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DIFFERENCES IN THE CAPACITY OF ADOPTION OF THE ENABLING ICTS FOR INDUSTRY 4.0 IN CHILE

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Abstract: *In the context of the Fourth Industrial Revolution this paper analyzes the factors that explain the degree of diffusion of some Information Technologies (ICTs) enabling Industries 4.0 in Chilean companies. In this group we find technologies such as: Big data, RIFD (Radio frequency identification), Cloud computing, ERP (Enterprise requirements planning), CRM (Customer relationship management), SCM (Supply chain management) and Computer security. Through the analysis of clusters, orderly logistic regression and decision tree, based on 2,081 companies reported in the Survey of Access and Use of Information Communication Technology (ICT) in Companies 2018 (MINECON, 2020). It is concluded that there is an important difference in technological adoption based on size from the volume of sales and the amount of direct labor. It is also noted that companies that subcontract and at the same time have ICT professionals are more likely to invest in this type of technology. We detected a "technological staggering" where companies begin by incorporating Cloud Computing and ERP and then increase in the number and complexity of the technologies used, achieving greater synergies and benefits in digital transformation. It is necessary to implement mechanisms for monitoring technical change to generate public policies aimed at leveling technological adoption in small and medium-sized enterprises. This work provides a global and intersectoral view of the process of diffusion of enabling technologies for Industry 4.0 through multivariate analysis techniques and data science, being a contribution to what is currently worked on focused on the study of business cases, on the monitoring of a specific technology or on an analysis of a specific productive sector.*

Keywords: *Technology adoption, ICT, Industry 4.0, technology promotion policy, digital transformation, technological synergy, ordered logit, statistical clusters, decision tree.*

JEL Classification: *O33, O14.*

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Introduction

This work seeks to identify the degree of diffusion of some enabling ICTs for industries in the Chilean productive fabric. Some technologies included here are: Big data, RIFD, Cloud computing, ERP, CRM, SCM and the area of IT security, which are basic elements for the Fourth Industrial Revolution. Data from the Survey on Access and Use of Information and Communication (ICT) in Companies 2018, which were published by the Ministry of Economy of Chile (MINECON, 2020), were used. It should be noted that a part of the total enabling technologies for Industry 4.0 is measured, which are not only focused on software, but also include innovation in electronics, optics and mechatronics. We currently are lacking the sufficiently comprehensive national statistics that allow us to fully follow the phenomenon of adoption of this type of technology.

This study begins with a conceptual review of the technology adoption model. Subsequently, the gap in this adoption among companies of varying sizes and in relation to the OECD average is estimated. Regarding the methodology, some data algorithms contained in the Weka software for data scrubbing (Interquartile Range), statistical clusters (*K*-means with Manhattan distance) and decision trees (J48). Some traditional multivariate analysis models are also presented: ordered logit and marginal effects calculations.

Among the main conclusions of the study, it is identified that in larger companies, depending on the sales volume and the number of workers, those that have outsourcing processes and have IT professionals have a greater probability of achieving a synergistic technological development, counting with more than four enabling ICTs for Industry 4.0 simultaneously.

The contribution of this paper is that we address the phenomenon of the adoption of enabling technologies in a wide group of companies through data tools and multivariate analysis, filling a space in the bibliographic review as it is a recent research topic. Our approach is different from the traditional ones associated with case studies or the monitoring of a certain technology, providing inputs for the development of new public policies that make it possible to bridge gaps in smaller companies.

1. Theoretical Background

The Fourth Industrial Revolution (Schwab, 2016), which implies the digitization of the different links in the value chain, will bring with it the birth of new business models (Botha, 2019; Dean & Spoehr, 2018), the reorganization of the industry and at the same time, an increase in unemployment, especially in a low-skilled and highly routine job (Nedelkoska & Quintini, 2018).

In this context, it is essential to analyze the degree of adoption and diffusion of some enabling ICTs for Industry 4.0. This involves reviewing the models of technology adoption, being the T.O.E. the best-known framework, which identifies factors at the Technological, Organizational and Environmental level to explain the adoption of technologies in a company (Rogers, 1995).

The following factors that explain the adoption of enabling technologies for Industry 4.0 are identified below through bibliographical review:

a) The qualification of labor affects the capacity of technological adoption on the part of the companies, as well as the ability to search for and correctly evaluate the technological complexity, adjusting the perceptions of the challenges imposed by adapting the new technologies to the business reality (Prause & Günther, 2019; Reyes et al., 2016). On the other hand, qualified human resources allow the company to have a more flexible organizational culture focused on continuous improvement and the creation of new business models, which favors the adoption of enabling technologies for Industry 4.0 (Chege et al., 2019; Kiraz et al., 2020; Müller et al., 2018; Vowles et al., 2011).

b) Having professionals with digital skills is essential for the adoption of enabling ICTs (Almeida et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2019). The diffusion rate of ICTs anticipates a high diffusion of 4.0 technologies at the level of companies and countries (Nhamo et al., 2020). To make a technological leap, a base of core technological competencies already acquired must be counted, determining the adoption capacity of companies (Maggi et al., 2020; Motta et al., 2019).

c) The size of the company positively affects technology adoption processes due to the significant financial and administrative effort involved in investment decisions and reinvestment of resources in this type of enabling technologies (Arnold et al., 2018; Brambilla, 2018; Dalenogarea et al., 2018; Gatica-Neira, 2022; Horváth & Szabo, 2019; Ingaldi & Ulewicz, 2020).

d) The higher the productivity per worker, the greater the probability of adopting a new technology, increasing the perception of relative advantages, as a result of the expected leaps in productivity (Brambilla, 2018). Depending on the productivity levels of the companies, the incorporation of enabling technologies will produce different impacts on unskilled employment through substitution and complementarity effects (Almeida et al., 2020).

e) The existence of outsourcing processes puts pressure on the capacity to coordinate and measure the entire value chain in real time, increasing the probability of adopting 4.0 technologies (Horváth & Szabo, 2019). The stimulus to increase the efficiency of the value chain, through digital technologies, will be greater when the company has strategies focused on cost (Dalenogarea et al., 2018).

The presence of these factors will condition the amount of enabling ICTs that can operate simultaneously in a company, significantly affecting profitability and asset turnover (Berger, 2016). The companies that achieve greater technological synergy will distance themselves from the rest of the national productive fabric, increasing the existing gaps through greater efficiency of their operations and the implementation of new businesses.

Some studies in Latin America are highlighting the importance of adoption factors. In this regard, Motta et al. (2019) in Argentina and Maggi et al. (2020) in Chile have made it possible to deepen the internal adoption process with an emphasis on technological management, highlighting the figure of the business leader, the importance of local suppliers and the pull of a large company usually intensive in natural resources. Gatica Neira and Ramos Maldonado (2020) confirms the development of enabling technologies for Industry 4.0 in export activities intensive in natural resources.

This study is complementary to the case analysis and allows a wider view of the diffusion process in the national economy, identifying the technology clusters and the explanatory factors for the different levels of adoption. Clearly, the state must play an active role in the creation of technology markets (Mazzucato & McPherson, 2019), which stimulate diffusion and innovation, especially in the SMEs segment. Accordingly, public policy initiatives that distinguish the variety of situations in the technology adoption in the national productive fabric, will be better oriented to generate innovative impulses in the national economy.

In general, Latin American countries do not have global policies aimed at stimulating digital transformation in SMEs. The emphasis has been on promoting training programs, accompaniment and the promotion of research and development. Support for technology adoption is still scarce. Initiatives are fragmented across ministries, corporations and regional governments, but there is no global policy. Countries often formulate 'digital agendas' where the focus is on access, education, and e-government, devoting little attention to productive issues (Dini et al., 2021). In the Chilean case, the most recent precedent is the launch of the proposal "Digital Transformation Strategy: Chile 2035", which to date is not transformed into a public policy, which adds to the Artificial Intelligence Policy 2021–2030 of the Ministry of Science and Technology. All these initiatives are very recent, which prevents their evaluation. At the Latin American level in some regions we beginto see mesoecornomic work initiatives aimed at the development of industries 4.0, the following stand out: the cases of Medellín in Colombia, Cordoba 4.0 in Argentina, to name a few.

International comparative studies in Latin America use data on internet connectivity (quality and coverage) and the use of e-commerce, but there are still few studies where technological adoption processes in companies are massively addressed. In this regard, Dini et al. (2021) confirms the existence of national surveys of companies where the incorporation of technology is analyzed, we find the cases of Brazil (2019), Ecuador (2018) and Mexico (2019). There is still heterogeneity in the definition of business sizes and there are differences in the breadth of the technologies analyzed. The results in general suggest that companies have internet connectivity, but make unsophisticated use of it. When more complex technologies are analyzed, the gap between companies according to size tends to increase, which is consistent with what was identified in the Chilean case.

2. Prior Data Review

As can be seen below, with data from the Survey on Access and Use of Information Technology and Communication (ICT) in Companies 2018 (MINECON, 2020), our study analyzes the adoption gaps according to size, the gap in the national average compared to the OECD average and the existence of several technologies acting simultaneously. This background serves the context for the field study.

2.1 Gaps According to Size and in Relation to Technological Frontier

Tab. 1 shows that on average 31.5% of large companies have or have used enabling ICTs for Industry 4.0. In contrast, only 8.8% of SMEs have succeeded in adopting them. There is currently a 3.6 times gap in adoption levels based on size. This first result shows how relevant it is to have specific public policies that allow supporting adoption in smaller companies. Looking at the specific technologies, it is found that the biggest gaps are in the implementation of the IT security area with a difference of 6.2 times between large companies and SMEs. In a second order we have the implementation of Radio Frequency Identification sensors (RFID) in which the gap is 5.5 times.

In an intermediate range, in which the gap between SMEs and large companies moves between 3 to 4 times, there is the use of Big data, Enterprise resource planning (ERP) and Customer relationship management (CRM).

Finally, we have a group of technologies in which the gaps between SMEs and large companies are relatively smaller, highlighting Cloud services (2.8) and supply chain management (Supply Chain Management SCM) with a gap of 2.0 times.

In the Chilean case, the average of enabling technologies is 10.6%, while in the OECD countries it is 23.3%. The gap is 2.2 times, which shows the leap that the national economic fabric must make in relation to frontier performance.

Three technologies are noted for their greatest lag. In principle, there is Big data, in which the gap between national companies with the OECD average is 6.5 times. Further back we have the CRM in which the distance is 4.8 times and finally the existence of an IT security area in which distance is 4.1 times.

In technologies in which the gap with OECD countries is smaller, it is in the use of Cloud services (1.4 times) and ERP systems (1.3 times).

2.2 Technological Synergy

For the purposes of our analysis, Fig. 1 is presented in which the presence of various technologies is related to the size of the organization.

In 59% of small companies there is no presence of any type of enabling ICTs for Industry 4.0. This situation confirms how relevant the size variable is when explaining the adoption of technologies. In this vein, 24% of medium-sized companies and 8% of large companies do not present enabling ICTs.

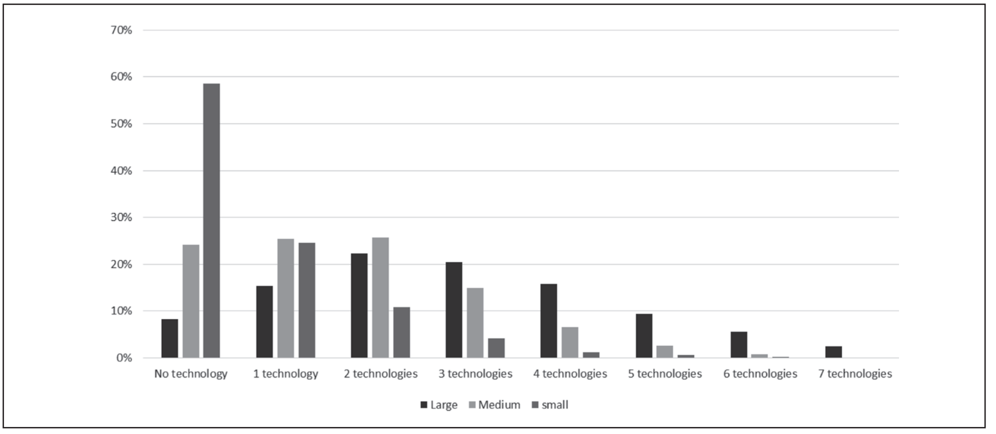
Tab. 1: A comparative view of new technologies according to the survey on access and use of information technology and communication (ICT) in companies 2018 (MINECON 2020)

Key dimension	A) Large companies (%)	B) SMEs (%)	C) Shortening of gaps between SMEs and large companies*	D) Total of Chilean companies (%)	E) OECD average (%)	F) Shortening of gaps with OECD**
Big data	7.2	1.7	4.2	2.0	13.0	6.5
Radio-frequency identification (RFID)	22.0	4.0	5.5	6.0	14.0	2.3
Cloud computing	50.0	18.0	2.8	21.0	30.0	1.4
IT security area	31.0	5.0	6.2	7.0	29.0	4.1
Enterprise resource planning (ERP)	77.0	22.0	3.5	26.0	33.0	1.3
Customer relationship management (CRM)	21.0	5.0	4.2	6.0	29.0	4.8
Supply chain management (SCM)	12.0	6.0	2.0	6.0	15.0	2.5
Linear average of technologies	31.5	8.8	3.6	10.6	23.3	2.2

Source: own

Note: *times = A/B; **times = E/D.

Fig. 1: Percentage distribution of enabling ICTs for Industry 4.0 by business segment



Source: own

When reviewing the graph data, we found that 25% of small companies have only one technology, something similar happens with medium-sized companies. Meanwhile, 15% of large companies have only one technology. To this extent we can say that companies have not developed technological synergies by not experiencing the combined effects of these.

From two to four technologies, the first synergies began to be experienced in the large company segment and to a lesser extent in the medium-sized segment. On average 20% of large companies have combined benefits of two to four technologies. A differential effect on growth and profitability rates will probably be observed in this group of companies. In the section ranging between 5 and 7 enabling ICTs, we mainly see large companies, in which 4% of these are already taking advantage of technological synergies.

In summary, from this first review, we find that national companies present a gap in relation to the OECD countries while at the same time there is a difference in adoption levels according to size. It is evident that large companies will be more likely to develop technological synergies. This condition of asymmetry will increase over time, affecting smaller companies.

3. Methodology

In the field study, the factors that explain the level of technological synergy of the firms will be identified and the technological combinations will be analyzed in order to visualize a technological staggering.

To this end, some data science algorithms (clusters and decision tree) and multivariate analysis models (ordered logit and marginal effects) were applied. This involved debugging the initial database, eliminating companies with incomplete data and extreme cases, the latter using Weka's unsupervised Interquartile Range algorithm. The number of companies was reduced from 3,344 to 2,081, which implied a 37.7% drop in the total data processed. The elimination of these data did not condition the explanatory capacity of the methodologies used in this study.

3.1 Identification of Technological Clusters

The clusters were extracted using the *K*-means algorithm and the Manhattan distance on a binary matrix of occurrence from Weka (Sharma et al., 2012). It should be noted that an adequate distance for this data corresponds to the Hamming distance, i.e., XOR (Kubat, 2017). Nevertheless, in this case, it is feasible to glimpse that both distances – Manhattan and Hamming – are equivalent due to distances between two elements totally different provide 0; meantime, for the same element, the distance is 1.

The *K*-means algorithm runs the following steps:

- The k points are placed in space representing the objects to be grouped. These points represent the centroids of the initial groups;
- each object is assigned to a group, which has the closest centroid;
- the positions of k centroids are recalculated;
- steps 2 and 3 are repeated until all points belong to a group;
- this produces a separation of objects into groups.

The visualization of these clusters has an exploratory and analytical emphasis. It does not affect the use of the other instruments of this work (ordered logit and decision tree), which use the number of technologies adopted by companies as an explanatory variable.

On the refined database, we worked with companies that already have enabling ICTs for Industry 4.0. This implied reducing the database from 2,081 to 1,348 companies. In this case, companies with no technologies are excluded so as not to distort the visualization of technology clusters, allowing better constructions of subgroups within the group of companies already adopting (basic and synergistic).

3.2 Identification of Explanatory Factors

Explanatory factors are identified for companies that are in a null, basic and synergistic phase of adoption. For these purposes, we worked with an ordered logistic regression model (ordered logit). This analysis is done on the total number of the refined database (n = 2,081). To this end, a free econometric software called Gretl is used (https://gretl.sourceforge.net/).

To generate the probabilistic model, a dependent variable called 'depth index' is built, explained by:

$Depth\ index = Level\ of\ presence\ (0/1)$ in:

$$ERP + CRM + SCM + Big\ data + RIFD + \\ + Cloud\ computing + IT\ Security\ area \quad (1)$$

where the index ranges between 0 and 7 in each company (n = 2,081).

When reviewing the distribution of the depth indicator, a discrete variable was generated in which the following groups are generated from a Weka discretization algorithm:

- Group 0: 'no development' – consists of companies that do not have more advanced ICTs technologies;
- group 1: 'basic level' – grouping those organizations that have 1, 2 and 3 technologies;
- group 2: 'synergic level' – integrated by companies that have 4, 5, 6 and 7 technologies.

3.3 Construction of Decision Tree

By using two attribute selection algorithms, CfsSubsetEval and Best First, available in Weka software, the main variables that can explain the level of depth in adoption are identified.

From this selection of attributes, on a sample of 2,081 companies, a decision tree is built by applying the J48 algorithm of Weka software. The quality of the proposed tree is evaluated from the number of correctly predicted cases. For these purposes, the confusion matrix is presented later in Tab. 6. The decision tree has a series of analytical advantages: it does not require the assumptions of probability distribution, it is fast, it facilitates the interpretation of results, robust results are delivered and the correlation between attributes does not alter its precision (Rojas-Córdova et al., 2020).

The J48 of Weka software is based on the C 4.5 algorithm, devised by J. Ross Quinlan (Witten et al., 2011), and as the decision parameter, it chooses the attribute with the highest information gain measured by the entropy difference. Its stages are:

- Incorporate base cases;
- calculate the entropy pool;
- for each attribute, calculate the information gain;
- find the attribute that gives the highest normalized information gain;
- repeat the process until the information gain is zero in the whole tree.

$$\text{Entropy}\ (p_1, p_2, \ldots, p_n) = \sum_{i=1}^{n} p_i \log_2(p_i) \quad (2)$$

where each p_i is a fraction = class i cases/total cases.

To avoid overfitting in the decision tree, the Weka software applies a 'pruning', with a confidence factor = 0.25 (the smallest value incurs more pruning) and a minimum of two instances per leaf, which is what is suggested in Weka's J48 algorithm (Witten et al., 2011).

Tab. 2 synthesizes the main variables that were examined in the field study and that are based on the theoretical framework and available data collected in the ICTs Survey of the Chilean Ministry of Economy.

Tab. 2: Explanatory variables of the depth in the adoption of enabling ICTs technologies for Industry 4.0

Variables and authors	Explanation	Hypothetical linkage
Sales (Arnold et al., 2018; Dalenogarea et al., 2018; Ingaldi & Ulewicz, 2020; Horváth & Szabo, 2019; Brambilla, 2018)	Annual sales income of each company excluding taxes (Source: data obtained from the survey)	A positive hypothetical linkage is expected.
Purchases	Annual purchase cost of each company without taxes (Source: data obtained from the survey)	A negative linkage is expected; if purchases are high, contribution margins are lower, making adoption more difficult.
Direct labor (Arnold et al., 2018; Dalenogarea et al., 2018; Ingaldi & Ulewicz et al., 2020; Horváth & Szabo et al., 2019; Brambilla, 2018).	Staff directly hired by the company (Source: data obtained from the survey)	A positive linkage is expected; more workers mean larger size and greater financial strength to adopt more complex technology.
Added value on sales (Arnold et al., 2018; Dalenogarea et al., 2018; Ingaldi & Ulewicz et al., 2020; Horváth & Szabo et al., 2019; Brambilla, 2018)	Result of = (sale − purchase)/ sale (Source: calculated from survey)	A positive linkage is expected; the higher the margin on sale, the company will have a greater financial slack to adopt technology.
Productivity (sale/labor) (Almeida et al., 2020; Brambilla, 2018).	Result of = sale/labor Source: calculated from survey	A positive linkage is expected; companies with higher productivity are more likely to invest in technologies.
Outsourcing (binary) (Dalenogarea et al., 2018; Horváth et al., 2019 ; Horváth & Szabo, 2019)	A binary is built from the number of subcontracted workers in the company; outsourcing is understood as the commercial relationship with another company for specific tasks that may involve labor. (Source: calculated from survey)	A positive linkage is expected between the adoption of technologies and the presence of outsourcing; subcontracting companies have greater organizational complexity which justifies adoption as a management tool.
ICTs specialists (binary) (Motta et al., 2019; Maggi et al., 2020; Almeida et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2019)	A binary is built from the number of ICT specialists available in the company during the year; they are employees who are able to develop, operate and maintain the company's information and communication systems (Source: calculated from survey)	A positive linkage is expected between the presence of skilled labor and the possibility of adopting technologies; companies that have ICT specialists have the capacity to absorb new technologies.

Source: own

The variables just presented do not have collinearity problems, showing variance inflation factors (VIF) below 10 in all parameters.

4. Field Research

The following provides a cluster analysis, an ordered logit, and a decision tree in order to identify how technological synergies behave and the factors that explain why a company has a certain level of technology adoption.

4.1 Technology Clusters

Through the analysis of statistical clusters, nine clusters are identified in which all the technologies studied appear (Tab. 3).

Tab. 3: Clustering results – cluster distribution for the enabling ICTs for Industry 4.0

Clusters	Number of companies	Distribution over the clustered group (%; *N* = 1,348)	Distribution over the total analyzed (%; *N* = 2,081)	Technologies
Cluster 0	525	39	25	ERP
Cluster 4	233	17	11	Cloud
Cluster 7	200	15	10	ERP, Cloud
Cluster 6	119	9	6	ERP, CRM, Cloud, SEGTIC
Cluster 2	120	9	6	ERP, CRM, SCM, Cloud
Cluster 8	67	5	3	ERP, RIFD, Cloud, SEGTIC
Cluster 1	45	3	2	ERP, CRM, SCM, Big cloud, SEGTIC
Cluster 3	25	2	1	ERP, Big cloud
Cluster 5	14	1	1	ERP, CRM, Big cloud
Total number of clustered companies	1,348		65	
Companies with no technologies 4.0	733		35	
Total number of companies	2,081		100	

Source: own based on the use of Weka software

Based on the grouping (Fig. 2), we find two large groups of clusters which allow us to facilitate reading of data.

It should be noted that this analysis excludes companies with no technologies which we previously classified as 'zero development', representing 35% of the total companies analyzed. Two levels of adoption are identified in addition to the null condition of adoption.

Basic Development

Clusters 0, 4 and 7 explain 71% of the clustered cases (NC = 1,348) and represent 46% of the total companies analyzed (NA = 2,081).

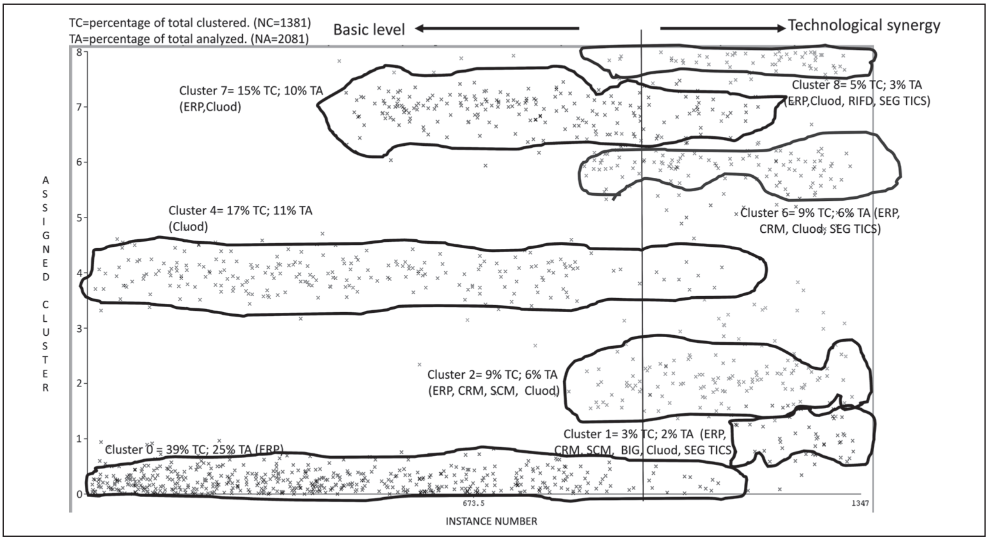
In these subgroups, the synergy between the ERP and CLOUD is confirmed, which crosses the other conglomerates transversally. These technologies make it possible to improve the efficiency of information management within companies and allow full use of the resources available in the Cloud. These companies are at a basic level of development and can take a leap by adopting a new enabling ICTs for Industry 4.0.

Synergistic Development

Clusters 1, 2, 3, 5, 6 and 8 explain 29% of the clustered cases (NC = 1,348) and represent only 19% of the companies analyzed (NA = 2,081).

These subgroups combine a greater number of technologies acting simultaneously. When reviewing Fig. 2, the clusters on the left of the graph are highlighted. In the case of cluster 8, this accounts for 5% of the total number of clustered companies among which stand out the companies that combine a basic ERP and Cloud platform with RIFD technology and computer security. In the same vein, we have clusters 6 and 2, which explain 9% of the clustered cases, presenting a base of ERP, Cloud, CRM. Additionally, the computer security function is detected in the first subgroup and, in the second, we find the supplier management systems (SCM).

Fig. 2: Visualization of enabling ICT clusters for Industry 4.0



Source: own based on data from the ICT survey and WEKA software

Note: Fig. 2 does not show conglomerates since they have very few companies; each point in the figure is a company.

In this context, cluster 1, located at the lower end of Fig. 2, can be described as 'first technological movers'. This group represents 3% of clustered companies and represents only 2% of the total analyzed. It comprises 45 companies that present a wide range of technologies, highlighting ERP, CRM, SCM, Big data, Cloud and IT security.

By reviewing Fig. 2, it is possible to see what the logical path should be for a digital transformation in the company. It begins with a Cloud and ERP base → moves forward with platforms SCM and CRM → finally, it incorporates Big data, IT security and RIFD technologies.

4.2 Explanatory Factors Analysis of the Level of Depth in Technological Adoption

Two complementary analyses are presented. On the one hand, an ordered logit model is developed, which includes the analysis of marginal effects and, secondly, a decision tree is presented, which allows the factors that explain the level of technological adoption to be related in a hierarchical way.

Ordered Logit Model

When reviewing Tab. 4, we find that the model allows 73.4% of the cases to be answered correctly, presenting a good explanatory capacity based on the likelihood test. It should be noted that our objective is to analyze the slopes of each explanatory variable rather than the magnitude of the coefficient.

The first result is the cut-off points calculated by the model. The first point (Cut = 0.41***) indicates that the null group goes from 0 to 0.41 technologies, therefore, there will be the companies that have not adopted ICT 4.0. The second cut-off point (Cut = 3.012***) distinguishes between the second and third group. Between 0.41 and 3.01 technologies we will have the basic group understood as that which has between 1, 2 and 3 technologies. The section goes from 3.01 technologies onwards are described as synergistic companies. These results confirm the discretization carried out in the Weka software algorithm, explained in the methodology, and which will be used later in the decision tree.

A direct and significant relationship is observed between sales levels and greater

Tab. 4: Results of classification analysis to explain the ordered variable – factors that can explain the depth in the adoption of enabling ICTs for Industry 4.0 (ordered logit)

Variables	Coefficients
Sales	0.0001***
Purchases	−0.00009**
Direct labor	0.0005***
Value added to sales [(sales − purchases)/sales]	0.002
Productivity (sales/labor)	0.01**
Outsourcing (binary)	0.46***
ICT specialist (binary)	1.97***
Cut 1	0.419***
Cut 2	3.012***
Percentage of cases correctly predicted (%)	73.4
Likelihood ratio (chi-squared test)	1,106 (0.000)

Source: own based on data from the ICT survey and Gretl software

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; dependent variable: group 0 (null), group 1 (basic), group 2 (synergistic); $N = 2{,}081$.

Tab. 5: Marginal effects based on the mean of ordered logit

Variables	Companies		
	Group 1 = null (no technologies; dp/dx)	**Group 2 = basic** (1, 2, 3 technologies; dp/dx)	**Group 3 = synergistic** (4 or more technologies; dp/dx)
Sales	−0.0000352***	0.00001***	0.000024***
Purchases	0.000019**	−0.0000057**	−0.000013**
Direct labor	−0.00011***	0.000034***	0.000079***
Value added to sales	−0.00041	0.00012	0.0002
Productivity (sales/labor)	−0.0029**	0.00089**	0.002**
Outsourcing (binary)	−0.085***	0.015***	0.06***
ICT specialist (binary)	−0.30***	−0.05***	0.35***

Source: own based on Gretl plugin (lp-mfx package, version 1.0)

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

technological synergy (sales = 0.0001***). The foregoing shows us that the size of the company conditions the probability of incorporating enabling ICTs, corroborating what is described in the theoretical framework. On the other hand, there is an inverse relationship between purchase volumes and greater technological synergy (purchases = −0.00009**). These separate results show the importance of having financial slack to face a digital transformation process.

The amount of direct labor is a good indicator to predict the level of technological adoption, showing a significant and positive relationship (direct labor = 0.0005***). In this respect, two explanations can be given. In principle, the number of workers is an expression of the size of the company, which allows anticipating the financial capacity at the time of adopting. A second explanation lies in the fact that having a greater amount of labor implies satisfying the need for coordination and control, being fertile ground for Cloud, ERP, RIFD technologies, to name a few.

There is no significant relationship between the ratio of value-added to sales [(sales − purchases)/sales] and the possibility of increasing technological synergy (value added to sales = 0.02). Contrary to what might be thought, the contribution margin does not turn out to be an explanatory variable of adoption.

The indicator of productivity per worker (sales/labor = 0.01**) presents a significant and positive relationship. The most productive companies are more likely to incorporate new enabling ICTs for Industry 4.0, favorably determining the perception of future benefits when evaluating incorporating new technologies.

The last two are binary variables. In principle, we have the presence of subcontracting in companies. The results show a positive and significant relationship between the outsourcing of company activities and the probability of incorporating technologies (outsourcing = 0.46***). The companies that outsource have a greater organizational complexity, which justifies the adoption of tools to support the operation management.

Finally, it is verified that having IT professionals has a high explanatory capacity for the adoption of enabling technologies for Industry 4.0 (ICT specialists = 1.97***), improving the technology's absorptive capacity, facilitating prospecting, adaptation and mainstreaming with existing technologies.

Complementing the previous analysis, the marginal effect was presented from the ordered logit model (Tab. 5). The objective of this analysis is to identify the variation in the estimated probability of each discrete outcome (dp) given a change in the independent variables (dx). For purposes of this study, we are interested in the sign and if this variation (dp/dx) is different from zero.

When analyzing the marginal effects, it is verified that in the case of the analyzed variables the signs have a coherent behavior according to the different levels of technological adoption already defined.

In the case of companies that have no development in enabling ICTs, the increase in the independent variables, except purchases, have a negative slope, that is, if they increase, it is less likely that any technological adoption can be detected in this group.

In the basic adoption group, it can be observed that the variables follow a hypothetical relationship. If sales, labor, productivity and subcontracting increase, the probability of adopting enabling ICTs is greater. In this context, the case of ICT specialists is interesting, which in the basic condition (group 2) they present a negative relationship (dp/dx = −0.05***) to the variation in the dependent variable. It should be noted that in this section from the cut-off points, it goes from 0.41 to 3.01 technologies. According to our results, in the basic level section, the mere incorporation of ICT professionals does not necessarily translate into an increase in the levels of adoption.

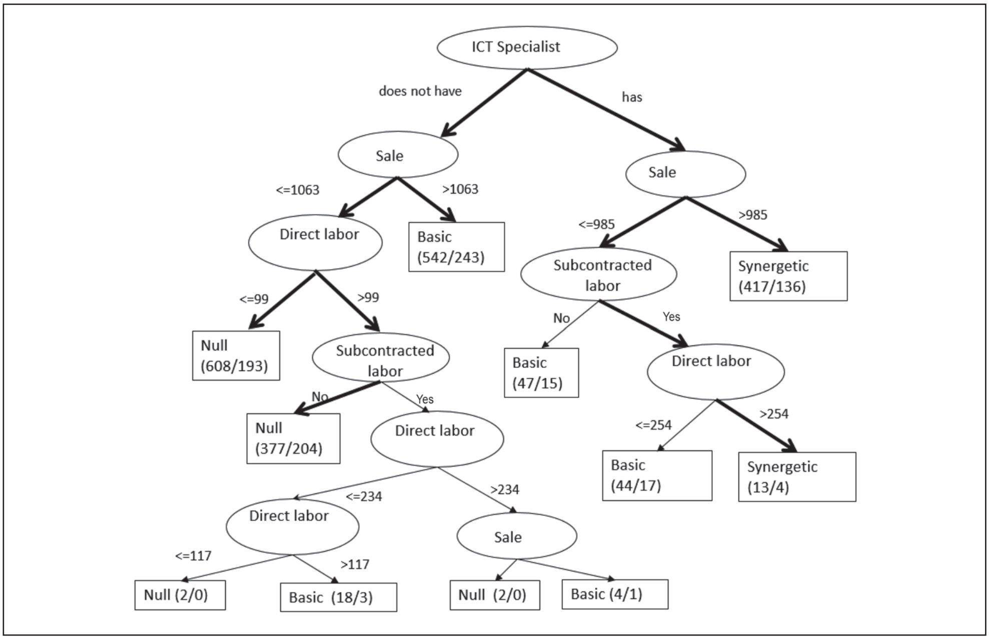
Finally, there is the synergistic development group in which the variables analyzed follow the stated hypothesis. Having a higher level of sales, a greater amount of labor, presenting greater productivity and subcontracting, and having ICT professionals allow to increase the synergy of being able to have 4 or more technologies operating simultaneously.

Decision Tree

The decision tree (Fig. 3) explains 60.7% of the cases with an absolute mean error of 0.33%. The confusion matrix (Tab. 6) shows that the hit rate is above the other intersections, which is a sign that the proposed tree has a good discriminative capacity, efficiently classifying the categories.

When efficiency in the classifications is analyzed, the success rate in the case of the null group is verified to be high, being 81.5%. In the case of the group of companies with a synergistic condition, the algorithm has a success rate of 60% which can be described as good. Finally, the algorithm has an acceptable regular result in the basic category with a success rate of 44%, classifying better than in the other categories.

Fig. 3: Decision tree on the depth of enabling ICTs adoption for Industry 4.0 (J48, pruned tree; *N* = 2,081)



Source: own based on data from the ICT survey and WEKA software

Note: Precision (accuracy) = 60.7%; statistical kappa = 0.39; mean absolute error = 0.33.

Tab. 6: Confusion matrix

Observed	Classification		
	Null	Basic	Synergistic
Null	598	127	8
Basic	353	376	132
Synergistic	45	152	290

Source: own based on data from the ICT survey and WEKA software

Fig. 2 shows the branches with a greater classification capacity, which makes it possible to simplify their presentation and subsequent analysis.

The algorithm defines the presence of ICT professionals as the first discriminant variable, defining it as the root attribute. As had been verified in the ordered logit model, and specifically in the marginal effects analysis, the presence of ICT specialists makes it possible to discriminate well between synergistic and null groups, leaving the basic group in a diffuse classification.

In the case of synergistic companies, based on the decision tree, it can be clearly seen that those organizations that have IT professionals and that at the same time have sales over $985 million per year (1.3 million dollars per year) have a greater probability of having more than four enabling ICTs for Industry 4.0.

In this same group of synergistic companies, a lower frequency combination is present in the algorithm, given by those companies that even having ICT professionals, present a sales level below $985 million. In this case, when the company subcontracts and at the same time has more than 254 direct workers, the possibility that the company may have more than four enabling technologies increases.

When there are no ICT specialists, but annual income levels are above $1,063 million per year (1.4 million dollars) there is a greater possibility of being at a basic adoption level (1 to 3 technologies). At this level, this is likely to see the implementation of tools such as ERP and Cloud being such a technological mix sufficient to meet its operational requirements.

The algorithm is more precise to identify situations of null development. In this case, when the company does not have ICT professionals, it presents an annual sales level below $1,063 million (1.4 million dollars) and simultaneously has less than 99 annual workers, the organization is unlikely to have enabling ICTs incorporated. In the same branch, if the company has more than 99 workers per year and does not outsource its activities, the company is unlikely to have any enabling ICTs for Industry 4.0, presenting a null development from the point of view of technological adoption.

5. Discussion

In principle, a technological gap of Chilean companies is verified in comparison to the OECD average and, in parallel, an important difference is confirmed in the levels of adoption, based on the size of the company. When the number of technologies is reviewed according to size, it is found that only a few large companies can benefit from technological synergy, which in the medium term will produce an increase in inequities in the national productive fabric.

Explanatory factors are analyzed, verifying that the sales levels and the number of hired workers allow to explain the higher level of adoption. This is associated with variables such as size, financial capacity and need for coordination. These results confirm what was stated by Arnold et al. (2018), Dalenogarea et al. (2020), Horváth and Szabo (2019), and Gatica-Neira (2022).

Along the same lines, the positive relationship between productivity levels and adoption is confirmed, which is in line with that stated by Almeida et al. (2020) and Brambilla (2018). The predisposition to adopt depends on the level of productivity that the company already has, affecting the perception of relative advantages when evaluating the incorporation of a new technology.

In this regard, the research confirms that companies that have ICT professionals have a greater probability of reaching higher technological levels, which is explained by the capacities and competencies that allow prospecting, hiring, and adapting, which is consistent with what was detected by Motta et al. (2019), Maggi et al. (2020), Almeida et al. (2020), and Cabrera-Sánchez and Villarejo-Ramos (2019).

However, it is verified that this relationship is not linear. When analyzing the marginal effects, we can see that the presence of ICT professionals generates an effect of technological takeoff in the synergistic company group, without being clear about their contribution in the companies in the intermediate situation. In this regard, there may be two situations: a) there is a critical size in which having a certain number of IT professionals allows the company to make a leap into more complex technologies; and b) the largest number of ICT professionals are likely to be oriented towards maintaining the current operating systems in the basic stage of adoption.

Another evidence from our analysis indicates that companies that outsource are more likely to scale in technology adoption. This is consistent with what was stated by Horváth and Szabo (2019) associated with the importance of strategic definitions as an explanatory element of adoption. The foregoing is explained by the need to have tools such as ERP, CRM, SCM and Cloud to coordinate and control a more complex productive network resulting from the outsourcing of activities.

In the decision tree, the presence of ICT professionals makes it possible to distinguish companies that have technological synergy from those that have no development at all. Companies with ICT professionals and at the same time have annual sales above $985 million (1.3 million dollars) have a high probability of being synergistic. Meanwhile, companies without IT professionals and with sales below $1,060 million per year (1.4 million dollars) and that have less than 99 workers have a high probability of presenting no technology adoption.

Conclusions

Identifying gaps between SMEs and large companies makes it possible to visualize the need for public policies to encourage digital transformation. The state must play a role in solving the problems of technological infrastructure, legal frameworks, IT security and in the generation of shared spaces through the creation of centers, technological institutes, and instances of articulation between clients and specialized providers (Chauhan et al., 2021; Lepore et al., 2021).

As part of this approach, it is key to have a global public policies that offer IT support to a group of smaller companies, helping in the tasks of training, searching, adaptation and maintenance of new technologies in each company. Case studies agree that technological leadership within the company is essential (Maggi et al., 2020; Motta et al., 2019). Therefore, it is key to make entrepreneurs aware of the importance of this type of technology through meetings, direct advice, and the generation of networks with public and private actors. The training system must also play a role in training workers in the digital skills necessary for Industry 4.0.

From the results, an empirical trajectory of digital transformation can be deduced that begins with a base of ERP and Cloud technologies, then the companies that incorporate CRM, SCM and, at a third level, there are companies that adopt Big data, IT security area and RFID. In the context of public policy, it is essential to visualize the ‘technological staggering’ allowing to gain feasibility in digital transformation initiatives.

The survey used in this study is the first of its kind at the national level and collects only some types of technologies, focusing on ICTs, leaving out others associated with electronics, optics, mechatronics, data engineering, among others. It is of paramount importance to have national and regional statistics, compared with international standards, to measure this emerging problem with better oriented public policies.

In this sense, in the survey the existence of a particular technology, in each company, was registered in binary form, whether or not it has a presence. We have no further background to identify the quality in the use of each technology and the links between technologies, limiting the visualization of the level of digitization within each production unit. Despite this limitation, the survey used has the merit of the breadth of companies analyzed (2,081) and is a first step to design tools that allow identifying different degrees of adoption of each technology in each company.

Regarding the limitations of this work, we can indicate that it is a first approximation to a broad base of companies. However, it is pertinent in further investigations:

- To consider sectoral patterns of enabling technologies adoption for Industry 4.0, capturing characteristics associated with a certain field of economic activity;
- to analyze adoption at the level of a productive fabric relating the company, suppliers, and customers, and;
- to incorporate the leadership variable of the technology manager, especially when we analyze digital transformation processes.

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