ARTICLES

ADOPTION AND DIFFUSION OF TECHNOLOGIES 4.0 BASED ON THE INNOVATIVE TRAJECTORY AND THE SCALE OF OPERATION: THE CASE OF CHILE

Adopción y difusión de las tecnologias 4.0 a partir de la trayectoria innovativa y la escala de operación: El caso de Chile

Adoção e difusão de tecnologias 4.0 baseadas na trajetória inovadora e na escala de operação: O Caso do Chile

Francisco Gatica-Neira[1] | fgatica@ubiobio.cl | ORCID: 0000-0002-1968-9384

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[1]Universidad del Bío-Bío, Departamento de Economia y Finanzas, Facultad de Ciencias Empresariales, Concepción, Chile

ABSTRACT

The factors that can explain the diffusion of 4.0 technologies in the chilean economy are analyzed. We work with companies that can be classified as "specialized suppliers" and "science-based" relevant to the analyzed technological field. The data from the Tenth National Innovation Survey carried out by the National Statistics Institute (INE, 2018) are used. A confirmatory factor analysis of the second order is performed to identify the variables that best explain the diffusion. Lisrel 8.8 software was used, making the estimations with the robust diagonal weighted least squares method (DWLS) because we work with ordinal variables. The main results show the relevance of future innovation projects and the number of workers hired by each company to stimulate technological diffusion.

Keywords: Technological diffusion processes, government policies, confirmatory factor analysis, industry 4.0, technological innovation.

RESUMEN

Se analizan los factores que pueden explicar la difusión de las tecnologías 4.0 en la economía chilena. Trabajamos con las empresas que pueden ser calificadas como "proveedoras especializadas" y "basadas en ciencias" pertinentes al campo tecnológico analizado. Se utilizan los datos de la Décima Encuesta Nacional de Innovación realizada por el Instituto Nacional de Estadística (2018). Se realiza un análisis factorial confirmatorio de segundo orden para identificar las variables que mejor explican la difusión. Se utilizó el software Lisrel 8.8 realizando las estimaciones con el método de mínimos cuadrados ponderados diagonales robustos (DWLS) debido a que se trabaja con variables ordinales. Los principales resultados dan cuenta de lo relevante de los proyectos de innovación futura y la cantidad de trabajadores contratados por cada empresa para estimular la difusión tecnológica.

Palabras Clave: *Procesos de difusión tecnológica, políticas gubernamentales, análisis factorial confirmatorio, industria 4.0, innovación tecnológica.*

RESUMO

São analisados os fatores que podem explicar a difusão de tecnologias 4.0 na economia chilena. Trabalhamos com empresas que podem ser classificadas como "fornecedores especializados" e "baseados na ciência" relevantes para o campo tecnológico analisado. São utilizados os dados da Décima Pesquisa Nacional de Inovação, realizada pelo Instituto Nacional de Estatística (2018). Uma análise fatorial confirmatória de segunda ordem é realizada para identificar as variáveis que melhor explicam a difusão. Utilizou-se o software Lisrel 8.8, realizando as estimativas com o método robusto de mínimos quadrados ponderados na diagonal (DWLS) devido ao trabalho com variáveis ordinais. Os principais resultados mostram a relevância de futuros projetos de inovação e o número de trabalhadores contratados por cada empresa para estimular a difusão tecnológica.

Palavras-Chave: *Processos tecnológicos de difusão, políticas governamentais, análise fatorial confirmatória, indústria 4.0, inovação tecnológica.*

INTRODUCTION

This article analyzes factors that can explain the diffusion of technologies 4.0. These technologies encompass the application of sensors, learning algorithms, process virtualization, the Internet of Things (IoT), and other developments that improve the profitability and flexibility of production processes.

The study explores the diffusion power of sectors linked to Industry 4.0 in the categories of specialized suppliers and science-based companies. A second-order confirmatory factor analysis was conducted, in line with the structural equation models, adopting ordinal variables and using robust diagonal weighted least squares (DWLS) as an estimation method. The research database consists of 313 Chilean companies, listed in the Tenth National Innovation Survey conducted by the Chilean National Statics Institute (2018).

The topic search conducted in April 2021 in the Web of Science core collection using first the term "Industry 4.0" and then "Chile" showed 11 studies. The themes addressed were the use of applications in the copper industry, forestry, aquaculture, environmental issues (CO2), nutrition, and manufacturing. This search did not find studies in Chile investigating factors connected with the adoption and diffusion of technologies 4.0 considering a global perspective and using structural equation models. The articles found focused on identifying barriers to the adoption of technologies in specific sectors. Therefore, to the best of my knowledge, this study fills a research gap by offering a model based on data that explains the determinants of the adoption and use of technologies 4.0.

One of the main conclusions is that the diffusion of technologies can be explained mainly by innovation rather than by the company's operation scale. The crucial variables that supported this finding were the possibility of future innovation, the capacity to innovate based on challenges perceived, the percentage of qualified employees, and the total number of employees.

EMERGENCE OF TECHNOLOGIES 4.0

Through digitizing different connections, the Fourth Industrial Revolution completely changes the configuration of value chains (Schwab, 2016; Tirole, 2017). The technologies 4.0 cross all sectors of the economy and allow for an improvement in modularity, service orientation, decision-making capacity, decentralization, virtualization, and interoperability of processes (Lasi, Fettke, Feld, Kemper & Hoffmann, 2014; Hermann, Pentek, & Otto, 2016; Lee, Bagheri, & Kao, 2015).

This technological revolution has strongly impacted employment, especially in developing countries (Nedelkoska & Quintini, 2018). Prospective studies in Western Europe (Berger, 2016) present a curve where the unemployment rate rises and, after 20 years, employment recovers and returns to the levels before the automation process. The speed of job recovery results in new companies from the relocation of new businesses, the emergence of the technological equipment industry, and the development of services based on technologies 4.0 (Berger, 2016).

In this context, Bogliacino and Pianta (2016) analyze Pavitt's taxonomies based on the review of innovation data from manufacturing and service companies in the European Union, verifying the heterogeneity of innovation models at the sectoral level. One conclusion is that public policies must focus on the categories of specialized suppliers and science-based companies, maximizing the diffusion of the technologies 4.0 emerging from these organizations to companies operating in other sectors of the economy. This diffusion may also occur via the implementation of collaboration opportunities between clients and suppliers or by connecting research centers (Lepore, Dubbini, & Micozzi, 2021).

This research studied the factors that explain the adoption and diffusion of technologies 4.0 in specialized suppliers and science-based companies (see Exhibit 1), which are fundamental to expand the benefits of Industry 4.0 to all companies of the Chilean economy.

Exhibit 1. Identification of the economic sectors

Identification of economic activity	Description of the economic activity for the sectors "science-based" and "specialized suppliers"
26	Manufacture of computers, electronic, and optical products.
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment
61	Telecommunications
72	Scientific research and development.

Source: Elaborated by the authors based on the Décima Encuesta Nacional de Innovación (2018).

In the Chilean case, technologies 4.0 are in an early stage of diffusion. The Ministry of Economy (Minecon, 2020) recently published a survey applied to 3,344 companies about the level of information and communication technologies (ICT) adoption, with emphasis on big data and radio frequency identification (RFID). Two conclusions stand out:

- There is a significant gap in the diffusion of these complex technologies concerning the average numbers of Organisation for Economic Co-operation and Development (OECD) countries. For example, 2% of Chilean companies use big data against 13% of companies in other OECD countries. As for RFID, 6% of Chilean companies use the technology, against 14% of businesses in OECD companies.

- There is a gap in the level of technology adoption according to the company size. For example, 7.2% of large companies use big data, while only 1.7% of small and medium-sized companies have adopted this technology. RFID is used in 22% of large companies and only in 4% of small and medium-sized companies.

In this scenario, public policies are essential to technologies 4.0 diffusion nationwide, reaching more small and medium companies. Currently, there is no public policy in Chile to develop and disseminate technologies 4.0 in different economic sectors. Instead, the focus is

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

on developing technologies 4.0 to apply sensors and monitor the mining sector and the natural resource-intensive industry (Gatica & Ramos, 2020).

It is essential to have an industrial policy that stimulates the adoption of technologies 4.0 and helps incorporate new management practices oriented to learning and developing the capacity for innovation, offering infrastructure, human capital, and strategic partnerships (Lepore et al., 2021). In this sense, public policy can:

- Solve technological infrastructure problems, build legal frameworks, and provide information security (Chauhan, Singh, & Luthra, 2021).

- Play a strategic role in facilitating innovation initiatives for this type of technology in small companies (Chege, Wang, & Suntu, 2020).

- Stimulate the creation of new business models as a way to generate jobs to boost economic development (Dean & Spoehr, 2018), and

- Promote the opening of markets with greater technological content, facilitating company emergence (Mazzucato, 2017).

This study provides information to stimulate the diffusion of these new technologies in the Chilean industry, filling a gap in the current literature.

LITERATURE REVIEW

This section presents a literature review to justify the different hypotheses of the structural equations model (Exhibit 2).

Companies with an innovative track record have greater organizational flexibility, a fundamental condition for adopting and disseminating technologies 4.0. Therefore, a business culture willing to innovate, together with a continuous improvement strategy of processes and products, facilitates the adoption of new technologies (Agostini & Filippini, 2019; Horváth & Szabo, 2019; Rojas-Córdova, Heredia-Rojas, B., & Ramírez-Correa, 2020). This promotes the generation of new business models through personalizing consumption, commercializing new algorithms that complement the production, and through more effectively operating a value network (Botha, 2019; Müller, Kiel, & Voigt, 2018).

The incorporation of technologies 4.0 demands significant financial, technological, and human resources (Arnold, Veile, & Voigt, 2018; Dalenogarea, Benitez, & Ayala, 2018; Ingaldi & Ulewicz, 2020). The leader must manage the uncertainty involved in all technical changes, breaking organizational inertias and fears (Chauhan et al., 2021). Given the scarcity of resources and high costs, companies must define feasible objectives to generate a successful digital transformation process (Kiraz, Canpolat, Özkurt, & Taşkın, 2020).

Companies with an innovative trajectory – i.e., those that innovated in the past, intend to engage in innovative projects in the future, and face fewer challenges to develop innovation – have a greater capacity to adopt and disseminate new technologies 4.0. Three hypotheses arise:

H1: There is a positive relationship between the past innovation rate and innovative capacity, increasing the technologies 4.0 diffusion power.

H2: There is a positive relationship between plans for future innovation projects and innovative capacity, which favors technologies 4.0 diffusion power.

H3: There is a positive relationship between the capacity to innovate based on perceived challenges and innovative capacity, increasing the technologies 4.0 diffusion power.

Analyses of the adoption processes of specific technologies – RFID, big data, B2B – show that qualified human capital is essential, allowing to explore, adapt, and integrate new technologies (Chege et al., 2019; Reyes & Visich, 2016; Vowles, Thirkell, & Sinha, 2011). Companies that have human resources with digital and innovative skills are more likely to adopt technologies 4.0, reducing resistance to the changes involved in this process (Agostini & Filippini, 2019; Cabrera-Sánchez & Villarejo-Ramos, 2019).

Qualified employees recognize the benefits of investing in technologies 4.0, which suggests that such technologies are more likely to be adopted in companies with this profile of employees (Prause & Günther, 2019; Reyes et al., 2016). The advantages of technologies 4.0 may be expanded as more qualified employees tend to make better use of them and gain efficiency (Fuente, Rojas, & Leiva, 2020). Thus, companies with qualified employees may be better positioned to visualize new markets and clients, which is key in deciding whether to start a digital transformation process (Kiraz et al., 2020).

Thus, companies must have skilled employees to search, recognize benefits, and implement new technologies, which leads to another three hypotheses:

H4: There is a positive relationship between the percentage of employees who hold a graduate degree and the company's innovative capacity, which favors the technologies 4.0 diffusion power.

H5: There is a positive relationship between the percentage of qualified employees and innovative capacity, which facilitates the technologies 4.0 diffusion power.

H6: There is a positive relationship between the sales variation and the innovative capacity, which contributes to the technologies 4.0 diffusion power.

Finally, the decision to invest in ICT depends on the company's size due to the high financial barriers involved (Brambilla, 2018). Large companies, especially multinationals, have fewer barriers to adopting technologies 4.0 (Horváth & Szabo, 2019). Ingaldi and Ulewicz (2020) identify that having obsolete technology makes adoption difficult, a situation more frequently observed in older companies, generating problems of compatibility and technological integration. Gatica (2018) concludes that the number of years of operation negatively affects the innovation rate, which can negatively affect the adoption of technologies 4.0. Therefore, the following hypotheses arise:

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

H7: There is a positive relationship between the volume of sales and a larger scale of operation of companies that disseminate technologies 4.0, increasing their diffusion power.

H8: There is a positive relationship between the total number of employees and the scale of operation of companies that disseminate technologies 4.0, increasing their diffusion power.

H9: There is a negative relationship between the years of operation of companies that disseminate technologies 4.0 and these companies' scale of operation.

METHODOLOGY

This study applied second-order confirmatory factor analysis adopted in structural equation modeling, following previous research on innovation economy analyzing technology adoption (Agostini & Filippini, 2019; Cabrera-Sánchez & Villarejo-Ramos, 2019; Chauhan et al., 2021; Chege et al., 2020; Müller et al., 2018). However, few studies specifically consider structural equation modeling and the adoption of Industry technologies 4.0 (Kiraz et al., 2020). In this sense, this research contributes to filling a gap in the literature.

The model was developed using the data available in the Chilean *Encuesta de Innovación* and worked with three latent variables:

- Innovative Capacity (Innov): the innovative force explained by the variables past innovation, future innovation, the capacity to innovate based on the perception of challenge, percentage of employees who hold a graduate degree, percentage of qualified employees, and sales variation. The working hypothesis in this research suggests a positive relationship between innovative capacity and the capacity to disseminate technologies 4.0.

- Scale of operation (scale): refers to the companies' size. The explanatory variables are the volume of sales, the total number of employees, and the company's years of operation. The working hypothesis suggests a positive relationship between the company's operation scale and its diffusion power regarding technologies 4.0.

- Diffusion power (Diffusion). This latent variable represents the capacity of specialized suppliers and science-based companies to disseminate technologies 4.0 to other sectors of the economy nationwide. According to the model, the diffusion power positively depends on the companies' capacity to innovate and scale of operation.

Figure 1 presents the latent and explanatory variables.

Figure 1. Relationship among explanatory variables of technology diffusion

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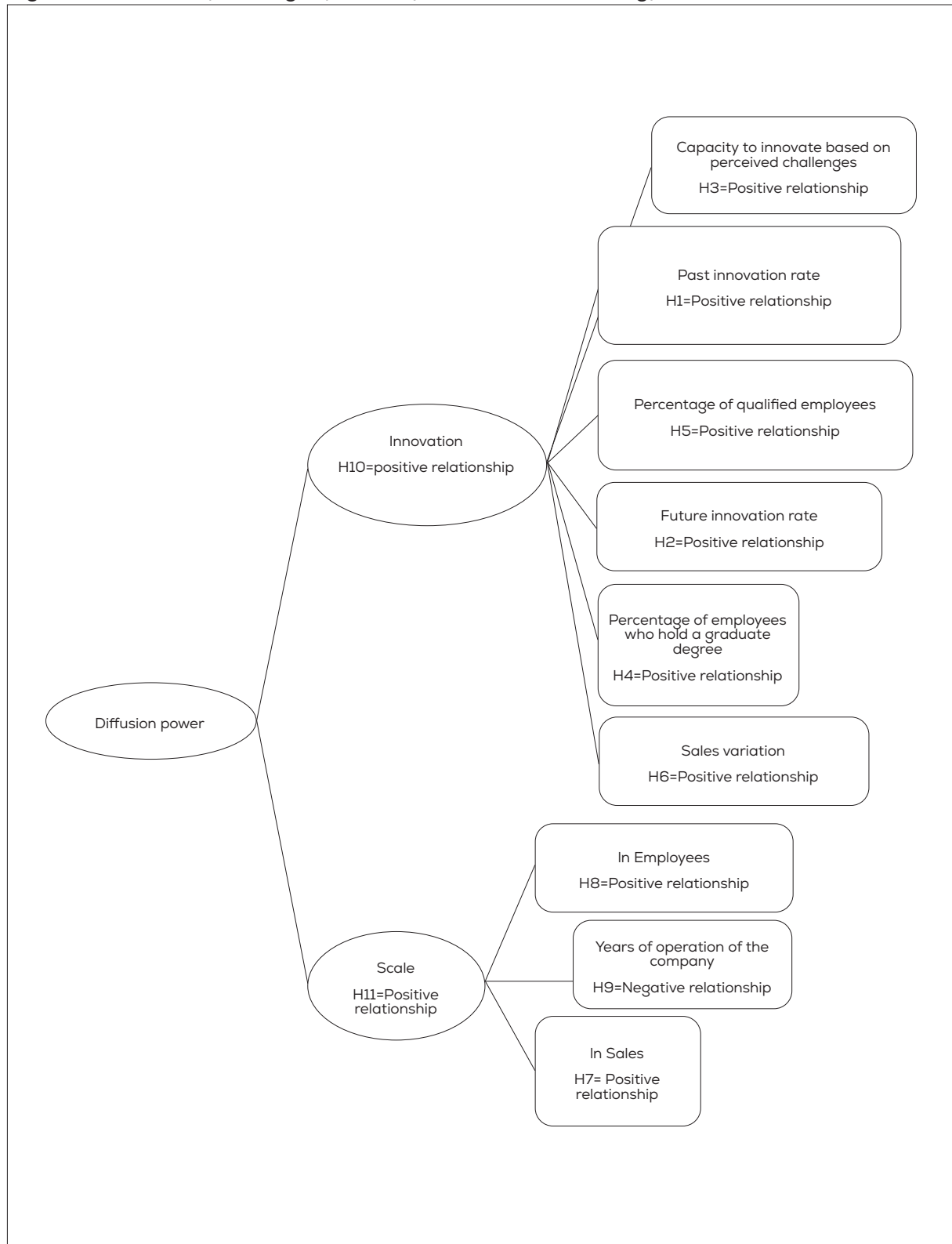
Francisco Gatica-Neira

Exhibit 2 presents the explanatory variables, the metric from the information available in the *Encuesta de Innovación*, the explanation, and the expected relationship in the model based on the literature review.

Exhibit 2. Identification of the explanatory variables and formulation of the hypothetical relationship

Explanatory variable	Metric	Explanation	The hypothesis regarding the latent variable and references in the literature
Past innovation rate (Pinn)	= [Σ score by company i (New goods + New services + Improved production method + Improved logistics method + Improved support + New practices of organizational process + New methods of organizational responsibility + New methods of external organizational relations + Changes in packaging design + New means of promotion + New methods for distribution channels + New pricing methods + Social innovation) / Σ maximum score] * 100	The company that presents a higher past innovation rate is more likely to incorporate technologies 4.0 and to contribute to their diffusion	H1: Positive relationship (+) between the past innovation rate and innovative capacity Horváth et al. (2019), Chauhan et al. (2021), Müller et al. (2018), Agostini et al. (2019), Rojas-Córdova et al. (2020)
Future innovation perspective (Finn)	= Σ of future innovation present in (product + process + MKT + organizational management + social) * 100	The company with more expectations of generating innovation on different fronts of organizational development has a greater capacity to disseminate technologies 4.0	H2: Positive relationship (+) between plans for future innovation projects and innovative capacity Horváth et al. (2019), Chauhan et al. (2021), Müller et al. (2018), Agostini et al. (2019), Botha (2019)
Capacity to innovate based on perceived challenges (InnChall)	= 1- [[Σ score by company *i* (Lack of own funds + Lack of external funding + Very high cost of innovation + Lack of qualified personnel + Lack of technology information + Lack of information on markets + Difficulty finding a partner + Market dominated by established companies + Uncertainty regarding the demand for goods + Not necessary due to previous innovation + Not necessary due to lack of demand for innovation + Regulatory challenges) / Σ maximum score] * 100]	The greater the perception of innovation facilities, the greater the capacity to innovate	H3: Positive relationship (+) between the capacity to innovate based on perceived challenges and innovative capacity. Reyes et al. (2016), Arnold et al. (2018), Cabrera-Sánchez (2019), Chege et al. (2020), Horváth et al. (2019), Kiraz et al. (2020), Agostini et al. (2019)

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Francisco Gatica-Neira

Exhibit 2. Identification of the explanatory variables and formulation of the hypothetical relationship

Explanatory variable	Metric	Explanation	The hypothesis regarding the latent variable and references in the literature
Percentage of employees who hold a graduate degree (PerEmpGrad)	= [(Number of employees who hold masters or PhD degrees / Total number of employees)] * 100	Having employees who hold a graduate degree increases the probability of innovation, facilitating technological diffusion	H4: Positive relationship (+) between the percentage of employees who hold a graduate degree and innovative capacity Ingaldi et al. (2020), Dalenogarea et al. (2018), Reyes et al. (2016), Vowles et al. (2011), Chege et al (2020), Agostini et al. (2019)
Percentage of qualified employees (PerQualEmp)	= ((Number of specialized employees / Total number of employees)) * 100	Having qualified employees increases the probability of innovating	H5: Positive relationship (+) between the percentage of qualified employees and innovative capacity Ingaldi et al. (2020), Dalenogarea et al. (2018), Reyes et al. (2016), Vowles et al. (2011), Chege et al. (2020)
Sales variation (SalesVari)	= [((Sales $ 2016-sales $ 2015) / Sales $ 2015)] * 100	An increase in sales can generate an incentive to adopt technology	H6: Positive relationship (+) between the sales variation and the innovative capacity Prause et al. (2019), Reyes et al. (2016)
Sales volume (lnSales)	Natural logarithm of sales volume ($)	The larger the sales volume, the greater the diffusion effect, since the company's size facilitates technology adoption)	H7: Positive relationship (+) between the volume of sales and the scale of operation of companies that disseminate technologies 4.0 Ingaldi et al. (2020), Reyes et al. (2016), Kiraz et al. (2020
Total number of employees (lnTotEmp)	Natural logarithm of the number of employees	The larger the company, the greater its diffusion power.	H8: Positive relationship (+) between the total number of employees and the scale of operation of companies that disseminate technologies 4.0 Ingaldi et al. (2020), Reyes et al. (2016), Chege et al. (2020), Brambilla (2018)
Years of operation (CompYear)	Years of operation of the company	The number of years since the company started its operations. The lower diffusion capacity is due to difficulties in adapting to new production models	H9: Negative relationship (–) between the years of operation of companies that disseminate technologies 4.0 and these companies' scale of operation Ingaldi et al. (2020), Gatica (2018)

(Concludes)

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Francisco Gatica-Neira

As mentioned above, the distribution presented by the variables does not meet the assumptions of multivariate normality, and specific models for ordinal variables were adopted (Jöreskog, 1994). In addition, Pearson, polychoric, and polyserial correlation matrices were used (Table 1). The analysis adopted a diagonal weighted least squares (DWLS) robust estimation method, included in the Lisrel 8.8 system and specially designed for ordinal variables.

Table 1. Correlation matrix

	InnChall	Finn	CompYear	InSales	SalesVari	InTotEmp	PerEmpGrad	PerQualEmp	Pinn
InnChall	1.00								
Finn	0.01 (PS)	1.00							
CompYear	0.04 (PE)	-0.07 (PS)	1.00						
InSales	0.19 (PS)	0.11 (PC)	0.26 (PS)	1.00					
SalesVari	0.08 (PE)	0.05 (PS)	-0.09 (PE)	0.16 (PS)	1.00				
InTotEmp	0.14 (PS)	0.13 (PC)	0.25 (PS)	0.80 (PC)	0.09 (PS)	1.00			
PerEmpGrad	-0.02 (PE)	0.02 (PS)	-0.07 (PE)	-0.02 (PS)	0.09 (PE)	-0.06 (PS)	1.00		
PerQualEmp	0.09 (PE)	0.20 (PS)	-0.15 (PE)	-0.05 (PS)	-0.03 (PE)	-0.13 (PS)	-0.01 (PE)	1.00	
Pinn	0.20 (PS)	0.58 (PC)	-0.12 (PS)	0.23 (PC)	-0.03 (PS)	0.26 (PC)	0.06 (PS)	0.20 (PS)	1.00

Note: The type of correlation is show in brackets: PE = Pearson, PC = Polychoric, PS = Polyserial
Source: Elaborated by the authors based on Lisrel results.

Tables 3 and 5 present different criteria to measure the quality of the models. The following indices are distinguished: goodness of fit, incremental fit, and parsimony fit. Considering the large sample analyzed, the ratio between chi-square and degrees of freedom is presented (Hooper, Coughlan, & Mullen, 2008).

The analysis started with 373 companies. After eliminating incomplete and erratic data, the final sample consisted of 313 companies (83% of the original number). The study encompasses 12 variables (latent and explanatory). Therefore, there is a ratio of 26.08 companies per variable, which is above the minimum required in this type of study (15 units per variable) (Hair, Andersen, Tathan, & Black, 1999).

RESULTS

A preliminary review of data is presented here to contextualize the final results. Subsequently, the first and second models are developed.

Preliminary review of data

Table 2 presents the indicators for the type of future and past innovation and obstacles to innovation perceived by companies that diffuse technologies 4.0.

Table 2. Distribution of types of future and past innovation and challenges to innovation

		Number of companies	Percentage (313 companies)
Future innovation (a company may intend to innovate in more than one area)	Future product innovation	162	51.6%
	Future process innovation	132	42.2%
	Does not contemplate innovation in the future	115	36.6%
	Future innovation in organizational management	100	32.0%
	Future innovations in MKT	94	30.1%
	Future innovations of a social nature	40	12.6%
		Number of companies	Percentage (313 companies)
Past innovation (a company may have innovated in more than one area)	It does not feature past innovation	213	68.0%
	New services	49	15.6%
	New practices of process organization.	47	15.1%
	New methods of organizing responsibilities	44	14.0%
	Improve support	40	12.7%
	Improved production method	34	10.8%
	New goods	31	10.0%
	New means of promotion.	27	8.6%
	New methods of external relations	25	8.1%
	New pricing methods	23	7.3%
	New methods for distribution channels	19	6.2%
	Changes in packaging design	18	5.7%
	Improved logistics method	13	4.0%
	Social innovation	6	1.9%

(Continue)

Table 2. Distribution of types of future and past innovation and challenges to innovation

		Number of companies	Percentage (313 companies)
		Number of companies	Percentage on a 313 basis
Main barriers to innovate (a company may appoint more than one item)	High costs of innovation	128	41.0%
	Lack of own funds	127	40.7%
	Lack of external funding	101	32.3%
	A market dominated by established companies	94	30.2%
	Uncertainty regarding the demand for goods	94	30.2%
	Difficulty finding a partner	83	26.4%
	Lack of qualified personnel	68	21.8%
	Lack of technology information	53	17.0%
	Lack of market information	52	16.7%
	Regulatory barriers	40	12.9%
	Lack of demand for innovation	30	9.7%
	Innovation is not required due to previous innovations	30	9.4%

(Concludes)

Of the companies analyzed, 36.6% do not contemplate innovating in the next two years. In the distribution of the innovation types: the "product innovation" present in 51.6% of the companies, and the "process innovation" with a participation of 42.2%, stand out. With a similar weight are the innovations in "marketing" and "organizational management" – 30.1% and 32.0%, respectively. Finally, there are those of a "social nature" with 12.6%.

Regarding innovation in the previous two years, it is interesting that 68% of the companies did not innovate at all. Compared to companies that want to innovate in the future (63.3%) with those that innovated in the previous two years (32.0%), there is a problem of innovative efficiency where many companies do not innovate, even though they intend to. The innovation rate of previous years (32.0%) is above the similar national average of 23.6% (Gatica, 2019).

New services stand out among past innovations (observed in 15.6% of the companies). Process innovation appears after, observed in 15.1%, followed by changes in the form of organization (14% of companies).

The biggest obstacle observed is financial. The high cost of innovation and the lack of funds to meet requirements are present in about 41%. Similarly, 32.3% of the companies that diffuse technologies 4.0 perceive difficulty obtaining external financing.

Three factors showed a lower level of relevance regarding structural variables in the sector. Of the companies analyzed, 30.2% mentioned that established companies dominate the market, and a similar percentage believe that the uncertainty regarding the demand for new goods slows innovation.

These results show the relevance of having resources to support the risk involved in undertaking an innovation process.

First model

Table 3 presents the main indicators of goodness of fit, incremental adjustment measures, and parsimony adjustment, comparing them with the reference parameters normally used in the literature (Escobedo, Hernández, Estabané, & Martínez, 2016; Hair et al., 1999).

Table 3. The goodness of fit of the first model

Types of Settings	Statistics	Observed value First Model	Reference value	Fit quality
Goodness-of-fit Indexes	Root Mean Square Error of Approximation (RMSEA)	0.00	<0.08	Acceptable
	Standardized RMR	0.07	<0.7 and CFI > 0.92	Acceptable
	Root Mean Square Residual (RMR)	0.07	<0.7 and CFI > 0.92	Acceptable
	Chi square / degrees of freedom	= (74.09/26) = 2.84	Between 2-5	Acceptable
Incremental fit Indexes	Normed Fit Index (NFI)	1.00	> 0.92	Acceptable
	Comparative Fit Index (CFI)	1.00	> 0.95	Acceptable
	Adjusted Goodness of Fit Index (AGFI)	0.96	>0.90	Acceptable
Parsimony fit -- Indexes	Parsimony Normed Fit Index (PNFI)	0.72	Between 0.5 and 0.7, considered acceptable	Out of range

Table 3 shows that the proposed model presents acceptable conditions to be analyzed. The parsimony fit is outside the accepted range. However, Newsom (2018), suggests evaluating the model independently of the parsimony fit. At the time of the analysis, the proposed model was convergent.

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ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

Figure 2. First Model

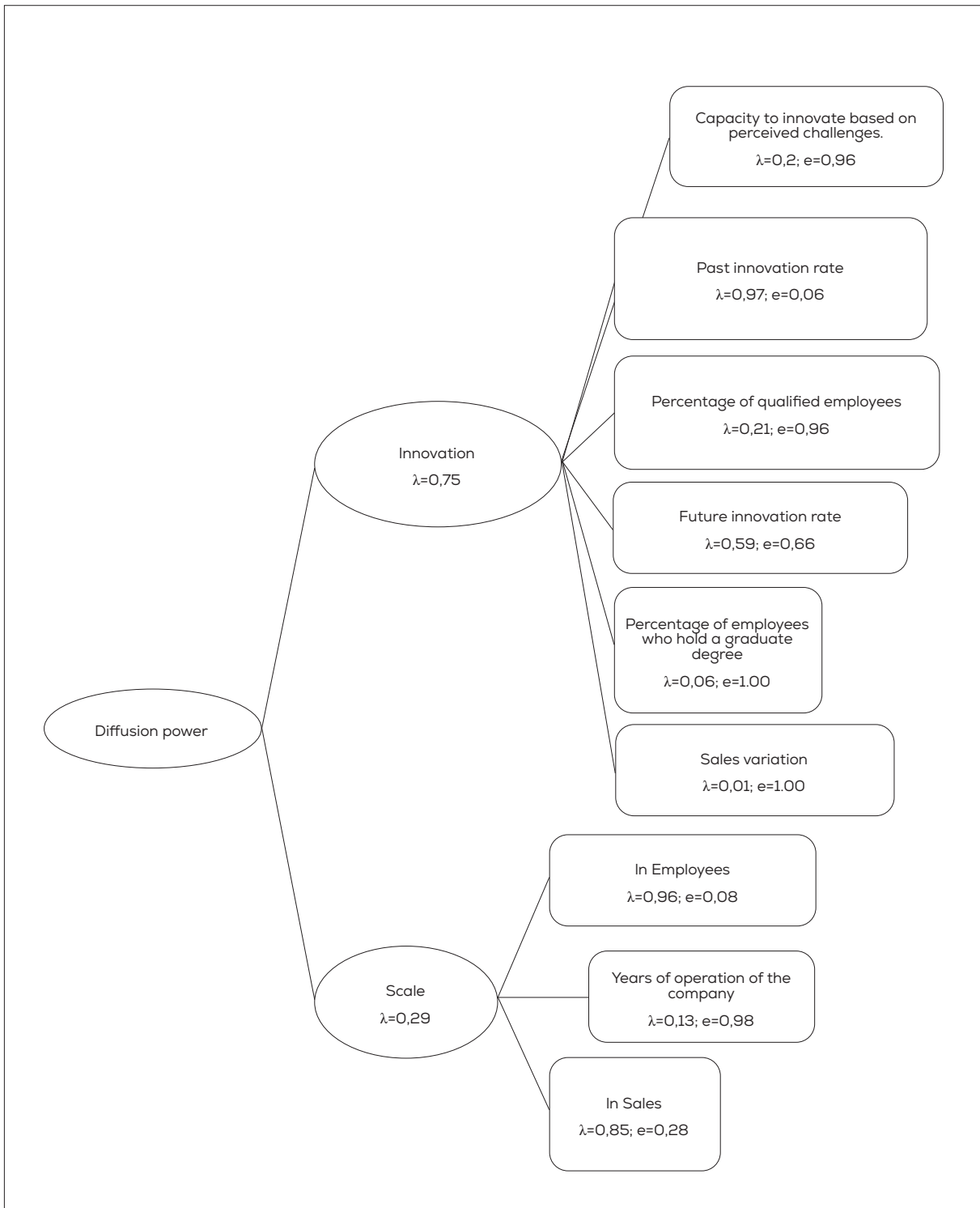Standardized factorial loads (λn) and estimation errors (e).

Table 4. Results of the first model, by variable

Latent variables	Explanatory variables	Estimate	Test T	Average variance extracted (AVE) (1)	Ordinal reliability coefficient (ω) (2)
Innovative Capacity	← Future innovation perspective (Finn)	0.60	7.65***		
Innovative Capacity	← Capacity to innovate based on perceived challenges (InnChall)	0.20	4.02***		
Innovative Capacity	← Percentage of qualified employees (PerQualEmp)	0.047	0.82		
Innovative capacity	← Past innovation rate (Pinn)	0.21	4.11***	0.2	0.5
Innovative Capacity	← In Total number of employees (lnTotEmp)	0.0067	0.14		
Innovative Capacity	← In Sales (lnSales)	1.00			
Scale of operation	← Years of operation (CompYear)	1.00			0.7
Scale of operation	← Innovative capacity	1.13	3.15***	0.5	
Scale of operation	← Scale of operation scale (Scale)	0.15	0.98		
Diffusion power	← Future innovation perspective (Finn)	1.00		0.38	0.4
Diffusion power	← Capacity to innovate based on perceived challenges (InnChall)	0.33	2.07**		

Discriminant validity check

	√AVE	Innovative Capacity	Scale of operation	Diffusion power
Innovative capacity	0.47		‹0.18 (3)	‹0.54 (3)
Scale of operation	0.74			›0.18
Diffusion power	0.56			

(***) 99% confidence; (**) 95% confidence and (*) 90% confidence.
Note 1 = Average variance extracted (AVE) = $[(\Sigma\lambda^2) / n]$; where n is the number of indicators.
Note 2 = Ordinal reliability coefficient (ω) = $[(\Sigma\lambda)^2 / ((\Sigma\lambda)^2 + (\Sigma 1-\lambda^2)]$
Note 3 = Low discriminant capacity of the latent variable.

Figure 2 presents the first model. The latent variables innovation and scale of operation explain the "diffusion power" (Table 4). From the standardized factorial loads (herein λ), the innovative capacity ($\lambda = 0.75$) is greater than the operation scale ($\lambda = 0.29$).

Among the explanatory variables for innovation, the percentage of employees with a graduate degree showed little significance ($\lambda = 0.06$; t = 0.82), rejecting hypothesis H4. However, the

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

percentage of qualified employees was found as highly explanatory of the companies' innovation capacity ($\lambda = 0.21$; $t = 4.11$), proving hypothesis H5 and justifying the intensive learning in the organizations.

The capacity to innovate based on challenges perceived is positively correlated with diffusion power ($\lambda = 0.20$; $t = 4.02$), confirming hypothesis H3. Also, the positive relationship between future innovation, innovation capacity, and, consequently, the diffusion power of the company ($\lambda = 0.59$, $t = 7.65$) was observed, confirming H2.

Compared to the previous year, the improvement in sales does not present a significant relationship with the innovation capacity ($\lambda = 0.01$; $t = 0.14$), rejecting hypothesis H6. Therefore, this factor is not relevant when analyzing a company's diffusion power.

Finally, the past innovation rate variable ($\lambda = 0.97$) was set at a unit value to run the confirmatory factor analysis. The relationship with the latent variable was positive from its factorial load, confirming hypothesis H1.

The analysis of the second latent variable demonstrated that the number of employees ($\lambda = 0.96$, $t = 3.15$) has a significantly positive relationship with the company's scale of operation and, therefore, with its diffusion power. This result corroborates hypothesis H8.

In this first model, there was no significative relation between the variable years of operation and the scale of operation of companies disseminating technologies 4.0 ($\lambda = 0.13$; $t = 0.98$), rejecting hypothesis H9.

Finally, the sales volume had a positive relationship with the scale of operation ($\lambda = 0.85$) of companies that disseminate technologies 4.0, confirming hypothesis H7. This variable was determined in a unit value to run the confirmatory factor analysis and is consistent with the model.

From this first model, it is possible to observe that the diffusion power is greater when there is: i) a more significant number of projects for innovation in the future; ii) more employees; iii) more qualified employees; iv) capacity to innovate based on perceived challenges.

Table 6 also shows the average extracted variance (AVE), the ordinal reliability coefficient (ꞔ), and the discriminant validity (Elosua & Zumbo, 2008; McDonald & Ho, 2002; Ventura-León & Caycho-Rodríguez, 2017; Viladrich, Angulo-Brunet, & Doval, 2017). The reliability for ordinal variables (ꞔ) was 0.5 and 0.7 for the two latent variables, which is acceptable. However, in the first model, the construct "innovative capacity" had a low discriminant capacity; in both cases, the square root of the AVE was less than the correlation of the construct.

Second model

The second model presents improvements in comparison to the first model developed. The construct "innovative capacity" was given discriminant validity, excluding variables that did not present a significant relationship in the first model (t<1.96, 95% confidence). Therefore, sales variation and the percentage of employees who hold a graduate degree were eliminated. Table 5 shows that the second model has incremental and parsimony goodness of fit, correcting the first model.

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

Table 5. The goodness of fit of the second model

| Types of Settings	Statistics	Improved observed value	Reference value	Quality of fit.
Goodness-of-fit Indexes	Root Mean Square Error of Approximation (RMSEA)	0.00	<0.08	Acceptable
	Standardized RMR	0.06	<0.7 con CFI > 0.92	Acceptable
	Root Mean Square Residual (RMR)	0.06	<0.7 con CFI > 0.92	Acceptable
	Chi square / degrees of freedom	=(41.9/12) = 3.4	Between 2-5	Acceptable
Incremental fit indices Indexes	Normed Fit Index (NFI)	1.00	About 0.92	Acceptable
	Comparative Fit Index (CFI)	1.00	About 0.95	Acceptable
	Adjusted Goodness of Fit Index (AGFI)	0.97	>0.90	Acceptable
Parsimony fit indices Indexes	Parsimony Normed Fit Index (PNFI)	0.57	Between 0.5 and 0.7 is considered acceptable	Acceptable

Figure 3. Second Model

Standardized factorial loads (λn) and estimation errors (e).
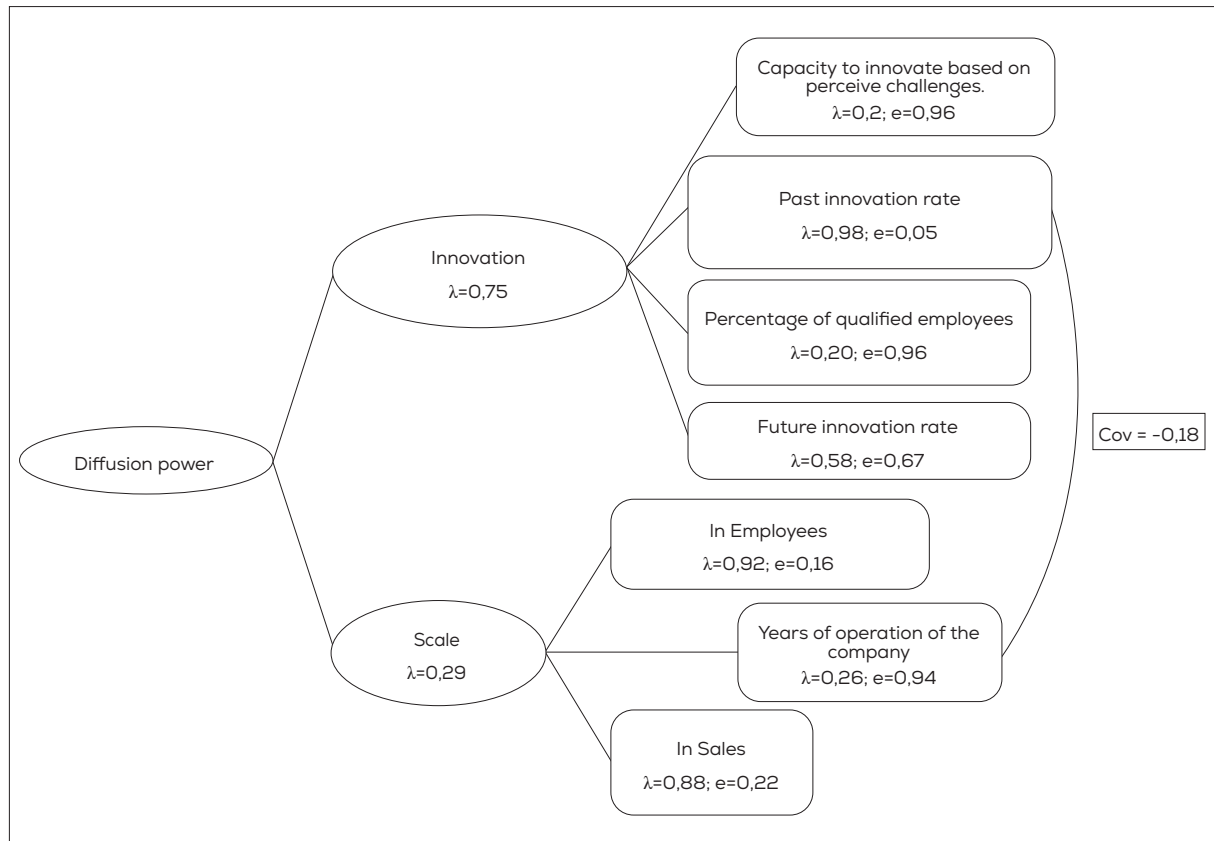
Table 6. Results of the second model, by variable

Latent variables	Explanatory variables	Estimate	Test T	Average variance extracted (AVE)(1)	Ordinal reliability coefficient (ω) (2)
Innovative Capacity	← Future innovation perspective (Finn)	0.59	7.56***	0,4	0.6
Innovative Capacity	← Capacity to innovate based on perceived challenges (InnChall)	0.20	3.99***		
Innovative capacity	← Percentage of qualified employees (PerQualEmp)	0.21	4.03***		
Innovative Capacity	← Past innovation rate (Pinn)	1.00			
Operation scale	← ln Total number of employees (lnTotEmp)	1.04	5.72***	0.6	0.8
Operation scale	← ln Sales (lnSales)	1.00			
Operation scale	← Years of operation (CompYear)	0.29	2.80***		
Diffusion power	← Innovative capacity	1.00		0.3	0.5
Diffusion power	← Scale of operation scale (Scale)	0.42	3.74***		

Discriminant validity check				
	√AVE	Innovative capacity	Scale of operation	Diffusion power
Capacidad innovativa	0.63		> 0.21	> 0.51
Escala de operación	0.77			> 0.21
Potencia difusora	0.56			

(***) 99% confidence; (**) 95% confidence and (*) 90% confidence.

Note 1 = Average variance extracted (AVE) = [(Σλ²) / n]; where n is the number of indicators.

Note 2 = Ordinal reliability coefficient (ω) = [(Σλ) ² / ((Σλ) ² + (Σ 1–λ²)]

Figure 3 presents the model. Table 6 shows that the ordinal reliability coefficient (ω) was acceptable for the latent variables (between 0.6 and 0.8) in the second model. The AVE for the variable "scale" was 0.6. The "innovative capacity" was from 0.2 to 0.4, closer to the optimum of 0.5. The second model has the discriminant capacity, stating that √AVE of the latent variables is greater than their correlation.

In the second model, companies with more projects to innovate in the future have a higher probability of being innovative and, therefore, are more likely to adopt and disseminate

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

technologies 4.0 (λ = 0.58, t = 7.56). Regardless of perceived challenges, their capacity to innovate was λ=0.2 and t=3.99, maintaining its importance as an explanatory variable. For the variable percentage of qualified employees, the innovative and, therefore, the diffusion capacity was λ=0.2 and t=4.03.

Finally, the "past innovation rate" was λ=0.98, determined in a unit value to create the second model. This variable has a negative relationship with years of operation, crossing two latent variables. This relationship made it possible to improve the overall presentation of the model in the goodness of fit indices.

Among the variables that explain the "scale of operation," the total number of employees is relevant, presenting the highest factor load (λ = 0.92, t = 5.72). Sales (λ = 0.88), as in the first model, were determined in a unit value to generate the corresponding calculations. Different from the first model, the variable years of operation was significant for the second model. The variable years or operation was shown to impact the scale of operation and the diffusion of technologies 4.0 (λ=0.26, t=2.8).

DISCUSSION OF THE RESULTS

The analysis demonstrated that both versions of the model present consistent results. Contrary to the first assumptions, the percentage of employees who hold a graduate degree and the increase in sales were not significant to influence technologies 4.0 diffusion. Regarding the increase in sales, it would be worthwhile to monitor the revenues for each specific technology – which is beyond the scope of this research.

The model suggests that companies with projects to innovate in the future can be good diffusers of technologies 4.0, corroborating the research by Horváth and Szabo (2019) and Agostini and Filippini (2019). In this sense, greater organizational flexibility, a culture of adaptation, continuous improvement practices, and new business models are elements that contribute to incorporate and disseminate technologies 4.0, as indicated by Müller et al. (2018).

Also, it was observed that each company's capacity to innovate based on a low perception of challenges is a measure of its capacity to disseminate technologies 4.0. The innovation bottlenecks can be grouped into financing problems, incentives to the economic sector, and the availability of public resources. These findings converge with the literature, as indicated by Arnold et al. (2018), Dalenogarea et al. (2018), and Ingaldi and Ulewicz (2020). The innovation challenges limit the diffusion power and explain why companies have future projects that they do not put into practice, as demonstrated in the preliminary data review.

On the other hand, this research confirms studies such as Brambilla (2018) and Horváth and Szabo (2019) about the importance of the company's size based on the total number of employees. This topic was observed in the theoretical framework presented above, demonstrating the problem faced by developing countries – and detected in the recent *Encuesta TIC* (ICT Survey) (Minecon, 2020) – where the size of the companies leads to differences regarding the adoption of technologies 4.0.

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

Our model confirms that qualified employees contribute to increase innovation and diffusion power, corroborating the literature. Qualified human capital helps to find, understand, implement, and exploit new technologies 4.0, lowering the resistance to adoption.

In the second model, the variable years of operation was not significant as an explanatory variable, different from hypothesis H9, designed based on Ingaldi and Ulewicz (2020) and Gatica (2018). The years of operation of a company, when looking at its scale of operation, positively affects its capacity to disseminate technologies 4.0. In the long term, new business models should be born based on technologies 4.0 (Botha, 2019), changing the relationship between the companies' years of operation and diffusion power, which may confirm the hypothesis.

The literature review conducted in the Web of Science core collection in April 2021 demonstrated the absence of studies analyzing the dissemination of technologies 4.0 in Chile using structural equation modeling. Furthermore, as indicated by Kiraz et al. (2020), very few studies at a global level analyze the adoption of technologies 4.0 based on structural equations, limiting the opportunities to compare results.

In this context, the study by Rojas-Córdova et al. (2020), using data science tools through decision trees, concluded that in large Chilean companies, the most significant barriers affecting the intention to innovate are costs, lack of demand for innovations, and lack of qualified personnel. On the other hand, the barriers in the small and medium-sized Chilean companies are lack of own resources, lack of demand for innovations, and lack of information on technology. Although obtained using another methodology, these results are in line with this research when highlighting the importance of innovative trajectories and scales of operation to understand the adoption and diffusion of technologies 4.0.

FINAL CONSIDERATIONS

Chile is behind in the adoption of ICT when compared to the average of OECD countries. According to Chauhan et al. (2021), Dean and Spoehr (2018), and Mazzucato (2017), the country's first tasks are to solve the technological infrastructure problems, prepare the legal frameworks and guarantee and information security, and promote new business models and new technological markets to achieve national economic development. Likewise, the model developed in this study highlights the need to elaborate policies toward smaller companies since they face more difficulties in investing in technology. This measure would contribute to maximizing the diffusion power of the entire national market.

The *Encuesta TIC* (Minecon, 2020) reported that only 9% of small and medium-sized companies in Chile have access to high-speed Internet (over 100 Mbps). Nhamo, Nhemachena, and Nhamo (2020) analyzed 212 countries on this matter, concluding that low ICT capacity anticipates a slow diffusion of technologies 4.0. Thus, public policies must strategically invest in ensuring a good connection speed for companies, especially smaller ones.

Equally important is to improve the educational system nationwide. The findings obtained in this study reinforce the importance of qualified employees to improve the organizations'

ARTICLES | **Adoption and diffusion of technologies 4.0 Based on the innovative trajectory and the scale of operation: The case of Chile**

Francisco Gatica-Neira

capacity to adopt and disseminate technologies 4.0. In Chile, Almeida, Fernandes, and Viollaz (2020) conclude that the educational system should be reinvented to facilitate the adoption of more advanced technology. The study by Safrankova, Sikyr, and Skypalova (2020) proposes that the preparation of human capital should develop skills such as communication, problem-solving, implementation, team learning, and teamwork so that the workforce is prepared to respond to the challenges of the Fourth Industrial Revolution.

Developing countries must implement a massive training plan in digital skills for workers, including those currently employed, facilitating technology adoption and creating new companies based on technologies 4.0.

Study limitations

The limitations of this study reveal four dimensions worth addressing in future research to analyze companies' diffusion power:

- Geographic proximity. The analysis does not capture the effect of spatial proximity, which is key when promoting future clusters of 4.0 companies based on the mobility of qualified employees and the creation of new technology businesses in specific territories.

- Input-output relationships. The knowledge of the chains allows identifying the activities that are more likely to help the diffusion of technologies 4.0.

- Dynamic vision of the process. Longitudinal analysis is important to observe the dynamics of adoption, diffusion, and innovation processes around technologies 4.0 in specific territories.

- Business leadership. The literature grounded on case studies suggests that the organizational leaders' vision and commitment to adopting new technologies are relevant. Business leadership is a variable that could not be addressed in this study, but it is essential in incorporating and disseminating technologies 4.0.

Note

Research group 195212 GI/EF *"Industria Inteligente y Sistemas Complejos"* (smart industry and complex systems) – GISCOM – from Universidad del Bío-Bío

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AUTHOR'S CONTRIBUTION

Francisco Gatica-Neira affirms that he has participated in all stages of the development of the manuscript, which includes: conceptualization and theoretical-methodological construction, theoretical review, data collection, data analysis, writing and final review.