of things, and artificial intelligence. The grouping methodology for both indexes is based on the World Economic Forum (WEF) (Atik & Ünlü, 2019).

It is also relevant to point out that for competitiveness the *RCI basic sub-index* is chosen over *RCI index* because the latter is configured also by another two sub-indexes (efficiency and innovation) which are highly correlated with other variables chosen for this research, such as population, educational attainment, innovation activity and ICT adoption. Full correlations are presented in the Results and Discussion section.

II.4 Results

Descriptive statistics and correlations for similarity matrices are obtained (**Table II.2** and **Table II.3**). The correlation among all the similarity matrices shows to be significant at 1% level, except for Occ with LC_Emp, LC_Est, and LC.

By using five methodologies to identify traded industries, five sets are configured (**Table II.4**). The set of traded industries chosen for further analysis is the one that meets two key attributes: the exclusion of industries that conceptually are classified as local (e.g., real state, retail, local transportation, and sewerage), and the improving of the correlation between similarity matrices of traded industries when compared with correlation between similarity matrices for all industries.

Table II.2. Descriptive Statistics for Similarity Matrices; 47 industries (CNAE-2009 2-digits codes) and N=2,162

Similarity Matrices M_{ij}	Mean	Median	Std. Dev.	Min.	Max
LC_Emp	0.672	0.767	0.300	-0.540	1.000
LC_Est	0.743	0.822	0.265	-0.914	0.998
COI	-0.001	0.000	0.021	-0.089	0.136
IO	0.014	0.007	0.023	0.000	0.343
Occ	0.130	0.050	0.220	-0.128	0.973
LC	0.708	0.782	0.267	-0.658	0.999
LC_COI	-0.029	0.150	0.780	-3.962	2.613
COI_IO_Occ	-0.074	-0.169	0.530	-1.403	2.847
ALL	-0.053	0.018	0.548	-2.186	1.876

SOURCE: Author’s elaboration.

NOTE: *N* stands for number of observations, where an observation is any pair of industries (*ij*, *i≠j*). All unidimensional matrices are based on 2019 data except for IO and Occ, which is based on 2016 and 2011 data, respectively.

Table II.3. Correlation between Similarity Matrices; 47 industries (CNAE-2009 2-digits codes) and N=2,162

	LC_Emp	LC_Est	COI	IO	Occ	LC	LC_COI	COI_IO_Occ	ALL
LC_Emp	1.000								
LC_Est	0.790	1.000							
COI	0.347	0.258	1.000						
IO	0.146	0.127	0.167	1.000					
Occ	<u>0.025</u>	<u>-0.010</u>	0.231	0.207	1.000				
LC	0.953	0.939	0.323	0.145	<u>0.009</u>	1.000			
LC_COI	0.898	0.864	0.643	0.181	0.095	0.932	1.000		
COI_IO_Occ	0.256	0.181	0.745	0.527	0.747	0.233	0.473	1.000	
ALL	0.802	0.759	0.654	0.406	0.440	0.826	0.918	0.740	1.000

SOURCE: Author’s elaboration.

NOTES: All coefficients are significant at 1% level, except those underlined.

Table II.4. List of 47 CNAE-2009 2-digit codes analyzed for classification using different methodologies to identify traded industries.

CODE	Description	Adj. Delgado, Bryden, et al. (2014)	Adj. Porter (2003)	Export to gross value-added ratio	Locational Gini Coefficient	Multi-criterion
IN05	Groups: B5 - Mining of coal and lignite; B6 - Extraction of crude petroleum and natural gas; B7 - Mining of metal ores; B8 - Other mining and quarrying; B9 - Mining support service activities	*	*	*	*	*
IN10	Groups: C10 - Manufacture of food products; C12 - Manufacture of tobacco products	*	*	*	*	*
IN13	Groups: C13 - Manufacture of textiles; C14 - Manufacture of wearing apparel; C15 - Manufacture of leather and related products	*	*	*	*	*

CODE	Description	Adj. Delgado, Bryden, et al. (2014)	Adj. Porter (2003)	Export to gross value-added ratio	Locational Gini Coefficient	Multi-criterion
IN16	C16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	*	*	*	*	*
IN17	C17 - Manufacture of paper and paper products	*	*	*	*	*
IN18	C18 - Printing and reproduction of recorded media	*	*		*	
IN19	C19 - Manufacture of coke and refined petroleum products	*	*	*	*	*
IN20	C20 - Manufacture of chemicals and chemical products	*	*	*	*	*
IN21	C21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	*	*	*	*	*
IN22	C22 - Manufacture of rubber and plastic products		*	*	*	*
IN23	C23 - Manufacture of other non-metallic mineral products	*	*	*	*	*
IN24	C24 - Manufacture of basic metals	*	*	*	*	*
IN25	C25 - Manufacture of fabricated metal products, except machinery and equipment		*	*	*	*
IN26	C26 - Manufacture of computer, electronic and optical products	*	*	*	*	*
IN27	C27 - Manufacture of electrical equipment	*	*	*	*	*
IN28	C28 - Manufacture of machinery and equipment n.e.c.	*	*	*	*	*
IN29	C29 - Manufacture of motor vehicles, trailers, and semi-trailers	*	*	*	*	*
IN30	C30 - Manufacture of other transport equipment	*	*	*	*	*
IN31	Groups: C31 - Manufacture of furniture; C32 - Other manufacturing		*	*	*	*
IN33	C33 - Repair and installation of machinery and equipment		*			
IN35	D35 - Electricity, gas, steam, and air conditioning supply	*	*			
IN36	E36 - Water collection, treatment, and supply	*	*		*	
IN37	Groups: E37 - Sewerage; E38 - Waste collection, treatment, and disposal activities; materials recovery; E39 - Remediation activities and other waste management services		*	*		
IN45	G45 - Wholesale and retail trade and repair of motor vehicles and motorcycles			*		
IN46	G46 - Wholesale trade, except of motor vehicles and motorcycles		*	*		
IN47	G47 - Retail trade, except of motor vehicles and motorcycles	*	*	*		
IN49	H49 - Land transport and transport via pipelines			*		
IN50	H50 - Water transport	*	*	*	*	*
IN51	H51 - Air transport	*	*	*	*	*
IN52	H52 - Warehousing and support activities for transportation		*	*		
IN53	H53 - Postal and courier activities	*	*			
IN55	Groups: I55 - Accommodation; I56 - Food and beverage service activities		*			
IN58	J58 - Publishing activities	*	*	*	*	*
IN59	Groups: J59 - Motion picture, video and television programme production, sound recording and music publishing activities; J60 - Programming and broadcasting activities	*	*	*	*	*
IN61	J61 - Telecommunications	*	*	*	*	*
IN62	Groups: J62 - Computer programming, consultancy, and related activities; J63 - Information service activities	*	*	*	*	*
IN68	L68 - Real estate activities	*	*			
IN69	Groups: M69 - Legal and accounting activities; M70 - Activities of head offices; management consultancy activities	*	*	*		
IN71	M71 - Architectural and engineering activities; technical testing and analysis	*		*		
IN72	M72 - Scientific research and development	*	*	*	*	*
IN73	M73 - Advertising and market research	*	*	*	*	*
IN74	Groups: M74 - Other professional, scientific, and technical activities; M75 - Veterinary activities	*				
IN77	N77 - Rental and leasing activities	*	*			

CODE	Description	Adj. Delgado, Bryden, et al. (2014)	Adj. Porter (2003)	Export to gross value-added ratio	Locational Gini Coefficient	Multi-criterion
IN78	N78 - Employment activities		*			
IN79	N79 - Travel agency, tour operator and other reservation service and related activities	*	*	*	*	*
IN80	Groups: N80 - Security and investigation activities; N81 - Services to buildings and landscape activities; N82 - Office administrative, office support and other business support activities	*	*	*		
IN95	S95 - Repair of computers and personal and household goods	*	*			
	Number of Traded Industries	**36**	**43**	**36**	**29**	**27**
	Traded Industries to Total Industries ratio	**76.6%**	**91.5%**	**76.6%**	**61.7%**	**57.4%**

SOURCE: Author's elaboration.

NOTES: Industries qualified as traded show an (*) depending on methodology.

The set of traded industries configured with the multi-criterion methodology meets better the defined requirements; 27 out of 47 industries are categorized as traded. The Traded Industries to Total Industries ratio for all configured sets of traded industries is consistent with literature (Delgado, Bryden, et al., 2014).

Adjusted similarity matrices are built using only traded industries (descriptive statistics and correlations for similarity matrices are shown at **Table II.5** and **Table II.6**). The correlation between similarity matrices is improved as expected.

Table II.5. Descriptive Statistics for Similarity Matrices; 27 traded industries (CNAE-2009 2-digits codes) and N=702

Similarity Matrices M_{ij}	Mean	Median	Std. Dev.	Min.	Max
LC_Emp	0.538	0.603	0.348	-0.540	1.000
LC_Est	0.661	0.757	0.326	-0.914	0.998
COI	-0.002	-0.003	0.034	-0.089	0.136
IO	0.011	0.003	0.026	0.000	0.343
Occ	0.235	0.179	0.268	-0.118	0.941
LC	0.600	0.678	0.323	-0.658	0.999
LC_COI	-0.053	0.053	0.805	-2.951	1.934
COI_IO_Occ	-0.105	-0.176	0.551	-1.091	1.896
ALL	-0.081	-0.055	0.599	-1.709	1.493

SOURCE: Author's elaboration.

NOTE: *N* stands for number of observations, where an observation is any pair of industries (*ij*, $i \neq j$). Since *N* changed, also standardized values changed for multidimensional similarity matrices M_{ij} that use such values.

Table II.6. Correlation between Traded-Industries Similarity Matrices; 27 industries (CNAE-2009 2-digits codes) and N=702

	LC_Emp	LC_Est	COI	IO	Occ	LC	LC_COI	COI_IO_Occ	ALL
LC_Emp	1.000								
LC_Est	0.836	1.000							
COI	0.474	0.330	1.000						
IO	0.181	0.157	0.197	1.000					
Occ	0.283	0.230	0.348	0.337	1.000				
LC	0.961	0.955	0.422	0.176	0.269	1.000			
LC_COI	0.929	0.877	0.699	0.211	0.339	0.943	1.000		
COI_IO_Occ	0.454	0.342	0.777	0.547	0.815	0.418	0.614	1.000	
ALL	0.859	0.798	0.695	0.414	0.620	0.866	0.938	0.816	1.000

SOURCE: Author's elaboration.

NOTES: All coefficients are significant at 1% level.

The cluster algorithm is applied over the nine similarity matrices of traded industries, and 126 groups of clusters (*C*) are obtained (the number is equal to all combinations among *F, ρ*, and M_{ij}). The quality of each group of clusters is assessed through the *VS* (**Table II.7**).

Table II.7. Validation scores (VS), partial validation scores (VS-Cluster and VS-Industry) and sub-scores (VS-Cluster Avg, VS-Cluster Pctile95, VS-Industry Avg, VS-Industry) for all groups of clusters (C).

Rank (*VS*)	*VS*	Method	Similarity Matrix M_{ij}	Numc	C code	Rank (VS-Cluster)	VS-Cluster	VS-Cluster Avg	VS-Cluster Pctile95	Rank (VS-Industry)	VS-Industry	VS-Industry Avg	VS-Industry Pctile95
1	72.9	H	ALL	7	H-ALL-7	4	72.9	80.0	65.7	1	73.0	90.4	55.6
2	72.6	K	COI_IO_Occ	8	K-COI_IO_Occ-8	1	76.3	85.0	67.5	3	68.9	88.9	48.9
3	71.6	H	COI_IO_Occ	7	H-COI_IO_Occ-7	2	74.3	88.6	60.0	3	68.9	88.9	48.9
4	70.3	K	COI_IO_Occ	7	K-COI_IO_Occ-7	3	72.9	74.3	71.4	5	67.8	83.7	51.9
5	66.6	K	Occ	7	K-Occ-7	4	72.9	94.3	51.4	17	60.4	91.1	29.6
6	64.8	K	COI_IO_Occ	9	K-COI_IO_Occ-9	7	63.3	75.6	51.1	7	66.3	87.4	45.2
7	63.3	K	ALL	9	K-ALL-9	9	58.9	64.4	53.3	4	67.8	84.4	51.1
8	62.4	H	COI	9	H-COI-9	8	60.0	71.1	48.9	10	64.8	85.2	44.4
9	62.3	H	Occ	7	H-Occ-7	5	67.1	88.6	45.7	23	57.4	87.4	27.4
10	62.1	K	ALL	7	K-ALL-7	13	57.1	65.7	48.6	6	67.0	86.7	47.4
11	61.9	H	ALL	8	H-ALL-8	16	53.8	62.5	45.0	2	70.0	85.2	54.8
12	61.2	H	COI	8	H-COI-8	10	58.8	70.0	47.5	12	63.7	86.7	40.7
13	60.9	K	COI_IO_Occ	11	K-COI_IO_Occ-11	11	58.2	67.3	49.1	12	63.7	82.2	45.2
14	60.9	K	ALL	10	K-ALL-10	14	57.0	66.0	48.0	10	64.8	83.7	45.9
15	60.5	H	COI_IO_Occ	8	H-COI_IO_Occ-8	15	55.0	67.5	42.5	8	65.9	83.7	48.1
16	60.4	H	Occ	8	H-Occ-8	6	63.8	82.5	45.0	24	57.0	86.7	27.4
17	59.8	K	ALL	11	K-ALL-11	11	58.2	67.3	49.1	15	61.5	82.2	40.7
18	59.5	K	COI_IO_Occ	10	K-COI_IO_Occ-10	15	55.0	66.0	44.0	11	64.1	83.7	44.4
19	59.4	H	COI_IO_Occ	9	H-COI_IO_Occ-9	17	53.3	62.2	44.4	9	65.6	83.0	48.1
20	58.4	K	ALL	8	K-ALL-8	21	51.3	60.0	42.5	9	65.6	84.4	46.7
21	58.0	H	ALL	9	H-ALL-9	24	48.9	55.6	42.2	6	67.0	83.0	51.1
22	57.3	K	Occ	8	K-Occ-8	12	57.5	80.0	35.0	24	57.0	87.4	26.7
23	56.9	K	ALL	12	K-ALL-12	17	53.3	61.7	45.0	17	60.4	79.3	41.5
24	56.7	H	ALL	10	H-ALL-10	23	50.0	60.0	40.0	13	63.3	83.7	43.0

Rank (*VS*)	*VS*	Method	Similarity Matrix M_{ij}	Numc	*C* code	Rank (VS-Cluster)	VS-Cluster	VS-Cluster Avg	VS-Cluster Pctile95	Rank (VS-Industry)	VS-Industry	VS-Industry Avg	VS-Industry Pctile95
25	55.3	H	COI	7	H-COI-7	19	52.9	65.7	40.0	22	57.8	85.9	29.6
26	54.8	H	Occ	10	H-Occ-10	18	53.0	72.0	34.0	25	56.7	82.2	31.1
27	54.8	K	ALL	13	K-ALL-13	23	50.0	60.0	40.0	19	59.6	77.8	41.5
28	54.6	H	COI_IO_Occ	10	H-COI_IO_Occ-10	28	47.0	56.0	38.0	14	62.2	79.3	45.2
29	54.2	H	LC_COI	8	H-LC_COI-8	25	48.8	60.0	37.5	19	59.6	83.0	36.3
30	53.6	K	LC_Emp	7	K-LC_Emp-7	27	47.1	57.1	37.1	18	60.0	80.7	39.3
31	53.3	H	Occ	9	H-Occ-9	22	51.1	71.1	31.1	29	55.6	83.7	27.4
32	53.3	H	LC_COI	7	H-LC_COI-7	32	44.3	54.3	34.3	14	62.2	84.4	40.0
33	52.0	K	COI_IO_Occ	12	K-COI_IO_Occ-12	29	46.7	55.0	38.3	23	57.4	75.6	39.3
34	51.9	K	Occ	9	K-Occ-9	20	52.2	68.9	35.6	40	51.5	78.5	24.4
35	51.7	H	Occ	11	H-Occ-11	26	48.2	63.6	32.7	30	55.2	78.5	31.9
36	50.7	K	LC_COI	7	K-LC_COI-7	36	42.9	54.3	31.4	20	58.5	81.5	35.6
37	50.6	H	COI	10	H-COI-10	35	43.0	54.0	32.0	21	58.1	78.5	37.8
38	50.5	H	COI_IO_Occ	11	H-COI_IO_Occ-11	41	40.9	49.1	32.7	18	60.0	75.6	44.4
39	50.4	H	LC_Emp	7	H-LC_Emp-7	43	40.0	54.3	25.7	16	60.7	80.7	40.7
40	50.0	H	LC	10	H-LC-10	33	44.0	56.0	32.0	27	55.9	78.5	33.3
41	49.9	K	LC_COI	10	K-LC_COI-10	30	46.0	56.0	36.0	33	53.7	75.6	31.9
42	49.3	K	LC	7	K-LC-7	31	45.7	54.3	37.1	36	53.0	81.5	24.4
43	49.3	H	ALL	11	H-ALL-11	43	40.0	45.5	34.5	20	58.5	76.3	40.7
44	49.3	H	LC_COI	9	H-LC_COI-9	38	42.2	53.3	31.1	26	56.3	79.3	33.3
45	48.6	K	COI_IO_Occ	13	K-COI_IO_Occ-13	37	42.3	50.8	33.8	31	54.8	73.3	36.3
46	48.3	H	LC	9	H-LC-9	39	41.1	53.3	28.9	29	55.6	78.5	32.6
47	48.1	H	LC_Emp	11	H-LC_Emp-11	34	43.6	56.4	30.9	37	52.6	75.6	29.6
48	48.0	H	ALL	13	H-ALL-13	43	40.0	46.2	33.8	27	55.9	72.6	39.3
49	47.3	H	LC_Est	10	H-LC_Est-10	46	39.0	48.0	30.0	28	55.6	77.0	34.1
50	47.3	H	LC	12	H-LC-12	42	40.8	51.7	30.0	33	53.7	74.8	32.6
51	47.3	H	COI_IO_Occ	12	H-COI_IO_Occ-12	51	37.5	45.0	30.0	24	57.0	71.9	42.2
52	47.2	H	LC_Emp	10	H-LC_Emp-10	40	41.0	54.0	28.0	34	53.3	75.6	31.1
53	46.9	H	LC_COI	10	H-LC_COI-10	46	39.0	48.0	30.0	31	54.8	77.0	32.6
54	46.9	K	LC_COI	8	K-LC_COI-8	51	37.5	50.0	25.0	26	56.3	84.4	28.1
55	46.7	H	LC_COI	13	H-LC_COI-13	44	39.2	52.3	26.2	32	54.1	74.1	34.1
56	46.5	H	COI	11	H-COI-11	48	38.2	49.1	27.3	31	54.8	74.8	34.8
57	46.5	H	LC_COI	11	H-LC_COI-11	48	38.2	52.7	23.6	31	54.8	77.8	31.9
58	46.1	H	ALL	12	H-ALL-12	53	36.7	41.7	31.7	29	55.6	72.6	38.5
59	45.9	K	LC_Emp	8	K-LC_Emp-8	43	40.0	52.5	27.5	39	51.9	77.8	25.9
60	45.7	H	COI_IO_Occ	13	H-COI_IO_Occ-13	47	38.5	49.2	27.7	36	53.0	72.6	33.3
61	45.6	H	LC_Est	9	H-LC_Est-9	58	35.6	44.4	26.7	29	55.6	79.3	31.9
62	45.4	K	COI	10	K-COI-10	46	39.0	52.0	26.0	39	51.9	77.0	26.7
63	45.3	H	LC_Est	8	H-LC_Est-8	59	35.0	47.5	22.5	29	55.6	80.7	30.4
64	45.2	K	LC_Emp	11	K-LC_Emp-11	48	38.2	50.9	25.5	38	52.2	74.8	29.6
65	45.2	H	LC_Emp	9	H-LC_Emp-9	49	37.8	51.1	24.4	37	52.6	75.6	29.6
66	45.0	H	LC	11	H-LC-11	54	36.4	47.3	25.5	33	53.7	74.8	32.6
67	45.0	H	LC_Emp	13	H-LC_Emp-13	50	37.7	47.7	27.7	38	52.2	70.4	34.1
68	45.0	H	Occ	12	H-Occ-12	45	39.2	48.3	30.0	41	50.7	71.1	30.4
69	44.9	H	LC	8	H-LC-8	59	35.0	47.5	22.5	31	54.8	79.3	30.4
70	44.8	K	LC_Est	8	K-LC_Est-8	55	36.3	47.5	25.0	34	53.3	78.5	28.1
71	44.7	H	LC	7	H-LC-7	60	34.3	42.9	25.7	30	55.2	80.7	29.6
72	44.7	K	LC_Est	10	K-LC_Est-10	56	36.0	48.0	24.0	34	53.3	77.8	28.9
73	44.5	H	LC_Emp	8	H-LC_Emp-8	62	33.8	47.5	20.0	30	55.2	77.8	32.6
74	44.5	K	LC_COI	11	K-LC_COI-11	48	38.2	45.5	30.9	41	50.7	71.9	29.6
75	43.8	H	LC_COI	12	H-LC_COI-12	57	35.8	48.3	23.3	39	51.9	74.1	29.6
76	43.7	K	LC_COI	9	K-LC_COI-9	64	33.3	44.4	22.2	32	54.1	80.0	28.1
77	43.5	H	COI	12	H-COI-12	53	36.7	50.0	23.3	42	50.4	71.9	28.9
78	43.5	K	Occ	10	K-Occ-10	52	37.0	50.0	24.0	43	50.0	74.1	25.9
79	43.3	K	LC_Est	9	K-LC_Est-9	64	33.3	44.4	22.2	34	53.3	77.0	29.6

Rank (*VS*)	*VS*	Method	Similarity Matrix M_{ij}	Numc	*C* code	Rank (VS-Cluster)	VS-Cluster	VS-Cluster Avg	VS-Cluster Pctile95	Rank (VS-Industry)	VS-Industry	VS-Industry Avg	VS-Industry Pctile95
80	43.2	K	COI	8	K-COI-8	59	35.0	47.5	22.5	40	51.5	78.5	24.4
81	43.1	H	LC_Est	13	H-LC_Est-13	50	37.7	49.2	26.2	47	48.5	71.9	25.2
82	43.1	H	LC_Est	12	H-LC_Est-12	57	35.8	46.7	25.0	42	50.4	71.9	28.9
83	43.0	K	LC_Est	7	K-LC_Est-7	78	28.6	40.0	17.1	23	57.4	81.5	33.3
84	43.0	H	LC_Est	7	H-LC_Est-7	78	28.6	40.0	17.1	23	57.4	81.5	33.3
85	42.9	H	LC_Est	11	H-LC_Est-11	63	33.6	43.6	23.6	38	52.2	73.3	31.1
86	42.8	K	LC_Est	12	K-LC_Est-12	53	36.7	50.0	23.3	46	48.9	74.8	23.0
87	42.7	K	LC	12	K-LC-12	66	32.5	41.7	23.3	35	53.0	72.6	33.3
88	42.7	K	LC_Emp	12	K-LC_Emp-12	57	35.8	45.0	26.7	44	49.6	70.4	28.9
89	42.7	H	LC_Emp	12	H-LC_Emp-12	57	35.8	45.0	26.7	44	49.6	70.4	28.9
90	42.2	K	LC_Emp	9	K-LC_Emp-9	68	32.2	40.0	24.4	38	52.2	74.8	29.6
91	41.4	H	COI	13	H-COI-13	61	33.8	46.2	21.5	46	48.9	68.1	29.6
92	41.2	K	LC	11	K-LC-11	74	30.9	41.8	20.0	40	51.5	73.3	29.6
93	41.2	K	LC_COI	13	K-LC_COI-13	65	33.1	44.6	21.5	45	49.3	70.4	28.1
94	40.9	K	Occ	11	K-Occ-11	63	33.6	43.6	23.6	48	48.1	69.6	26.7
95	40.8	H	Occ	13	H-Occ-13	61	33.8	44.6	23.1	49	47.8	67.4	28.1
96	40.5	K	LC_Est	11	K-LC_Est-11	70	31.8	45.5	18.2	45	49.3	76.3	22.2
97	40.4	H	LC	13	H-LC-13	67	32.3	40.0	24.6	47	48.5	67.4	29.6
98	40.1	K	LC_COI	12	K-LC_COI-12	71	31.7	38.3	25.0	47	48.5	68.1	28.9
99	40.0	K	COI	7	K-COI-7	72	31.4	48.6	14.3	47	48.5	78.5	18.5
100	39.8	K	LC	9	K-LC-9	75	30.0	40.0	20.0	44	49.6	75.6	23.7
101	39.1	K	LC_Emp	10	K-LC_Emp-10	69	32.0	40.0	24.0	51	46.3	70.4	22.2
102	38.8	K	LC	8	K-LC-8	83	25.0	35.0	15.0	37	52.6	78.5	26.7
103	38.1	K	LC	13	K-LC-13	76	29.2	35.4	23.1	50	47.0	65.2	28.9
104	37.8	K	LC	10	K-LC-10	80	27.0	38.0	16.0	47	48.5	74.1	23.0
105	37.6	K	LC_Est	13	K-LC_Est-13	76	29.2	38.5	20.0	52	45.9	68.1	23.7
106	37.4	K	IO	10	K-IO-10	73	31.0	46.0	16.0	56	43.7	72.6	14.8
107	37.2	K	Occ	12	K-Occ-12	77	29.2	40.0	18.3	54	45.2	65.9	24.4
108	36.5	K	COI	13	K-COI-13	75	30.0	43.1	16.9	58	43.0	67.4	18.5
109	36.0	K	COI	12	K-COI-12	79	28.3	40.0	16.7	56	43.7	69.6	17.8
110	35.7	K	Occ	13	K-Occ-13	81	26.9	38.5	15.4	55	44.4	63.7	25.2
111	35.6	K	COI	9	K-COI-9	82	25.6	35.6	15.6	53	45.6	72.6	18.5
112	34.9	K	IO	7	K-IO-7	84	24.3	37.1	11.4	53	45.6	72.6	18.5
113	34.1	K	IO	9	K-IO-9	82	25.6	40.0	11.1	59	42.6	70.4	14.8
114	32.6	K	COI	11	K-COI-11	86	21.8	32.7	10.9	57	43.3	69.6	17.0
115	30.8	K	LC_Emp	13	K-LC_Emp-13	88	20.8	26.2	15.4	60	40.7	60.0	21.5
116	29.1	K	IO	11	K-IO-11	86	21.8	32.7	10.9	61	36.3	61.5	11.1
117	27.1	H	IO	10	H-IO-10	85	23.0	28.0	18.0	64	31.1	49.6	12.6
118	26.0	H	IO	8	H-IO-8	90	18.8	25.0	12.5	62	33.3	50.4	16.3
119	25.7	K	IO	13	K-IO-13	89	19.2	29.2	9.2	63	32.2	51.9	12.6
120	25.1	H	IO	11	H-IO-11	87	20.9	25.5	16.4	65	29.3	45.2	13.3
121	23.5	K	IO	12	K-IO-12	93	15.8	25.0	6.7	64	31.1	52.6	9.6
122	22.4	H	IO	9	H-IO-9	91	17.8	24.4	11.1	66	27.0	44.4	9.6
123	21.5	H	IO	12	H-IO-12	92	17.5	20.0	15.0	68	25.6	40.0	11.1
124	17.6	H	IO	13	H-IO-13	95	13.1	13.8	12.3	69	22.2	34.8	9.6
125	17.3	K	IO	8	K-IO-8	94	15.0	20.0	10.0	70	19.6	34.8	4.4
126	16.7	H	IO	7	H-IO-7	96	7.1	11.4	2.9	67	26.3	44.4	8.1

SOURCE: Author’s elaboration.

NOTES: Rank shows the relative position of *C* compared with the others when considering the relevant score. For *VS-Cluster* and *VS-Industry*, some scores are the same, so the rank are too.

Following the quality measure, the elected group of clusters (C^*) corresponds to seven individual clusters (c) grouped with the Hierarchical-Ward's function, using the ALL multidimensional similarity matrix M_{ij}. It is relevant to highlighting the fact that the COI_IO_Occ multidimensional similarity matrix M_{ij} shows the highest *VS* among all (with an average of 58.5, above the 57.8 of the ALL multidimensional similarity matrix M_{ij}) (**Table II.8**), Therefore, it is convenient to choose the second-ranked in the *VS* rank as the group of clusters for comparison purposes (C^{**}); eight individual clusters grouped with the Kmean function, using the COI_IO_Occ multidimensional similarity matrix M_{ij}.

Table II.8. Descriptive Statistics for Validation scores (VS) of Similarity Matrices (N=14).

Similarity Matrices M_{ij}	Mean	Median	Std. Dev.	Min.	Max
LC_Emp	44.5	45.1	5.3	30.8	53.6
LC_Est	43.4	43.1	2.3	37.6	47.3
COI	45.0	43.4	9.4	32.6	62.4
IO	25.6	25.4	6.5	16.7	37.4
Occ	50.1	51.8	9.7	35.7	66.6
LC	43.5	43.7	4.2	37.8	50.0
LC_COI	47.0	46.8	4.2	40.1	54.2
COI_IO_Occ	58.5	59.5	9.1	45.7	72.6
ALL	57.8	58.2	6.9	46.1	72.9

SOURCE: Author's elaboration.

NOTE: *N* stands for number of observations, where an observation is any Validation score (VS) for a group of clusters obtained from a specific similarity matrix M_{ij}.

A number is assigned to each individual cluster in the chosen group of clusters. A comparison table is built between groups of clusters C^* and C^{**} (**Table II.9**). The Overlap Score between C^* and C^{**} is equivalent to 79.9%.

Table II.9. List of industries configuring each individual cluster (*c*) for groups of clusters C^* and C^{**}.

c number	C^*		C^{**}	
01	IN05	Groups: B5 - Mining of coal and lignite; B6 - Extraction of crude petroleum and natural gas; B7 - Mining of metal ores; B8 - Other mining and quarrying; B9 - Mining support service activities		
	IN10	Groups: C10 - Manufacture of food products; C12 - Manufacture of tobacco products	IN10	Groups: C10 - Manufacture of food products; C12 - Manufacture of tobacco products
	IN16	C16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	IN16	C16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
	IN23	C23 - Manufacture of other non-metallic mineral products		
	IN31	Groups: C31 - Manufacture of furniture; C32 - Other manufacturing	IN31	Groups: C31 - Manufacture of furniture; C32 - Other manufacturing

c number		C*		C**
02	IN13	Groups: C13 - Manufacture of textiles; C14 - Manufacture of wearing apparel; C15 - Manufacture of leather and related products	IN13	Groups: C13 - Manufacture of textiles; C14 - Manufacture of wearing apparel; C15 - Manufacture of leather and related products
	IN17	C17 - Manufacture of paper and paper products	IN17	C17 - Manufacture of paper and paper products
	IN20	C20 - Manufacture of chemicals and chemical products	IN20	C20 - Manufacture of chemicals and chemical products
	IN22	C22 - Manufacture of rubber and plastic products	IN22	C22 - Manufacture of rubber and plastic products
			IN23	C23 - Manufacture of other non-metallic mineral products
03	IN19	C19 - Manufacture of coke and refined petroleum products		
	IN30	C30 - Manufacture of other transport equipment	IN30	C30 - Manufacture of other transport equipment
04	IN21	C21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	IN21	C21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations
	IN26	C26 - Manufacture of computer, electronic and optical products	IN26	C26 - Manufacture of computer, electronic and optical products
	IN72	M72 - Scientific research and development	IN72	M72 - Scientific research and development
05	IN24	C24 - Manufacture of basic metals	IN24	C24 - Manufacture of basic metals
	IN25	C25 - Manufacture of fabricated metal products, except machinery and equipment	IN25	C25 - Manufacture of fabricated metal products, except machinery and equipment
	IN27	C27 - Manufacture of electrical equipment	IN27	C27 - Manufacture of electrical equipment
	IN28	C28 - Manufacture of machinery and equipment n.e.c.	IN28	C28 - Manufacture of machinery and equipment n.e.c.
	IN29	C29 - Manufacture of motor vehicles, trailers, and semi-trailers	IN29	C29 - Manufacture of motor vehicles, trailers, and semi-trailers
06	IN50	H50 - Water transport	IN50	H50 - Water transport
			IN51	H51 - Air transport
			IN79	N79 - Travel agency, tour operator and other reservation service and related activities
07	IN51	H51 - Air transport		
	IN58	J58 - Publishing activities	IN58	J58 - Publishing activities
	IN59	Groups: J59 - Motion picture, video and television programme production, sound recording and music publishing activities; J60 - Programming and broadcasting activities	IN59	Groups: J59 - Motion picture, video and television programme production, sound recording and music publishing activities; J60 - Programming and broadcasting activities
	IN61	J61 - Telecommunications;	IN61	J61 - Telecommunications
	IN62	Groups: J62 - Computer programming, consultancy, and related activities; J63 - Information service activities	IN62	Groups: J62 - Computer programming, consultancy, and related activities; J63 - Information service activities
	IN73	M73 - Advertising and market research	IN73	M73 - Advertising and market research
	IN79	N79 - Travel agency, tour operator and other reservation service and related activities		
08			IN05	Groups: B5 - Mining of coal and lignite; B6 - Extraction of crude petroleum and natural gas; B7 - Mining of metal ores; B8 - Other mining and quarrying; B9 - Mining support service activities
			IN19	C19 - Manufacture of coke and refined petroleum products

SOURCE: Author's elaboration.

NOTE: Clusters were numbered looking for maximum similarity between clusters of *C** and *C***. Table was arranged to clearly show similarities between clusters. Cluster number 08 exists only for *C***.

CCD are assigned to each *c* (**Table II.10**). There are only *two identical clusters* in both *C** and *C***: 04 *Biotechnological cluster* and 05 *Electromechanical and automotive cluster*. For the others, there are limited differences from one to two industries, highlighting the fact that cluster 08 *Extraction and mining cluster* is exclusive for *C*** and that specific cluster grouped all the natural-resource-dependent industries.

Table II.10. Cluster Category Definitions (CCD).

***c* number**	***C****	***C*****
01	Extraction, mining, and agro-industrial cluster	Agro-industrial cluster
02	Packaging, covers and lining – manufacturing cluster	Packaging, covers and lining - manufacturing cluster
03	Fuel and multipurpose vehicles – manufacturing cluster	Multipurpose vehicles – manufacturing cluster
04	Biotechnological cluster	Biotechnological cluster
05	Electromechanical and automotive cluster	Electromechanical and automotive cluster
06	Water-travel cluster	Transportation and tourism – services cluster
07	Tourism, ICT and creativity – services cluster	ICT and creativity – services cluster
08		Extraction and mining cluster

SOURCE: Author's elaboration.

The presence of clusters in regions is presented in **Table II.11** and **Table II.12** for *C** and *C***, respectively, distinguishing among clusters presence by top employment specialization (TESp), by top employment share (TESh), and by top employment specialization & share (TESS). As shown, Catalonia and Community of Madrid stand out reaching the maximum number of clusters by TESh. In contrast, the number of clusters by TESp is more evenly distributed among regions. Besides, the number of clusters by TESS is smaller since it combines both previous criteria.

Table II.11. Clusters presence by autonomous community (C* set).

C*	01 Extraction, mining, and agro-industrial cluster	02 Packaging, covers and lining – manufacturing cluster	03 Fuel and multipurpose vehicles – manufacturing cluster	04 Biotechnological cluster	05 Electromechanical and automotive cluster	06 Water-travel cluster	07 Tourism, ICT and creativity – services cluster	TESp	TESh	TESS
Andalusia			***				*	2	1	1
Aragon								0	0	0
Asturias, Principality of								0	0	0
Balearic Islands						*	*	2	0	0
Basque Country			*		***			2	1	1
Canary Islands						***	*	2	1	1
Cantabria								0	0	0
Castile and León	***							1	1	1
Castilla – La Mancha	*	*	*					3	0	0
Catalonia		***		***	**		**	2	4	2
Extremadura	*							1	0	0
Galicia	**							0	1	0
Madrid, Community of			**	***			***	2	3	2
Murcia, Region of								0	0	0
Navarre, Ch. Community of					*			1	0	0
Rioja, La		*						1	0	0
Valencian Community		***				**		1	2	1
Total								20	14	9

SOURCE: Author's elaboration.

NOTE: The table distinguish clusters presence by top employment specialization (TESp)(*), by top employment share (TESh)(**), and by top employment specialization & share (TESS)(***).

Table II.12. Clusters presence by autonomous community (C** set).

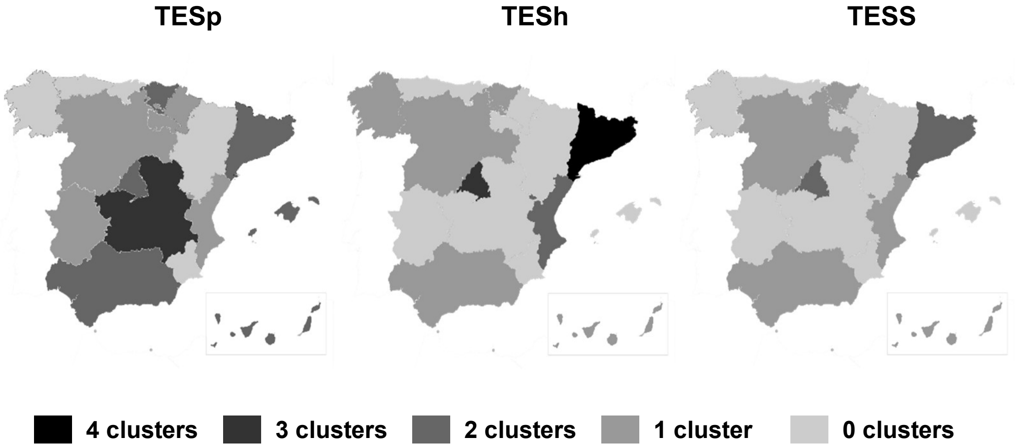
C**	01 Agro-industrial cluster	02 Packaging, covers and lining - manufacturing cluster	03 Multipurpose vehicles – manufacturing cluster	04 Biotechnological cluster	05 Electromechanical and automotive cluster	06 Transportation and tourism – services cluster	07 ICT and creativity – services cluster	08 Extraction and mining cluster	TESp	TESh	TESS
Andalusia			***			*	*	**	3	2	1
Aragon									0	0	0
Asturias, Principality of					*				1	0	0
Balearic Islands						*	*		2	0	0
Basque Country			*		***				2	1	1
Canary Islands						*	*		2	0	0
Cantabria					*				1	0	0
Castile and León	**								0	1	0
Castilla – La Mancha	*	*							2	0	0
Catalonia		***		***	**	**	**		2	5	2
Extremadura									0	0	0
Galicia	**		*						1	1	0
Madrid, Community of			**	***		***	***	**	3	5	3
Murcia, Region of	*								1	0	0
Navarre, Ch. Community of					*				1	0	0
Rioja, La		*							1	0	0
Valencian Community		***							1	1	1
Total									23	16	8

SOURCE: Author's elaboration.

NOTE: The table distinguish clusters presence by top employment specialization (TESp)(*), by top employment share (TESh)(**), and by top employment specialization & share (TESS)(***).

These results can be drawn in multiple maps. For example, **Figure II.2** shows the intensity of clusters presence by TESp, TESh, and TESS over regions, based on *C**. It draws attention that regions with high population concentration show a high presence of industrial clusters, as happens with Catalonia and Community of Madrid.

Figure II.2. Intensity of clusters presence by TESp, TESh, and TESS over autonomous communities (based on *C**).



SOURCE: Authors´ elaboration.

Finally, descriptive statistics are obtained for variables classified as economics, population and employment, innovation, competitiveness, ICT, and Industry 4.0 (**Table II.13**). **Table II.14** shows regional performance for both ICT index and Industry 4.0 index. Catalonia and Community of Madrid stand out with the best performance in both indices; contrastingly, Cantabria and Canary Islands hold the lowest performance in the ICT index, and Canary Islands and La Rioja for the industry 4.0 index.

Table II.13. Descriptive Statistics for autonomous communities' variables (N=17).

Categories	Variables	Mean	Median	Std. Dev.	Min.	Max
ECON.	GDP per capita (euros)	24808.773	23197.379	4930.420	18275.749	34805.061
	Earning per worker (euros)	23642.193	22877.130	2627.158	19940.680	29476.210
	Natural resources dependency	0.040	0.043	0.018	0.012	0.074
POP. & EMP.	Population (miles)	2760.900	2038.700	2558.826	314.400	8448.200
	% Population with a grade or more	0.143	0.136	0.032	0.103	0.231
	Unemployment rate	0.133	0.118	0.042	0.082	0.215
INNOV.	Patent application to million inhab. ratio	29.147	28.500	15.672	7.000	66.000
COMP.	RCI basic sub-index	-0.070	-0.078	0.138	-0.213	0.302
ICT	ICT index	0.548	0.576	0.164	0.245	0.829
IND. 4.0	Industry 4.0 index	0.466	0.435	0.170	0.212	0.808

SOURCE: Author's elaboration.

NOTE: *N* stands for number of observations, one for each autonomous community.

Table II.14. Regional ICT index and Industry 4.0 index.

Region	ICT index	Industry 4.0 index
Andalusia	0.605	0.373
Aragon	0.648	0.515
Asturias, Principality of	0.526	0.456
Balearic Islands	0.497	0.243
Basque Country	0.588	0.579
Canary Islands	0.332	0.212*
Cantabria	0.245*	0.615
Castile and León	0.454	0.435
Castilla – La Mancha	0.365	0.392
Catalonia	0.829**	0.723
Extremadura	0.321	0.392
Galicia	0.604	0.434
Madrid, Community of	0.800	0.808**
Murcia, Region of	0.572	0.349
Navarre, Ch. Community of	0.576	0.630
Rioja, La	0.631	0.226
Valencian Community	0.715	0.539

SOURCE: Author's elaboration.

NOTE: ** Highest score. *Lowest score.

ICT index shows positive and significant correlation with nine out of ten measures grouped (the correlation with social networks is positive but not statistically significant); Industry 4.0 index shows positive and significant correlation with five out of six measures grouped (the correlation with use of industrial robots is positive but not statistically significant).

Such information is shown in the full correlation matrices computed for both sets of clusters: *C** and *C*** (**Table II.15** and **Table II.16**).

Table II.15. Correlation between prevalence of clusters (*C**) and selected variables (N=17).

	TESp	TESh	TESS	01	02	03	04	05	06	07	GDP per capita	Earning per worker	Natural resources dependency	Population	% Population with a Grade or more	Unemployment rate	Patent app. to million inhab. ratio	RCI basic sub-index	ICT index	Industry 4.0 index
TESp	1.000																			
TESh	0.362	1.000																		
TESS	.496*	.925**	1.000																	
01	0.044	-0.156	-0.223	1.000																
02	0.345	0.326	0.176	0.019	1.000															
03	.645**	0.206	0.375	0.019	0.019	1.000														
04	0.326	.850**	.772**	-0.203	0.228	0.228	1.000													
05	0.246	0.339	0.313	-0.257	0.107	0.107	0.310	1.000												
06	0.246	0.071	0.091	-0.257	0.107	-0.257	-0.169	-0.214	1.000											
07	.576*	.548*	.622**	-0.358	-0.054	0.251	.566*	0.040	0.378	1.000										
GDP per capita	0.160	0.416	0.416	-0.405	-0.011	0.208	.568*	.603*	-0.174	0.169	1.000									
Earning per worker	0.158	0.343	0.375	-0.461	-0.096	0.364	0.466	.727**	-0.284	0.092	.894**	1.000								
Natural resources dependency	-0.254	-0.451	-.571*	.709**	0.025	-0.189	-0.475	-.522*	-0.174	-0.368	-.66**	-.68**	1.000							
Population	0.437	.820**	.817**	-0.159	0.219	0.464	.645**	0.134	0.008	.643**	0.124	0.151	-0.268	1.000						
% Population with a grade or more	0.239	.579*	.623**	-0.294	-0.002	0.459	.635**	0.406	-0.162	0.186	.830**	.833**	-.64**	0.403	1.000					
Unemployment rate	0.244	-0.105	-0.005	0.261	-0.070	0.127	-0.224	-0.436	0.240	0.264	-.79**	-.68**	0.348	0.216	-.557*	1.000				
Patent app. to million inhab. ratio	-0.354	0.079	0.045	-0.398	-0.074	0.008	0.159	0.351	-0.334	-0.282	.593*	.577*	-.497*	0.020	.532*	-.62**	1.000			
RCI basic sub-index	0.301	.556*	.544*	-0.199	0.269	0.456	.763**	0.303	-0.307	0.157	.673**	.615**	-.565*	0.359	.764**	-0.467	0.441	1.000		
ICT index	0.057	.662**	.543*	-0.389	0.304	0.146	.612**	0.339	-0.095	0.264	.592*	.505*	-.488*	.600*	.642**	-0.406	.555*	0.476	1.000	
Industry 4.0 index	-0.017	.593*	.518*	-0.178	0.014	0.243	.665**	.502*	-0.379	0.023	.630**	.691**	-0.456	0.411	.755**	-.493*	.589*	.763**	0.470	1.000

SOURCE: Author's elaboration. NOTE: *Coefficients are significant at 5% level. **Coefficients are significant at 1% level.

Table II.16. Correlation between prevalence of clusters (*C***) and selected variables (N=17).

	TESp	TESh	TESS	01	02	03	04	05	06	07	08	GDP per capita	Earning per worker	Natural resources dependency	Population	% Population with a Grade or more	Unemployment rate	Patent app. to million inhab. ratio	RCI basic sub-index	ICT index	Industry 4.0 index
TESp	1.000																				
TESh	.547*	1.000																			
TESS	.627**	.937**	1.000																		
01	-0.217	-0.154	-0.308	1.000																	
02	0.090	0.195	0.183	0.019	1.000																
03	.551*	0.457	.510*	0.019	-0.308	1.000															
04	0.463	.933**	.873**	-0.203	0.228	0.228	1.000														
05	0.034	0.105	0.098	-0.358	-0.054	-0.054	0.165	1.000													
06	.748**	.592*	.555*	-0.358	-0.054	0.251	.566*	-0.133	1.000												
07	.748**	.592*	.555*	-0.358	-0.054	0.251	.566*	-0.133	1.00**	1.000											
08	.666**	.588*	.658**	-0.203	-0.203	.658**	0.433	-0.236	.566*	.566*	1.000										
GDP per capita	0.251	.503*	.565*	-0.328	-0.011	0.292	.568*	0.395	0.169	0.169	0.157	1.000									
Earning per worker	0.354	0.443	.540*	-0.343	-0.096	0.379	0.466	.655**	0.092	0.092	0.186	.894**	1.000								
Natural resources dependency	-0.381	-0.410	-.543*	0.405	0.025	-0.054	-0.475	-0.326	-0.368	-0.368	-0.179	-.67**	-.68**	1.000							
Population	.634**	.842**	.805**	-0.135	0.219	.501*	.645**	-0.091	.643**	.643**	.707**	0.124	0.151	-0.268	1.000						
% Population with a grade or more	0.371	.662**	.776**	-0.232	-0.002	0.442	.635**	0.293	0.186	0.186	0.413	.830**	.833**	-.64**	0.403	1.000					
Unemployment rate	0.143	-0.147	-0.142	0.030	-0.070	-0.023	-0.224	-0.435	0.264	0.264	0.227	-.79**	-.68**	0.348	0.216	-.557*	1.000				
Patent app. to million inhab. ratio	-0.194	0.144	0.227	-0.233	-0.074	0.095	0.159	0.274	-0.282	-0.282	0.099	.593*	.577*	-.497*	0.020	.532*	-.62**	1.000			
RCI basic sub-index	0.345	.664**	.738**	-0.074	0.269	0.176	.763**	0.202	0.157	0.157	0.318	.673**	.615**	-.565*	0.359	.764**	-0.467	0.441	1.000		
ICT index	0.291	.686**	.690**	-0.170	0.304	0.354	.612**	0.022	0.264	0.264	0.355	.592*	.505*	-.488*	.600*	.642**	-0.406	.555*	0.476	1.000	
Industry 4.0 index	0.148	.660**	.689**	-0.214	0.014	0.279	.665**	.529*	0.023	0.023	0.277	.630**	.691**	-0.456	0.411	.755**	-.493*	.589*	.763**	0.470	1.000

SOURCE: Author's elaboration. NOTE: *Coefficients are significant at 5% level. **Coefficients are significant at 1% level.

II.5 Discussion

This thesis applies for first time this methodology to the Spanish context, using raw data to build specific Spanish Cluster Category Definitions (CCD) at the NUTS-2 level. Such approach separates this effort from others previously made since they depart from CCD built for the US. Moreover, the analysis is sharp enough to show the relevance of industries for specific regions, and reinforces previous findings about regional cluster presence in Spain made through case-studies (Elola et al., 2012; Jofre-Monseny et al., 2014; Molina-Morales et al., 2017; Ortega-Colomer et al., 2016; Vlaisavljevic et al., 2020). Additionally, this cluster mapping exercise groups industries using empirical measures rather than a conceptual aggregation of sectors without a robust theoretical justification, as the industrial district mapping has done before (Boix & Trullén, 2010; Canello & Pavone, 2016).

The study proves the feasibility of the application of an end-to-end methodology to map clusters in Europe, placing a serious question about why the current cluster mapping efforts assume that locational patterns found on the US are representative for those found in the EU, and tend to homologate American CCD for Europe (Ketels & Protsiv, 2021). That *representativeness assumption* could not be reasonable for less-large, less-diversified, less-dynamic, and less-industrialized economies (Brodzicki, 2010); besides, Delgado et al. (2016) states that current and past barriers to trade across Europe shaped different patterns of agglomeration when compared with the US, and that American CCD aim to be a benchmark for other economies.

This research supports the idea that such representativeness assumption is questionable at least for the Spanish case, due to the next three reasons.

First, the spatial units of study for the American case are the *Economic Areas (EA)*, which represent regional relevant markets delimited for economic purposes; in contrast, in the EU the cluster mapping is made over administrative divisions (generally NUTS-2), which are defined by each member country following local criteria (in the case of Spain, historical and socio-political antecedents shaped the administrative divisions). This is relevant because the nature of the spatial units has an impact over the capacity of the similarity matrices to identify cross-industry linkages. For example, in the US the Co-location pattern for establishments (LC_Est) and Input-Output Links (IO) have the best performance as unidimensional matrices, and Geographic concentration of employment

(COI) and Labor Occupation Links (Occ) have the worst ones. In contrast, for Spain the LC_Est and IO have the worst performance and COI and Occ the best ones. Additionally, for the US case the similarity matrix with the best performance is a multidimensional one (LC_IO_Occ), and the authors never mix the LC and COI as they assume that such indicators capture similar linkages among industries. For the Spanish case that assumption is overlooked, and results show that the similarity matrix with the best performance is one constructed with the COI: the COI_IO_Occ.

Second, while this chapter departs from traded industries as the study of Delgado et al. (2016) does, the three-criteria methodology to identify traded industries of the latter study is not capable to effectively discriminate by itself between local and traded industries for the Spanish case. Instead, this study applies a different multi-criterion methodology based on export to gross value-added ratio and the locational Gini Coefficient; for the last criterion, the cutoff is set at 0.01, as multiple cutoffs are tested in incremental ranges of 0.01 looking for the set of traded industries with the maximum overlap compared with the set defined by the three-criteria methodology of Delgado et al. (2014)[13].

Third, the North America's industrial classification is not harmonized with the EU's one; therefore, the adaptation of the American CCD for Europe depends on the reinterpretation of the American industrial codes for the European case, which is not always a straightforward task (Brodzicki, 2010). Besides, since the cluster algorithm relies on the data of individual industries, the differences on the interpretation of *what is* each industry will have a direct impact on the assessed cross-industry linkages and thus in the identified clusters.

The presented arguments support the idea that a robust and reliable cluster mapping effort must depart for locally-measured relatedness among industries; otherwise, the adaptation of foreign CCD could disregard local cross-industry linkages and overestimate other less relevant ones. Besides, this research also demonstrates that depending on the economy being analyzed, the methodology could require the

[13] The geometric mean is used to measure the industry overlap in each direction.

modification or complementation of procedures, criteria, and indicators with the purpose of improving the results and meeting the conceptual requirements.

This is a call for European researchers, policymakers, and economic development practitioners to take with reservation the data about local agglomeration when it is derived from the adaptation of foreign measures for cross-industry linkages. Failing to do so could lead to deficient industrial policy design, inadequate cluster performance assessment and misinterpretation of cluster's externalities. Besides, initiatives like the European Cluster Collaboration Platform and the European Clusters Excellence program present maps that show and assess presence of *cluster organizations* and not empirical evidence of the presence of industrial clusters, which could lead to the misinterpretation of the existence of industrial clusters as a real agglomeration phenomenon and not as a policy tool.

In a different train of thought, the correlation analysis between clusters presence and different variables also shows insightful results to discuss. Overall, the correlation between clusters presence and the assessed variables tends to be stronger and more statistically significant for *C*** than for *C**.

The correlations presented have different responses when the clusters presence is assessed by national-level measures than when it is assessed with regional-level measures. In other words, the clusters presence measured by TESh (which departs from national-level measures of employment share for each CCD) presents more statistically significant correlations with other variables than the clusters presence measured by TESp (which departs from regional-level measures of employment and establishments based in LQ). Such finding, which is consistent for both sets of clusters, suggests that the employment concentration on specific industries at the national-level of data aggregation could be more useful when exploring the effects of industrial clusters over economy.

This analysis also supports previous findings related to the correlation of clusters presence and variables like population education level, natural resource dependency, and competitiveness, showing different levels of statistical significance depending on the measure of presence but being consistent in the sign of the coefficients (Babkin et al., 2017; Delgado, Porter, et al., 2014; Slaper et al., 2018). However, at this level of data aggregation, the findings related to the other variables differ between both sets of clusters; for *C**, no significant correlation is found between clusters presence and GDP per capita, earning per worker, innovation, and unemployment variables, which are commonly linked by researchers and policymakers with the industrial agglomeration; in contrast, for *C*** the correlations reach statistical significance with GDP per capita and earning per worker variables, while the findings for innovation, and unemployment variables are consistent with *C**. These findings reinforce two ideas; first, the clusters' relations with other phenomena are complex and not so evident at meso and macro levels (Grashof & Fornahl, 2021); and two, the *VS* criterion to elect the set of clusters for mapping does not guarantee the best correlation performance, which could impact the results of further analysis based on inferential statistics.

Mention apart deserves the correlation between the clusters presence and the ICT/ Industry 4.0 Indexes: the sign of the correlation is positive in all the cases and statistically significant for national-level measures of presence, reaching a higher level of significance for the second set of clusters. These results support previous findings made at micro-level that suggest that industrial clusters improve the rates of ICT and Industry 4.0 adoption; besides, the research provides to researchers and policymakers with insightful data about the overall level of technological adoption in Spanish regions. Furthermore, this approach overcomes limitations of previous research made in Spain and Europe about Industry 4.0 and industrial clusters, since they rely on case studies, specific regions, or specific technologies (Götz & Jankowska, 2017; Grashof et al., 2021; Hervas-Oliver et al., 2019).

To conclude, the correlation analysis makes possible to assess the correlation of individual CCD with the elected variables of economic performance. In this matter, two CCD (the *04 Biotechnological cluster* and *05 Electromechanical and automotive cluster* for both sets of clusters) outperform the correlations showed by the other CCD, even showing statistically significant correlations with variables like GDP per capita and earning per worker. Noteworthy, those two CCD involve engineering and manufacturing related to biochemicals, electronics, machinery, and computing, suggesting that positive externalities could find stronger linkages with those industries, as Tavares et al. (2021) suggest.

The findings provide to practitioners and researchers interested in industrial clusters with useful information to focus their efforts on identifying native competitive networks naturally present over their territory, aiming to develop their industrial clusters in a more effective way. Furthermore, for the Spanish case, policymakers could depart from this research to assess not only their efforts into developing particular clusters over their regions, but also to put the spotlight on overlooked cross-industry linkages and to develop and improve their territorial presence, aiming to boost their returns and reach new clients and suppliers.

Although economic development and technology adoption are complex phenomena to assess, the results of this research not only provide to researchers, government, and industry leaders a solid basis for industrial policy and competitive strategy, but also a solid methodology to explore the existence of industrial clusters in different contexts. Additionally, the final insights invite researchers to explore the impact of industrial clusters using novel approaches, like the Structural Equation Modeling, capable to identify complex relations among multiple variables that could operate as mediators between the industrial cluster presence and the economic development.

II.6 Conclusions

This research applies, for the first time, a full quantitative methodology of cluster mapping for the Spanish context, adapted from state-of-the-art literature, based on statistical modeling and broadly applicable, with a multi-regional/multi-industry scope. The results find the presence over territory of different industrial clusters based in native cross-industry linkages naturally present over territory, departing from the CNAE-2009 2-digits level and the use of autonomous communities as spatial units to analyze data (NUTS-2), excluding Ceuta and Melilla. Additionally, the study explores the correlations between clusters presence and a group of relevant variables for the economic development understanding. The findings contribute to literature from four different perspectives.

First, from a methodological perspective the study demonstrates that even when the foundations of the methodology applied remain the same, there are procedures, criteria, and indicators that researchers must modify or complement with the purpose of improving the results of its application in particular economies.

Second, the conceptual perspective makes a call to researchers and policymakers to question the *representativeness assumption* made over the American cross-industry linkages, and to promote the creation of local Cluster Category Definitions for individual countries or even for Europe, departing from the quantitative assessment of local cross-industry linkages. The use of homologated-and-foreign Cluster Category Definitions for the European case could underestimate relevant linkages or overestimate irrelevant ones, misleading conclusions about clusters' presence, performance, and externalities.

Third, the externalities perspective shows that the clusters presence measured with national-level employment data correlates better with variables related to education, technology adoption and competitiveness, in contrast to the clusters presence measured with regional-level employment and establishments data. Besides, the correlation between the clusters presence and variables like GDP per capita, earning per worker, and innovation appears to be sensitive to subtle differences in clusters' configurations, showing different levels of statistical significance but maintaining the expected correlation sign. These final insights invite researchers to explore the impact of industrial clusters using different approaches and criteria, to find more complex relations among variables and industries.

Fourth, from the practical perspective this chapter offers, right out-of-the-box, useful information to take the regional and industrial assessment further. Researchers, policymakers, and practitioners can find the list of industries classified as traded, the groups of industries that shape each cluster, the clusters location, and even two indexes of technological adoption (ICT and Industry 4.0 indexes) for all autonomous communities. The index construction presented in this study is the first one to group into a single indicator the technology adoption of different regions using harmonized data for all of them, being the first exercise of its kind for Spanish regions.

Nonetheless, the study is limited by the aggregation level of the data, not to mention that complete data for some industries is unavailable or hidden due to statistical confidentiality. Thus, although there are challenges related to more complete and disaggregate data availability, further analysis is recommended at NUTS-3 and CNAE-2009 3-digits to generate more detailed Cluster Category Definitions and provide useful information at even more local level. Additionally, this could make possible deep exploration of relations among variables, using Ordinary Least Squares regression and Structural Equation Modeling. Furthermore, this research's methodology could be improved including indicators related to technological similarity, community linkages, and natural advantages, which could be helpful to find novel cross-industry linkages departing from other approaches like the industrial district mapping.

Finally, this research shows a contemporaneous outlook to industrial structure in Spain and expects to be useful not only as a benchmark for future research, but also for policymakers and industry leaders currently working on industrial policy and competitive strategy.

References

Almeida, F., Duarte, J., & Monteiro, J. (2020). The challenges and opportunities in the digitalization of companies in a post-COVID-19 world. *IEEE Engineering Management Review*, *48*(3), 97–103. https://doi.org/10.1109/EMR.2020.3013206

Atik, H., & Ünlü, F. (2019). The measurement of Industry 4.0 performance through Industry 4.0 Index: An empirical investigation for Turkey and European countries. *Procedia Computer Science*, *158*, 852–860. https://doi.org/10.1016/j.procs.2019.09.123

Babkin, A., Plotnikov, V., & Vertakova, Y. (2018). The analysis of industrial cooperation models in the context of forming digital economy. *SHS Web of Conferences*, *44*, 12. https://doi.org/10.1051/shsconf/20184400012

Babkin, A., Vertakova, Y., & Plotnikov, V. (2017). Study and assessment of clusters activity effect on regional economy. *SHS Web of Conferences*, *35*, 63. https://doi.org/10.1051/shsconf/20173501063

Bathelt, H., & Li, P. F. (2014). Global cluster networks-foreign direct investment flows from Canada to China. *Journal of Economic Geography*, *14*(1), 45–71. https://doi.org/10.1093/jeg/lbt005

Becattini, G. (1990). The Marshallian industrial district as a socio-economic concept. In F. Pike, G. Becattini, & W. Sengenberger (Eds.), *Industrial Districts and Inter-Firm Cooperation in Italy* (pp. 37–51). ILO.

Boix, R., & Galletto, V. (2009). Innovation and industrial districts: A first approach to the measurement and determinants of the I-district effect. *Regional Studies*, *43*(9), 1117–1133. https://doi.org/10.1080/00343400801932342

Boix, R., & Trullén, J. (2010). Industrial districts, innovation and I-district effect: Territory or industrial specialization? *European Planning Studies*, *18*(10), 1707–1729. https://doi.org/10.1080/09654313.2010.504351

Brodzicki, T. (2010). Critical review of cluster mapping studies in Poland. *Analizy i Opracowania KEIE UG*, *1*(3), 3–20.

Burki, A. A., & Khan, M. A. (2011). Agglomeration economies and their effects on technical inefficiency of manufacturing firms: Evidence from Pakistan. In *International Growth Centre* (Issue March). https://www.theigc.org/project/agglomeration-economies-and-their-effects-on-productivity-and-efficiency-of-manufacturing-firms-evidence-from-pakistan/

Caloffi, A., Lazzeretti, L., & Sedita, S. R. (2018). The story of cluster as a cross-boundary concept: From local development to management studies. In F. Belussi & J. L. Hervas-Oliver (Eds.), *Agglomeration and Firm Performance. Advances in Spatial Science* (pp. 123–137). Springer. https://doi.org/10.1007/978-3-319-90575-4_8

Canello, J., & Pavone, P. (2016). Mapping the Multifaceted Patterns of Industrial Districts: A New Empirical Procedure with Application to Italian Data. *Regional Studies*, *50*(8), 1374–1387. https://doi.org/10.1080/00343404.2015.1011611

Carlino, G., & Kerr, W. R. (2015). Agglomeration and innovation. In G. Duranton, J. V Henderson, & W. Strange (Eds.), *Handbook of Regional and Urban Economics* (1st ed., Vol. 5, pp. 349–404). Elsevier B.V. https://doi.org/10.1016/B978-0-444-59517-1.00006-4

Delgado, M., Bryden, R., & Zyontz, S. (2014). *Categorization of traded and local industries in the US economy*. 1–9. https://clustermapping.us/sites/default/files/files/page/Categorization of Traded and Local Industries in the US Economy.pdf

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38. https://doi.org/10.1093/jeg/lbv017

Diodato, D., Neffke, F., & O'Clery, N. (2018). Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, *106*, 1–26. https://doi.org/10.1016/j.jue.2018.05.002

Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, *3*(1), 3–45. https://repository.upenn.edu/real-estate_papers/2

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J. F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (pp. 2063–2117). Elsevier.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195–1213. https://doi.org/10.1257/aer.100.3.1195

Elola, A., Valdaliso, J., Lopez, S. M., & Aranguren, M. J. (2012). Cluster life cycles, path dependency and regional economic development: Insights from a meta-study on Basque clusters. *European Planning Studies*, *20*(2), 257–279. https://doi.org/10.1080/09654313.2012.650902

Elola, A., Valdaliso, J. M., Franco, S., & López, S. M. (2017). Public policies and cluster life cycles: insights from the Basque Country experience. *European Planning Studies*, *25*(3), 539–556. https://doi.org/10.1080/09654313.2016.1248375

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis*. Wiley.

Glaeser, E. L., & Kerr, W. R. (2009). Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain? *Journal of Economics & Management Strategy*, *18*(3), 623–663. https://doi.org/https://doi.org/10.1111/j.1530-9134.2009.00225.x

Götz, M., & Jankowska, B. (2017). Clusters and Industry 4.0 - Do they fit together? *European Planning Studies*, *25*(9), 1633–1653. https://doi.org/10.1080/09654313.2017.1327037

Grashof, N., & Fornahl, D. (2021). "To be or not to be" located in a cluster?—A descriptive meta-analysis of the firm-specific cluster effect. In *Annals of Regional Science* (Vol.

67, Issue 3). Springer Berlin Heidelberg. https://doi.org/10.1007/s00168-021-01057-y

Grashof, N., Kopka, A., Wessendorf, C., & Fornahl, D. (2021). Industry 4.0 and clusters: Complementaries or substitutes in firm's knowledge creation? *Competitiveness Review*, *31*(1), 83–105. https://doi.org/10.1108/CR-12-2019-0162

Grimmer, J., & King, G. (2011). General purpose computer-assisted clustering and conceptualization. *Proceedings of the National Academy of Sciences*, *108*(7), 2643–2650. https://doi.org/10.1073/pnas.1018067108

Hermans, F. (2021). The contribution of statistical network models to the study of clusters and their evolution. *Papers in Regional Science*, *100*(2), 379–403. https://doi.org/10.1111/pirs.12579

Hervás-Oliver, J. L. (2021). Industry 4.0 in industrial districts: regional innovation policy for the Toy Valley district in Spain. *Regional Studies*, *55*(10–11), 1775–1786. https://doi.org/10.1080/00343404.2021.1939861

Hervas-Oliver, J. L., Estelles-Miguel, S., Mallol-Gasch, G., & Boix-Palomero, J. (2019). A place-based policy for promoting Industry 4.0: the case of the Castellon ceramic tile district. *European Planning Studies*, *27*(9), 1838–1856. https://doi.org/10.1080/09654313.2019.1642855

ICEX España Exportación e Inversiones. (n.d.). *Why invest in Spain? - Economy*. Ministerio de Industria, Comercio y Turismo. Retrieved January 9, 2020, from https://www.investinspain.org/en/why-spain/economy

Jasinska, K., & Jasinski, B. (2019). Clusters under industry 4.0 conditions - Case study: the concept of Industry 4.0 cluster in Poland. *Transformations in Business & Economics*, *18*(2B), 802–823. http://www.transformations.knf.vu.lt/47b/article/clus

Jofre-Monseny, J., Marin-Lopez, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: evidence from the location of new firms in Spain. *Journal of Regional Science*, *54*(2), 313–337. https://doi.org/10.1111/jors.12076

Ketels, C. (2017). Cluster mapping as a tool for development. In *Harvard Business School* (Issue June). https://www.hbs.edu/faculty/Pages/item.aspx?num=53385

Ketels, C., & Protsiv, S. (2021). Cluster presence and economic performance: a new look based on European data. *Regional Studies*, *55*(2), 208–220. https://doi.org/10.1080/00343404.2020.1792435

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Leamer, E. E., & Storper, M. (2001). The economic geography of the Internet age. *Journal of International Business Studies*, *32*(4), 641–665. https://doi.org/10.1057/palgrave.jibs.84909988

Lorenzini, F., & Lombardi, S. (2018). L'identificazione dei distretti industriali: una rassegna metodologica [Mapping industrial districts: A methodological review]. *Scienze Regionali, Italian Journal of Regional Science*, *17*(2), 225–260. https://doi.org/10.14650/90223

Mano, R., & Castillo, M. (2015). The level of productivity in traded and non-traded sectors for a large panel of countries. *IMF Working Papers*, *15*(48), 1. https://doi.org/10.5089/9781484392140.001

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., & Krejcar, O. (2018). Consequences of Industry 4.0 in business and economics. *Economies*, *6*(3), 14. https://doi.org/10.3390/economies6030046

Marshall, A. (1920). *Principles of economics* (8th ed., p. 69). Macmillan (original work published 1890).

Molina-Morales, F. X., Martinez-Chafer, L., & Valiente-Bordanova, D. (2017). Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones Regionales-Journal of Regional Research*, *39*, 39–57. https://investigacionesregionales.org/es/article/disruptive-technological-innovations-as-new-opportunities-for-mature-industrial-clusters-the-case-of-digital-printing-innovation-in-the-spanish-ceramic-tile-cluster/

Oosterhaven, J., Eding, G. J., & Stelder, D. (2001). Clusters, linkages and interregional spillovers: Methodology and policy implications for the two Dutch mainports and the rural North. *Regional Studies*, *35*(9), 809–822. https://doi.org/10.1080/00343400120090239

Ortega-Colomer, F. J., Molina-Morales, F. X., & Fernández-de-Lucio, I. (2016). Discussing the concepts of cluster and industrial district. *Journal of Technology Management & Innovation*, *11*(2), 139–147. https://doi.org/10.4067/S0718-27242016000200014

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *62*(2), 73–93. https://www.hbs.edu/faculty/Pages/item.aspx?num=6105

Porter, M. E. (2003). The economic performance of regions. *Regional Studies*, *37*(6–7), 549–578. https://doi.org/10.1080/0034340032000108688

Romanelli, E., & Khessina, O. M. (2005). Regional industrial identity: Cluster configurations and economic development. *Organization Science*, *16*(4), 344–358. https://doi.org/10.1287/orsc.1050.0131

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191–229. https://doi.org/10.1006/juec.2001.2230

Scherer, F. M. (1984). Using linked patent and R&D data to measure interindustry technology flows. In Z. Griliches (Ed.), *R&D, Patents, and Productivity* (pp. 417–461). University of Chicago Press.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest and the business cycle* (1th ed., p. 255). Transaction Publishers.

Sforzi, F. (2015). Rethinking the industrial district: 35 years later. *Investigaciones Regionales*, *32*(2015), 11–29. http://www.aecr.org/images/ImatgesArticles/2015/11/2_Sforzi.pdf?_ga=2.131452296.680042952.1678926565-1405984931.1678409478

Skokan, K., & Zotyková, L. (2014). Evaluation of business cluster performance during its lifecycle. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *62*(6), 1395–1405. https://doi.org/10.11118/actaun201462061395

Slaper, T., Harmon, K., & Rubin, B. (2018). Industry clusters and regional economic performance: A study across US Metropolitan Statistical Areas. *Economic Development Quarterly*, *32*(1), 44–59. https://doi.org/10.1177/0891242417752248

Slaper, T., & Ortuzar, G. (2015). Industry clusters and economic development. *Indiana*

Business Review, *90*(1), 7–9. https://www.ibrc.indiana.edu/ibr/2015/spring/pdfs/article2.pdf

Szanyi, M., Iwasaki, I., Csizmadia, P., Illésy, M., & Makó, C. (2010). Cluster development in Hungary: searching for a 'critical mass' of business via cluster mapping. In B. Dallago & C. Guglielmetti (Eds.), *Local economies and global competitiveness* (pp. 113–133).

Tavares, M. S. D., Gohr, C. F., Morioka, S., & da Cunha, T. R. (2021). Systematic literature review on innovation capabilities in clusters. *Innovation and Management Review*, *18*(2), 192–220. https://doi.org/10.1108/INMR-12-2019-0153

Titze, M., Brachert, M., & Kubis, A. (2011). The identification of regional industrial clusters using qualitative input-output analysis (QIOA). *Regional Studies*, *45*(1), 89–102. https://doi.org/10.1080/00343400903234688

Vlaisavljevic, V., Cabello-Medina, C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting and Social Change*, *155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Ybarra, J. A., & Domenech-Sanchez, R. (2012). Innovative business groups: territory-based industrial policy in Spain. *European Urban and Regional Studies*, *19*(2), 212–218. https://doi.org/10.1177/0969776411428558 WE - Social Science Citation Index (SSCI)

Yelkikalan, N., Soylemezoglu, E., Kiray, A., Sonmez, R., Ezilmez, B., & Altun, M. (2012). Clustering approach as a regional development tool. *8th International Strategic Management Conference*, *58*, 503–513. https://doi.org/10.1016/j.sbspro.2012.09.1027

Zhu, S., & Pickles, J. (2016). Institutional embeddedness and regional adaptability and rigidity in a Chinese apparel cluster. *Geografiska Annaler, Series B: Human Geography*, *98*(2), 127–143. https://doi.org/10.1111/geob.12095

CHAPTER III

Unleashing the synergies: exploring the dynamics of industrial clusters, digitalization, and economic development

III.1 Introduction

In recent decades, the concept of industrial clusters has garnered significant attention in the fields of economic development and industrial agglomeration, primarily because of its perceived capacity to stimulate economic development (Babkin et al., 2017; Hermans, 2021). Researchers and policymakers recognize the potential of industrial agglomeration, and extensive research has explored the multifaceted nature of this phenomenon. Furthermore, the growing prominence of clusters as policy tools, extensive studies have been conducted from various perspectives, primarily focusing on competitiveness in terms of innovation, productivity, and institutional support (Babkin et al., 2018; Vlaisavljevic et al., 2020; Wilson et al., 2022).

The intersection of industrial clusters, digital transformation, and economic development has garnered substantial interest from researchers, industrialists, and policymakers, becoming a subject of contemporary discussion due to the complexity and dynamism of such relation. The advent of digital economy and concepts like Industry 4.0 have brought forth new opportunities and challenges, whilst industrial clusters have continued to develop complex economic networks that fuel regional growth (Richter et al., 2017; Yudina, 2019).

While digitalization and industrial clusters have evolved at their own pace, recent research indicates that the adoption of information and communication technologies (ICT) within industrial clusters is influenced by the environmental conditions created by these agglomerations (Corradini et al., 2021; Guo et al., 2020). However, the relationship between digital transformation and industrial agglomerations remains an area of ongoing debate. Concerns have been raised about the negative externalities that industrial agglomeration and digitalization can pose over economy mainly due to the technological lock-in, whereby clusters may delay the adoption of state-of-the-art ICT owing to competition-related anxieties and issues related to privacy and confidentiality (Grashof & Fornahl, 2021; Muller et al., 2018). Despite these challenges, clusters have proven to be better-organized networks that enable suitable environments for the emergence, testing, development, and promotion of novel technologies as Industry 4.0 (Götz, 2021).

Therefore, there is still a need for more comprehensive and empirical studies that explore the intricate relationships between industrial clusters, technology adoption, and competitiveness, and their influence on economic outcomes. A deeper understanding of this relationship would provide valuable insights for practitioners, industrialists, and policymakers seeking to develop new policy tools that reconcile digital transformation and industrial agglomeration.

Considering the aforementioned discussion, this chapter aims to explore the impact of industrial clusters on technology adoption and competitiveness, as well as their role in fostering economic development. Drawing upon a comprehensive literature review, the study will examine the existing empirical evidence and theoretical frameworks to shed light on the dynamics of industrial clusters, digital transformation, competitiveness, and economic development. By addressing these research gaps, this chapter can contribute to the development of informed policies and strategies that harness the synergistic potential of industrial clusters and digital transformation.

This research aims to explore the impact of industrial clusters and technology adoption on economic development, as well as their role in fostering competitiveness, in a specific European country: Spain. The study adopts an end-to-end methodology to map industrial clusters at a granular level of geographical disaggregation, specifically at NUTS-3 level. This level of detail allows for a more precise analysis of cluster dynamics and their impact on economic development. Furthermore, the research employs a structural equation modeling (SEM) approach to assess the direct and mediation relationships between industrial clusters, technology adoption, competitiveness, and two dimensions of economic development: wealth creation measured by GDP *per capita* and returns to labor expressed as earnings *per worker*.

By employing a granular mapping methodology and the SEM as analysis framework, this study contributes to a deeper understanding of the dynamics and mechanisms that shape regional economic development in the context of industrial clusters and digitalization, unraveling the complex and interdependent nature of its relationships.

The findings of this research have implications for policymakers, industrials, and academics. Policymakers can utilize the insights from this study to formulate effective strategies and policies that promote the development of industrial clusters, enhance technological innovation, and foster competitiveness. Industrial stakeholders can leverage these findings to make informed decisions regarding business location, resource allocation, and technology adoption, thereby improving their overall market performance. Finally, the research contributes to the academic community by expanding the knowledge base on the relationships between industrial clusters, technology adoption, competitiveness, and their impact on economic development.

The chapter is divided into three main sections. The first section delves into the impact of industrial clusters on digital transformation and discusses their influence on competitiveness and economic development; additionally, this exploration leads to the formulation of research hypotheses that guides the subsequent analysis and contribute to the existing body of knowledge in this field. The second section introduces the research methodology that incorporates two statistical techniques: the *cluster analysis*, and the *Variance-Based Partial Least Squared Structural Equation Modeling*. The third section presents the results divided into two parts: the first part focuses on the industrial clusters map for Spain, using raw data at the NUTS-3 level; it serves as a foundation for the subsequent part that examinates the relationships between industrial clusters, technology adoption, competitiveness, and economic development. The fourth section, the discussion, explores the underling meaning of the results and aims to elucidate the complex dynamics and interdependencies among the assessed variables, providing insights into the multifaceted nature of industrial clusters and their influence on economic outcomes. Finally, the fifth section offers general conclusions and limitations of the study, as valuable insights for future research.

III.2 Theoretical background

The industrial cluster has become one of the most studied phenomena in the last 30 years, in the frame of economic development and industrial agglomeration (Babkin et al., 2017; Hermans, 2021; Ortega-Colomer et al., 2016).

Chapter I defines the industrial cluster as a group of organizations geographically concentrated and interconnected through multiple links, shaping value systems with the purpose of increasing the returns of the participants. Such phenomenon, which popularity has transformed it into a policy tool, is settled on economic, sociological, historical, and geographical foundations that have been widely studied from multiple perspectives, including different models of industrial agglomeration, such as the industrial district (Babkin et al., 2018; Delgado et al., 2016; Delgado, Porter, et al., 2014; Duranton, 2011; Elola et al., 2012; Jasinska & Jasinski, 2019; Ortega-Colomer et al., 2016; Romanelli & Khessina, 2005; Vlaisavljevic et al., 2020; Wilson et al., 2022).

The industrial clusters exhibit multiple effects over regions, which are discussed in detail in this section. The first part presents latest studies that discuss the idea of how the presence of clusters facilitate the digital transformation through the adoption of ICT and Industry 4.0. The second part presents literature addressing the impact of industrial clusters and technology on economic development, and particularly on competitiveness, innovation, labor productivity, wealth creation and returns to labor. Additionally, research hypotheses are introduced throughout the presentation of literature.

III.2.1 The industrial clusters and its impact on digital transformation

Economists recognize the relevance of digitalization for industrial agglomeration, as it enhances and expands networks (Alcacer et al., 2016; Almeida et al., 2020; Angehrn, 1997; Johansson et al., 2006; Scott & Storper, 2007). Therefore, industrial clusters are genuinely interested in digital transformation as a means to achieve a broader and more efficient geographical distribution (Jasinska & Jasinski, 2019).

Digital transformation and industrial clusters have evolved independently. The former has enabled the creation of a new virtual and digital economy, incorporating concepts such as Industry 4.0 (Afonasova et al., 2019; Baggio & Del Chiappa, 2014; Lehdonvirta & Ernkvist, 2011; Popescu & Popescu, 2011; Richter et al., 2017; Yudina, 2019). The latter has developed complex economic networks that are geographically concentrated and contribute to regional development (Caloffi et al., 2018; Jofre-Monseny et al., 2014; Sforzi, 2015; Tavares et al., 2021). Both have been initially observed as real-world phenomena and later utilized as policy tools for economic growth (Babkin et al., 2018; Del Chiappa & Baggio, 215; Hervás-Oliver, 2021; Porter et al., 2007; Ybarra & Domenech-Sanchez, 2012).

However, the relationship and impact of digitalization on industrial clusters remain subjects of contemporary discussion, as ICT promote powerful forces of delocalization (Brettel et al., 2014; Erboz, 2017; Hermann et al., 2016). Nevertheless, recent research indicates that industrial clusters create environmental conditions that facilitate and homogenize ICT adoption among their members since they tend to ease and homogenize the digital penetration (Götz & Jankowska, 2017; Guo et al., 2020; Jasinska & Jasinski, 2019; Karnitis & Karnitis, 2017; Maresova et al., 2018; Temouri et al., 2021; Watanabe et al., 2018). Additionally, in industrialized countries, digitalization promotes further agglomeration forces in the manufacturing industry (Götz, 2019a; Jankowska et al., 2021; M. Wang et al., 2023).

Those findings have led to researcher, industrials, and policymakers to make serious efforts to understand how the cluster-based industrial policies can drive the process of digital transformation. Currently, countries and regions known for promoting industrial agglomeration are also digital champions (Corradini et al., 2021; Geissbauer et al., 2018). Additionally, clusters offer a conducive environment for the emergence, testing, development, and promotion of novel technologies, including those associated with Industry 4.0 (Götz, 2019b, 2021).

Are clusters capable to adopt and promote the most contemporaneous advances in ICT? Gagnidze (2022) suggests that they are, since clusters are better-organized networks and systems that can adopt and promote the latest ICT. However, it will depend on the kind of agglomerated industries and the life-cycle stage of the cluster (Elola et al., 2017; Skokan & Zotyková, 2014; Solvell, 2015).

Unfortunately, research about the relation of digital transformation and industrial agglomerations is still scarce and not conclusive. The technological lock-in has been highlighted as a negative externality of clusters, delaying the recognition, development, and adoption of state-of-the-art ICT (Elola et al., 2012; Zhu & Pickles, 2016). Such findings have been linked mainly to large firms with worries about competition, discouraging the adoption of novel technologies due to concerns relates to privacy and confidentiality (Grashof et al., 2021; Muller et al., 2018).

More research is necessary to understand this relationship and provide to practitioners, industrials, and policymakers of insightful information to develop new policy tools that conciliate digital transformation and industrial agglomeration (Crupi et al., 2020; Golov et al., 2021).

In this context, this research proposes the first hypothesis:

Hypothesis 1 (H1): *The presence of clusters promotes technology adoption.*

III.2.2 Industrial clusters and digital transformation: the dynamic duo for economic development

Since its conceptualization and subsequent instrumentalization as a policy tool, the economic and business community has made wide efforts to assess the impact of industrial clusters on development (Wilson et al., 2022). However, the conceptual heterogeneity of clusters and the complex nature of economic development, added to the difficulty to establish geographic delimitations of industrial agglomeration, make difficult for to generalize empirical findings about the impact of clusters on economic development (Delgado et al., 2016; Feser, 1998; Rocha, 2004).

Porter (1990) introduced the industrial cluster concept within the framework of competitiveness, presenting his *Diamond Model* as a straightforward explanation of the cluster's sources of competitiveness. However, the model overlooked previous advances in agglomeration theory, limiting its ability to understand the foundations and effects of agglomeration (Sforzi, 2015). The discussion on competitiveness in clusters is divided, with some economists focusing on productivity and competition (Duranton, 2011). This position is justified, since the instrumentalization of the concept competitiveness, which happens throughout the creation of indices, tends to group multiple variables that are commonly studied separately, as innovation, institutional support, adoption of digital technologies, and labor productivity. That is the case of the Regional Competitiveness Index (RCI), developed by the European Commission (D'Urso et al., 2022). Researchers suggest that an individual assessment of each variable provides more insightful information for the cluster policy making and the tracking of its impact on competitiveness (Buitrago et al., 2022).

Despite the debate, the competitiveness indicators still capture different aspects of economy that are overlooked by other variables, such as the support of institutions, macroeconomic stability, infrastructures, health, and basic education (Lines & Monypenny, 2006). Furthermore, researchers observed that industrial clusters tend to improve such aspects in regions where they are present (Bathelt & Turi, 2011; Molina-Morales et al., 2017; Ortega-Colomer et al., 2016; Wilson et al., 2022).

In addition, clusters are associated to fostering innovative activities, another traditional component of competitiveness (Almeida et al., 2020; Bayliss, 2007; Tavares et al., 2021; Vlaisavljevic et al., 2020). The rationale behind such relationship is that the clusters have a positive impact on knowledge recombination and creativity, as the access of cluster members to specialized resources and information is easier (Aleksandrovich, 2019; Bathelt et al., 2004; Buteau, 2021; Cuevas-Vargas et al., 2021; Gertler & Wolfe, 2006; Owen-Smith & Powell, 2004; Scarle et al., 2012; Schwarzer et al., 2019). Some authors even refer to industrial clusters as innovation networks (Babkin et al., 2013; Bathelt & Turi, 2011; Götz & Jankowska, 2017).

The labor productivity is also a concern for industrial clusters' researchers because it is closely linked to the idea of competitiveness. Literature suggests that the economic foundations of clusters promote productivity among their members, since the concentration of labor, inputs, and know-how increase the returns and productivity of firms (Babkin et al., 2017; Ketels, 2017; Krugman, 1991; Porter, 2003; Rocha, 2004; Rosenthal & Strange, 2001; Stojčić et al., 2019; Yelkikalan et al., 2012).

However, potential flaws of the cluster model, such as technological lock-in, have been recognized (Elola et al., 2017; Zhu & Pickles, 2016). Researchers have also highlighted the penalization of industrial clusters to lagging behind regions, which are geographically distant and with lack of infrastructure (Cortright, 2006; Leamer & Storper, 2001). Additionally, different studies point out the *congestion costs* and the *monopoly of innovation* as the main threats for innovation and productivity inside the clusters, affecting firms and regions equally (Bathelt & Taylor, 2002; Delgado, Porter, et al., 2014; Duranton, 2011; Grashof & Fornahl, 2021; Slaper et al., 2018; Storper, 2009).

Despite the heterogeneous literature about the impact of clusters on competitiveness, and the multiple factors that can influence such effect, the evidence remains consistent enough to present the second research hypothesis:

Hypothesis 2 (H2): *The presence of clusters promotes competitiveness.*

Clusters are expected to have a positive impact on the competitiveness and economic development of regions. However, the topic is ample and complex, thus literature prefers to deal with specific variables capable to capture the idea of regional development. Among the most popular variables are the wealth creation and the returns to labor, expressed as the evolution and size of the GDP per capita and the earnings per worker (Slaper & Ortuzar, 2015).

The study of Slaper et al. (2018) found that clusters positively influenced GDP per capita, wage levels and total income per worker. Other research also supports the effectiveness of regional clustering in promoting economic development (Almeida et al., 2020; Babkin et al., 2017; Delgado, Porter, et al., 2014; Duranton, 2011; Gamidullaeva et al., 2022; Portugal et al., 2012; Stojčić et al., 2019; Watanabe et al., 2018; Zeibote & Muravska, 2018).

Furthermore, literature also demonstrates that specialized, high-tech, and traded industries within industrial clusters tend to provide greater benefits to regions compared to diversified, low-tech, and local industries (Cortright, 2006; Grashof & Fornahl, 2021; Porter et al., 2007; Slaper & Ortuzar, 2015; Tavares et al., 2021). Traded industries also attract foreign direct investment, making them more appealing for industrial cluster policies (Babkin et al., 2013; Bathelt & Li, 2014; Delgado, Bryden, et al., 2014; Porter, 2003).

However, some studies present contradictory findings or highlight different considerations. The life-cycle stage of clusters can influence their impact on regions, and in later stages, the effect may even become negative (Elola et al., 2012, 2017; Potter & Watts, 2010). Additionally, De Blasio and Di Addario (2005) stated that working in a cluster does not provide average wage premia.

In view of the evidence, the third hypothesis is posed for contrast:

Hypothesis 3 (H3): *The presence of clusters promotes economic development.*

Another aspect that captured the attention of researchers, industrials, and policymakers is digitalization, due to its potential impact over innovation, productivity, and economic development (Babkin et al., 2018). As mentioned before, the level of technology adoption is also commonly incorporated to competitiveness indices; however, the growing interest in the phenomenon has led to the designing of exclusive indices to measure the level of digitalization of countries and regions (Atik & Ünlü, 2019; Geissbauer et al., 2018).

The ICT developments have make possible to overcome contemporaneous challenges in business and economics, creating new business models, improving the knowledge management, enhancing business performance, and diminishing the relevance of geography (Almeida et al., 2020; Knell, 2021; Usai et al., 2021). Moreover, state-of-the-art technologies commonly associated with the concept of Industry 4.0 have make possible improve the efficiency throughout the real-time and decentralized communication among people, machines and systems (Erboz, 2017; Hermann et al., 2016; Schwab, 2016).

Despite alternative research poses relevant questions about the bottom-line effect of digitalization in economy due to the loss of relational capital and the *productivity paradox*, the final effect of technology adoption seems to have a positive impact on economic variables as innovation, productivity, and economic development (Ahmad & Schreyer, 2016; Lember et al., 2019; Watanabe et al., 2018).

Thus, the fourth and fifth research hypotheses are presented:

Hypothesis 4 (H4): *Technology adoption positively influences competitiveness.*

Hypothesis 5 (H5): *Technology adoption positively influences economic development.*

Additionally, all the rationale behind competitiveness, a concept framed by classic ideas like productivity and innovation and other more contemporaneous such as digital adoption and institutional support, suggests that its improvement will undoubtedly drive to economic development (Buitrago et al., 2021; D'Urso et al., 2022; Porter et al., 2007; Schumpeter, 1934). According to such rationale, this research proposes the sixth research hypotheses:

Hypothesis 6 (H6): *Competitiveness positively influences economic development.*

At this stage, a relevant question arises related to agglomeration, digitalization, and competitiveness: how do those phenomena relate among them in a world where all are happening at the same time? The question is legitimate, particularly for industry leaders and policymakers, since all three phenomena are associated to economic development and, thus, commonly supported by public policy.

The mediating role of technology in the presence of industrial agglomeration has been less assessed than its direct effect on competitiveness; nonetheless, the issue has been around for a while (Baptista & Swann, 1998; Tavares et al., 2021). There is evidence that Industry 4.0 has a mediating role in the impact of industrial clusters to competitiveness-related variables, such as innovation (Park, 2018; Tsakalerou & Akhmadi, 2021). Moreover, technology adoption has proven to mediate the relationship among the knowledge transfer, found in clusters, and competitiveness; this effects is strongly associated to the improvement that technology provides to cluster networks (Husain et al., 2016; Rambe & Khaola, 2022).

Despite the scarcity of literature and the multiple factors that can influence such mediating effect, the previous evidence drives this research to present the seventh research hypothesis:

Hypothesis 7 (H7): *Technology adoption mediates the relationship between the presence of clusters and competitiveness.*

The relationship between clusters, technology, and economic performance has been more widely assessed; however, it has been mainly throughout qualitative and case-based analysis (Barzotto & De Propris, 2021). Nevertheless, there are quantitative studies worth to mention.

Ding et al. (2022) state that the effect of the overall level of digitalization in high-quality development is not remarkable, but such effect is promoted when the spatial knowledge-spillover is present. Besides, previous literature proposes that industrial clusters promote digital adoption and, at the same time, depend on technology to enhance their effect on economic development (Golov et al., 2021; Götz & Jankowska, 2017). Nevertheless, the direction and nature of such effect is still not clear (Buchinskaia, 2022; Y. Zhao et al., 2023).

Given the presented literature, this research proposes the eighth hypothesis:

Hypothesis 8 (H8): *Technology adoption mediates the relationship between the presence of clusters and economic development.*

The role of competitiveness as a mediating variable between cluster presence and economic development is also an issue of concern.

Innovation, as an inherent element of regional competitiveness, has proven to be an effective mediator between multiple phenomena and economic development (S. Wang et al., 2022). In the particular case of industrial clusters, the evidence shows that their effect over economic development is fundamentally connected to institutional and social support, otherwise such effect becomes weak (Rodríguez-Pose & Comptour, 2012). The social and institutional support is a traditional feature of competitiveness, and the same research demonstrates that also is a relevant player for innovation (Buitrago et al., 2021).

According to that rationale, the nineth research hypothesis is presented:

Hypothesis 9 (H9): *Competitiveness mediates the relationship between the presence of clusters and economic development.*

To conclude, technology appears to be a key driver of economic growth and development, as it enhances productivity, efficiency, and innovation, which are features of competitiveness (Afonasova et al., 2019; Ahmad & Schreyer, 2016). Besides, the impact of technology is not solely determined by its adoption but also by the competitiveness of firms and the overall business development. While technology is seen as a key driver of development, the competitiveness of firms determines how effectively technology is utilized and leveraged to achieve sustainable economic development (Awad & Albaity, 2022)

Such ideas drive to this research to present the tenth and last hypothesis:

Hypothesis 10 (H10): *Competitiveness mediates the relationship between technology adoption and economic development.*

III.3 Methodology

This chapter conducts empirical research with quantitative, descriptive, exploratory, and predictive approach, based on non-experimental and cross-sectional design.

The methodology comprises two statistical techniques. The first technique is related to the cluster mapping exercise and uses the *cluster analysis* to assess data (Everitt et al., 2011), which is a numerical method useful to group similar objects. The second technique is the *Variance-Based Partial Least Squared Structural Equation Modeling* (PLS-SEM), which employs the statistical software SmartPLS 4 (Ringle et al., 2022). The PLS-SEM is elected over the *Covariance-Based Structural Equation Modeling* CB-SEM following the next reasons: (1) it works better with small samples; (2) it works with non-parametric tests through the use of bootstrapping; (3) it allows to use reflective and formative models; and (4) it is recommended for exploratory and predictive purposes (Becker et al., 2012; Dash & Paul, 2021; Hair et al., 2017, 2022).

III.3.1 Data and sources

The data used for the cluster analysis corresponding to employment, location, and activity sector are obtained from a sample of 1,804,714 Spanish establishments, supplied by the SABI database (Iberian Balance Sheet Analysis System - sabi.bvdinfo.com). As in Chapter II, the data are retrieved for the year 2019 to avoid the economic impact of the COVID19 pandemic.

For the conduction of the PLS-SEM analysis, the research retrieves information for 50 Spanish provinces (excluding Ceuta and Melilla) from multiple sources[14]:

- The ICT Index and Industry 4.0 Index, computed for Spanish autonomous communities in Chapter II.
- The RCI for sub-index *basic* (year 2019), obtained from the European Commission.
- The labor productivity (year 2019), computed with information of the Spanish Statistical Office.
- The regional patent application per million inhabitants as innovative activity (average 2018-2019), obtained from the Spanish Patent and Trademark Office.
- The regional accounting for the real GDP per capita (year 2019), computed with information of the Spanish Statistical Office.
- The average earnings per worker of each province (year 2019), obtained from the Spanish Tax Office[15].

[14] Data were retrieved from: https://www.ine.es for real GDP per capita; http://consultas2.oepm.es/ipstat/faces/IpsBusqueda.xhtml for regional patent application per million inhabitants; and https://ec.europa.eu/regional_policy/es/information/maps/regional_competitiveness/ for Regional Competitiveness Index (RCI).

[15] For the province of Navarre, the information was obtained from the Spanish Statistical Office; in the case of the Basque Country's provinces, the information was computed with data of the Basque Statistical Institute.

III.3.2 About the cluster analysis

The methodology departs from that presented in Chapter II, which describes the current algorithm used to establish *Cluster Category Definitions* in Spain, and it is an adaptation of the methodology previously applied in the US (Delgado et al., 2016). However, in this chapter the analysis leaves from the National Classification of Economic Activities for Spanish industries (CNAE-2009) at 3-digits level (272 codes) and uses provinces as spatial units to analyze data (NUTS-3, 50 provinces excluding Ceuta and Melilla).

Additionally, this chapter implements minor adaptations to the six steps presented in Chapter II, with the purpose of improving the results considering the different level of disaggregation of the data. Such adaptations are summarized in the next points:

- This analysis uses only three unidimensional similarity matrices (co-location pattern for employment, co-location pattern for establishments, and geographic concentration of employment), and two multidimensional ones (a combination of co-location patterns, and a combination of all dimensions).
- The study applies a variation of the multi-criterion methodology used to identify traded industries. It keeps the export to gross value-added ratio criterion but changes the cutoff of the locational Gini Coefficient[16]. Since the ratio is computed at CNAE-2009 2-digit level due data limitations, the Gini Coefficient is computed for 2-digit and 3-digit levels separately, obtaining two different groups of traded industries for subsequent and separate analyses.
- There is an additional final step for “cleaning-and-debugging” the identified clusters that aims to improve their quality (Delgado et al., 2016). It evaluates each individual cluster to find outsiders, which are industries that according to expert judgment do not fit in their assigned cluster. The outsiders are reassigned to different groups through the reviewing of different cluster combinations provided by the algorithm; those outsiders that keep isolated are discarded since individual clusters of one single industry are pointless for the analysis.

[16] The cutoff is set at 0.03, in contrast with the selection of 0.01 in Chapter II, as multiple cutoffs were tested looking for the set of traded industries with the maximum overlap with the set defined in the previous chapter.

III.3.3 The PLS-SEM analysis

III.3.3.1 Items and constructs

The items and constructs used for the structural model are listed below, which are based on the collected data[17].

Cluster presence (Cl) as *exogenous variable*. This first-order-and-one-single-item construct is measured by one dimension: the count of industrial clusters that exist in each Spanish province assessed by TESh (top employment share) (*C_Esh*). This discrete variable is computed with data of this research; the cluster presence by TESh is selected over TESp (top employment specialization) and TESS (top employment specialization & share) because it correlates better with economic development variables, as demonstrated in Chapter II.

[17] The next notes explain the basic terms of Partial Least Squares Structural Equation Modeling (PLS-SEM) according to Hair et al. (2022). Please note that related terminology can vary slightly across different sources and scholars.

- Construct: In the context of PLS SEM theory, a construct refers to an underlying concept or idea that is not directly observable (latent variable) but is inferred from multiple observed variables (manifest variables).
- Item: An item is an observed variable or indicator used to measure a construct. Items are the measurable components that provide information about the underlying construct.
- First-Order Construct: A first-order construct is a latent variable that is directly measured by its indicators (items). It represents a single underlying concept or dimension.
- Formative Construct: A formative construct is a type of construct where the indicators together form or define the construct. In other words, the indicators contribute to shaping the construct. Contrastingly, in a reflective construct the indicators are a manifestation of the construct.

Level of technology adoption (*Tech Ad*) as *mediating variable*. This first-order construct of a formative type is measured by two items: the ICT index (*ICT_Index*) and the Industry 4.0 index (*IN4_Index*). Both continuous variables are computed in the previous chapter at NUTS-2 level since there are not representative statistical information at NUTS-3, then the data for the region is allocated to each of its provinces.

Competitiveness (*Comp*) as *mediating variable*. This first-order construct of a formative type is measured by three items: the RCI basic sub-index *(RCI_Basic)*, the productivity per worker (€ per year) (*Prod_2019*), and patent applications to million inhabitant ratio (*Inn_2019*). The latter two continuous variables are computed for the year 2019 at NUTS-3 level, while the former at NUTS-2 level since there are not representative statistical information at NUTS-3 (the data for the region is allocated to each of its provinces as in the previous cases).

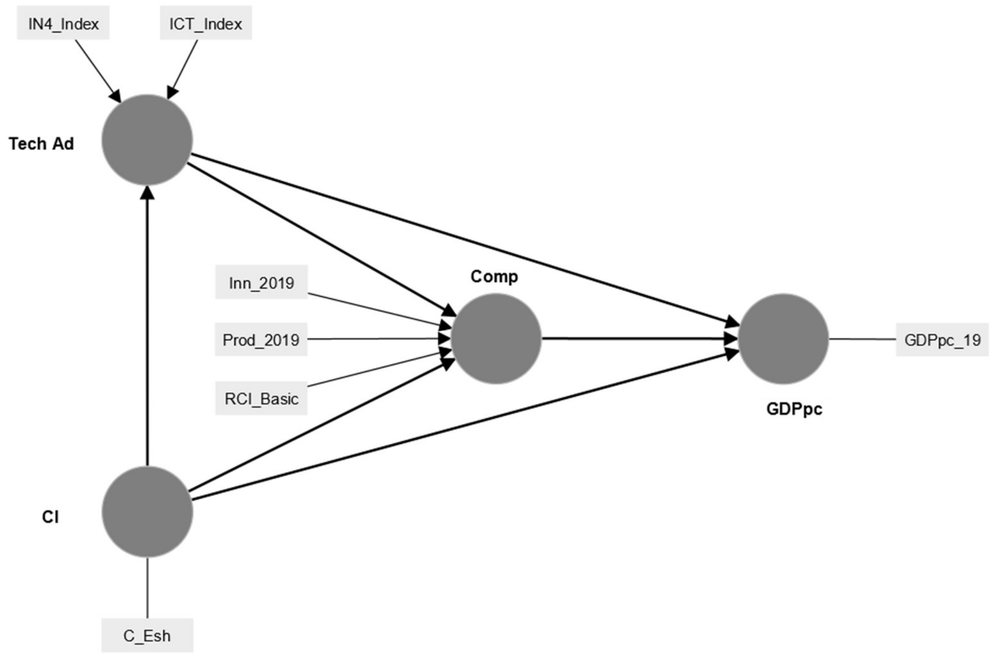
Gross domestic product per capita (*GDPpc*) as *endogenous variable*. This first-order-and-one-single-item construct is measured by one dimension: the gross domestic product per capita of each province (€ per year) (*GDPpc_19*). This continuous variable is computed for the year 2019 and is elected as a proxy for economic development.

Earnings per worker (*EpW*) as *endogenous variable*. This first-order-and-one-single-item construct is measured by one dimension: the average earnings per worker of each province (€ per year) (*EpW_19*). This continuous variable is computed for the year 2019 and is also elected as a proxy for economic development.

III.3.3.2 The measurement models: validity and reliability

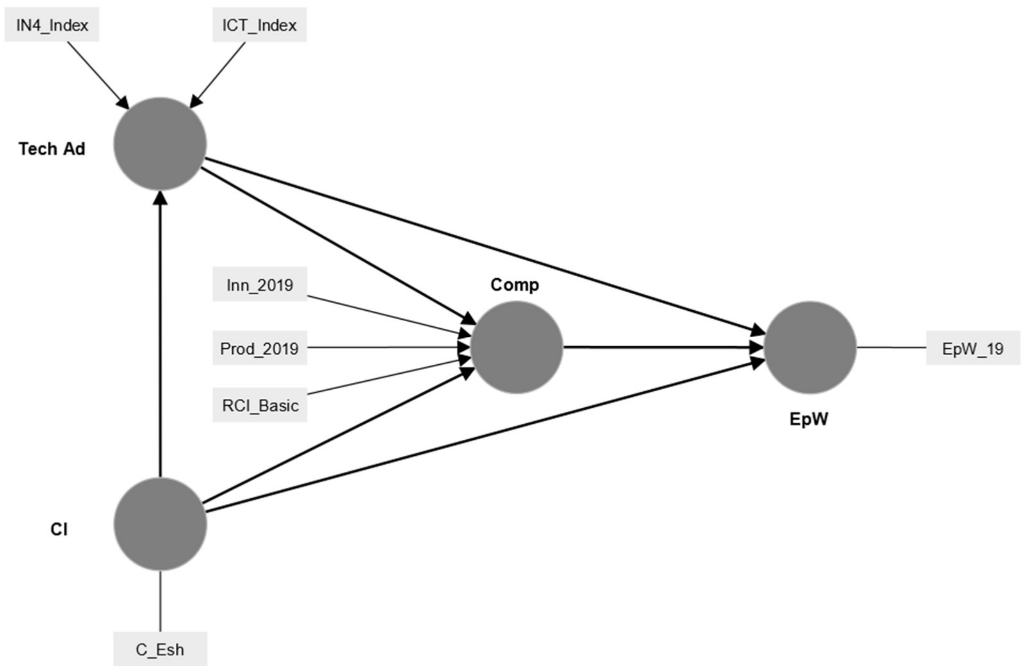
Due to there are two endogenous variables (*GDPpc* and *EpW*), there are also two structural models: *Model a* and *Model b* (**Figure III.1** and **Figure III.2**). Each model uses the same exogenous and mediating variables and the same items. Thus, each hypothesis will be contrasted twice, depending on which endogenous variable is involved.

Figure III.1. Structural *Model a* with GDPpc as endogenous variable.



SOURCE: Author's elaboration.

Figure III.2. Structural *Model b* with EpW as endogenous variable.

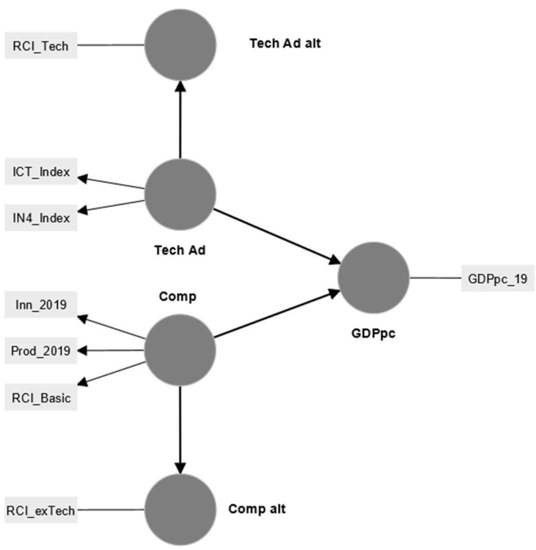


SOURCE: Author's elaboration.

The study evaluates the validity and reliability of the formative measurement models, following three steps proposed by literature (Hair et al., 2022; Hanafiah, 2020). These steps seek to assess convergent validity, collinearity issues, and the statistical significance and relevance of the formative items. Such evaluations consider only the first-order formative-constructs and depart from the PLS-SEM algorithm.

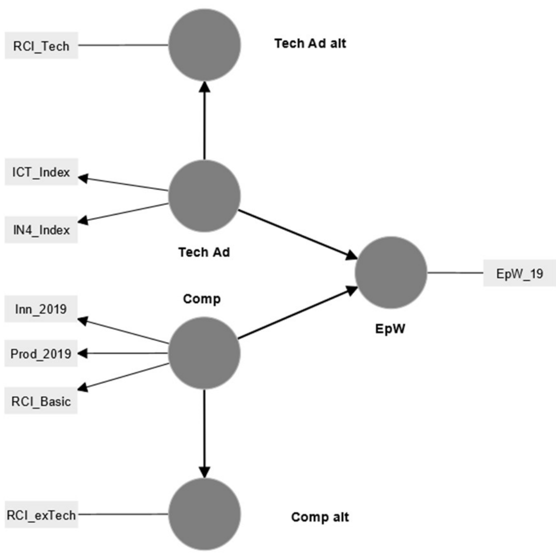
Step 1 assesses the convergent validity through the redundancy analysis (Cheah et al., 2018; Chin, 1998; Houston, 2004). To assess the formative constructs (*Tech Ad* and *Comp*), the study uses one global construct of one-single-item for each construct. The first global construct (*Tech Ad alt*) is measured by an alternative index that assess technology adoption (*RCI_Tech*); the second global construct (*Comp alt*) is measured by an alternative competitiveness index that excludes technology adoption (*RCI_exTech*). Two structural models are built to assess the convergent validity, one for *Model a* and other for *Model b* (**Figure III.3** and **Figure III.4**).

Figure III.3. Structural model for the convergent validity assessment of *Model a* with GDPpc as endogenous variable.



SOURCE: Author's elaboration.

Figure III.4. Structural model for the convergent validity assessment of *Model b* with EpW as endogenous variable.



SOURCE: Author's elaboration.

Step 2 assesses the existence of collinearity issues (Hair et al., 2014). The recommended metric for assessing the formative items' collinearity is the Variance Inflation Factor (VIF).

Step 3 assesses the statistical significance and relevance of the formative items for both models (Hanafiah, 2020). This chapter runs bootstrapping (based on 5,000 subsamples) to obtain the weights and loadings for each item, including their statistical significance.

III.4 Results

III.4.1 The cluster analysis results

Departing from 272 industries classified by CNAE-2009 3-digit codes, the study configures two sets of traded industries: one adjusted for CNAE-2009 2-digits and another for the full 3-digits. Both sets meet the key attributes established in Chapter II: the exclusion of industries that conceptually are classified as local (e.g., real state, retail, local transportation, and sewerage), and the improving of the correlation between similarity matrices of traded industries when compared with correlation between similarity matrices for all industries.

The cluster algorithm is applied over the ten similarity matrices (five for each set of traded industries) and 620 groups of clusters (*C*) are obtained (the number is equal to all possible combinations of the cluster algorithm parameters). The quality of the groups of clusters is assessed, and following the quality measures the elected group of clusters (*C**) corresponds to 31 individual clusters grouped with the Hierarchical-Ward's function, using the *co-location pattern for employment* similarity matrix (LC_Emp) that departs from the set of traded industries adjusted for CNAE-2009 2-digits.

The *C** is evaluated to find outsiders in each individual cluster; the analysis finds 29 outsiders. Fourteen outsiders are reassigned to other cluster and other 15 are discarded from the study, following the criteria for “cleaning-and-debugging” presented in the methodology. The final configuration of *C** includes 30 clusters and 144 industries. **Table III.1** presents the Cluster Category Definitions for the Spanish territory.

Table III.1. Cluster Category Definitions (CCD) for each individual cluster (c), preceded by a consecutive 2-digits code; columns *IN* (industry) show the detail of the industries included in each cluster (CNAE-2009 3-digit codes).

IN	CCD	IN	CCD	IN	CCD
011	01 Agricultural cluster	072	11 Non-ferrous metal	267	24 Research, computer, and
012		503	extractions and transportation	591	business services cluster
015		504	cluster	592	
016		089	12 Dairy and beef cluster	602	
022		101		620	
023		105		631	
103		099	13 Precast concrete cluster	639	
013	02 Agribusiness	236		662	
104	cluster	024	14 Furniture and apparel	731	
106		141	cluster	732	
014	03 Livestock cluster	161		791	
109		162		799	
292		310		802	
061	04 Heavy-vehicles	108	15 Biochemical cluster	803	
091	cluster	201		812	
192		205		813	
301		211		821	
302		261	16 Automotive cluster	823	
303		265		829	
304		271		511	25 Communication and
381		282		581	professional services
512	05 Telecommunications	291		601	
582	and financial services	321		613	
611	cluster	329		661	
612		107	17 Food cluster	701	
619		110		702	
642		142		811	
643		212		244	26 Telecoms equipment
649		231	18 Basic-electronics cluster	263	manufacturing cluster
663		264		239	27 Abrasives, non-ferrous
801		274		272	aggregates, and batteries
					manufacturing cluster
822		325		243	28 Mechanical cluster
021	06 Forestry cluster	131	19 Textile cluster	245	
283		132		253	
390		133		257	
081	07 Metallic infrastructure	151		281	
242	cluster	139	20 Chemical cluster	284	
251		202		293	
252		204		309	
031	08 Fish and seafood	222		255	29 Metal manufacturing
032		143	21 Manufacturing based on	256	cluster
102		273	fibers and cables cluster	259	
051	09 Steel cluster	323		279	
052		152	22 Footwear and toy	289	
191		324	cluster	203	30 Coats and dyes cluster
232		235	23 Construction aggregates	233	
241		237	cluster	234	
062	10 Iron and natural gas	382			
071	extraction cluster				

SOURCE: Author's elaboration.

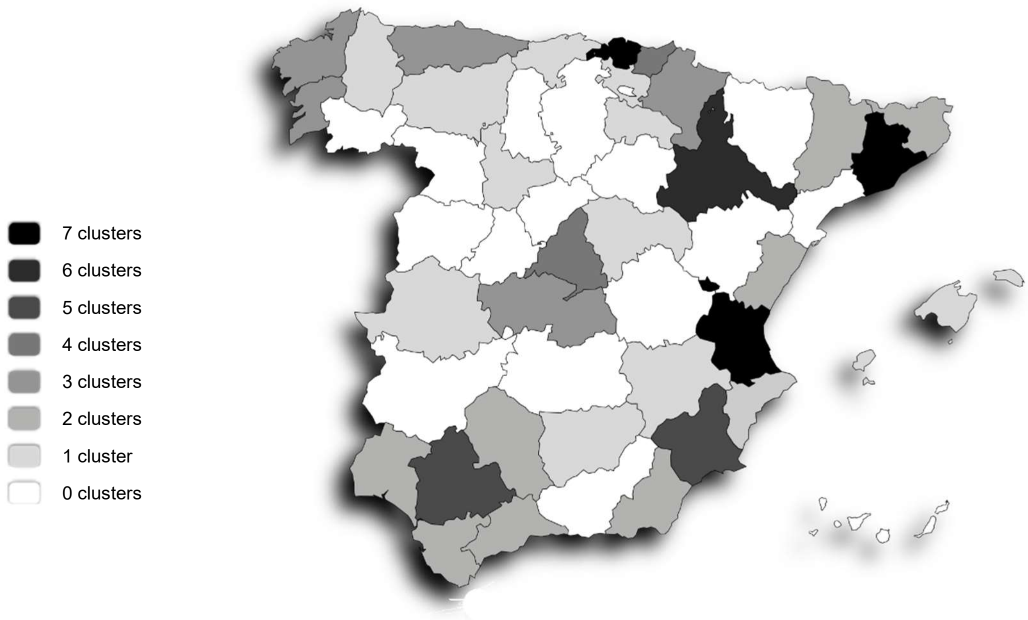
The total number of clusters present in each province is shown in **Table III.2**, distinguishing among clusters presence by TESp, TESh, and TESS (the specific cluster presence in each province can be found in **Table III.3**). **Figure III.5** presents a map-chart that departs from clusters presence by TESS.

Table III.2. Cluster presence by top employment specialization (TESp), top employment share (TESh), and top employment specialization & share (TESS).

Province (NUTS-3)	TESp	TESh	TESS	Province (NUTS-3)	TESp	TESh	TESS
a Coruña	4	3	3	La Rioja	6	1	1
Alava	9	1	1	Las Pal. de G. Can.	7	0	0
Albacete	6	1	1	León	8	1	1
Alicante	4	5	4	Lleida	4	2	2
Almería	3	2	2	Lugo	8	1	1
Asturias	6	3	3	Madrid	4	23	4
Avila	0	0	0	Málaga	3	2	2
Badajoz	4	0	0	Murcia	5	7	5
Baleares	4	1	1	Navarra	7	6	3
Barcelona	7	22	7	Ourense	7	0	0
Burgos	7	0	0	Palencia	0	0	0
Cáceres	5	1	1	Pontevedra	6	3	3
Cádiz	5	2	2	Salamanca	3	0	0
Cantabria	8	1	1	Sta. Cruz de Ten.	3	0	0
Castellón	5	2	2	Segovia	2	0	0
Ciudad Real	9	0	0	Sevilla	5	6	5
Córdoba	8	2	2	Soria	0	0	0
Cuenca	2	0	0	Tarragona	7	0	0
Girona	7	2	2	Teruel	4	0	0
Granada	5	1	0	Toledo	11	3	3
Guadalajara	1	2	1	Valencia	7	17	7
Guipuzcoa	7	5	4	Valladolid	1	1	1
Huelva	3	2	2	Vizcaya	7	10	7
Huesca	5	0	0	Zamora	3	0	0
Jaen	9	1	1	Zaragoza	8	7	6
Total					259	149	91

SOURCE: Author's elaboration.

Figure III.5. Cluster presence by top employment specialization & share (TESS).



SOURCE: Author's elaboration.

Table III.3. Clusters presence by province (C* set).

	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
a Coruña							***	***						***												*				
Alava				*			*		*								*	***			*						*	*	*	
Albacete	*						*							*				*				***								*
Alicante															**				***	***		***	***							
Almería	***																						*				***			
Asturias							*		***		***							*								***			*	
Avila																														
Badajoz	*	*							*																		*			
Baleares																						*	*	*	***					
Barcelona		**	**		**	**	**					**	**	**	***	***	**	***	***	***	***		**	***	**	**		**	**	**
Burgos				*			*						*				*			*								*	*	
Cáceres	*	*				*				***			*																	
Cádiz				*				*	***								*		***											
Cantabria							*	***	*										*		*		*					*	*	
Castellón								*						*	*												***			***
Ciudad Real	*		*				*						*	*			*		*							*	*			
Córdoba	*	***	*			*			*				***	*		*														
Cuenca													*	*																
Girona												***			*				***	*	*								*	*
Granada		*				*			*	**		*												*						
Guadalajara											***																**			
Guipuzcoa				***					***				**			*					***						*	*	***	
Huelva	***							*			***																			
Huesca	*	*	*			*									*															
Jaen		***		*		*								*				*	*	*								*		*
La Rioja														*			*			*		***							*	*
Las Pal. de G. Can.	*							*			*						*	*						*	*					

	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
León						*	*					*			*		*				***		*						*	
Lleida	*		***			***							*																	
Lugo			*			*	*	***				*					*						*							*
Madrid			**	***	***	**	**		**	**		**	**	**	**	**	**	**		**	**		**	***	***	**	**		**	**
Málaga		***																						*	***					
Murcia	***				**							**		***	***					***		***								
Navarra	**		**						*						*	***	**			*							***	***	*	
Ourense						*	*				*			*						*	*		*							
Palencia																														
Pontevedra								***								*					*		***			***		*		
Salamanca			*									*							*											
Sta. Cruz de Ten.	*																							*	*					
Segovia			*									*																		
Sevilla	***	***		***							***						**							***						
Soria																														
Tarragona		*					*	*							*				*	*								*		
Teruel			*						*			*																		*
Toledo			*	*			*					*	***	*		*						***	*			*				***
Valencia				**	**	**	**					**		***	***		**	***	***	***			***	**	**			**	**	***
Valladolid																***														
Vizcaya				***	**		**	***	***	**														***		***		***	***	
Zamora		*										*															*			
Zaragoza			**			***				***						***		***			***	*				*		***		

SOURCE: Author’s elaboration.

NOTE: The numbers at the top represent the 2-digits code for each Cluster Category Definition. The table distinguish clusters presence by top employment specialization (TESp) (*), by top employment share (TESh) (**), and by top employment specialization & share (TESS) (***).

III.4.2 The structural models results

Once clusters are mapped all over the Spanish provinces, it is possible to start with the PLS-SEM analysis.

Table III.4 presents the descriptive statistics for all items and **Table III.5** the correlations among them. According to the Shapiro–Wilk test (Shapiro & Wilk, 1965), the data of all items are not normally distributed, except for *Inn_2019*, supporting the decision of applying PLS-SEM instead of CB-SEM (Hair et al., 2017).

Table III.4. Descriptive statistics for items (N=50).

	Mean	Median	Std. Dev.	Min.	Max
C_Esh	2.980	1.000	5.073	0.000	23.000
ICT_Index	0.550	0.588	0.149	0.245	0.829
IN4_Index	0.458	0.435	0.132	0.212	0.808
RCI_Basic	-0.084	-0.116	0.122	-0.213	0.302
Prod_2019	56861.339	55069.299	8698.692	41946.567	84400.958
Inn_2019	21.684	20.430	13.010	0.000	59.592
GDPpc_19	23525.221	21963.580	4866.707	16885.687	37140.531
EpW_19	19518.308	19120.450	3554.472	14261.500	30146.685

SOURCE: Author's elaboration.

NOTE: *N* stands for number of observations, one for each province excluding Ceuta and Melilla.

Table III.5. Correlations between items.

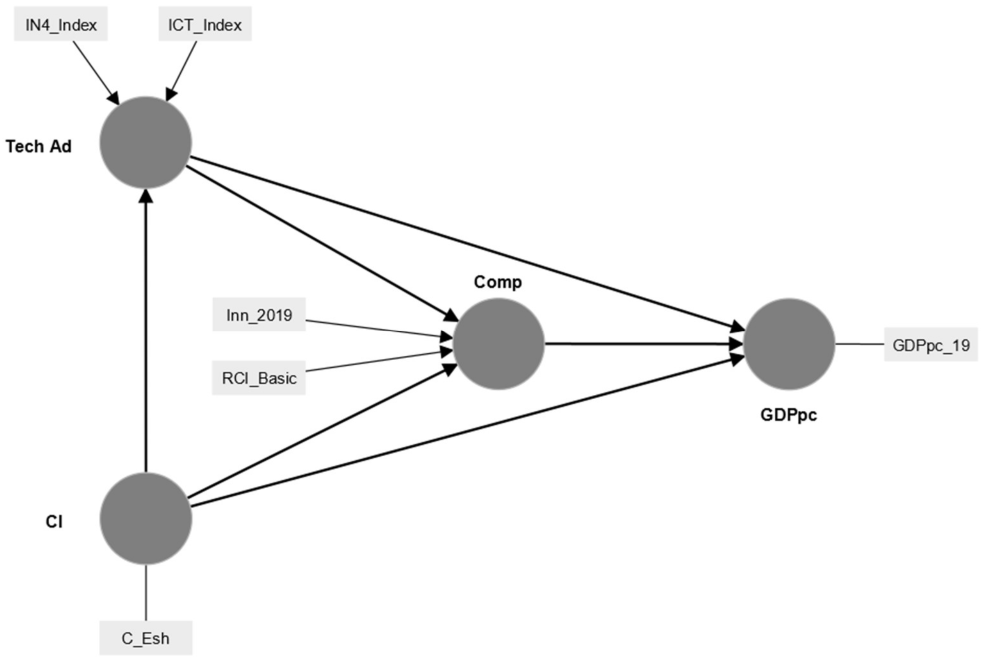
	C_Esh	ICT_Index2	IN4_Index2	RCI_Basic	Prod_2019	Innov_2019	GDPpc_19	EpW_19
C_Esh	1.000							
ICT_Index	.490**	1.000						
IN4_Index	.514**	.598**	1.000					
RCI_Basic	.447**	.304*	.718**	1.000				
Prod_2019	.335*	.407**	.610**	.452**	1.000			
Innov_2019	.451**	.289*	.350*	.196	.454**	1.000		
GDPpc_19	.383**	.423**	.639**	.578**	.936**	.455**	1.000	
EpW_19	.484**	0.253	.573**	.501**	.803**	.503**	.840**	1.000

SOURCE: Author's elaboration.

NOTE: *Coefficients are significant at 5% level. **Coefficients are significant at 1% level.

Before continuing with the validity and reliability assessment of the structural models, an alternative *Model a* is tested excluding the item *Prod_2019* due to the high correlation between the items *GDPpc_19* and *Prod_2019*, added to their conceptual similarity. Further assessment demonstrates that the exclusion of such item from the construct *Comp* in *Model A* improves the significance of total effects and indirect effects in the structural model. Therefore, such model is reformulated so that *Comp* is measured only for two items (*RCI_Basic* and *Inn_2019*) in such model, modifying the original proposal (see **Figure III.6**).

Figure III.6. Reformulated structural *Model a* with GDPpc as endogenous variable.



SOURCE: Author’s elaboration.

The validity and reliability assessment of the measurement models obtained the next results.

- **Step 1.** For *Model a*, the results of the redundancy analysis yield a standardized path coefficient (β) of 0.813 and 0.785 for *Tech Ad* and *Comp*, respectively. For *Model b*, the results of the redundancy analysis yield a β of 0.812 and 0.869 for *Tech Ad* and *Comp*, respectively. All four values are above the recommended threshold of 0.708 (Hair et al., 2022), providing support for the formatively measured constructs’ convergent validity.
- **Step 2. Table III.6** shows the VIF values for the formative measurement models. According to the collinearity evaluation, the results indicate that none of the items reached the threshold value of 3.3. Therefore, collinearity is not an issue in this research (Kock, 2017).
- **Step 3. Table III.7** shows the outer weights and loadings for the items in *Model a* and *Model b*. According to the rules of thumb of Hair et al. (2022), all items provide a relative contribution for their respective constructs (statistically significant weights), except *ICT_Index*, which only provides an

absolute contribution (the outer loading is higher than 0.5). However, such indicator is retained with the others, since its absolute contribution can still be as substantial for the measurement models as the relative contributions of the other indicators (Cenfetelli & Bassellier, 2009).

Table III.6. Collinearity test to assess common method bias for *Model a* and *Model b*.

	Variance inflation factor (VIF) values	
	Model a	**Model b**
ICT_Index	1.558	1.558
IN4_Index	1.558	1.558
Inn_2019	1.040	1.260
RCI_Basic	1.040	1.256
Prod_2019		1.522

SOURCE: Author's calculations obtained with SmartPLS 4.

Table III.7. Outer weights and loadings for the items in Model a (Ma) and Model b (Mb) obtained throughout the bootstrapping technique (5,000 subsamples).

	Outer weights		Outer loadings	
	Model a	**Model b**	**Model a**	**Model b**
ICT_Index -> Tech Ad	0.096	0.042	0.658**	0.625**
IN4_Index -> Tech Ad	0.940**	0.974**	0.997**	0.999**
Inn_2019 -> Comp	0.455**	0.211**	0.614**	0.570**
RCI_Basic -> Comp	0.805**	0.458**	0.895**	0.767**
Prod_2019 -> Comp		0.591**		0.894**

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: **The value shows statistical significance at 99% for both *t-value* and *p-value*.

Given that both models overcome the 3-Step validity and reliability assessment, it is expected that the obtained results from the structural model assessment are valid and reliable, thus capable to contrast the research hypotheses. Consequently, the study assesses the structural models through the PLS-SEM algorithm, using bootstrapping with 5,000 subsamples, yielding the following results based on one-tailed tests (Kock, 2015).

The outcomes suggest that the structural model has in-sample explanatory capacity (Ringle et al., 2022). The coefficients of determination (R^2) of the endogenous constructs range from 0.281 to 0.556 in *Model a* and from 0.272 to 0.675 in *Model b* (**Table III.8**). The cluster presence explains the level technology adoption in 28.1% for *Model a* and 27.2% for *Model b*. The competitiveness is explained by the cluster presence and the level technology adoption in 55.7% for *Model a* and 59.6% for *Model b*. Likewise, *GDPpc* is explained in 50.3% by the cluster presence, competitiveness, and the level technology adoption in *Model a*, and *EpW* is explained in 67.5% by the same constructs in *Model b*. The explanatory capacity of both models remains consistent for the level technology adoption as expected; something similar occurs for competitiveness, in spite of the excluded item (Prod_2019) in such construct for *Model a*.

Table III.8. Explanatory capacity of the structural Model a (Ma) and Model b (Mb).

Endogenous variables	R^2	Explanatory capacity	f^2	Power
Model a				
Level of technology adoption (Tech Ad)	0.281	Weak	0.391	0.991
Competitiveness (Comp)	0.557	Moderate	1.257	1.000
Gross domestic product per capita (GDPpc)	0.503	Moderate	1.012	0.999
Model b				
Level of technology adoption (Tech Ad)	0.272	Weak	0.374	0.988
Competitiveness (Comp)	0.596	Moderate	1.475	1.000
Earnings per worker (EpW)	0.675	Substantial	2.077	1.000

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: Reference for R^2 values (Ringle et al., 2022): >0.20 = weak; >0.33 = moderate; >0.67 = substantial. Reference for f^2 (effect-size) (Cohen, 1988): >0.02 = small effect; >0.15 = medium effect; >0.35 = large effect.

Additionally, the study performs a post-hoc evaluation (computing achieved power) using G*Power 3.1.9.7 (Faul et al., 2009) to assess the explanatory capacity of the models and evaluate their statistical power. The assessment departs from the R^2 values of the endogenous variables, which are used as reference to estimate the effect size of the exogenous/mediating variables in their respective model (f^2)[18]. The estimated power for each mediating and endogenous variable is above the threshold value of 0.80, indicating that both research models have statistical power.

III.4.2.1 Direct effects assessment

According to the evaluation of the direct effects and the test of the first group of hypotheses (H1 to H6), this research reaches the findings shown in **Table III.9**. The significance assessment of all effects is based on *p-values* of β, and their bias-corrected-and-accelerated confidence intervals (Ci) (Aguirre-Urreta & Rönkkö, 2018; Hair et al.,

---

[18] The additional reference values for the assessment are α=0.05, total sample size=50, and the number of predictors is equal to the number of exogenous/mediating variables pointing to the respective endogenous variable.

2022); additionally, the direct effect-size assessment is based on the work of Cohen (1988).

Table III.9. Direct effects assessment of the structural *Model a* and *Model b*.

	Path	β	*p-value*	f^2	95% Ci bias-corrected	Decision
Model a						
$H1_{GDP}$	CI -> Tech Ad	0.530	0.000	0.391	[0.225,0.730]	Supported
$H2_{GDP}$	CI -> Comp	0.248	0.006	0.105	[0.102,0.425]	Supported
$H3_{GDP}$	CI -> GDPpc	-0.055	0.309	0.004	[-0.233,0.121]	Not supported
$H4_{GDP}$	Tech Ad-> Comp	0.598	0.000	0.607	[0.356,0.732]	Supported
$H5_{GDP}$	Tech Ad-> GDPpc	0.335	0.020	0.101	[0.050,0.582]	Supported
$H6_{GDP}$	Comp -> GDPpc	0.459	0.003	0.179	[0.199,0.742]	Supported
Model b						
$H1_{EPW}$	CI -> Tech Ad	0.521	0.001	0.373	[0.208,0.724]	Supported
$H2_{EPW}$	CI -> Comp	0.138	0.107	0.034	[-0.030,0.328]	Not supported
$H3_{EPW}$	CI -> EpW	0.138	0.067	0.041	[-0.007,0.294]	Not supported
$H4_{EPW}$	Tech Ad-> Comp	0.691	0.000	0.859	[0.507,0.795]	Supported
$H5_{EPW}$	Tech Ad-> EpW	-0.164	0.086	0.032	[-0.368,0.019]	Not supported
$H6_{EPW}$	Comp -> EpW	0.866	0.000	0.934	[0.650,1.028]	Supported

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: The standardized path coefficient (β) is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta & Rönkkö, 2018; Hair et al., 2022). Reference for f^2 (effect-size) (Cohen, 1988): >0.02 = small effect; >0.15 = medium effect; >0.35 = large effect.

Concerning to H1, the cluster presence has a positive and large effect on the level of technology adoption ([β=0.530, f^2=0.391] and [β=0.521, f^2=0.373] for *Model a* and *Model b*, respectively). Therefore, H1 is supported, and the results confirms previous studies (Alcacer et al., 2016; Almeida et al., 2020; Corradini et al., 2021; Geissbauer et al., 2018).

Regarding to H2, the cluster presence has a positive and small effect on competitiveness for *Model a* (β=0.248, f^2=0.105), whereas for *Model b* the cluster presence does not demonstrates a significant effect on competitiveness. Consequently, $H2_{GDP}$ is supported as suggested by literature (Babkin et al., 2017; Ortega-Colomer et al., 2016; Tavares et al., 2021; Wilson et al., 2022), while $H2_{EPW}$ is not, reopening the debate promoted by Grashof & Fornahl (2021).

For H3, the analysis does not find a significant effect from cluster presence to *GDPpc* nor to *EpW*; therefore, this research does not support that hypotheses in contrast with previous studies that assess such relation (Delgado, Porter, et al., 2014; Gamidullaeva et al., 2022; Slaper et al., 2018).

As to H4, the level of technology adoption has a positive and large effect on competitiveness ([β=0.598, f^2=0.607] and [β=0.691, f^2=0.859] for *Model a* and *Model b*, respectively). Thus, H4 is supported, similarly to previous findings made by Atik and Ünlü (2019), and Babkin et al. (2018).

Regarding to H5, the level of technology adoption has a positive and small effect on *GDPpc* (β=0.335, f^2=0.101), whilst not significant effect from the level of technology adoption to *EpW* is found. Therefore, $H5_{GDP}$ is supported in accordance with previous literature (Knell, 2021; Usai et al., 2021). However, $H5_{EPW}$ is not supported, backing the discussion about the relation between technology and salaries (Ahmad & Schreyer, 2016; Lember et al., 2019; Watanabe et al., 2018).

Finally, concerning to H6, the competitiveness demonstrates to have a positive and medium effect on *GDPpc*, and a positive and large effect on *EpW* ([β=0.459, f^2=0.179] and [β=0.866, f^2=0.934] for *Model a* and *Model b*, respectively). These results support H6 and validates previous research in the competitiveness topic (Buitrago et al., 2021; D'Urso et al., 2022).

III.4.2.2 Mediation effects assessment

Additionally, this research evaluates mediation effects in the form of specific indirect effects[19]. To support such analysis, the total effect assessment is made for variables which relationship is expected to be mediated by another one; if the total effect is significant, there is a better chance to find a mediation and direct effects (Baron & Kenny, 1986). The assessment finds that there are significant total effects among all the concerned variables for both models (**Table III.10**).

[19] While the direct effects are given by the computed standardized path coefficient (β) between two constructs, the indirect effect is the product of two or more direct effects found among three or more constructs, where there is at least one exogenous, one mediating and one endogenous. The total indirect effect is the sum of all the indirect effects found in a multi-mediation model.

Table III.10. Total effects assessment of the structural *Model a* and *Model b*.

		Total effect	***p-value***	**95% Ci bias-corrected**
Model a				
CI	-> Comp	0.565	0.000	[0.291,0.737]
CI	-> GDPpc	0.383	0.006	[0.101,0.594]
Tech Ad	-> GDPpc	0.610	0.000	[0.416,0.758]
Model b				
CI	-> Comp	0.498	0.001	[0.177,0.697]
CI	-> EpW	0.484	0.000	[0.242,0.626]
Tech Ad	-> EpW	0.435	0.000	[0.253,0.597]

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: The total effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta & Rönkkö, 2018; Hair et al., 2022).

Once the total effects are demonstrated, the mediation analysis tests the second group of hypotheses (H7 to H10). In this matter, the research obtains the results shown in **Table III.11**. Additionally, the Variance Accounted For (*VAF*) criterion is applied to assess *only complementary partial mediations*[20] (Hair et al., 2022; X. Zhao et al., 2010).

Table III.11. Indirect effects assessment of the structural *Model a* and *Model b*.

		Indirect effect	***p-value***	**95% Ci bias-corrected**	**Decision**
Model a					
H7$_{GDP}$	CI -> Tech Ad -> Comp	0.317*	0.001	[0.136,0.460]	Supported
H8$_{GDP}$	CI -> Tech Ad -> GDPpc	0.178**	0.045	[0.042,0.393]	Supported
H9$_{GDP}$	CI -> Comp -> GDPpc	0.114**	0.027	[0.039,0.242]	Supported
H10$_{GDP}$	Tech Ad -> Comp -> GDPpc	0.274*	0.014	[0.119,0.529]	Supported
Model b					
H7$_{EPW}$	CI -> Tech Ad -> Comp	0.360**	0.001	[0.157,0.546]	Supported
H8$_{EPW}$	CI -> Tech Ad -> EpW	-0.085	0.094	[-0.219,-0.003]	Not supported
H9$_{EPW}$	CI -> Comp -> EpW	0.120	0.113	[-0.026,0.299]	Not supported
H10$_{EPW}$	Tech Ad -> Comp -> EpW	0.598**	0.000	[0.384,0.776]	Supported

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: *Partial mediation; **Full mediation (according to Hair et al. (2022) and X. Zhao et al. (2010)). The indirect effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta & Rönkkö, 2018; Hair et al., 2022).

[20] If VAF: <20% = no mediation; >=20% and <80% = partial mediation; >80% = full mediation. The VAF is computed and presented in text only for cases of complementary partial mediation.

Concerning to H7, the level of technology adoption mediates the relation between the cluster presence and competitiveness. However, in the case of *Model a*, there is a partial mediation (total effect = 0.565, VAF=56.1%) since there is also a direct and significant effect from cluster presence to competitiveness. In contrast, for the case of *Model b*, there is a full mediation as there is not a direct and significant effect from cluster presence to competitiveness. Therefore, the hypotheses is supported as literature indicates (Husain et al., 2016; Park, 2018; Rambe & Khaola, 2022).

In relation to H8, the research finds a full mediation of the level of technology adoption between the cluster presence and *GDPpc.* In contrast, the analysis does not find a mediation of the level of technology adoption between the cluster presence and *EpW.* Thus, $H8_{GDP}$ is supported but $H8_{EPW}$ is not, fostering the discussion started by literature (Buchinskaia, 2022; Ding et al., 2022; Golov et al., 2021).

In the case of H9, the analysis finds a full mediation of competitiveness between the cluster presence and *GDPpc.* Differently*,* the research does not find a mediation of competitiveness between the cluster presence and *EpW.* Thus, $H9_{GDP}$ is supported and $H9_{EPW}$ is not, posing another debate over previous findings (Buitrago et al., 2021; Rodríguez-Pose & Comptour, 2012; S. Wang et al., 2022).

To conclude, concerning to H10, the competitiveness demonstrates to partially mediate the relationship between the level of technology adoption and *GDPpc* (total effect = 0.610, VAF=45.0%), and fully mediate the relationship between the level of technology adoption and *EpW,* validating previous research in the competitiveness topic (Afonasova et al., 2019; Ahmad & Schreyer, 2016; Awad & Albaity, 2022).

The mediation analysis also reports specific indirect effects that are valuable for further discussion, even when they are out of the scope of the hypothesis testing. **Table III.12** shows two findings: cluster presence has a significant-and-relevant specific indirect effect over *GDPpc* that follows the path CI -> Tech Ad -> Comp -> GDPpc, which provides the 33.2% of the total indirect effect of *CI* over *GDPpc* (0.437). Similar but even more significant-and-relevant is the specific indirect effect of *CI* over *EpW* that follows the path CI -> Tech Ad -> Comp -> EpW, which represents the 90.2% of the total indirect effect of such relation (0.346).

Table III.12. Specific indirect effects assessment of the structural *Model a* and *Model b*.

	Indirect effect	***p-value***	**95% Ci Bias Corrected**
Model a			
CI -> Tech Ad -> Comp -> GDPpc	0.145	0.033	[0.050,0.324]
Model b			
CI -> Tech Ad -> Comp -> EpW	0.312	0.004	[0.115,0.507]

SOURCE: Author's calculations obtained with SmartPLS 4.

NOTE: The specific indirect effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta & Rönkkö, 2018; Hair et al., 2022).

III.4.2.3 Predictive power assessment

To conclude the assessment, the predictive power of the structural models is evaluated with the PLSpredict algorithm, aiming to know the out-of-sample predictive power of the models or, in other words, how well their results could be generalized beyond the sample. (Shmueli et al., 2016).

The Q^2 values for all manifest variables in *Model a* and *Model b* are greater than zero, suggesting that they have predictive relevance (Hair et al., 2013). Consequently, the study advances in the assessment of the predictive power of the whole structural models through the evaluation of the Mean Absolute Errors (MAE) (Shmueli et al., 2019). Such measure is preferred over the Root Mean Square Error (RMSE) because the prediction error distributions are nonsymmetric (long right-tails are observed). The PLSpredict MAE values for each manifest values are compared against their benchmark, the Naïve Linear Regression (LM) MAE values.

As **Table III.13** shows, the majority of the PLSpredict MAE values in each model yield smaller prediction errors when compared to the LM MAE (three out of five in *Model a*, and four out of six for *Model b*); however, the difference in negligible in two cases, going beyond the three decimals. Still, according to Shmueli et al. (2019) both structural models have medium predictive power.

Table III. 13. Predictive relevance of the manifest variables (Q^2) and predictive performance of the structural models, *Model a* and *Model b*, by the Mean Absolute Errors (MAE) benchmark.

	Q^2 predict	PLSpredict MAE	LM MAE
Model a			
ICT_Index	0.204	0.109	0.106
IN4_Index	0.243	0.084*	0.084
Inn_2019	0.177	8.969*	9.161
RCI_Basic	0.165	0.092*	0.094
GDPpc_19	0.110	3887.772	3887.772
Model b			
ICT_Index	0.194	0.110	0.106
IN4_Index	0.241	0.085	0.084
Inn_2019	0.161	9.138*	9.161
Prod_2019	0.070	6507.304*	6562.400
RCI_Basic	0.149	0.093*	0.094
EpW_19	0.168	2319.657*	2319.657

SOURCE: Authors' calculations obtained with SmartPLS 4.

NOTE: *The PLSpredict MAE value is lower than the LM MAE value (Shmueli et al., 2019). In some cases, the difference between values is not noticeable because is beyond the three decimal places.

III.5 Discussion

The results of the cluster mapping study using raw data at the NUTS-3 level show consistent findings with Chapter II. The study reinforces and demonstrates again the feasibility of the application of an end-to-end methodology to map clusters in Europe, providing enough information for creating the *Spanish Benchmark Cluster Definitions* designed to enable systemic comparison across regions.

However, it should be highlighted that the cluster mapping methodology must be adapted in each exercise of cluster mapping to ensure the correct selection of traded industries and guarantee the quality of the analysis. The results of the cluster mapping offer to Spanish practitioners and policy makers of valuable information to design, implement, and evaluate industrial policy based in industrial agglomeration at a more local level. Besides, the findings provide to industrials with invaluable information for business location decisions.

The results of the PLS-SEM analysis expand the understanding of the industrial agglomeration effect in the economic development phenomenon. However, while some results reinforce the findings of previous literature, others open the debate and demand for further research. The discussion of these results becomes meaningful since the models demonstrated explanatory capacity and predictive power.

III.5.1 The industrial clusters and their influence on economic context

Two models, one for *GDPpc* and another for *EpW*, demonstrated empirically the positive and large effect of industrial agglomeration on the level of technology adoption, supporting previous findings of literature based on case-studies and making it possible to expand theory throughout a cross-sectional analysis. Even though the direct effect and the effect-size of such relation is slightly different between the models, the values are similar, supporting the idea that the geographical concentration of industrial clusters promotes the adoption of traditional ICT and more advanced technologies like Industry 4.0.

However, the relationship between cluster presence and competitiveness is more complex. A multidimensional concept as competitiveness could make necessary to disaggregate its different elements to obtain more meaningful insights from economic research; in this research, the technological dimension was extracted for a separate analysis, and the exclusion of one item from the competitiveness construct was necessary to avoid conceptual duplicity. Nonetheless, despite the suggestive but not conclusive results about the relationship of cluster presence and competitiveness, the contribution of the latter construct to the whole model is undeniable as the discussion goes further.

Additionally, according to the structural models the cluster presence does not have a direct effect on *GDPpc* and *EpW*, which were elected as two dimensions of economic development. The finding contrasts with previous empirical studies based on *Ordinary Least Squares* (OLS) linear regressions.

Nevertheless, the same assessment shows that the cluster presence has a positive total effect over those variables. The outcomes support the selection of the SEM approach to evaluate the impacts and the relations of those multifaceted phenomena, which influence and are influenced by multiple factors.

III.5.2 Technology and competitiveness as key players for development

The results support technology as a powerful force that promotes competitiveness, as an expression of innovation, institutional support, and productivity. Furthermore, the construct built with two technological indices (traditional and Industry 4.0) proves to be more relevant in promoting competitiveness than the cluster presence by itself, endorsing technology as a meaningful way to improve regional competitiveness.

Differently, the relations among the mediating variables (technology adoption and competitiveness) and the endogenous ones (*GDPpc* and *EpW*) demonstrates to be more intricate.

The empirical evidence stimulates the discussion about the effects of technology in economic development, proving that technology is a multidimensional phenomenon that could have implications still out of the traditional understanding of economics. The evidence states that the technology does not enhance the economic development *per se*, but it is more about a chain-effect and the coexistence of multiple factors, which will be discussed further in this section.

For competitiveness, its relationship with economic development is clearer, since it was expected that innovation, institutional support, and productivity impact positively economic development in general.

III.5.3 Technology adoption and competitiveness: the catalyzers

In the assessment of the mediating effect the models found more dissimilar results, consolidating only two mediation effects out of four evaluated.

The results suggest that technology is a key catalyzer for the effect of industrial agglomeration on competitiveness. In other words, the outcomes imply that clusters must go across ICT and Industry 4.0 to have an insightful impact on innovation, institutional support, and productivity.

Similarly, competitiveness carries out the indirect effect of technology on economic development, also becoming a catalyzer of the total effect of technology. Therefore, the level of technology adoption is an important promoter of economic development when it comes to have effects on innovation, institutions, and productivity.

However, the mediation role of technology is not as straightforward as expected. In the case of wealth creation, technology works as an intermediary for clusters, carrying with all the effect of industrial agglomeration on *GDPpc*. Differently, technology does not demonstrate to play a mediating role in the case of *EpW*, suggesting that the industrial agglomeration not only lacks direct effect on the returns to labor but also does not impact such variable when technology is involved as a single mediator.

For competitiveness as a mediating construct, the outcomes are like the previous ones, as full mediation is found in the relation of clusters and *GDPpc* but not in the relation with *EpW*. These findings shed light on the relationship between industrial clusters and *GDPpc*, where the lack of a direct effect indicates the existence of mediation effects. In contrast, at this stage of the discussion *EpW* remains as a variable not influenced directly or indirectly by industrial clusters.

III.5.4 The complex relation between clusters and economic development

Whilst the results of both models are not equivalent for all the analyses, they appear to be more conclusive for phenomena like technology adoption and competitiveness, and their direct/mediating effects over economic development. However, the impact of the presence of industrial clusters is less clear, especially regarding the second model that pertains to labor returns. Therefore, the analysis of specific indirect effects becomes relevant, providing further insight into this matter.

The assessment uncovers two insightful and specific indirect effects. Firstly, the presence of industrial clusters positively influences *GDPpc*, mediated concurrently by technology and competitiveness. Secondly, the industrial agglomeration has a positive effect on *EpW*, mediated simultaneously by technology and competitiveness.

In summary, the cluster presence, the degree of digitalization, and the level of competitiveness in a region are influential factors in determining economic development.

However, the influence does not occur in a straightforward manner. First, clusters must be capable of encourage the adoption of ICT and Industry 4.0. Second, clusters must be also capable to impact directly or indirectly factors associated with competitiveness, such as innovation, productivity, and institutional support; importantly, the technology must serve as medium for clusters to ignite competitiveness. Once those conditions are met, industrial clusters will have an effective and substantial role in boosting economic development.

This research holds relevance for policymakers, industrials, and academics by providing valuable insights to broaden the understanding of industrial agglomeration, and the role of industrial clusters, technology, and competitiveness in driving wealth creation and larger returns to labor, benefiting business and population located in regions where industrial agglomeration occurs.

Policymakers can utilize this information to formulate effective strategies and policies that promote the development of industrial clusters, enhance technological innovation, and foster competitiveness. This research helps policymakers make informed decisions to stimulate economic progress and create favorable conditions for sustainable development.

Besides, industrials can leverage these findings to understand the benefits of locating within or near industrial clusters, adopting advanced technologies as Industry 4.0, and enhancing competitiveness. This knowledge can guide them in making smarter investment decisions, optimizing resource allocation, and improving their overall performance in the market.

Finally, the research contributes to the academic community by expanding the knowledge base on the relationships between industrial clusters, technology, competitiveness, and their externalities on economic development. It provides a foundation for further research and analysis in related fields, fostering a deeper understanding of the dynamics and mechanisms that drive economic development. Academics can build upon these findings to explore new avenues of research, develop theoretical frameworks, and contribute to the existing body of knowledge.

III.6 Conclusions

This chapter introduces two key contributions. Firstly, it applies a cluster mapping methodology to Spain with an unprecedented level of disaggregation for a quantitative study in Europe. Secondly, it utilizes the Structural Equation Modeling (SEM) approach to assess the effects of industrial clusters on the economy. This approach allows for a comprehensive analysis of the complex nature of this economic phenomenon by unraveling its multiple effects.

The study's results demonstrate that the presence of industrial clusters, the level of digitalization, and the degree of competitiveness in a region are influential factors in determining economic development. However, the relationship between these factors and their impact on the economy is not straightforward and linear. Instead, their ultimate positive effect depends on the intricate interactions and synergies among them, acting as catalysts for economic development.

The analysis reveals that industrial clusters serve as a reliable promoter of technology adoption, which in turn impacts competitiveness. Technology emerges as a powerful force that promotes innovation, institutional support, and productivity. The findings highlight the importance of technology in improving regional competitiveness and driving economic development.

The relationship between industrial agglomeration and economic development is complex. The results indicate that industrial clusters do not have a direct effect on the assessed endogenous variables (*GDP per capita* and *earnings per worker*) but they have a positive total effect. This suggests that the impact of industrial clusters on economic development is mediated by other factors, such as technology adoption and competitiveness. The mediating variables play a significant role in the relationship between industrial clusters and economic development.

The specific indirect effects observed in the study provide further insights into the relationships between industrial clusters, technology, competitiveness, and economic development. These effects demonstrate statistically significant associations and indicate their significant impacts on the respective endogenous variables. They highlight the importance of considering the interplay between these factors for a comprehensive understanding of their influence on economic development.

This research holds significant relevance for policymakers, industrials, and academics. The findings contribute valuable insights that broaden the understanding of industrial agglomeration and its role in driving economic development. This research offers policymakers valuable insights to formulate effective strategies and policies that foster the development of industrial clusters. Furthermore, industrials can utilize these findings to make informed investment decisions, optimize resource allocation, and enhance their overall market performance. Moreover, this research contributes to the academic community by expanding the understanding of the relationships between industrial clusters, technology, competitiveness, and their influence on economic development.

Nonetheless, this research has its limitations. First, the relatively small sample size, limited to Spain, may limit the generalizability of the findings to other contexts. Second, the data availability and quality, limited to NUTS-2 for the technological indexes and challenged by the conceptual limitations of the competitiveness concept, could affect the accuracy of the findings. Third, the causal inference may be limited due the difficulty to determine the precise causal mechanisms at play; furthermore, other unmeasured factors or confounding/moderating variables could be influencing the observed relationships. Fourth, the research is conducted within a specific timeframe, which could limit its ability to capture long-term trends or changes over time. Fifth and last, the study may be subject to certain methodological limitations, since the PLS-SEM approach has been widely tested over reflective models and ordinal data, but that is not the case for reflective models and interval/ratio data.

To conclude, this research underscores the complex nature of the relationships between industrial clusters, technology, competitiveness, and economic development. It emphasizes the need to consider multiple factors and their interactions to fully grasp the dynamics of these phenomena. Despite the limitations of the research, its findings enhance the understanding of the industrial agglomeration dynamics, helping policymakers, industrials, and academics to make informed decisions, optimize their strategies, and contribute to sustainable and inclusive economic development.

References

Afonasova, M. A., Panfilova, E. E., Galichkina, M. A., & Slusarczyk, B. (2019). Digitalization in economy and innovation: The effect on social and economic processes. *Polish Journal of Management Studies*, *19*(2), 22–32. https://doi.org/10.17512/pjms.2019.19.2.02

Aguirre-Urreta, M. I., & Rönkkö, M. (2018). Statistical inference with PLSc using bootstrap confidence intervals. *MIS Quarterly*, *42*(3), 1001–1020. https://doi.org/10.25300/MISQ/2018/13587

Ahmad, N., & Schreyer, P. (2016). Are GDP and productivity measures up to the challenges of the digital economy? *International Productivity Monitor*, *30*, 4–27.

Alcacer, J., Cantwell, J., & Piscitello, L. (2016). Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies*, *47*(5), 499–512. https://doi.org/10.1057/jibs.2016.22

Aleksandrovich, S. K. (2019). Цифровая экономика и ее роль в управлении современными социально-экономическими отношениями [Digital Economy and Its Role in Management of Modern Social and Economic Relations]. *State and Municipal Management Scholar Notes*, *1*(4), 102–105. https://doi.org/10.22394/2079-1690-2019-1-4-102-105

Almeida, F., Duarte, J., & Monteiro, J. (2020). The challenges and opportunities in the digitalization of companies in a post-COVID-19 world. *IEEE Engineering Management Review*, *48*(3), 97–103. https://doi.org/10.1109/EMR.2020.3013206

Angehrn, A. (1997). Designing mature internet business strategies: The ICDT model. *European Management Journal*, *15*(4), 361–369. https://ideas.repec.org/a/eee/eurman/v15y1997i4p361-369.html

Atik, H., & Ünlü, F. (2019). The measurement of Industry 4.0 performance through Industry 4.0 Index: An empirical investigation for Turkey and European countries. *Procedia Computer Science*, *158*, 852–860. https://doi.org/10.1016/j.procs.2019.09.123

Awad, A., & Albaity, M. (2022). ICT and economic growth in Sub-Saharan Africa: Transmission channels and effects. *Telecommunications Policy*, *46*(8), 102381. https://doi.org/https://doi.org/10.1016/j.telpol.2022.102381

Babkin, A., Kudryavtseva, T., & Utkina, S. (2013). Formation of industrial clusters using method of virtual enterprises. *International Conference on Applied Economics (Icoae)*, 68–72. https://doi.org/10.1016/s2212-5671(13)00011-7

Babkin, A., Plotnikov, V., & Vertakova, Y. (2018). The analysis of industrial cooperation models in the context of forming digital economy. *SHS Web of Conferences*, *44*, 12. https://doi.org/10.1051/shsconf/20184400012

Babkin, A., Vertakova, Y., & Plotnikov, V. (2017). Study and assessment of clusters activity effect on regional economy. *SHS Web of Conferences*, *35*, 63. https://doi.org/10.1051/shsconf/20173501063

Baggio, R., & Del Chiappa, G. (2014). Real and virtual relationships in tourism digital ecosystems. *Information Technology & Tourism*, *14*(1), 3–19. https://doi.org/10.1007/s40558-013-0001-5

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, *27*(5), 525–540. https://doi.org/https://doi.org/10.1016/S0048-7333(98)00065-1

Baron, R., & Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*, 1173–1182.

https://doi.org/10.1037//0022-3514.51.6.1173

Barzotto, M., & De Propris, L. (2021). The value of firm linkages in the age of industry 4.0: a qualitative comparative analysis. *Annals of Regional Science*, *67*(2), 245–272. https://doi.org/10.1007/s00168-021-01047-0

Bathelt, H., & Li, P. F. (2014). Global cluster networks-foreign direct investment flows from Canada to China. *Journal of Economic Geography*, *14*(1), 45–71. https://doi.org/10.1093/jeg/lbt005

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Bathelt, H., & Taylor, M. (2002). Clusters, power and place: inequality and local growth in time–space. *Geografiska Annaler: Series B, Human Geography*, *84*(2), 93–109. https://doi.org/10.1111/j.0435-3684.2002.00116.x

Bathelt, H., & Turi, P. (2011). Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. *Geoforum*, *42*(5), 520–529. https://doi.org/10.1016/j.geoforum.2011.04.007

Bayliss, D. (2007). Dublin's digital hubris: Lessons from an attempt to develop a creative industrial cluster. *European Planning Studies*, *15*(9), 1261–1271. https://doi.org/10.1080/09654310701529268

Becker, J. M., Klein, K., & Wetzels, M. (2012). Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models. *Long Range Planning*, *45*(5–6), 359–394. https://doi.org/10.1016/j.lrp.2012.10.001

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 perspective. *World Academy of Science, Engineering and Technology. International Journal of Information and Communication Engineering*, *8*(1), 37–44. https://doi.org/10.5281/zenodo.1336426

Buchinskaia, O. N. (2022). Knowledge as a mediator in the relationship between digital and economic development. *Economic and Social Changes: Facts, Trends, Forecast*, *15*(6), 139–152. https://doi.org/10.15838/esc.2022.6.84.8

Buitrago, R. E., Camargo, M. I. B., & Vitery, F. C. (2021). Emerging economies' institutional quality and international competitiveness: A pls-sem approach. *Mathematics*, *9*(9). https://doi.org/10.3390/math9090928

Buitrago, R. E., Torralba Barreto, D. R., & Reyes, G. E. (2022). Are competitiveness rankings and institutional measures helping emerging economies to improve? *Competitiveness Review: An International Business Journal*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/CR-04-2021-0064

Buteau, S. (2021). Roadmap for digital technology to foster India's MSME ecosystem—opportunities and challenges. *CSI Transactions on ICT*, *9*(4), 233–244. https://doi.org/10.1007/s40012-021-00345-4

Caloffi, A., Lazzeretti, L., & Sedita, S. R. (2018). The story of cluster as a cross-boundary concept: From local development to management studies. In F. Belussi & J. L. Hervas-Oliver (Eds.), *Agglomeration and Firm Performance. Advances in Spatial Science* (pp. 123–137). Springer. https://doi.org/10.1007/978-3-319-90575-4_8

Cenfetelli, R. T., & Bassellier, G. (2009). Interpretation of Formative Measurement in Information Systems Research. *MIS Quarterly*, *33*(4), 689–707. https://doi.org/10.2307/20650323

Cheah, J.-H., Sarstedt, M., Ringle, C. M., Ramayah, T., & Ting, H. (2018). Convergent validity assessment of formatively measured constructs in PLS-SEM. *International Journal of Contemporary Hospitality Management*, *30*(11), 3192–3210. https://doi.org/10.1108/IJCHM-10-2017-0649

Chin, W. W. (1998). The Partial Least Squares approach for Structural Equation Modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–236). Lawrence Erlbaum Associates Publishers.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates, Publishers.

Corradini, C., Santini, E., & Vecciolini, C. (2021). The geography of Industry 4.0 technologies across European regions. *Regional Studies*, *55*(10–11), 1667–1680. https://doi.org/10.1080/00343404.2021.1884216

Cortright, J. (2006). *Making Sense of Clusters: Regional Competitiveness and Economic*

Development (p. 66). The Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/wp-content/uploads/2016/06/20060313_Clusters.pdf

Crupi, A., Del Sarto, N., Di Minin, A., Gregori, G. L., Lepore, D., Marinelli, L., & Spigarelli, F. (2020). The digital transformation of SMEs – a new knowledge broker called the digital innovation hub. *Journal of Knowledge Management*, *24*(6), 1263–1288. https://doi.org/10.1108/JKM-11-2019-0623

Cuevas-Vargas, H., Fernandez-Escobedo, R., Cortes-Palacios, H. A., & Ramirez-Lemus, L. (2021). The relation between adoption of information and communication technologies and marketing innovation as a key strategy to improve business performance. *Journal of Competitiveness*, *13*(2), 23–40. https://doi.org/10.7441/joc.2021.02.02

D'Urso, P., Giovanni, L. D., Sica, F. G. M., & Vitale, V. (2022). Measuring competitiveness at NUTS3 level and territorial partitioning of the Italian provinces. *Social Indicators Research*. https://doi.org/10.1007/s11205-021-02836-y

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*(August), 121092. https://doi.org/10.1016/j.techfore.2021.121092

De Blasio, G., & Di Addario, S. (2005). Do workers benefit from industrial agglomeration? *Journal of Regional Science*, *45*(4), 797–827. https://doi.org/10.1111/j.0022-4146.2005.00393.x

Del Chiappa, G., & Baggio, R. (2015). Knowledge transfer in smart tourism destinations: Analyzing the effects of a network structure. *Journal of Destination Marketing & Management*, *4*(3), 145–150. https://doi.org/10.1016/j.jdmm.2015.02.001

Delgado, M., Bryden, R., & Zyontz, S. (2014). *Categorization of traded and local industries in the US economy*. 1–9. https://clustermapping.us/sites/default/files/files/page/Categorization of Traded and Local Industries in the US Economy.pdf

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38. https://doi.org/10.1093/jeg/lbv017

Ding, C., Liu, C., Zheng, C., & Li, F. (2022). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. In *Sustainability* (Vol. 14, Issue 1). https://doi.org/10.3390/su14010216

Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, *3*(1), 3–45. https://repository.upenn.edu/real-estate_papers/2

Elola, A., Valdaliso, J., Lopez, S. M., & Aranguren, M. J. (2012). Cluster life cycles, path dependency and regional economic development: Insights from a meta-study on Basque clusters. *European Planning Studies*, *20*(2), 257–279. https://doi.org/10.1080/09654313.2012.650902

Elola, A., Valdaliso, J. M., Franco, S., & López, S. M. (2017). Public policies and cluster life cycles: insights from the Basque Country experience. *European Planning Studies*, *25*(3), 539–556. https://doi.org/10.1080/09654313.2016.1248375

Erboz, G. (2017). How to define Industry4.0: The main pillars of Industry 4.0. *Managerial Trends in the Development of Enterprises in Globalization Era*, 761–767. https://www.researchgate.net/publication/326557388_How_To_Define_Industry_40_Main_Pillars_Of_Industry_40

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis*. Wiley.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Feser, E. J. (1998). Old and new theories of industry clusters. In M. Steiner (Ed.), *Clusters and Regional Specialisation. European Research in Regional Science* (Vol. 8, pp. 18–40). Pion.

Gagnidze, I. (2022). Industry 4.0 and industry 5.0: can clusters deal with the challenges? (A systemic approach). *Kybernetes*. https://doi.org/10.1108/K-07-2022-1005

Gamidullaeva, L., Korostyshevskaya, E., Myamlin, A., & Podkorytova, O. (2022). Exploring Regional Industrial Growth: Does Specialization Explain It? *Economies*, *10*(7). https://doi.org/10.3390/economies10070172

Geissbauer, R., Lübben, E., Schrauf, S., & Pillsbury, S. (2018). *Global digital operations study 2018 - Digital champions: How industry leaders build integrated operations ecosystems to deliver end-to-end customer solutions.* https://www.pwc.es/es/productos-industriales/industria-4-0-global-digital-operations-study-2018.html

Gertler, M. S., & Wolfe, D. A. (2006). Spaces of knowledge flows: Clusters in a global context. In R. Martin, B. Asheim, & P. Cooke (Eds.), *Clusters and Regional Development: Critical Reflections and Explorations* (Vol. 29, pp. 218–235). Routledge.

Golov, R. S., Palamarchuk, A. G., Anisimov, K. V., & Andrianov, A. M. (2021). Cluster Policy in a Digital Economy. *Russian Engineering Research*, *41*(7), 631–633. https://doi.org/10.3103/S1068798X21070108

Götz, M. (2019a). The industry 4.0 induced agility and new skills in clusters. *Foresight and STI Governance*, *13*(2), 72–83. https://doi.org/10.17323/2500-2597.2019.2.72.83

Götz, M. (2019b). Unpacking the provision of the industrial commons in Industry 4.0 cluster. *Economics and Business Review*, *5*(4), 23–48. https://doi.org/10.18559/ebr.2019.4.2

Götz, M. (2021). Cluster role in industry 4.0 – a pilot study from Germany. *Competitiveness Review*, *31*(1), 54–82. https://doi.org/10.1108/CR-10-2019-0091

Götz, M., & Jankowska, B. (2017). Clusters and Industry 4.0 - Do they fit together? *European Planning Studies*, *25*(9), 1633–1653. https://doi.org/10.1080/09654313.2017.1327037

Grashof, N., & Fornahl, D. (2021). “To be or not to be” located in a cluster?—A descriptive meta-analysis of the firm-specific cluster effect. In *Annals of Regional Science* (Vol. 67, Issue 3). Springer Berlin Heidelberg. https://doi.org/10.1007/s00168-021-01057-y

Grashof, N., Kopka, A., Wessendorf, C., & Fornahl, D. (2021). Industry 4.0 and clusters: Complementaries or substitutes in firm’s knowledge creation? *Competitiveness Review*, *31*(1), 83–105. https://doi.org/10.1108/CR-12-2019-0162

Guo, H., Yang, Z., Huang, R., & Guo, A. Q. (2020). The digitalization and public crisis responses of small and medium enterprises: Implications from a COVID-19 survey. *Frontiers of Business Research in China*, *14*(1), 25. https://doi.org/10.1186/s11782-020-00087-1

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). SAGE Publications, Inc. https://us.sagepub.com/en-us/nam/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem/book244583

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123. https://doi.org/10.1504/IJMDA.2017.087624

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, *46*(1), 1–12. https://doi.org/10.1016/j.lrp.2013.01.001

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hanafiah, M. H. (2020). Formative vs. reflective measurement model: Guidelines for structural equation modeling research. *International Journal of Analysis and Applications*, *18*(5), 876–889.

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industry 4.0 scenarios. *49th Hawaii International Conference on System Sciences (HICSS)*, 3928–3937. https://doi.org/10.1109/hicss.2016.488

Hermans, F. (2021). The contribution of statistical network models to the study of clusters and their evolution. *Papers in Regional Science*, *100*(2), 379–403. https://doi.org/10.1111/pirs.12579

Hervás-Oliver, J. L. (2021). Industry 4.0 in industrial districts: regional innovation policy for the Toy Valley district in Spain. *Regional Studies*, *55*(10–11), 1775–1786. https://doi.org/10.1080/00343404.2021.1939861

Houston, M. B. (2004). Assessing the validity of secondary data proxies for marketing constructs. *Journal of Business Research*, *57*(2), 154–161. https://doi.org/https://doi.org/10.1016/S0148-2963(01)00299-5

Husain, Z., Dayan, M., & Di Benedetto, C. A. (2016). The impact of networking on competitiveness via organizational learning, employee innovativeness, and innovation process: A mediation model. *Journal of Engineering and Technology Management*, *40*, 15–28. https://doi.org/https://doi.org/10.1016/j.jengtecman.2016.03.001

Jankowska, B., Maria, E. D., & Cygler, J. (2021). Do clusters matter for foreign subsidiaries in the Era of industry 4.0? The case of the aviation valley in Poland. *European Research on Management and Business Economics*, *27*(2). https://doi.org/10.1016/j.iedeen.2021.100150

Jasinska, K., & Jasinski, B. (2019). Clusters under industry 4.0 conditions - Case study: the concept of Industry 4.0 cluster in Poland. *Transformations in Business & Economics*, *18*(2B), 802–823. http://www.transformations.knf.vu.lt/47b/article/clus

Jofre-Monseny, J., Marin-Lopez, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: evidence from the location of new firms in Spain. *Journal of Regional Science*, *54*(2), 313–337. https://doi.org/10.1111/jors.12076

Johansson, B., Karlsson, C., & Stough, R. R. (2006). The emerging digital economy: Conclusions. In B. Johansson, C. Karlsson, & R. R. Stough (Eds.), *The Emerging Digital Economy. Advances in Spatial Science* (5th ed., pp. 331–339). Springer.

Karnitis, G., & Karnitis, E. (2017). Sustainable growth of EU economies and Baltic context: Characteristics and modelling. *Journal of International Studies*, *10*(1), 209–224. https://doi.org/10.14254/2071-8330.2017/10-1/15

Ketels, C. (2017). Cluster mapping as a tool for development. In *Harvard Business School* (Issue June). https://www.hbs.edu/faculty/Pages/item.aspx?num=53385

Knell, M. (2021). The digital revolution and digitalized network society. *Review of Evolutionary Political Economy*, *2*(1), 9–25. https://doi.org/10.1007/s43253-021-00037-4

Kock, N. (2015). One-tailed or two-tailed P values in PLS-SEM? *International Journal of E-Collaboration*, *11*(2), 1–7. https://doi.org/10.4018/ijec.2015040101

Kock, N. (2017). Common method bias: A full collinearity assessment method for PLS-SEM. In H. Latan & R. Noonan (Eds.), *Partial Least Squares path modeling: Basic concepts, methodological issues and applications* (pp. 245–257). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_11

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Leamer, E. E., & Storper, M. (2001). The economic geography of the Internet age. *Journal of International Business Studies*, *32*(4), 641–665. https://doi.org/10.1057/palgrave.jibs.84909988

Lehdonvirta, V., & Ernkvist, M. (2011). *Knowledge map of the virtual economy* (p. 59). infoDev/World Bank. https://doi.org/10.1596/27361

Lember, V., Brandsen, T., & Tõnurist, P. (2019). The potential impacts of digital technologies on co-production and co-creation. *Public Management Review*, *21*(11), 1665–1686. https://doi.org/10.1080/14719037.2019.1619807

Lines, T., & Monypenny, R. (2006). *Industrial clustering*. Proceedings of the Sustainable Economic Growth for Regional Australia National Conference - SEGRA, August 28-30, 2006. https://www.researchgate.net/profile/Richard-Monypenny/publication/238712690_Industrial_Clustering/links/5bd8fe6c4585150b2b934b96/Industrial-Clustering.pdf

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., & Krejcar, O. (2018). Consequences of Industry 4.0 in business and economics. *Economies*, *6*(3), 14. https://doi.org/10.3390/economies6030046

Molina-Morales, F. X., Martinez-Chafer, L., & Valiente-Bordanova, D. (2017). Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones Regionales-Journal of Regional Research*, *39*, 39–57. https://investigacionesregionales.org/es/article/disruptive-technological-innovations-as-new-opportunities-for-mature-industrial-clusters-the-case-of-digital-printing-innovation-in-the-spanish-ceramic-tile-cluster/

Muller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247. https://doi.org/10.3390/su10010247

Ortega-Colomer, F. J., Molina-Morales, F. X., & Fernández-de-Lucio, I. (2016). Discussing the concepts of cluster and industrial district. *Journal of Technology Management & Innovation*, *11*(2), 139–147. https://doi.org/10.4067/S0718-27242016000200014

Owen-Smith, J., & Powell, W. W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, *15*(1), 5–21. https://doi.org/10.1287/orsc.1030.0054

Park, S. C. (2018). The Fourth Industrial Revolution and implications for innovative cluster policies. *AI and Society*, *33*(3), 433–445. https://doi.org/10.1007/s00146-017-0777-5

Popescu, V. A., & Popescu, C. R. (2011). Real economy versus virtual economy - New challenges for nowadays society. *Manager*, *13*(1), 7–15. https://manager.faa.ro/archive/manager_13/articles/1303.pdf

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *62*(2), 73–93. https://www.hbs.edu/faculty/Pages/item.aspx?num=6105

Porter, M. E. (2003). The economic performance of regions. *Regional Studies*, *37*(6–7), 549–578. https://doi.org/10.1080/0034340032000108688

Porter, M. E., Ketels, C., & Delgado, M. (2007). The microeconomic foundations of prosperity: Findings from the Business Competitiveness Index. In A. Lopez-Claros (Ed.), *The Global Competitiveness Report 2006–2007* (Vol. 2006, pp. 51–80). World Economic Forum.

Portugal, M., Ribeiro, F., Kramer, B., Maccari, E. A., & Ritor, H. (2012). Impact of the types of clusters on the innovation output and the appropriation of rents from innovation. *Journal of Technology Management & Innovation*, *7*, 70–80. http://doi.org/10.4067/S0718-27242012000400006

Potter, A., & Watts, H. D. (2010). Evolutionary agglomeration theory: increasing returns, diminishing returns, and the industry life cycle. *Journal of Economic Geography*, *11*(3), 417–455. https://doi.org/10.1093/jeg/lbq004

Rambe, P., & Khaola, P. (2022). The impact of innovation on agribusiness competitiveness: the mediating role of technology transfer and productivity. *European Journal of Innovation Management*, *25*(3), 741–773. https://doi.org/10.1108/EJIM-05-2020-0180

Richter, C., Kraus, S., Brem, A., Durst, S., & Giselbrecht, C. (2017). Digital entrepreneurship: Innovative business models for the sharing economy. *Creativity and Innovation Management*, *26*(3), 300–310. https://doi.org/10.1111/caim.12227

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS (v4.0) [Computer software]* (4.0). SmartPLS GmbH. www.smartpls.com

Rocha, H. O. (2004). Entrepreneurship and development: The role of clusters. *Small Business Economics*, *23*(5), 363–400. https://doi.org/10.1007/s11187-004-3991-8

Rodríguez-Pose, A., & Comptour, F. (2012). Do clusters generate greater innovation and growth? An analysis of European regions. *The Professional Geographer*, *64*(2), 211–231. https://doi.org/10.1080/00330124.2011.583591

Romanelli, E., & Khessina, O. M. (2005). Regional industrial identity: Cluster configurations and economic development. *Organization Science*, *16*(4), 344–358. https://doi.org/10.1287/orsc.1050.0131

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191–229. https://doi.org/10.1006/juec.2001.2230

Scarle, S., Arnab, S., Dunwell, I., Petridis, P., Protopsaltis, A., & de Freitas, S. (2012). E-commerce transactions in a virtual environment: Virtual transactions. *Electronic Commerce Research*, *12*(3), 379–407. https://doi.org/10.1007/s10660-012-9098-4

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest and the business cycle* (1th ed., p. 255). Transaction Publishers.

Schwab, K. (2016). *The fourth industrial revolution* (1th ed., p. 192). World Economic Forum.

Schwarzer, J., Chen, L., Cheng, W., Ciuriak, D., Kimura, F., Nakagawa, J., Pomfret, R.,

& Rigoni, G. (2019). The digital economy for economic development: Free flow of data and supporting policies. *Proceedings of the T20 Japan Task Force 8: Trade, Investment and Globalization*, 20. https://t20japan.org/policy-brief-digital-economy-economic-development/

Scott, A. J., & Storper, M. (2007). Regions, globalization, development. *Regional Studies*, *41*(1), 191–205. https://doi.org/10.1080/00343400701232157

Sforzi, F. (2015). Rethinking the industrial district: 35 years later. *Investigaciones Regionales*, *32*(2015), 11–29. http://www.aecr.org/images/ImatgesArticles/2015/11/2_Sforzi.pdf?_ga=2.131452296.680042952.1678926565-1405984931.1678409478

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, *52*(3/4), 591–611. https://doi.org/10.2307/2333709

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Skokan, K., & Zotyková, L. (2014). Evaluation of business cluster performance during its lifecycle. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *62*(6), 1395–1405. https://doi.org/10.11118/actaun201462061395

Slaper, T., Harmon, K., & Rubin, B. (2018). Industry clusters and regional economic performance: A study across US Metropolitan Statistical Areas. *Economic Development Quarterly*, *32*(1), 44–59. https://doi.org/10.1177/0891242417752248

Slaper, T., & Ortuzar, G. (2015). Industry clusters and economic development. *Indiana Business Review*, *90*(1), 7–9. https://www.ibrc.indiana.edu/ibr/2015/spring/pdfs/article2.pdf

Solvell, O. (2015). *On strategy and competitiveness: 10 recipes for analytical success*

(2nd ed.). Ivory Tower Publisher and SIR. https://irp-cdn.multiscreensite.com/bcb8bbe3/files/uploaded/doc_3540.pdf

Stojčić, N., Anić, I.-D., & Aralica, Z. (2019). Do firms in clusters perform better? Lessons from wood-processing industries in new EU member states. *Forest Policy and Economics*, *109*, 102043. https://doi.org/https://doi.org/10.1016/j.forpol.2019.102043

Storper, M. (2009). Roepke lecture in economic geography - Regional context and global trade. *Economic Geography*, *85*(1), 1–21. https://doi.org/10.1111/j.1944-8287.2008.01001.x

Tavares, M. S. D., Gohr, C. F., Morioka, S., & da Cunha, T. R. (2021). Systematic literature review on innovation capabilities in clusters. *Innovation and Management Review*, *18*(2), 192–220. https://doi.org/10.1108/INMR-12-2019-0153

Temouri, Y., Pereira, V., Muschert, G. W., Ramiah, V., & Babula, M. (2021). How does cluster location and intellectual capital impact entrepreneurial success within high-growth firms? *Journal of Intellectual Capital*, *22*(1), 171–189. https://doi.org/10.1108/JIC-02-2020-0066

Tsakalerou, M., & Akhmadi, S. (2021). Agents of innovation: Clusters in industry 4.0. *Procedia Manufacturing*, *55*(C), 319–327. https://doi.org/10.1016/j.promfg.2021.10.045

Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*(May), 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Vlaisavljevic, V., Cabello-Medina, C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting and Social Change*, *155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Wang, M., Zhang, M., Chen, H., & Yu, D. (2023). How Does Digital Economy Promote the Geographical Agglomeration of Manufacturing Industry? *Sustainability*, *15*(2), 1727. https://doi.org/10.3390/su15021727

Wang, S., Hou, D., Guo, Y., & Dai, L. (2022). The mediation effect of innovation in the domestic and international economic development circulation. *Technology Analysis & Strategic Management*, 1–13. https://doi.org/10.1080/09537325.2022.2069003

Watanabe, C., Naveed, K., Tou, Y., & Neittaanmaki, P. (2018). Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technological Forecasting and Social Change*, *137*, 226–240. https://doi.org/10.1016/j.techfore.2018.07.053

Wilson, J., Wise, E., & Smith, M. (2022). Evidencing the benefits of cluster policies: towards a generalised framework of effects. *Policy Sciences*, *55*(2), 369–391. https://doi.org/10.1007/s11077-022-09460-8

Ybarra, J. A., & Domenech-Sanchez, R. (2012). Innovative business groups: territory-based industrial policy in Spain. *European Urban and Regional Studies*, *19*(2), 212–218. https://doi.org/10.1177/0969776411428558 WE - Social Science Citation Index (SSCI)

Yelkikalan, N., Soylemezoglu, E., Kiray, A., Sonmez, R., Ezilmez, B., & Altun, M. (2012). Clustering approach as a regional development tool. *8th International Strategic Management Conference*, *58*, 503–513. https://doi.org/10.1016/j.sbspro.2012.09.1027

Yudina, T. (2019). Digital segment of the real economy: digital economy in the context of analog economy. *St. Petersburg State Polytechnical University Journal. Economics*, *12*(2), 7–18. https://doi.org/10.18721/JE.12201

Zeibote, Z., & Muravska, T. (2018). Promoting the regional competitiveness through clusters' approach: Case of the Latvian information technology cluster. *European Integration Studies*, *12*, 77–91. https://doi.org/10.5755/j01.eis.0.12.20846

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257

Zhao, Y., Song, Z., Chen, J., & Dai, W. (2023). The mediating effect of urbanisation on digital technology policy and economic development: Evidence from China. *Journal of Innovation & Knowledge*, *8*(1), 100318. https://doi.org/https://doi.org/10.1016/j.jik.2023.100318

Zhu, S., & Pickles, J. (2016). Institutional embeddedness and regional adaptability and rigidity in a Chinese apparel cluster. *Geografiska Annaler, Series B: Human Geography*, *98*(2), 127–143. https://doi.org/10.1111/geob.12095

Conclusions and remarks

Findings

This thesis aims to contribute to the advancement of the field of economic geography, regional development, and digital economy, by offering more robust methodologies to assess industrial agglomeration presence and evaluate its impact on digital transformation and regional economic development. Additionally, it proposes a novel policy tool that aims to reconcile digital transformation and industrial agglomeration: the *Digital Industrial Cluster*.

The thesis draws upon the existing literature on the industrial cluster model while acknowledging the insights provided by various models of industrial agglomeration. In addition, the research put forth a novel definition for industrial clusters, aiming to incorporate elements that are overlooked in the traditional Porterian definition. By expanding and refining the conceptual understanding of industrial clusters, this study presents a more comprehensive framework for analyzing and interpreting their dynamics. The research also leverages the influence of the industrial cluster literature to expand its impact and reach among policymakers and industrialists.

Each chapter focuses on providing a clear and sustained answer to the general research questions presented at the introduction. The following presents the answers and the main findings and arguments supporting them.

Question #1. *Is it theoretically feasible to develop a policy tool founded on industrial clusters and digital transformation?* Yes, it is theoretically feasible to develop a policy tool founded on industrial clusters and digital transformation.

The arguments presented in Chapter I highlight the compatibility and potential synergy between industrial clusters and digital transformation, introducing the Digital Industrial Cluster (DIC) as a novel policy tool based in digital agglomeration. The DIC concept aims to replicate the cooperation and competition dynamics found in traditional industrial clusters within a virtual space.

Additionally, while technology and COVID-19 pandemic defied geographical limitations, they also showed the potential for localization. Digitalization can support the evolution of traditional industrial clusters by facilitating the integration of economic entities into a virtual space. The DIC seeks to leverage digital capabilities to strengthen and promote multi-regional interactions and integration, stimulate competition and industrial diversity, enhance agility and value co-creation, and reduce the organizational friction toward digital transformation, driving to innovation and economic development in regions where it is implemented.

However, the DIC rests on the utilization of Industry 4.0 and ICT advancements to enable digital integration and decentralized interactions within clusters. These technologies provide the infrastructure and tools necessary for the development of digital platforms and the digitalization of organizational functions.

Overall, the arguments in the chapter propose a theoretical foundation for the development of a policy tool founded on industrial clusters and digital transformation. The DIC concept aligns with the principles of agglomeration, embraces the potential of Industry 4.0 and ICT, and aims to overcome challenges associated with digitalization. While further empirical research is needed to assess its potential benefits and identify suitable regions and actors, the theoretical feasibility of the DIC is supported by the arguments presented.

Question #2. *Is it possible to adapt and implement an end-to-end methodology to identify industrial clusters over territories outside US, according to state-of-the-art methodologies?* Yes, it is possible to adapt and implement an end-to-end methodology to identify industrial clusters over territories outside the US.

Chapter II successfully applies such a methodology to the Spanish context, utilizing raw data at NUTS-2 level. This effort departed from previous cluster mapping efforts, demonstrating the feasibility of applying this methodology to European countries and challenging the *representativeness assumption*, which states that the locational patterns found in the US are representative of those found in Europe.

This chapter highlights several reasons supporting the adaptability of the methodology to non-US contexts. Firstly, it emphasizes the importance of using locally-measured relatedness among industries rather than relying solely on foreign measures. The differences in spatial units of study between countries necessitate the development of similarity matrices that capture cross-industry linkages specific to the local context. Furthermore, the study introduces a multi-criterion methodology for identifying traded industries in the Spanish case, accounting for the unique characteristics of the country's economy. Moreover, the research highlights the differences between industrial classifications for Europe and US, underscoring the importance of considering the variations in industrial codes and their impact on assessing cross-industry linkages and identifying clusters accurately. All these adaptations ensure that the methodology is tailored to the specific context and enables the identification of relevant cross-industry linkages.

Additionally, the correlation analysis presented in the chapter demonstrates that the clusters presence, when measured using national-level employment concentration, shows stronger and more statistically significant correlations with other variables compared to regional-level measures. This finding suggests that the adaptation of the methodology to the local context improves the understanding of the effects of industrial clusters on the economy.

To conclude, the arguments provide a compelling case for the possibility of adapting and implementing an end-to-end methodology to identify industrial clusters outside the US, considering state-of-the-art methodologies and the specific characteristics of each region or country. Moreover, the chapter emphasizes the need for a cautious approach when utilizing foreign measures for cross-industry linkages without considering local circumstances.

Question #3. *Are industrial clusters and technology positively related to economic development and what is the role of competitiveness in such relation?* Yes, industrial clusters and technology have a positive and significant relationship with economic development, as supported by the findings; however, the role of competitiveness emerges as an influential factor in this complex relationship.

In Chapter III, the presence of industrial clusters demonstrates its impact on promoting the adoption of technology, including both traditional ICT and advanced technologies associated with Industry 4.0. This suggests that industrial clusters serve as catalysts for technological advancement and digitalization within regions.

According to the evidence, the positive relationship between industrial clusters and technology adoption is crucial for driving economic development. By concentrating related industries and resources in a specific geographic area, industrial clusters create an environment conducive to knowledge sharing, collaboration, and networking. This fosters a culture of technological advancement, leading to the adoption of cutting-edge technologies and practices. The adoption of technology, in turn, brings about various benefits such as increased productivity, efficiency gains, and the ability to compete on a global scale.

However, the relationship between industrial clusters and economic development is not solely dependent on technology adoption. The role of competitiveness emerges as a significant factor in this complex relationship. Competitiveness encompasses various elements such as innovation, productivity, and institutional support, which are crucial for sustainable economic growth.

Competitiveness, as a mediating construct, plays a crucial role in the relationship between industrial clusters, technology adoption, and economic development. It acts as a conduit for the indirect effects of industrial agglomeration and technology adoption on economic development, in terms of GDP *per capita* and earnings *per worker*. Additionally, competitiveness has a meaningful and direct impact on driving economic development. Overall, this indicates that the level of technology adoption, facilitated by industrial clusters, significantly influences innovation, productivity, and institutional support, leading to enhanced economic development.

It is important to note that the relationship between industrial clusters, technology, and economic development is intricate and multifaceted. The findings presented in the arguments highlight the interplay between these factors, underscoring the need for a comprehensive understanding of their interactions. While industrial clusters provide the foundation for technology adoption, their ultimate positive impact on the economy is dependent on the complex interactions and synergies among various factors, with competitiveness playing a pivotal role.

In conclusion, the research findings suggest that industrial clusters and technology have a positive relationship with economic development. Industrial clusters facilitate the adoption of technology, which enhances the competitiveness shaped by innovation, productivity, and institutional support. Competitiveness acts as a mediating construct, carrying out the indirect effects of industrial clusters and technology adoption on economic development. It plays a crucial role in driving economic growth, serving as a catalyst for the overall impact. Therefore, industrial clusters, technology adoption, and competitiveness collectively contribute to fostering sustainable economic development.

Contributions

This thesis expands the body of knowledge in economic geography and contributes to the development of the theory of agglomeration by considering the disruptive effects of digital transformation.

Chapter I, as a theoretical development, finds its main limitations in the empirical field. Multiple questions emerge concerning to the feasibility of the DIC in the real world, the compatibility of the policy tools with existing clusters, and the empirical demonstration of its positive externalities.

However, while this thesis does not aim to empirically identify and assess an actual *Digital Innovation Cluster* (DIC), the findings of Chapter II provide empirical foundations to the theoretical developments made in the Chapter I. The findings reveal positive and statistically significant correlations between the presence of clusters and ICT/Industry 4.0 indexes. This offers further evidence that industrial clusters and technological adoption tend to move in the same direction. It is noteworthy that these indexes are introduced as a novelty in this thesis, as they are designed and computed for the first time at the NUTS-2 level in a European country. Additionally, the study offers a detailed analysis, including a list of industrial clusters that are better aligned with the digital transformation, based on their individual correlations. These empirical results support part of the conclusions drawn in Chapter I and contribute to the understanding of the level of technological adoption in Spanish regions and the feasibility of implementing a DIC.

Nonetheless, Chapter II also experiences limitations. Although it provides valuable methodological insights into identifying cross-industry linkages and agglomeration across the Spanish territory, the analysis is constrained by the small number of regions studied. As a result, the application of more sophisticated inferential statistical tools is limited, and the generalization of the results is also constrained.

Chapter III overcomes those limitations, building upon the methodological and empirical insights from Chapter II. It expands the cluster mapping to a higher level of disaggregation, resulting in a larger and more representative sample for more comprehensive statistical analysis. This chapter demonstrates the practical implications of Chapter II's findings and takes the cluster mapping to the NUTS-3 level. In addition, the inferential analysis departs from the correlations presented in the previous chapter to build upon a structural equation modeling (SEM) and multi-mediation approach. The analysis unveils a complex dynamic that involves industrial agglomeration, technology adoption, competitiveness, and economic development. The findings demonstrate the effect of clusters on digital transformation and the role of competitiveness as an efficient mediator for economic development. Importantly, the analysis reaches predictive power and explanatory capacity, indicating that the results are both useful and significant in supporting the understanding of the assessed phenomenon.

Moreover, the last chapter also brings empirical support to Chapter I, showing that a policy tool founded on industrial clusters and technology could be a powerful ally to detonate economic development. The findings support the theoretical developments about the DIC's positive externalities over innovation, productivity, institutional support, and economic enhancement.

Overall, the three chapters construct a strong argument in support of industrial agglomeration and digital transformation as concurrent and contemporaneous drivers of economic development, contributing to the development and implementation of novel models of digital agglomeration as the DIC. Furthermore, the thesis contributes to the field by addressing several traditional limitations and challenges associated with industrial agglomeration models.

Firstly, it tackles the lack of methodological application for cluster mapping. This research assesses the replicability of state-of-the-art methodologies, providing methodological insights and practical implications for future research. By doing so, it offers a tailored approach that can be effectively applied to diverse economic realities.

Secondly, it addresses the oversimplification of the agglomeration phenomenon. This work delves deeper into the complexities of the phenomenon by considering multiple variables and adopting novel approaches to analyze their complex dynamics. It provides a more comprehensive analysis that captures the true complexity of industrial clusters.

Thirdly, this research takes a dynamic perspective on industrial agglomeration, particularly in the context of digital transformation. By recognizing the evolving nature of clusters in the digital era, it captures the dynamic aspects of the phenomenon and offers insights into how novel policy tools can facilitate adaptation. This perspective enables a better understanding of the changing dynamics within industrial clusters.

Fourthly, the research focuses on developing practical and applicable solutions. The thesis develops solutions that can be practically implemented across various contexts, expanding the scope of their utilization, and increasing their effectiveness.

Lastly, the research helps to overcome the limited understanding of the relationships among variables in industrial clusters. This research bridges the gap and provides a more holistic and nuanced understanding of the problem by conducting a thorough analysis of the complex relationships among clusters, digitalization, competitiveness, and economic development. It employs advanced analytical techniques to capture the multidimensional nature and effects of industrial agglomeration.

In summary, this thesis contributes to the field of economic geography by providing more robust methodologies, capturing the complexity of industrial clusters, adopting a dynamic viewpoint, enhancing the applicability of solutions, and leading to more effective strategies, interventions, and policies. It presents valuable insights for both academia and practitioners by addressing the traditional limitations of the field.

Implications

The implications for policy resulting from this thesis are significant. The findings and arguments presented have practical implications for policymakers in the areas of economic development, regional planning, and digital transformation. The implications can be summarized in the development of a policy tool, the methodological adaptation for cluster mapping, the promotion of technology adoption and competitiveness as agents of economic development, and the understanding of the industrial agglomerations and its relationships.

The thesis proposes the concept of the *Digital Industrial Cluster* (DIC) as a policy tool founded on industrial clusters and digital transformation. The DIC aims to replicate the cooperation and competition dynamics found in traditional industrial clusters within a virtual space. The DIC concept offers a novel approach to reconcile digital transformation and industrial agglomeration, promoting multi-regional interactions, competition, and industrial diversity. Policymakers can consider implementing the DIC concept in regions to leverage digital capabilities, stimulate innovation, and drive economic development.

Additionally, the thesis demonstrates the feasibility of adapting and implementing an end-to-end methodology for identifying industrial clusters outside the United States. It emphasizes the importance of using locally-measured relatedness among industries and considering variations in industrial codes and characteristics specific to each country or region. This methodological adaptation enables policymakers to accurately identify relevant cross-industry linkages, understand industrial clusters' presence, and tailor policies accordingly. Policymakers can utilize this methodology to assess and map industrial clusters in their respective regions, supporting evidence-based decision-making.

The thesis also highlights the positive relationship between industrial clusters, technology adoption, and economic development. Industrial clusters serve as catalysts for technological advancement and digitalization, leading to increase productivity, efficiency gains, and global competitiveness. Policymakers can focus on fostering the adoption of cutting-edge technologies within industrial clusters by providing supportive infrastructure, research, and development funding, and facilitating knowledge sharing, collaboration, and networking. By creating such environment, policymakers can foster technological advancement and digitalization, leading to increased productivity, efficiency gains, and global competitiveness.

Furthermore, policymakers should consider promoting competitiveness through measures such as innovation support, productivity enhancement, and institutional reforms, as these factors mediate the relationship between industrial clusters, technology adoption, and economic development. This can be achieved through targeted policies that foster entrepreneurship, provide access to finance and resources, support research and development activities, and strengthen the institutional framework. By enhancing competitiveness, policymakers can catalyze economic development and ensure the sustainability of industrial clusters.

To conclude, this thesis contributes to a more comprehensive understanding of the complex relationships among industrial clusters, technology adoption, competitiveness, and economic development. Policymakers can utilize this knowledge to design integrated policies that consider the interdependencies and interactions among these factors. A holistic approach to policymaking, informed by the research findings, can lead to more effective strategies, interventions, and policies that foster sustainable economic growth, innovation, and regional development.

But the thesis also has implications for researchers and industrials.

The research provides methodological insights for researchers in the field of economic geography and regional development. Researchers can benefit from the developed methodologies and replicate them in their own studies, contributing to the advancement of the field.

The thesis delves deeper into the complexities of industrial clusters by considering multiple variables and adopting novel approaches to analyze their dynamics, as the application of the *Variance-Based Partial Least Squared Structural Equation Modeling* (PLS-SEM), which was elected over more traditional approaches as the *Ordinary Least Squares* (OLS) linear regression. This comprehensive and multi-mediation analysis provides a more nuanced understanding of the phenomenon and contributes to the development of more accurate models and theories.

In addition, by adopting a dynamic perspective on industrial agglomeration in the context of digital transformation, the research captures the evolving nature of clusters. Researchers can further explore the changing dynamics within industrial clusters and investigate the implications of digitalization on regional development. Moreover, the research bridges the gap between economic geography, digital transformation, and regional development, encouraging interdisciplinary collaboration among researchers from different fields, such as economics, technology, and policy, to deepen the understanding of the relationships among clusters, technology adoption, competitiveness, and economic development.

Similarly, this thesis provides industrials with insightful knowledge. Industrials can utilize this knowledge to develop regional development strategies that foster the formation of industrial clusters, promote technology adoption, and enhance competitiveness. By concentrating related industries and resources in specific geographic areas, industrials can create an environment conducive to knowledge sharing, collaboration, and innovation, leading to economic prosperity.

Industrialists operating within industrial clusters can benefit from the research's emphasis on collaboration and networking. The findings demonstrate that industrial clusters facilitate technology adoption and create a culture of innovation. Industrials can actively engage in collaborative initiatives as the DIC, sharing knowledge and resources, and leveraging the collective strengths of the cluster to drive their own digital transformation and enhance their competitiveness.

Additionally, the thesis recognizes the potential of digital integration within industrial clusters. Industrials can explore opportunities for digital transformation within their organizations, leveraging Industry 4.0 and ICT advancements to enhance operational efficiency, productivity, and competitiveness. By embracing digital capabilities, industrials can adapt to the changing business landscape and position themselves for growth and success in the Digital Era.

Overall, the findings have implications for policy, academia, and industry. Researchers can benefit from the methodological insights, comprehensive analysis, and dynamic perspective presented by the research. Industrials, on the other hand, can leverage the proposed policy tool, incorporate the research findings into regional development strategies, foster collaboration and networking within clusters, and embrace digital integration to drive their own digital transformation and economic development. Finally, this thesis provides policymakers with valuable insights and practical implications for addressing the challenges of industrial clusters and digital transformation. Therefore, policymakers can make informed decisions and develop strategies that foster economic development, innovation, and regional prosperity.

Limitations and recommendations

In spite of the valuable insights and contributions provided by this thesis, it is important to acknowledge its limitations to provide a balanced understanding of the findings.

Theoretical approach of the DIC. While the thesis presents the theoretical foundations of the policy tool and offers a deployment model, it does not include an empirical assessment of a DIC. However, despite not empirically identifying and assessing an actual DIC, the study provides empirical evidence of its feasibility and potential effects.

Generalizability and sample size. The conducted empirical analysis is limited to the Spanish context and a relatively small number of regions, which may constrain the generalization of the results to other contexts. The findings should be interpreted within the specific geographical and socioeconomic context in which they were derived.

Statistical Tools. The study's use of the PLS-SEM approach may have certain methodological limitations since it is not widely used in the case of reflective models with interval/ratio data. Researchers should carefully consider the appropriateness of the chosen methodology and its implications for the study's findings.

Data Availability and Quality. The accuracy of the findings may be affected by limitations in data availability and quality. The mixed use of NUTS-2 and NUTS-3 level data and the conceptual limitations of certain variables, such as competitiveness, could impact the precision of the results.

Causal Inference. While associations among the phenomena have been identified, determining precise causal mechanisms can be challenging. Other unmeasured factors or confounding variables may influence the observed relationships. The study should be cautious in making causal claims and acknowledge the limitations in establishing causality.

Timeframe. The research is conducted within a specific timeframe, which may limit its ability to capture long-term trends or changes over time. The findings should be interpreted as reflecting the specific period under investigation and may not capture evolving dynamics.

Based on the limitations identified, several recommendations can be made to guide future research and inform decision-making by policymakers, industry leaders, and academics.

Firstly, future research should aim to empirically study and evaluate the DIC concept in specific regions, considering its compatibility with existing clusters and quantifying its positive externalities. It is important to move beyond conceptual discussions and focus on practical implementation, assessing the real-world application and its benefits. This would involve conducting case studies and empirical analysis to understand the dynamics, challenges, and opportunities associated with DICs in different contexts.

Secondly, the conduction of comparative studies across different countries can provide valuable insights into the contextual factors that influence the effectiveness of agglomeration and digitalization as promoters of economic development. Such studies can shed light on the specific conditions that facilitate the emergence and success of clusters and help identify best practices and lessons learned. Furthermore, comparative studies may provide relevant insights for the future implementation of policy tools based on agglomeration, informing decision-making processes and fostering cross-country learning.

Thirdly, undertaking longitudinal studies to assess the temporal dynamics of industrial clusters, digitalization, competitiveness, and economic development can offer a deeper understanding of the long-term effects and evolution of these factors over time. This would involve tracking the progress and performance of industrial agglomeration over an extended period, examining their adaptability to technological advancements and changes in market conditions. Longitudinal studies can provide valuable insights into the sustainability and resilience of clusters and help to identify factors that contribute to their long-term success.

Fourthly, to enhance the credibility and validity of the study's findings, several recommendations can be made. It is important to assess the suitability of alternative methodologies and model specifications, conducting sensitivity analyses and robustness tests to validate the results. Rigorous research designs, such as experimental or quasi-experimental approaches, should be employed to strengthen causal inference. Identifying and accounting for potential confounding variables and refining the conceptualization and measurement of variables, particularly competitiveness, are crucial for accurate conclusions. Addressing limitations in data availability and quality by seeking comprehensive and accurate data sources is also recommended. By implementing these recommendations, future research can strengthen the methodological rigor, validity, and reliability of the findings, providing more robust insights into the topic under investigation.

Finally, upcoming research should incorporate the perspectives of policymakers, industrialists, and other relevant stakeholders to gain a comprehensive understanding of the challenges, opportunities, and practical implications associated with industrial clusters, digital transformation, and the DIC. This can be achieved through qualitative research methods such as interviews, surveys, and focus groups. By involving stakeholders from various sectors, researchers can capture diverse viewpoints and ensure that the research outcomes are relevant and actionable for decision-makers.

In conclusion, future research should expand its scope to include a larger and more diverse sample of regions and countries to enhance the representativeness of the findings. This would require additional cluster mapping exercises, resulting in comprehensive maps of industrial agglomeration across Europe or other relevant regions. These maps can serve as invaluable tools for policymakers and industry leaders in the development of effective industrial policies, investment strategies, and targeted support for the DIC. If future research addresses these recommendations, it can contribute to the advancement of the economic geography and facilitate evidence-based decision-making in the realm of industrial clusters and digital transformation.

Full list of references

Adebanjo, D. (2010). The complexities of e-reverse-auction-facilitated aggregated procurement in digitally clustered organisations. *Supply Chain Management-an International Journal*, *15*(1), 69–79. https://doi.org/10.1108/13598541011018139

Afonasova, M. A., Panfilova, E. E., Galichkina, M. A., & Slusarczyk, B. (2019). Digitalization in economy and innovation: The effect on social and economic processes. *Polish Journal of Management Studies*, *19*(2), 22–32. https://doi.org/10.17512/pjms.2019.19.2.02

Aguirre-Urreta, M. I., & Rönkkö, M. (2018). Statistical inference with PLSc using bootstrap confidence intervals. *MIS Quarterly*, *42*(3), 1001–1020. https://doi.org/10.25300/MISQ/2018/13587

Ahmad, N., & Schreyer, P. (2016). Are GDP and productivity measures up to the challenges of the digital economy? *International Productivity Monitor*, *30*, 4–27.

Alcacer, J., Cantwell, J., & Piscitello, L. (2016). Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies*, *47*(5), 499–512. https://doi.org/10.1057/jibs.2016.22

Aleksandrovich, S. K. (2019). Цифровая экономика и ее роль в управлении современными социально-экономическими отношениями [Digital Economy and Its Role in Management of Modern Social and Economic Relations]. *State and Municipal Management Scholar Notes*, *1*(4), 102–105. https://doi.org/10.22394/2079-1690-2019-1-4-102-105

Almeida, F., Duarte, J., & Monteiro, J. (2020). The challenges and opportunities in the digitalization of companies in a post-COVID-19 world. *IEEE Engineering Management Review*, *48*(3), 97–103. https://doi.org/10.1109/EMR.2020.3013206

Angehrn, A. (1997). Designing mature internet business strategies: The ICDT model. *European Management Journal*, *15*(4), 361–369. https://ideas.repec.org/a/eee/eurman/v15y1997i4p361-369.html

Anthony Jnr, B., & Abbas Petersen, S. (2020). Examining the digitalisation of virtual enterprises amidst the COVID-19 pandemic: A systematic and meta-analysis. *Enterprise Information Systems*, *15*(5), 617–650. https://doi.org/10.1080/17517575.2020.1829075

Atik, H., & Ünlü, F. (2019). The measurement of Industry 4.0 performance through Industry 4.0 Index: An empirical investigation for Turkey and European countries. *Procedia Computer Science*, *158*, 852–860. https://doi.org/10.1016/j.procs.2019.09.123

Awad, A., & Albaity, M. (2022). ICT and economic growth in Sub-Saharan Africa: Transmission channels and effects. *Telecommunications Policy*, *46*(8), 102381. https://doi.org/https://doi.org/10.1016/j.telpol.2022.102381

Babkin, A., Kudryavtseva, T., & Utkina, S. (2013). Formation of industrial clusters using method of virtual enterprises. *International Conference on Applied Economics (Icoae)*, 68–72. https://doi.org/10.1016/s2212-5671(13)00011-7

Babkin, A., Plotnikov, V., & Vertakova, Y. (2018). The analysis of industrial cooperation models in the context of forming digital economy. *SHS Web of Conferences*, *44*, 12. https://doi.org/10.1051/shsconf/20184400012

Babkin, A., Vertakova, Y., & Plotnikov, V. (2017). Study and assessment of clusters activity effect on regional economy. *SHS Web of Conferences*, *35*, 63. https://doi.org/10.1051/shsconf/20173501063

Baggio, R., & Del Chiappa, G. (2014). Real and virtual relationships in tourism digital ecosystems. *Information Technology & Tourism*, *14*(1), 3–19. https://doi.org/10.1007/s40558-013-0001-5

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, *27*(5), 525–540. https://doi.org/https://doi.org/10.1016/S0048-7333(98)00065-1

Baron, R., & Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*, 1173–1182. https://doi.org/10.1037//0022-3514.51.6.1173

Barzotto, M., & De Propris, L. (2021). The value of firm linkages in the age of industry 4.0: a qualitative comparative analysis. *Annals of Regional Science*, *67*(2), 245–272. https://doi.org/10.1007/s00168-021-01047-0

Bathelt, H. (2008). Clusters and regional development: Critical reflections and explorations. *Economic Geography*, *84*(1), 109–112. https://doi.org/10.1111/j.1944-8287.2008.tb00394.x

Bathelt, H., & Boggs, J. S. (2003). Toward a reconceptualization of regional development paths: Is Leipzig's media cluster a continuation of or a rupture with the past? *Economic Geography*, *79*(3), 265–293. https://doi.org/10.1111/j.1944-8287.2003.tb00212.x

Bathelt, H., & Li, P. F. (2014). Global cluster networks-foreign direct investment flows from Canada to China. *Journal of Economic Geography*, *14*(1), 45–71. https://doi.org/10.1093/jeg/lbt005

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Bathelt, H., & Taylor, M. (2002). Clusters, power and place: inequality and local growth in time–space. *Geografiska Annaler: Series B, Human Geography*, *84*(2), 93–109. https://doi.org/10.1111/j.0435-3684.2002.00116.x

Bathelt, H., & Turi, P. (2011). Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. *Geoforum*, *42*(5), 520–529. https://doi.org/10.1016/j.geoforum.2011.04.007

Bayliss, D. (2007). Dublin's digital hubris: Lessons from an attempt to develop a creative industrial cluster. *European Planning Studies*, *15*(9), 1261–1271. https://doi.org/10.1080/09654310701529268

Becattini, G. (1990). The Marshallian industrial district as a socio-economic concept. In F. Pike, G. Becattini, & W. Sengenberger (Eds.), *Industrial Districts and Inter-Firm Cooperation in Italy* (pp. 37–51). ILO.

Becker, J. M., Klein, K., & Wetzels, M. (2012). Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models. *Long Range Planning*, *45*(5–6), 359–394. https://doi.org/10.1016/j.lrp.2012.10.001

Berman, A., Marino, A., & Mudambi, R. (2020). The global connectivity of regional innovation systems in Italy: a core–periphery perspective. *Regional Studies*, *54*(5), 677–691. https://doi.org/10.1080/00343404.2019.1672865

Boix, R., & Galletto, V. (2009). Innovation and industrial districts: A first approach to the measurement and determinants of the I-district effect. *Regional Studies*, *43*(9), 1117–1133. https://doi.org/10.1080/00343400801932342

Boix, R., & Trullén, J. (2010). Industrial districts, innovation and I-district effect: Territory or industrial specialization? *European Planning Studies*, *18*(10), 1707–1729. https://doi.org/10.1080/09654313.2010.504351

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 perspective. *World Academy of Science, Engineering and Technology. International Journal of Information and Communication Engineering*, *8*(1), 37–44. https://doi.org/10.5281/zenodo.1336426

Brodzicki, T. (2010). Critical review of cluster mapping studies in Poland. *Analizy i Opracowania KEIE UG*, *1*(3), 3–20.

Buchinskaia, O. N. (2022). Knowledge as a mediator in the relationship between digital and economic development. *Economic and Social Changes: Facts, Trends, Forecast*, *15*(6), 139–152. https://doi.org/10.15838/esc.2022.6.84.8

Buitrago, R. E., Camargo, M. I. B., & Vitery, F. C. (2021). Emerging economies' institutional quality and international competitiveness: A pls-sem approach. *Mathematics*, *9*(9). https://doi.org/10.3390/math9090928

Buitrago, R. E., Torralba Barreto, D. R., & Reyes, G. E. (2022). Are competitiveness rankings and institutional measures helping emerging economies to improve?

Competitiveness Review: An International Business Journal, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/CR-04-2021-0064

Burki, A. A., & Khan, M. A. (2011). Agglomeration economies and their effects on technical inefficiency of manufacturing firms: Evidence from Pakistan. In *International Growth Centre* (Issue March). https://www.theigc.org/project/agglomeration-economies-and-their-effects-on-productivity-and-efficiency-of-manufacturing-firms-evidence-from-pakistan/

Buteau, S. (2021). Roadmap for digital technology to foster India's MSME ecosystem—opportunities and challenges. *CSI Transactions on ICT*, *9*(4), 233–244. https://doi.org/10.1007/s40012-021-00345-4

Caloffi, A., Lazzeretti, L., & Sedita, S. R. (2018). The story of cluster as a cross-boundary concept: From local development to management studies. In F. Belussi & J. L. Hervas-Oliver (Eds.), *Agglomeration and Firm Performance. Advances in Spatial Science* (pp. 123–137). Springer. https://doi.org/10.1007/978-3-319-90575-4_8

Canello, J., & Pavone, P. (2016). Mapping the Multifaceted Patterns of Industrial Districts: A New Empirical Procedure with Application to Italian Data. *Regional Studies*, *50*(8), 1374–1387. https://doi.org/10.1080/00343404.2015.1011611

Carlino, G., & Kerr, W. R. (2015). Agglomeration and innovation. In G. Duranton, J. V Henderson, & W. Strange (Eds.), *Handbook of Regional and Urban Economics* (1st ed., Vol. 5, pp. 349–404). Elsevier B.V. https://doi.org/10.1016/B978-0-444-59517-1.00006-4

Carson, K. A. (2012). [Review of the book The great stagnation: How America ate all the low-hanging fruit of modern history, got sick, and will (eventually) feel better, by T. Cowen]. In *Freeman* (Vol. 62, Issue 5).

Cenfetelli, R. T., & Bassellier, G. (2009). Interpretation of Formative Measurement in Information Systems Research. *MIS Quarterly*, *33*(4), 689–707. https://doi.org/10.2307/20650323

Charykova, O. G., & Markova, E. S. (2019). Региональная кластеризация в цифровой экономике [Regional clustering in the digital economy]. *Economy of Region*, *15*(2), 409–419. https://doi.org/10.17059/2019-2-8

Cheah, J.-H., Sarstedt, M., Ringle, C. M., Ramayah, T., & Ting, H. (2018). Convergent validity assessment of formatively measured constructs in PLS-SEM. *International Journal of Contemporary Hospitality Management*, *30*(11), 3192–3210. https://doi.org/10.1108/IJCHM-10-2017-0649

Chin, W. W. (1998). The Partial Least Squares approach for Structural Equation Modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–236). Lawrence Erlbaum Associates Publishers.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates, Publishers.

Corradini, C., Santini, E., & Vecciolini, C. (2021). The geography of Industry 4.0 technologies across European regions. *Regional Studies*, *55*(10–11), 1667–1680. https://doi.org/10.1080/00343404.2021.1884216

Cortright, J. (2006). *Making Sense of Clusters: Regional Competitiveness and Economic Development* (p. 66). The Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/wp-content/uploads/2016/06/20060313_Clusters.pdf

Crabtree, A., Lodge, T., Colley, J., Greenhalgh, C., Mortier, R., & Haddadi, H. (2016). Enabling the new economic actor: Data protection, the digital economy, and the databox. *Personal and Ubiquitous Computing*, *20*(6), 947–957. https://doi.org/10.1007/s00779-016-0939-3

Crupi, A., Del Sarto, N., Di Minin, A., Gregori, G. L., Lepore, D., Marinelli, L., & Spigarelli, F. (2020). The digital transformation of SMEs – a new knowledge broker called the digital innovation hub. *Journal of Knowledge Management*, *24*(6), 1263–1288. https://doi.org/10.1108/JKM-11-2019-0623

Cruz, S. C. S., & Teixeira, A. A. C. (2010). The evolution of the cluster literature: Shedding light on the regional studies-Regional science debate. *Regional Studies*, *44*(9), 1263–1288. https://doi.org/10.1080/00343400903234670

Cuevas-Vargas, H., & Fernández-Escobedo, R. (2022). How strategic opportunities enhance the tendency to implement Industry 4.0 in Mexican SMEs. A multiple mediation approach. *Procedia Computer Science*, *214*(C), 636–643. https://doi.org/10.1016/j.procs.2022.11.222

Cuevas-Vargas, H., Fernandez-Escobedo, R., Cortes-Palacios, H. A., & Ramirez-Lemus, L. (2021). The relation between adoption of information and communication technologies and marketing innovation as a key strategy to improve business performance. *Journal of Competitiveness*, *13*(2), 23–40. https://doi.org/10.7441/joc.2021.02.02

Cuevas-Vargas, H., Parga-Montoya, N., & Fernandez-Escobedo, R. (2022). The adoption of ICT as an enabler of frugal innovation to achieve customer satisfaction. The mediating effect of frugal innovation. *Procedia Computer Science*, *199*, 198–206. https://doi.org/10.1016/j.procs.2022.01.025

D'Urso, P., Giovanni, L. D., Sica, F. G. M., & Vitale, V. (2022). Measuring competitiveness at NUTS3 level and territorial partitioning of the Italian provinces. *Social Indicators Research*. https://doi.org/10.1007/s11205-021-02836-y

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*(August), 121092. https://doi.org/10.1016/j.techfore.2021.121092

De Blasio, G., & Di Addario, S. (2005). Do workers benefit from industrial agglomeration? *Journal of Regional Science*, *45*(4), 797–827. https://doi.org/10.1111/j.0022-4146.2005.00393.x

De Waele, W., & De Cleyn, S. H. (2014). Belgium: Building a digital cluster of innovation in the heart of Europe. In J. S. Engel (Ed.), *Global Clusters of Innovation: Entrepreneurial Engines of Economic Growth around the World* (pp. 120–140). Edward Elgar Publishing Ltd.

Del Chiappa, G., & Baggio, R. (2015). Knowledge transfer in smart tourism destinations: Analyzing the effects of a network structure. *Journal of Destination Marketing & Management*, *4*(3), 145–150. https://doi.org/10.1016/j.jdmm.2015.02.001

Delgado, M., Bryden, R., & Zyontz, S. (2014). *Categorization of traded and local industries in the US economy*. 1–9. https://clustermapping.us/sites/default/files/files/page/Categorization of Traded and Local Industries in the US Economy.pdf

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799.

https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1–38. https://doi.org/10.1093/jeg/lbv017

Della, M. R., Del Giudice, M., Lombardi, R., & Soto-Acosta, P. (2018). Open innovation, product development, and inter-company relationships within regional knowledge clusters. *Journal of the Knowledge Economy*, *9*(2), 680–693. https://doi.org/10.1007/s13132-016-0356-x

Ding, C., Liu, C., Zheng, C., & Li, F. (2022). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. In *Sustainability* (Vol. 14, Issue 1). https://doi.org/10.3390/su14010216

Diodato, D., Neffke, F., & O'Clery, N. (2018). Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, *106*, 1–26. https://doi.org/10.1016/j.jue.2018.05.002

Duranton, G. (2011). California dreamin': The feeble case for cluster policies. *Review of Economic Analysis*, *3*(1), 3–45. https://repository.upenn.edu/real-estate_papers/2

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J. F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (pp. 2063–2117). Elsevier.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195–1213. https://doi.org/10.1257/aer.100.3.1195

Elola, A., Valdaliso, J., Lopez, S. M., & Aranguren, M. J. (2012). Cluster life cycles, path dependency and regional economic development: Insights from a meta-study on Basque clusters. *European Planning Studies*, *20*(2), 257–279. https://doi.org/10.1080/09654313.2012.650902

Elola, A., Valdaliso, J. M., Franco, S., & López, S. M. (2017). Public policies and cluster life cycles: insights from the Basque Country experience. *European Planning Studies*, *25*(3), 539–556. https://doi.org/10.1080/09654313.2016.1248375

Erboz, G. (2017). How to define Industry4.0: The main pillars of Industry 4.0. *Managerial Trends in the Development of Enterprises in Globalization Era*, 761–767.

https://www.researchgate.net/publication/326557388_How_To_Define_Industry_40_Main_Pillars_Of_Industry_40

European Cluster Collaboration Platform. (n.d.). *Cluster definitions*. Retrieved April 1, 2022, from https://clustercollaboration.eu/cluster-definitions#:~:text=Cluster organisations are the legal,activities%2C especially in SMEs2.

Evans, G. L. (2019). Emergence of a digital cluster in east London: Birth of a new hybrid firm. *Competitiveness Review*, *29*(3), 253–266. https://doi.org/10.1108/cr-08-2018-0047

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis*. Wiley.

Faraj, S., Renno, W., & Bhardwaj, A. (2021). Unto the breach: What the COVID-19 pandemic exposes about digitalization. *Information and Organization*, *31*(1), 100337. https://doi.org/10.1016/j.infoandorg.2021.100337

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Feferman, F. (2014). Brazil: Good governance in the tropics - The rise of the Porto digital cluster of innovation. In J. S. Engel (Ed.), *Global Clusters of Innovation: Entrepreneurial Engines of Economic Growth around the World* (pp. 296–337). Edward Elgar Publishing Ltd.

Fernandez, S. R., Castillo, D., & Martinez, L. A. (2018). Clúster virtual: Nueva alternativa a la competitividad eficaz en las empresas [Virtual cluster: New alternative to effective competitiveness in enterprises]. *Tendencias*, *19*(1), 164–186. https://doi.org/10.22267/rtend.181901.92

Feser, E. J. (1998). Old and new theories of industry clusters. In M. Steiner (Ed.), *Clusters and Regional Specialisation. European Research in Regional Science* (Vol. 8, pp. 18–40). Pion.

Flores, M., & Molina, A. (2000). Virtual industry clusters: Foundation to create virtual enterprises. In L. M. Camarinha-Matos, H. Afsarmanesh, & H. Erbe (Eds.), *Advances in networked enterprises: Virtual organizations, balanced automation and system integration* (pp. 111–120). Springer Science+Business Media.

Fujita, M., & Mori, T. (2005). Frontiers of the new economic geography. *Papers in Regional Science*, *84*(3), 377–405. https://doi.org/10.1111/j.1435-5957.2005.00021.x

Fuks, K., & Kawa, A. (2013). e-Sourcing clusters in network economy. In A. Hakansson & R. Hartung (Eds.), *Agent and Multi-Agent Systems in Distributed Systems - Digital Economy and E-Commerce. Studies in Computational Intelligence* (pp. 33–51). Springer.

Gagnidze, I. (2022). Industry 4.0 and industry 5.0: can clusters deal with the challenges? (A systemic approach). *Kybernetes*. https://doi.org/10.1108/K-07-2022-1005

Gamidullaeva, L., Korostyshevskaya, E., Myamlin, A., & Podkorytova, O. (2022). Exploring Regional Industrial Growth: Does Specialization Explain It? *Economies*, *10*(7). https://doi.org/10.3390/economies10070172

Geissbauer, R., Lübben, E., Schrauf, S., & Pillsbury, S. (2018). *Global digital operations study 2018 - Digital champions: How industry leaders build integrated operations ecosystems to deliver end-to-end customer solutions*. https://www.pwc.es/es/productos-industriales/industria-4-0-global-digital-operations-study-2018.html

Gertler, M. S., & Wolfe, D. A. (2006). Spaces of knowledge flows: Clusters in a global context. In R. Martin, B. Asheim, & P. Cooke (Eds.), *Clusters and Regional Development: Critical Reflections and Explorations* (Vol. 29, pp. 218–235). Routledge.

Glaeser, E. L., & Kerr, W. R. (2009). Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain? *Journal of Economics & Management Strategy*, *18*(3), 623–663. https://doi.org/https://doi.org/10.1111/j.1530-9134.2009.00225.x

Golov, R. S., Palamarchuk, A. G., Anisimov, K. V., & Andrianov, A. M. (2021). Cluster Policy in a Digital Economy. *Russian Engineering Research*, *41*(7), 631–633. https://doi.org/10.3103/S1068798X21070108

Götz, M. (2019a). The industry 4.0 induced agility and new skills in clusters. *Foresight and STI Governance*, *13*(2), 72–83. https://doi.org/10.17323/2500-2597.2019.2.72.83

Götz, M. (2019b). Unpacking the provision of the industrial commons in Industry 4.0 cluster. *Economics and Business Review*, *5*(4), 23–48. https://doi.org/10.18559/ebr.2019.4.2

Götz, M. (2021). Cluster role in industry 4.0 – a pilot study from Germany. *Competitiveness Review*, *31*(1), 54–82. https://doi.org/10.1108/CR-10-2019-0091

Götz, M., & Jankowska, B. (2017). Clusters and Industry 4.0 - Do they fit together? *European Planning Studies*, *25*(9), 1633–1653. https://doi.org/10.1080/09654313.2017.1327037

Grashof, N., & Fornahl, D. (2021). “To be or not to be” located in a cluster?—A descriptive meta-analysis of the firm-specific cluster effect. In *Annals of Regional Science* (Vol. 67, Issue 3). Springer Berlin Heidelberg. https://doi.org/10.1007/s00168-021-01057-y

Grashof, N., Kopka, A., Wessendorf, C., & Fornahl, D. (2021). Industry 4.0 and clusters: Complementaries or substitutes in firm’s knowledge creation? *Competitiveness Review*, *31*(1), 83–105. https://doi.org/10.1108/CR-12-2019-0162

Grimmer, J., & King, G. (2011). General purpose computer-assisted clustering and conceptualization. *Proceedings of the National Academy of Sciences*, *108*(7), 2643–2650. https://doi.org/10.1073/pnas.1018067108

Grover, V., & Sabherwal, R. (2020). Making sense of the confusing mix of digitalization, pandemics and economics. *International Journal of Information Management*, *55*(September), 102234. https://doi.org/10.1016/j.ijinfomgt.2020.102234

Guo, H., Yang, Z., Huang, R., & Guo, A. Q. (2020). The digitalization and public crisis responses of small and medium enterprises: Implications from a COVID-19 survey. *Frontiers of Business Research in China*, *14*(1), 25. https://doi.org/10.1186/s11782-020-00087-1

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). SAGE Publications, Inc. https://us.sagepub.com/en-us/nam/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem/book244583

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-

SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123. https://doi.org/10.1504/IJMDA.2017.087624

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, *46*(1), 1–12. https://doi.org/10.1016/j.lrp.2013.01.001

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hanafiah, M. H. (2020). Formative vs. reflective measurement model: Guidelines for structural equation modeling research. *International Journal of Analysis and Applications*, *18*(5), 876–889.

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industry 4.0 scenarios. *49th Hawaii International Conference on System Sciences (HICSS)*, 3928–3937. https://doi.org/10.1109/hicss.2016.488

Hermans, F. (2021). The contribution of statistical network models to the study of clusters and their evolution. *Papers in Regional Science*, *100*(2), 379–403. https://doi.org/10.1111/pirs.12579

Hervás-Oliver, J. L. (2021). Industry 4.0 in industrial districts: regional innovation policy for the Toy Valley district in Spain. *Regional Studies*, *55*(10–11), 1775–1786. https://doi.org/10.1080/00343404.2021.1939861

Hervas-Oliver, J. L., Estelles-Miguel, S., Mallol-Gasch, G., & Boix-Palomero, J. (2019). A place-based policy for promoting Industry 4.0: the case of the Castellon ceramic tile district. *European Planning Studies*, *27*(9), 1838–1856. https://doi.org/10.1080/09654313.2019.1642855

Hoover, E. M. (1948). *The location of economic activity* (p. 310). McGraw-Hill.

Houston, M. B. (2004). Assessing the validity of secondary data proxies for marketing constructs. *Journal of Business Research*, *57*(2), 154–161. https://doi.org/https://doi.org/10.1016/S0148-2963(01)00299-5

Husain, Z., Dayan, M., & Di Benedetto, C. A. (2016). The impact of networking on competitiveness via organizational learning, employee innovativeness, and innovation process: A mediation model. *Journal of Engineering and Technology Management*, *40*, 15–28. https://doi.org/https://doi.org/10.1016/j.jengtecman.2016.03.001

ICEX España Exportación e Inversiones. (n.d.). *Why invest in Spain? - Economy*. Ministerio de Industria, Comercio y Turismo. Retrieved January 9, 2020, from https://www.investinspain.org/en/why-spain/economy

Jankowska, B., Maria, E. D., & Cygler, J. (2021). Do clusters matter for foreign subsidiaries in the Era of industry 4.0? The case of the aviation valley in Poland. *European Research on Management and Business Economics*, *27*(2). https://doi.org/10.1016/j.iedeen.2021.100150

Jasinska, K., & Jasinski, B. (2019). Clusters under industry 4.0 conditions - Case study: the concept of Industry 4.0 cluster in Poland. *Transformations in Business & Economics*, *18*(2B), 802–823. http://www.transformations.knf.vu.lt/47b/article/clus

Jofre-Monseny, J., Marin-Lopez, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: evidence from the location of new firms in Spain. *Journal of Regional Science*, *54*(2), 313–337. https://doi.org/10.1111/jors.12076

Johansson, B., Karlsson, C., & Stough, R. R. (2006). The emerging digital economy: Conclusions. In B. Johansson, C. Karlsson, & R. R. Stough (Eds.), *The Emerging Digital Economy. Advances in Spatial Science* (5th ed., pp. 331–339). Springer.

Junge, M., Severgnini, B., & Sorensen, A. (2016). Product-marketing innovation, skills, and firm productivity growth. *Review of Income and Wealth*, *62*(4), 724–757. https://doi.org/10.1111/roiw.12192

Karnitis, G., & Karnitis, E. (2017). Sustainable growth of EU economies and Baltic context: Characteristics and modelling. *Journal of International Studies*, *10*(1), 209–224. https://doi.org/10.14254/2071-8330.2017/10-1/15

Kayley, P. (2017). Interpersonal relationships as key drivers of cluster performance. *12th European Conference on Innovation and Entrepreneurship (ECIE)*, 362–367. https://www.researchgate.net/publication/321185237_Interpersonal_Relationships_as_key_Drivers_of_Cluster_Performance/citations

Ketels, C. (2004). *Cluster-based economic development: What have we learned*. Department of Trade and Industry, London, March 17, 2004. https://www.hbs.edu/faculty/Pages/item.aspx?num=47012

Ketels, C. (2017). Cluster mapping as a tool for development. In *Harvard Business School* (Issue June). https://www.hbs.edu/faculty/Pages/item.aspx?num=53385

Ketels, C., & Memedovic, O. (2008). From clusters to cluster-based economic development. *International Journal of Technological Learning, Innovation and Development*, *1*(3), 375–392. https://doi.org/10.1504/IJTLID.2008.019979

Ketels, C., & Protsiv, S. (2021). Cluster presence and economic performance: a new look based on European data. *Regional Studies*, *55*(2), 208–220. https://doi.org/10.1080/00343404.2020.1792435

Knell, M. (2021). The digital revolution and digitalized network society. *Review of Evolutionary Political Economy*, *2*(1), 9–25. https://doi.org/10.1007/s43253-021-00037-4

Kock, N. (2015). One-tailed or two-tailed P values in PLS-SEM? *International Journal of E-Collaboration*, *11*(2), 1–7. https://doi.org/10.4018/ijec.2015040101

Kock, N. (2017). Common method bias: A full collinearity assessment method for PLS-SEM. In H. Latan & R. Noonan (Eds.), *Partial Least Squares path modeling: Basic concepts, methodological issues and applications* (pp. 245–257). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_11

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Lanshina, T., Barinova, V., Kondratyev, A., & Romantsov, M. (2020). Sustainable development and digitalization: The unusual COVID-19 crisis requires original solutions. *International Organisations Research Journal*, *15*(4), 91–114. https://doi.org/10.17323/1996-7845-2020-04-05

Leamer, E. E., & Storper, M. (2001). The economic geography of the Internet age. *Journal of International Business Studies*, *32*(4), 641–665. https://doi.org/10.1057/palgrave.jibs.84909988

Lehdonvirta, V., & Ernkvist, M. (2011). *Knowledge map of the virtual economy* (p. 59).

infoDev/World Bank. https://doi.org/10.1596/27361

Lember, V., Brandsen, T., & Tõnurist, P. (2019). The potential impacts of digital technologies on co-production and co-creation. *Public Management Review*, *21*(11), 1665–1686. https://doi.org/10.1080/14719037.2019.1619807

Lines, T., & Monypenny, R. (2006). *Industrial clustering*. Proceedings of the Sustainable Economic Growth for Regional Australia National Conference - SEGRA, August 28-30, 2006. https://www.researchgate.net/profile/Richard-Monypenny/publication/238712690_Industrial_Clustering/links/5bd8fe6c4585150b2b934b96/Industrial-Clustering.pdf

Lorenzini, F., & Lombardi, S. (2018). L'identificazione dei distretti industriali: una rassegna metodologica [Mapping industrial districts: A methodological review]. *Scienze Regionali, Italian Journal of Regional Science*, *17*(2), 225–260. https://doi.org/10.14650/90223

Malmberg, A., & Maskell, P. (2002). The elusive concept of localization economies: Towards a knowledge-based theory of spatial clustering. *Environment and Planning A*, *34*(3), 429–449. https://doi.org/10.1068/a3457

Mano, R., & Castillo, M. (2015). The level of productivity in traded and non-traded sectors for a large panel of countries. *IMF Working Papers*, *15*(48), 1. https://doi.org/10.5089/9781484392140.001

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., & Krejcar, O. (2018). Consequences of Industry 4.0 in business and economics. *Economies*, *6*(3), 14. https://doi.org/10.3390/economies6030046

Marshall, A. (1920). *Principles of economics* (8th ed., p. 69). Macmillan (original work published 1890).

Maskell, P., & Malmberg, A. (1999). The competitiveness of firms and regions - "Ubiquitification" and the importance of localized learning. *European Urban and Regional Studies*, *6*(1), 9–25. https://doi.org/10.1177/096977649900600102

Molina-Morales, F. X., Martinez-Chafer, L., & Valiente-Bordanova, D. (2017). Disruptive technological innovations as new opportunities for mature industrial clusters. The case of digital printing innovation in the Spanish ceramic tile cluster. *Investigaciones*

Regionales-Journal of Regional Research, *39*, 39–57. https://investigacionesregionales.org/es/article/disruptive-technological-innovations-as-new-opportunities-for-mature-industrial-clusters-the-case-of-digital-printing-innovation-in-the-spanish-ceramic-tile-cluster/

Mostafa, N., Hamdy, W., & Alawady, H. (2019). Impacts of internet of things on supply chains: A framework for warehousing. *Social Sciences*, *8*(3). https://doi.org/10.3390/socsci8030084

Muller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247. https://doi.org/10.3390/su10010247

Oosterhaven, J., Eding, G. J., & Stelder, D. (2001). Clusters, linkages and interregional spillovers: Methodology and policy implications for the two Dutch mainports and the rural North. *Regional Studies*, *35*(9), 809–822. https://doi.org/10.1080/00343400120090239

Ortega-Colomer, F. J., Molina-Morales, F. X., & Fernández-de-Lucio, I. (2016). Discussing the concepts of cluster and industrial district. *Journal of Technology Management & Innovation*, *11*(2), 139–147. https://doi.org/10.4067/S0718-27242016000200014

Owen-Smith, J., & Powell, W. W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, *15*(1), 5–21. https://doi.org/10.1287/orsc.1030.0054

Palacios-Marqués, D., Popa, S., & Pilar Alguacil Mari, M. (2016). The effect of online social networks and competency-based management on innovation capability. *Journal of Knowledge Management*, *20*(3), 499–511. https://doi.org/10.1108/JKM-05-2015-0175

Park, S. C. (2018). The Fourth Industrial Revolution and implications for innovative cluster policies. *AI and Society*, *33*(3), 433–445. https://doi.org/10.1007/s00146-017-0777-5

Popescu, V. A., & Popescu, C. R. (2011). Real economy versus virtual economy - New challenges for nowadays society. *Manager*, *13*(1), 7–15. https://manager.faa.ro/archive/manager_13/articles/1303.pdf

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *62*(2), 73–93. https://www.hbs.edu/faculty/Pages/item.aspx?num=6105

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15–34. https://doi.org/10.1177/089124240001400105

Porter, M. E. (2003). The economic performance of regions. *Regional Studies*, *37*(6–7), 549–578. https://doi.org/10.1080/0034340032000108688

Porter, M. E., & Ketels, C. (2007). *Competitiveness in the global economy: Sweden's position*. Globaliseringsrådet, Stockholm, April 27, 2007. https://www.hbs.edu/faculty/Pages/item.aspx?num=46514

Porter, M. E., Ketels, C., & Delgado, M. (2007). The microeconomic foundations of prosperity: Findings from the Business Competitiveness Index. In A. Lopez-Claros (Ed.), *The Global Competitiveness Report 2006–2007* (Vol. 2006, pp. 51–80). World Economic Forum.

Portugal, M., Ribeiro, F., Kramer, B., Maccari, E. A., & Ritor, H. (2012). Impact of the types of clusters on the innovation output and the appropriation of rents from innovation. *Journal of Technology Management & Innovation*, *7*, 70–80. http://doi.org/10.4067/S0718-27242012000400006

Potter, A., & Watts, H. D. (2010). Evolutionary agglomeration theory: increasing returns, diminishing returns, and the industry life cycle. *Journal of Economic Geography*, *11*(3), 417–455. https://doi.org/10.1093/jeg/lbq004

Rambe, P., & Khaola, P. (2022). The impact of innovation on agribusiness competitiveness: the mediating role of technology transfer and productivity. *European Journal of Innovation Management*, *25*(3), 741–773. https://doi.org/10.1108/EJIM-05-2020-0180

Ratten, V. (2016). International collaboration and knowledge transfer among universities and firms affecting regional competitiveness. *Thunderbird International Business Review*, *58*(1), 91–93. https://doi.org/10.1002/tie.21724

Ricarte, É. (2020). Digitalization process expansion during the COVID-19 pandemic. *Finisterra*, *55*(115), 53–60. https://doi.org/10.18055/Finis20350

Richter, C., Kraus, S., Brem, A., Durst, S., & Giselbrecht, C. (2017). Digital entrepreneurship: Innovative business models for the sharing economy. *Creativity and Innovation Management*, *26*(3), 300–310. https://doi.org/10.1111/caim.12227

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS (v4.0) [Computer software]* (4.0). SmartPLS GmbH. www.smartpls.com

Rocha, H. O. (2004). Entrepreneurship and development: The role of clusters. *Small Business Economics*, *23*(5), 363–400. https://doi.org/10.1007/s11187-004-3991-8

Rodríguez-Pose, A., & Comptour, F. (2012). Do clusters generate greater innovation and growth? An analysis of European regions. *The Professional Geographer*, *64*(2), 211–231. https://doi.org/10.1080/00330124.2011.583591

Romanelli, E., & Khessina, O. M. (2005). Regional industrial identity: Cluster configurations and economic development. *Organization Science*, *16*(4), 344–358. https://doi.org/10.1287/orsc.1050.0131

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, *50*(2), 191–229. https://doi.org/10.1006/juec.2001.2230

Sarkar, R., Prabhakar, T. V, & Chatterjee, J. (2007). Towards digital ecosystems for skill based industrial clusters: Lessons from the “Digital Mandi” project. *IEEE International Conference on Digital Ecosystems and Technologies*, 128–133. https://doi.org/10.1109/DEST.2007.371958

Scarle, S., Arnab, S., Dunwell, I., Petridis, P., Protopsaltis, A., & de Freitas, S. (2012). E-commerce transactions in a virtual environment: Virtual transactions. *Electronic Commerce Research*, *12*(3), 379–407. https://doi.org/10.1007/s10660-012-9098-4

Scherer, F. M. (1984). Using linked patent and R&D data to measure interindustry technology flows. In Z. Griliches (Ed.), *R&D, Patents, and Productivity* (pp. 417–461). University of Chicago Press.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest and the business cycle* (1th ed., p. 255). Transaction Publishers.

Schwab, K. (2016). *The fourth industrial revolution* (1th ed., p. 192). World Economic Forum.

Schwarzer, J., Chen, L., Cheng, W., Ciuriak, D., Kimura, F., Nakagawa, J., Pomfret, R., & Rigoni, G. (2019). The digital economy for economic development: Free flow of data and supporting policies. *Proceedings of the T20 Japan Task Force 8: Trade, Investment and Globalization*, 20. https://t20japan.org/policy-brief-digital-economy-economic-development/

Scott, A. J., & Storper, M. (2007). Regions, globalization, development. *Regional Studies*, *41*(1), 191–205. https://doi.org/10.1080/0034340032000108697

Senyo, P. K., Liu, K., & Effah, J. (2019). Digital business ecosystem: Literature review and a framework for future research. *International Journal of Innovation Management*, *47*, 52–64. https://doi.org/10.1016/j.ijinfomgt.2019.01.002

Sforzi, F. (2015). Rethinking the industrial district: 35 years later. *Investigaciones Regionales*, *32*(2015), 11–29. http://www.aecr.org/images/ImatgesArticles/2015/11/2_Sforzi.pdf?_ga=2.131452296.680042952.1678926565-1405984931.1678409478

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, *52*(3/4), 591–611. https://doi.org/10.2307/2333709

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Skokan, K., & Zotyková, L. (2014). Evaluation of business cluster performance during its lifecycle. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *62*(6), 1395–1405. https://doi.org/10.11118/actaun201462061395

Slaper, T., Harmon, K., & Rubin, B. (2018). Industry clusters and regional economic performance: A study across US Metropolitan Statistical Areas. *Economic Development Quarterly*, *32*(1), 44–59. https://doi.org/10.1177/0891242417752248

Slaper, T., & Ortuzar, G. (2015). Industry clusters and economic development. *Indiana Business Review*, *90*(1), 7–9. https://www.ibrc.indiana.edu/ibr/2015/spring/pdfs/article2.pdf

Solvell, O. (2015). *On strategy and competitiveness: 10 recipes for analytical success* (2nd ed.). Ivory Tower Publisher and SIR. https://irp-cdn.multiscreensite.com/bcb8bbe3/files/uploaded/doc_3540.pdf

Stojčić, N., Anić, I.-D., & Aralica, Z. (2019). Do firms in clusters perform better? Lessons from wood-processing industries in new EU member states. *Forest Policy and Economics*, *109*, 102043. https://doi.org/https://doi.org/10.1016/j.forpol.2019.102043

Storper, M. (2009). Roepke lecture in economic geography - Regional context and global trade. *Economic Geography*, *85*(1), 1–21. https://doi.org/10.1111/j.1944-8287.2008.01001.x

Szanyi, M., Iwasaki, I., Csizmadia, P., Illésy, M., & Makó, C. (2010). Cluster development in Hungary: searching for a 'critical mass' of business via cluster mapping. In B. Dallago & C. Guglielmetti (Eds.), *Local economies and global competitiveness* (pp. 113–133).

Tavares, M. S. D., Gohr, C. F., Morioka, S., & da Cunha, T. R. (2021). Systematic literature review on innovation capabilities in clusters. *Innovation and Management Review*, *18*(2), 192–220. https://doi.org/10.1108/INMR-12-2019-0153

Temouri, Y., Pereira, V., Muschert, G. W., Ramiah, V., & Babula, M. (2021). How does cluster location and intellectual capital impact entrepreneurial success within high-growth firms? *Journal of Intellectual Capital*, *22*(1), 171–189. https://doi.org/10.1108/JIC-02-2020-0066

Titze, M., Brachert, M., & Kubis, A. (2011). The identification of regional industrial clusters using qualitative input-output analysis (QIOA). *Regional Studies*, *45*(1), 89–102. https://doi.org/10.1080/00343400903234688

Tsakalerou, M., & Akhmadi, S. (2021). Agents of innovation: Clusters in industry 4.0. *Procedia Manufacturing*, *55*(C), 319–327. https://doi.org/10.1016/j.promfg.2021.10.045

Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*(May), 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*(July 2018), 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vlaisavljevic, V., Cabello-Medina, C., & Van Looy, B. (2020). The role of policies and the contribution of cluster agency in the development of biotech open innovation ecosystem. *Technological Forecasting and Social Change*, *155*, 119987. https://doi.org/10.1016/j.techfore.2020.119987

Wang, M., Zhang, M., Chen, H., & Yu, D. (2023). How Does Digital Economy Promote the Geographical Agglomeration of Manufacturing Industry? *Sustainability*, *15*(2), 1727. https://doi.org/10.3390/su15021727

Wang, S., Hou, D., Guo, Y., & Dai, L. (2022). The mediation effect of innovation in the domestic and international economic development circulation. *Technology Analysis & Strategic Management*, 1–13. https://doi.org/10.1080/09537325.2022.2069003

Watanabe, C., Naveed, K., Tou, Y., & Neittaanmaki, P. (2018). Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technological Forecasting and Social Change*, *137*, 226–240. https://doi.org/10.1016/j.techfore.2018.07.053

Wilson, J., Wise, E., & Smith, M. (2022). Evidencing the benefits of cluster policies: towards a generalised framework of effects. *Policy Sciences*, *55*(2), 369–391. https://doi.org/10.1007/s11077-022-09460-8

Wixted, B. (2009). *Innovation system frontiers: Cluster networks and global value* (p. 226). Springer. https://doi.org/10.1007/978-3-540-92786-0

Ybarra, J. A., & Domenech-Sanchez, R. (2012). Innovative business groups: territory-based industrial policy in Spain. *European Urban and Regional Studies*, *19*(2), 212–218. https://doi.org/10.1177/0969776411428558 WE - Social Science Citation Index (SSCI)

Yelkikalan, N., Soylemezoglu, E., Kiray, A., Sonmez, R., Ezilmez, B., & Altun, M. (2012). Clustering approach as a regional development tool. *8th International Strategic Management Conference*, *58*, 503–513. https://doi.org/10.1016/j.sbspro.2012.09.1027

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the Digitized World. *Organization Science*, *23*(5), 1398–1408. http://www.jstor.org/stable/23252314

Yudina, T. (2019). Digital segment of the real economy: digital economy in the context of analog economy. *St. Petersburg State Polytechnical University Journal. Economics*, *12*(2), 7–18. https://doi.org/10.18721/JE.12201

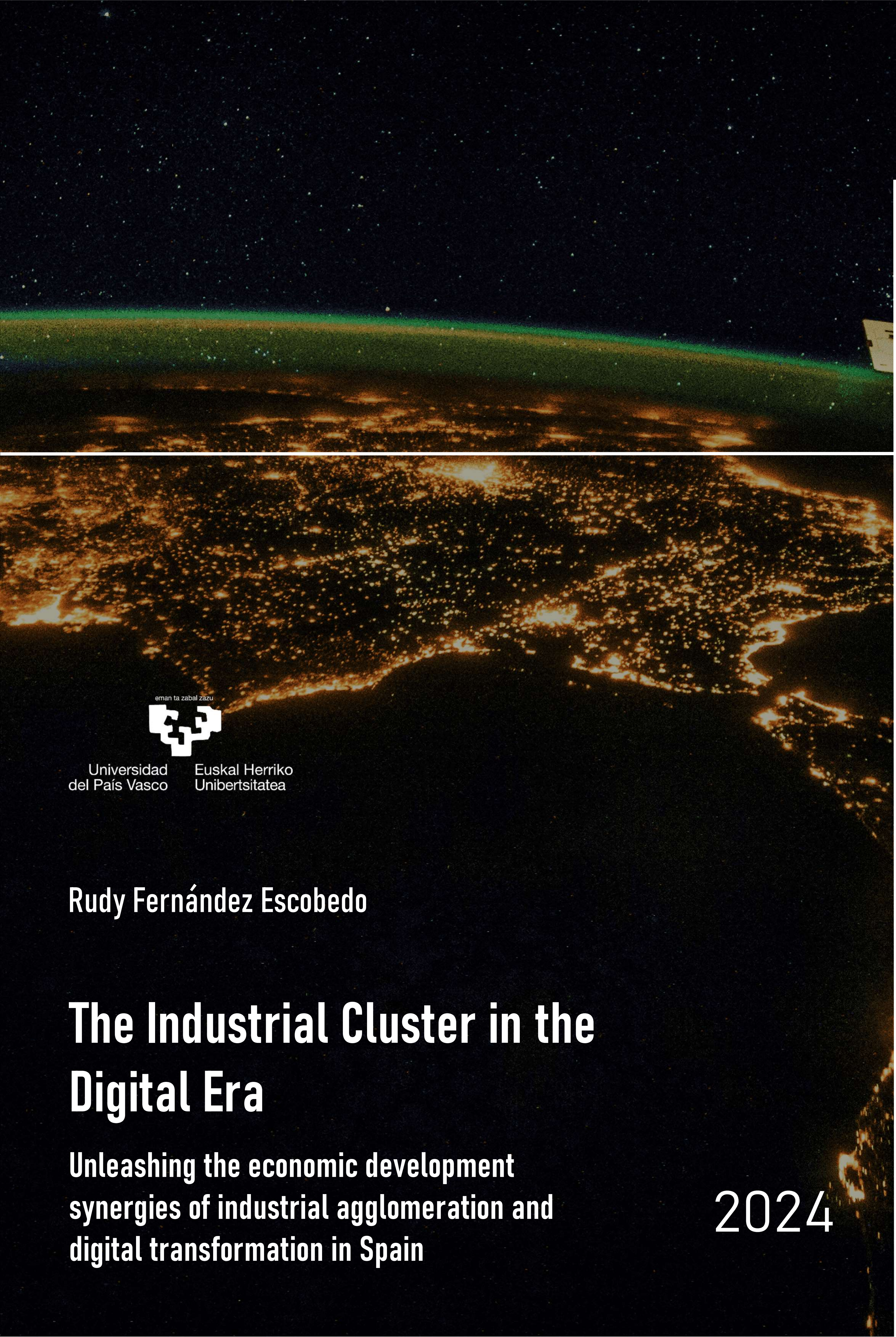
Zeibote, Z., & Muravska, T. (2018). Promoting the regional competitiveness through clusters' approach: Case of the Latvian information technology cluster. *European Integration Studies*, *12*, 77–91. https://doi.org/10.5755/j01.eis.0.12.20846

Zezulka, F., Marcon, P., Vesely, I., & Sajdl, O. (2016). Industry 4.0 - An introduction in the phenomenon. *IFAC PapersOnLine*, *49*(25), 8–12. https://doi.org/10.1016/j.ifacol.2016.12.002

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257

Zhao, Y., Song, Z., Chen, J., & Dai, W. (2023). The mediating effect of urbanisation on digital technology policy and economic development: Evidence from China. *Journal of Innovation & Knowledge*, *8*(1), 100318. https://doi.org/https://doi.org/10.1016/j.jik.2023.100318

Zhu, S., & Pickles, J. (2016). Institutional embeddedness and regional adaptability and rigidity in a Chinese apparel cluster. *Geografiska Annaler, Series B: Human Geography*, *98*(2), 127–143. https://doi.org/10.1111/geob.12095



eman ta zabal zazu

Universidad del País Vasco

Euskal Herriko Unibertsitatea

Rudy Fernández Escobedo

The Industrial Cluster in the Digital Era

Unleashing the economic development synergies of industrial agglomeration and digital transformation in Spain

2024