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Configurational Drivers of Digital Technology Adoption in Manufacturing SMEs: Evidence from Chile

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Abstract

Digital transformation has become a key driver of competitiveness and productivity among small and medium-sized enterprises (SMEs). However, the factors that enable firms to deepen the adoption of digital technologies remain insufficiently understood, particularly in emerging industrial regions. This study analyses the configurations of technological and organizational factors that explain the level of digital technology adoption among manufacturing SMEs. Using fuzzy-set qualitative comparative analysis (fsQCA) and a sample of 52 firms located in the Bío-Bío Region of Chile, the research is guided by the Technology–Organization–Environment (TOE) framework. The results identify several configurations explaining higher levels of digital technology adoption, highlighting the importance of internal capabilities. In particular, the presence of ICT professionals, technological knowledge, an organizational culture supportive of digital innovation, and leadership motivation emerge as key conditions. These findings suggest that digital technology adoption is explained primarily by technological and organizational capabilities, while the environmental conditions analysed play a more limited role. The study contributes to the literature on digital transformation and provides implications for public policies aimed at strengthening innovation capabilities in manufacturing SMEs.

Keywords: Digital Transformation; Technology Adoption; SMEs; TOE Framework; FsQCA; Technological Capabilities.

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1. Introduction

Digital transformation is reshaping industrial competitiveness and creating new opportunities for regional development, particularly for small and medium-sized enterprises (SMEs) (Fiorini et al., 2022).

This study identifies the configurations of factors that explain the depth of digital technology adoption in manufacturing SMEs. Rather than being driven by a single determinant, digital transformation follows different pathways, suggesting that firms may require differentiated support mechanisms.

The analysis is based on a survey of 52 manufacturing SMEs participating in the FIC-R Digital Transformation Program for Manufacturing SMEs, funded by the Regional Government of Bío-Bío, Chile. Surveys were conducted between 2023 and 2024 among owners and managers with some prior awareness of Industry 4.0 technologies.

Given the sample size and the configurational nature of the phenomenon, fuzzy-set Qualitative Comparative Analysis (fsQCA) was employed (Ragin et al., 2017). This approach allows the identification of multiple combinations of conditions leading to similar outcomes and offers an alternative to traditional linear approaches (Pappas et al., 2021).

The study contributes to a still limited body of research combining the Technology–Organization–Environment (TOE) framework and fsQCA to analyse digital transformation in SMEs. While most existing evidence comes from Europe and China, this research provides evidence from a Latin American industrial region characterized by technological lagging and strong manufacturing traditions.

The findings indicate that technological knowledge, access to ICT professionals, organizational culture, and leadership motivation are the most relevant conditions explaining higher levels of digital technology adoption, whereas the environmental conditions analysed play a more limited role. The study contributes to the literature on SME digital transformation and provides evidence for the design of more effective public policies.

2. Literature Review

The literature on technology adoption includes several models that identify the key factors that influence the incorporation of new technologies within companies. Among the best known are the Theory of Reasoned Action (Fishbein et al., 1975), the Technological Acceptance Model (TAM) and the Theory of Planned Behavior (Ajzen, 1991; Gentry et al., 2002). In this context, two integrative models stand out that synthesize multiple theoretical approaches to technological adoption.

A first model is the Unified Theory of Technology Acceptance and Use (UTAUT), developed by Venkatesh et al. (2012), which identifies

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several key determinants of technology adoption: performance expectations, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Although this model has been widely used, it focuses mainly on individual decision-making processes, particularly in the context of the adoption of information and communication technologies (ICTs).

A second model, better suited to analysing technological adoption within firms, is the Technology–Organization–Environment (TOE) framework, developed by Tornatzky et al., (1990) and later expanded by Rogers (1995). This model identifies three major groups of factors: (i) technological factors, including perceptions of relative advantage, compatibility, and technological challenges; (ii) organizational factors, such as firm size, leadership support, and absorptive capacity; and (iii) environmental factors, including the level of competition, uncertainty, and the availability of external support. Given its focus on organizational technology adoption, the TOE framework is particularly suitable for analysing the factors that influence the adoption of Industry 4.0 technologies in manufacturing firms.

Under the TOE framework, several studies have analysed the adoption of digital technologies in manufacturing firms. The main findings of this literature include the following:

- Firm size determines the capacity to adopt and absorb new technologies, as it conditions the financial and administrative resources available to acquire and adapt them (Ingaldi et al., 2020; Kiraz et al., 2020). At the same time, firm size may limit operational scale, which can either encourage or discourage the adoption of new technologies.

- Internet connection quality—specifically speed and stability—emerges as a critical factor in the adoption of digital technologies (Wang et al., 2023).

- A workforce with digital skills significantly increases the likelihood of adopting and advancing digital technologies, particularly in areas such as technology scouting, decision-making, system integration, and maintenance (Almeida et al., 2020; Cabrera-Sánchez et al., 2019). This capability enables firms to reach more advanced levels of technological adoption (Gatica et al., 2022).

- Leadership capable of envisioning technological adoption pathways increases the likelihood of successful digital transformation in SMEs (Motta et al., 2019; Maggi et al., 2020). This leadership facilitates the scaling of digital technologies across different layers of organizational integration (Battistoni et al., 2023).

- Organizational culture also plays a determining role in the adoption of digital technologies. Firms that have previously experienced innovation processes tend to show greater flexibility when incorporating new digital tools (Gatica, 2024; Horváth et al., 2019; Chauhan et al., 2021; Marrucci et al., 2025). In this regard, Li et al., (2023) conclude that strategic alignment between technological and organizational factors is essential for the success of digital transformation in SMEs. The relationship between technologies, tasks, people and organisational structures plays a key role in adoption processes and determines the technical and social benefits of new technologies (Margherita et al., 2021).

- Technological knowledge is another critical factor in technology adoption. It facilitates the assessment of relative advantages, improves the understanding of potential challenges associated with adoption, and helps firms address compatibility issues between new and existing technological systems (Marrucci et al., 2025).

Recent studies combining the TOE framework and fsQCA to analyse digital transformation remain relatively limited, particularly in the context of SMEs. Most of the available evidence comes from China and Europe, while studies focusing on manufacturing SMEs in Latin America remain scarce. Xu (2025) notes that only a limited number of studies have applied the TOE framework and fsQCA to identify the configurations that explain digital transformation. Among the existing literature, five studies are particularly relevant to the objectives of this research (see Table 1). Overall, the available evidence suggests that digital transformation is explained by different combinations of technological, organizational, and environmental factors rather than by isolated variables. Studies conducted in manufacturing firms and SMEs identify multiple configurations associated with digital transformation, digital innovation, and digital servitization (Li et al., 2023; Wang et al., 2023; Zhang et al., 2024; Xu, 2025; Marrucci et al., 2025).

However, empirical evidence from manufacturing SMEs in Latin America remains limited. Therefore, this study seeks to contribute to the existing literature by identifying the configurations that explain the depth of digital technology adoption among manufacturing SMEs in an industrial region of Chile.

The TOE framework suggests that the adoption of digital technologies in firms results from the interaction between technological, organizational and environmental factors. However, these factors rarely operate independently. Instead, different combinations of conditions may lead firms to similar levels of digital technology adoption. Codara et al., (2023), drawing on a study of multiple cases, conclude that there are different paths to digitalisation, emphasising in particular the alignment between organisational capabilities and the strategies adopted as a key factor in explaining organisational resilience.

In this context, configurational approaches provide an appropriate methodological perspective to analyse these relationships. Fuzzy-set qualitative comparative analysis (fsQCA) allows the identification of different combinations of conditions that explain the presence of a specific outcome. This approach is particularly suitable for analysing SMEs, where multiple pathways may lead to successful digital transformation.

In summary, the literature suggests three main conclusions. First, most empirical evidence on digital transformation and configurational approaches is concentrated in China and Europe. Second, digital transformation in SMEs is not explained by a single factor, but by different combinations of technological, organizational, and

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environmental conditions. Third, the TOE framework provides a suitable analytical perspective for examining these configurations and understanding the factors that explain different levels of digital technology adoption.

Tabla 1: Principales estudios de aplicación FSQCA + TOE

Autores	Scope of application	Main conclusion	Main Contribution to this Study
Marrucci et al., (2025)	A sample of 305 European SMEs	Their results show that the implementation of Industry 4.0 technologies is influenced by the interaction between technological, organizational, and environmental dimensions.	Industry 4.0 adoption
Wang et al., (2023)	172 Chinese SMEs	The authors identify 11 possible configurations leading to successful digital transformation, including the "Three-Dimensional Pull Type", where the three TOE dimensions interact, as well as "Technological–Organizational" and "Technological–Environmental" configurations	TOE configurations
Li et al., (2023)	141 Chinese firms.	Among their main findings, they highlight that successful digital innovation results from a combination of factors, including the ability to adapt strategies to technological changes and the capacity to discard obsolete knowledge.	Organizational agility
Xu, (2025)	Chinese listed companies 2,437 firms.	The study highlights the importance of strategic leadership with clear digital strategies that capitalise on opportunities in the environment, cooperation with financial and technological players, and the monitoring of market trends	Multiple transformation pathways
Zhang et al., (2024)	The analysis is based on 28 listed companies.	Identify pathways through which factors influence digital servitisation in manufacturing. Among the key findings is that there is no single condition sufficient to explain servitisation, and that there is a pathway combining technological and organisational variables for digital transformation	Technology–organization pathways

Prepared by the author based on the bibliographic review.

3. Methodology

Given the configurational nature of digital technology adoption and the relatively small sample size, fsQCA is considered an appropriate methodological approach because it allows the identification of different combinations of conditions leading to similar outcomes (Zhang et al., 2024). Due to the limited sample size (n = 52), structural equation modelling and regression analysis were considered unsuitable.

The surveys were conducted between 2023 and 2024 and applied to SME owners or managers. The FIC project included manufacturing companies from the metalworking and woodworking sectors in the Bío-Bío Region, grouped into two main associations: the Association of Metalworking Companies (AGMET) and the Association of Woodworking SMEs (Pymemad). Together, both associations comprise a total of 85 member companies.

Based on the total population, a sample size of 71 firms would be required under conventional probabilistic assumptions (95% confidence level and 5% margin of error). However, given the exploratory and configurational nature of the study, together with the characteristics of fsQCA, the final sample of 52 firms was considered adequate for the analysis. No data loss occurred during the information processing stage. The surveys were conducted by a professional specialising in digitalisation and were administered to the manager or owner of the company. Most of the surveys were carried out in urban areas, although some may also operate in rural areas.

The analysis was conducted using fuzzy-set variables, which allow the identification of different degrees of membership within a dataset. Variables were classified according to their membership values: 1 indicates full membership in a condition, 0 indicates no membership, and 0.5 represents the point of maximum ambiguity (Saridakis et. Al, 2022).

The following steps were implemented:

- **Calibration of variables**. Variables were calibrated using three thresholds: 0.95 (full membership), 0.50 (crossover point), and 0.05 (non-membership). The calibration procedure was based on the maximum, mean, and minimum values of each variable. All calibrations were performed using the algorithm implemented in the fsQCA software. The empirical calibration values for each variable are reported in Table 3.

- **Necessary condition analysis.** For each variable, consistency and coverage indicators were calculated. Consistency measures the degree to which a causal condition (X) is a subset of the outcome (Y), while coverage indicates the empirical relevance of a consistent set (Kent, 2008). In the analysis, no variable reached the threshold of a necessary condition (>0.9), and consistencies above 0.8 were considered for further analysis (Ragin et al., 2017).

- **Truth table construction.** A truth table was constructed presenting all possible configurations of conditions explaining the level of adoption. The total number of configurations corresponds to 2^k, where k represents the number of analysed variables.

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To reduce the complexity of the table, the default criteria provided by the fsQCA software were applied. Given the sample size (N = 52), a frequency threshold of one case was adopted. Using a higher threshold would have excluded empirically relevant configurations and substantially reduced configurational diversity (Ragin et al. 2017). For each model, parsimonious, intermediate, and complex solutions were estimated. The intermediate and complex solutions converged, showing the same configurational paths, solution coverage, and consistency. Therefore, the complex solution was reported.

• **Solution analysis.** A standard analysis was performed to generate complex, intermediate, and parsimonious solutions. To identify whether a condition is central or peripheral within a configuration, the parsimonious solution was used. Central conditions are represented by large black circles (●), peripheral conditions by small black circles (●), and the absence of a condition by empty circles (●).

• **Graphical validation of the solution.** For the selected configuration, the estimated solution was calculated based on the calibrated variables. An XY Plot was then generated using the fsQCA software to compare the observed outcome (X) and the estimated outcome (Y), allowing the dispersion around the diagonal line to be observed.

To quantify the quality of the estimation, correlation coefficients (Spearman's Rho and Kendall's Tau) were calculated between the observed and estimated values using the Gretl econometric software.
Table 2 presents the indicators used in the analysis, based on the information obtained from the 52 surveyed firms. The dependent variable in the analysis is the level of adoption, defined as a rate per firm based on the presence (1) or absence (0) of the following technologies: production planning software, ERP systems, internal and external communication platforms, machine learning tools, CAD systems, robots, CNC machines, PLC systems, and renewable energy technologies.

Adoption level by firm = (Σ adoption by technology / Σ maximum score) (1)

Table 2: Main statistics, using observations 1 – 52. Source: Authors' elaboration using the survey questions.Variable to be explained:
Adoption level by company = (Σ adoption by technology / Σ maximum score)

Dimension	Variable	Abbreviation	Variable Type	Indicator
T	Knowledge level	Cconoc	Numerical	For each technology: SW for production planning; ERP, Internal and External Communication, Machine Learning; CAD; Robots, CNC, PLC and renewable energy, the following levels of knowledge are identified. 0=None; 1.- Low; 2.- Medium; 3.- High Level of knowledge by company = (Σ levels per technology / Σ maximum score)
T	Innovation Rate	cinv	Numerical	For each dimension: Product; Process; Organization, Design; Logistics, Marketing, the following levels were identified: 0 = Does not innovate and does not intend to innovate; 1 = present innovate in the future; 2: It is currently innovating: Innovation rate per company = (Σ levels per dimension / Σ maximum score)
T	ICT Professional	Cprotic	Categorical	0= The company does not have ICT professionals and cannot outsource them 1= The company does not have ICT professionals, but can outsource for support hours. 2.- The company has professionals specialized in the management of ICT.
T	Internet quality	Cinte	Categorical	0 = Poor quality 1= Fair quality 2= Good quality 3. Excellent quality
O	Years of Experience	Canos	Numerical	Years of experience in the field
O	Total Workers	Ctrab	Numerical	Total number of workers in the company (Administrative, production, other)
O	Leading motivation	Cmotvb	Binary	0=little or no interest 1=There is an interest in incorporating technologies.
O	Culture	Ccultu	Categorical	0= There is no culture and strong resistance to change. 1= Partially installed culture. 2= There is a digital culture and a willingness to adopt it
O	Leader's age segment	Cedadlid	Binary	0= Leaders under 50 years of age 1= Leaders over 50 years of age.
E	Sectoral diversification	Cdivs	Numerical	Number of sectors where the company supplies
E	Number of actors	Cnuac	Numerical	Number of social actors with whom the company has contact.
E	Sale to large companies.	Cventagram	Binary	0 = Does not sell to the large forestry, fishing and agro-industrial companies 1 = If it sells to the large forestry, fishing and agro-industrial companies.

Note 1. In the first column appears the TOE dimension related to each variable.

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Table 3: Calibration Anchors. Source: Authors'

Variable	Abbreviation	Full membership (0.95)	Crossover point (0.5)	Non-membership (0.05)
Knowledge level	cnoc	100,0	50,3	13,0
Innovation Rate	cinv	67,0	37,3	0,00
ICT Professional	Cprotic	2,00	1,06	0,00
Internet quality	cinte	3,00	2,21	0,00
Years of Experience	canos	57,0	23,7	3,00
Total Workers	ctrab	167	34,0	4,00
Leading motivation	cmotiv	1,00	0,80	0,00
Culture	ccultur	2,00	1,42	0,00
Leader's age segment	Cedalid	1,00	0,40	0,00
Sectoral diversification	cdinv	7,00	3,38	1,00
Number of actors	cnuac	4,00	0,98	0,00
Sale to large companies.	Cventagran	1,00	0,65	0,00
Adoption Level.	**cniadop**	**90,0**	**41,3**	**0,00**

In the analysis, new renewable energy technologies were incorporated. There is an interesting synergy between digital technologies and the green economy (Luo et al., 2022), where timely information can support corporate management practices that are more environmentally responsible. Moreover, there is a growing set of public policies aimed at promoting the development of renewable energy technologies.

Before implementing the qualitative comparative analysis, a preliminary review of the data was conducted. This included analysing the distribution of technologies across the firms, the average level of technological knowledge, and a non-parametric correlation matrix using Kendall's Tau and Spearman coefficients.

4. Prior Data Analysis

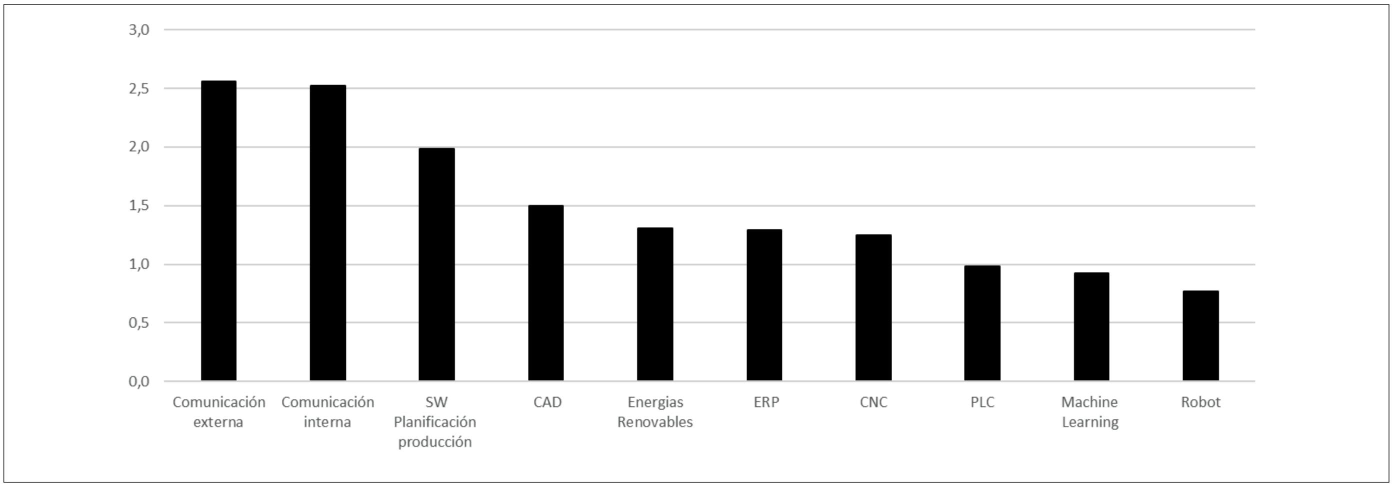
Table 4 shows that internal and external communication technologies are the most widely adopted digital tools among the surveyed firms, being present in 90.4% of the cases. Production planning and scheduling software ranks second (59.6%), followed by Computer-Aided Design (CAD) technologies (51.9%). Intermediate adoption levels are observed for Enterprise Resource Planning (ERP) systems (32.7%), Computer Numerical Control (CNC) technologies (26.9%), and Programmable Logic Controllers (PLCs) (21.2%). More advanced Industry 4.0 technologies remain less common, with machine learning applications present in 17.3% of firms, industrial robots in 9.6%, and renewable energy technologies in only 7.7% of the surveyed companies. Overall, the results suggest that manufacturing SMEs have achieved higher adoption rates for communication and operational management technologies, while more sophisticated digital technologies remain at an early stage of diffusion.

Table 4: Distribution of technologies.

Technology analyzed	Sum	% Presence
Internal communication	47	90,4%
External communication	47	90,4%
SW Planning	31	59,6%
CAD	27	51,9%
Average	21	41%
ERP	17	32,7%
CNC	14	26,9%
PLC	11	21,2%
Machine Learning	9	17,3%
Robot	5	9,6%

Source: Authors' elaboration based on the survey
Note. The percentages should not add up to 100.

Figure 1: Average knowledge (0 none; 1 Low; 2 Medium; 3 High)



Prepared by the author based on survey data.

A second dimension analysed was the average level of technological knowledge. For each technology, respondents indicated whether their level of knowledge was none (0), low (1), medium (2), or high (3). Figure 1 presents the average scores obtained for each technology.

Higher levels of knowledge are observed for external communication (2.6), internal communication (2.5), and production planning software (2.0), which is consistent with their relatively high adoption rates. Intermediate levels are found for CAD technologies (1.5), renewable energy solutions (1.3), ERP systems (1.3), and CNC technologies (1.3). Finally, PLCs (1.0), machine learning (0.9), and robotics (0.8) show the lowest knowledge levels. Overall, the results suggest a positive relationship between technological knowledge and adoption, although some technologies, such as renewable energy, exhibit higher levels of awareness than actual implementation.

Finally, a non-parametric correlation matrix is presented (Table 5). In general, no coefficients above 0.8 are observed, indicating the absence of collinearity problems between the variables. In addition, the Variance Inflation Factor (VIF) indicator was calculated using the Gretl econometric software, confirming that all values are below the threshold of 10.

In the initial analysis, the variables Level of Knowledge (ccnoc), Organizational Culture (ccultu), Internet Quality (cinte), Presence of ICT Professionals (cprotic), and Number of Workers (ctrab) present Tau and Rho coefficients above 0.3 with the dependent variable Level of Adoption (cniadop). The variable most strongly associated with adoption is the firm's technological knowledge level, with coefficients of Rho = 0.68 and Tau = 0.54.

Table 5: Nonparametric correlation matrix.

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	canos	ctrab	ccnoc	cinv	cdivs	cnuac	cniadop	ccultu	cinte	cprotic	cmotvb	cedadlid	cventagram
canos	1	0.01	0.01	-0.2	-0.1	0.2	-0.06	-0.05	-0.08	-0.05	-0.07	-0.3	0.04
ctrab	0.01	1	0.21	0.11	0.05	0.08	0.24	0.14	0.05	0.31	0.18	-0.18	0.14
ccnoc	0.01	0.2	1	0.28	0.34	0.22	0.54	0.43	0.41	0.36	0.43	0.14	0.47
cinv	-0.39	0.15	0.38	1	0.31	0.04	0.17	0.18	0.01	0.22	0.32	0.40	0.26
cdivs	-0.14	0.05	0.34	0.42	1	0.30	0.17	0.40	0.06	0.11	0.38	0.14	0.67
cnuac	0.28	0.1	0.28	0.05	0.36	1	0.15	0.27	0.01	0.13	0.21	-0.02	0.35
cniadop	-0.07	0.32	0.68	0.21	0.22	0.19	1	0.40	0.41	0.36	0.13	0.05	0.26
ccultu	-0.06	0.17	0.51	0.22	0.46	0.30	0.44	1	0.34	0.28	0.55	0.12	0.48
cinte	-0.1	0.06	0.50	0.02	0.07	0.01	0.47	0.37	1	0.08	0.07	0.17	0.08
cprotic	-0.06	0.38	0.39	0.26	0.14	0.14	0.41	0.31	0.09	1	0.22	0.06	0.29
cmotvb	-0.08	0.21	0.43	0.37	0.43	0.23	0.15	0.57	0.08	0.23	1	0.20	0.56
cedadlid	-0.36	-0.2	0.17	0.46	0.16	-0.03	0.06	0.12	0.17	0.06	0.20	1	0.02
cventagram	0.05	0.16	0.56	0.30	0.76	0.38	0.29	0.49	0.09	0.30	0.56	0.02	1
	RHO DE SPEARMAN												

Source: authors' elaboration based on the survey

5. Results

The objective of this study is to identify the factors that explain the deepening of digital technology adoption. Specifically, the research seeks to answer the following question: What are the configurations of factors that explain the depth in the adoption of new digital technologies in manufacturing SMEs?. This study aims to provide a comprehensive understanding of the factors that foster technological synergies within manufacturing SMEs in the Bío-Bío Region of Chile.

5.1. Analysis of the Necessary Condition.

When reviewing Table 6, it can be observed that no variable exceeds the consistency threshold of 0.90. Therefore, no single factor explains the dependent variable by itself.

Following the criteria proposed by Ragin et al., (2017), variables with a consistency index above 0.80 can be incorporated into the configurational analysis. Based on this threshold, the following variables were selected: internet quality, leadership motivation to implement Industry 4.0 technologies, the presence of ICT professionals, organizational culture supportive of digital technologies, and the level of technological knowledge. These variables present coverage levels ranging from 85% to 53% of the analysed cases, which is consistent with the correlation analysis presented in Table 4.

Qualitative comparative analysis is inherently configurational. Therefore, the absence of conditions (~) was also incorporated into the analysis. In this regard, the absence of the variable number of workers (~Ctrab) was selected, presenting a consistency of 0.82 and a coverage of 0.57.

In summary, six explanatory variables were identified to assess the depth of digital technology adoption. These variables are: internet quality, leadership motivation, access to ICT professionals, organizational culture supportive of technological change, technological knowledge, and the number of employees.

Table 6: Analysis of the necessary condition.
Outcome variable: Adoption level calibrated

Calibrated variable	Abbreviation	Consistency	Coverage
Internet quality	**Cinte**	**0.86**	**0.72**
Motivation	**Cmotvb**	**0.84**	**0.53**
ICT Professionals	**Cprotic**	**0.83**	**0.77**
Culture	**Ccultu**	**0.82**	**0.65**
Knowledge of technologies	**Cconoc**	**0.80**	**0.85**
Innovation Rate	cinv	0.74	0.70
Selling to large companies	Cventagram	0.73	0.56
Sectoral diversification	Cdivs	0.73	0.72
Years of existence	Canos	0.69	0.72
Number of social actors	Cnuac	0.54	0.72
Number of workers	Ctrab	0.47	0.79
Age of the leader	Cedadlid	0.45	0.54
Lack of internet quality	~Cinte	0.56	0.66
Lack of motivation	~Cmotvb	0.25	0.54
Absence of ICT professionals	~Cprotic	0.68	0.70
Absence of culture	~Ccultu	0.43	0.56
Lack of knowledge of technologies	~Cconoc	0.68	0.62
Absence Sale to large companies	~Cventagran	0.35	0.48
Absence Sectoral diversification	~Cdivs	0.66	0.64
Absence Years of existence	~Cnuac	0.74	0.58
Absence Number of workers	**~Ctrab**	**0.82**	**0.57**
Absence of the leader's age	~Cedadlid	0.62	0.51

Source: own elaboration using FSQCA software

The truth table contains the different configurations or combinations between variables and is determined by 2^k, where k represents the number of variables analysed. Considering six variables, a total of 64 possible combinations would be obtained.

Given the sample size (N = 52), the analysis was limited to five conditions, resulting in 32 possible configurations. This approach is consistent with the recommendation of Shalahuddin et al. (2024) for studies based on relatively small samples.

Thus, the models were defined as follows:

Model 1
Adoption level = f (Technological knowledge, Organizational culture, ICT professionals, Internet quality, Leadership motivation)

Model 2
Adoption level = f (Leadership motivation, ICT professionals, Organizational culture, Technological knowledge, Number of workers)

To incorporate the variable number of workers, internet quality was excluded from the second model, as it showed limited explanatory power in the first model. The second model was estimated as a sensitivity analysis by replacing Internet quality with Number of workers, allowing the consistency of the main configurational results to be assessed.

5.2. First model

Examining Table 7, the complex solution identifies five relevant configurations, presenting a consistency of 0.84 and coverage of 0.80, which can be considered acceptable. The solution consistency is above the consistency cutoff threshold (0.84 > 0.83).

A general review shows that internet quality is not a relevant variable in explaining the adoption of Industry 4.0 technologies. In configurations 1 and 2 it appears with a low presence, in configuration 3 it does not appear, and in configurations 4 and 5 it appears only as a peripheral variable.

This suggests that internet access operates as a minimum enabling condition, but its presence alone cannot explain the technological scaling of SMEs.

Table 7: Configurations that explain the depth of technological adoption (cniadop). Complex solution.
Model 1: cniadop = f(cconoc, cultu, cprotic, cinte, motvb)
Algorithm: Quine-McCluskey

Calibrated variable	**Abbreviation**	**C.1**	**C. 2**	**C. 3**	**C. 4**	**C. 5**
Internet quality	Cinte	○	○		•	•
Motivation	Cmotvb	•	•	•	○	•
ICT Professionals	Cprotic		⬤	⬤	⬤	○
Culture	Ccultu	⬤		⬤	○	○
Knowledge of technologies	Cconoc	○	⬤	⬤	○	⬤
Raw coverage		0.36	0.37	0.60	0.18	0.21
Unique coverage		0.04	0.01	0.27	0.08	0.01
Consistency		0.84	0.90	0.92	0.87	0.90

Frequency cutoff = 1
Consistency cutoff = 0.83
Solution coverage = 0.80
Solution consistency = 0.84

Source: Authors' elaboration using FSQCA software
Note 1: Black circles indicate a very high presence of a condition and white circles indicate a very low presence (i.e., absence) of a condition. Blank spaces indicate "I don't care." The size of the black circle is associated with the central condition from the parsymonic solution.
Note 2: C=Configurations or Combinations

Regarding the other variables, leadership motivation appears in configurations 1, 2, 4 and 5, although mainly as a peripheral condition.

In contrast, the central variables explaining the depth of adoption are:

- access to ICT professionals
- organizational culture supportive of technological change
- technological knowledge.

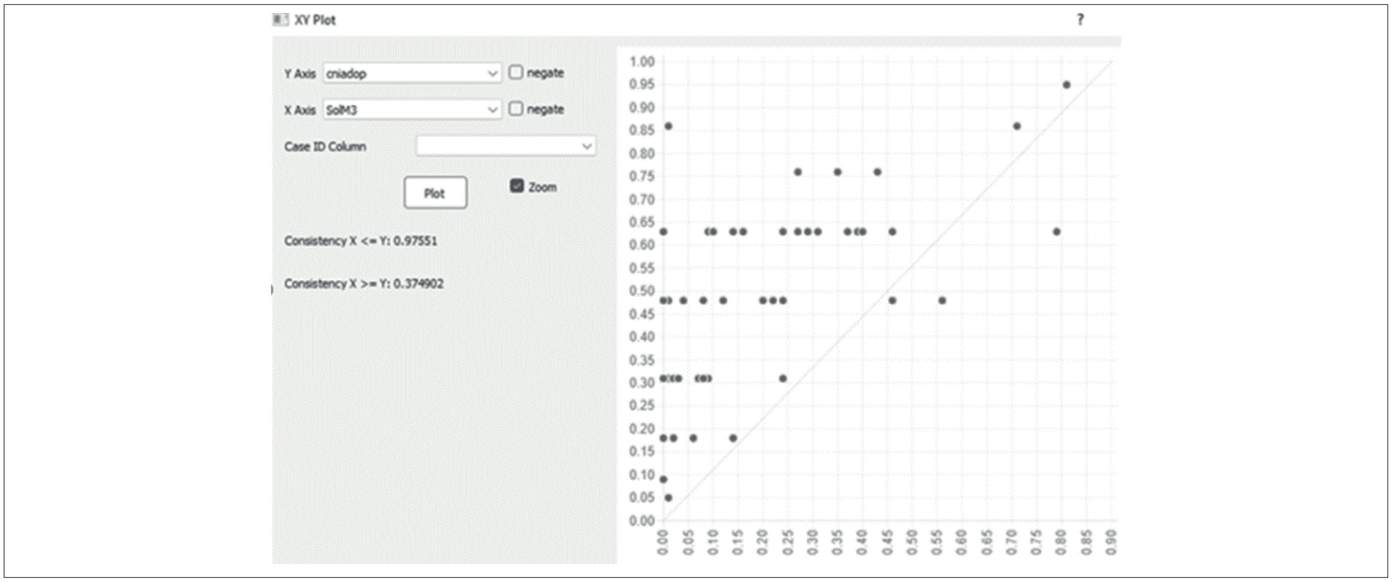
The presence of ICT professionals appears as a central condition in configurations 2, 3 and 4. Similarly, technological knowledge appears as a central condition in configurations 2, 3 and 5. Organizational culture appears as a central condition in configurations 1 and 3.

Among the identified configurations, configuration 3 presents the strongest explanatory power, with a raw coverage of 0.60 and a consistency of 0.92. Its unique coverage (0.27) is also higher than the other configurations in the first model.

In summary, the combination of ICT professionals, an organizational culture supportive of digital technologies, technological knowledge, and leadership motivation explains the adoption of Industry 4.0 technologies in manufacturing SMEs.

Configuration 3 from the first model was further analysed using an XY Plot, where the observed level of adoption is represented on the Y-axis and the proposed configuration on the X-axis (Figure 2). The results show that most cases fall within the model, indicating a consistent configuration with strong empirical coverage.

Figure 2: XY Plot.
Adoption Rate Calibration and Solution 3 Chosen.
Model 1: cniadop = f(cconoc, cultu, cprotic, cinte, motvb)
C 3: cconoc*ccultu*cprotic*cmotvb



Source: elaboration using FSQCA software

The analysed cases show a positive correlation between the proposed configuration and the observed adoption levels (Spearman Rho = 0.57; Kendall Tau = 0.44). However, the dispersion of the data indicates that the configuration tends to slightly underestimate the observed adoption levels while maintaining a consistent positive trend.

5.3. Second Model

In the second model, internet quality was removed and the number of workers variable was incorporated, based on the results obtained in the necessary condition analysis.

Table 8: Configurations that explain the depth of technological adoption (cniadop). Complex solution
Model 2: cniadop = f(cmotvb, cprotic, ccultu, cconoc, ctrab)
Algorithm: Quine-McCluskey

Calibrated variable	Abrevia-tura	C.1	C. 2	C. 3	C. 4	C. 5
Motivation	Cmotvb	●	●	●	●	○
ICT Professionals	Cprotic	◦		•	•	•
Culture	Ccultu		◦		•	◦
Knowledge of technologies	Cconoc	○	●	●		○
Number of workers	Ctrab	○	○	○	●	●
Raw coverage		0.43	0.25	0.54	0.37	0.14
Unique coverage		0.04	0.014	0.11	0.11	0.04
Consistency		0.78	0.86	0.91	0.92	0.99
Frequency cutoff = 1 Consistency cutoff = 0.81 Solution coverage = 0.80 Solution consistency = 0.81						

Source: Authors' elaboration using FSQCA software
Note 1: Black circles indicate a very high presence of a condition and white circles indicate a very low presence (i.e., absence) of a condition. Blank spaces indicate "I don't care." The size of the black circle is associated with the central condition from the parsymonic solution.
Note 2: C=Configurations or Combinations

The consistency of the solution (0.81) is equal to the established threshold and therefore can be considered acceptable. Similarly, the coverage of 0.80 indicates an acceptable, although limited, explanatory capacity.

Table 8 shows that leadership motivation becomes a central variable in configurations 1, 2, 3 and 4. In configuration 5, however, motivation appears as an absent condition.

Regarding the number of workers, this variable appears as absent in configurations 1, 2 and 3, and present in configurations 4 and 5. Overall, the variable does not appear to play a decisive role in explaining the adoption process.

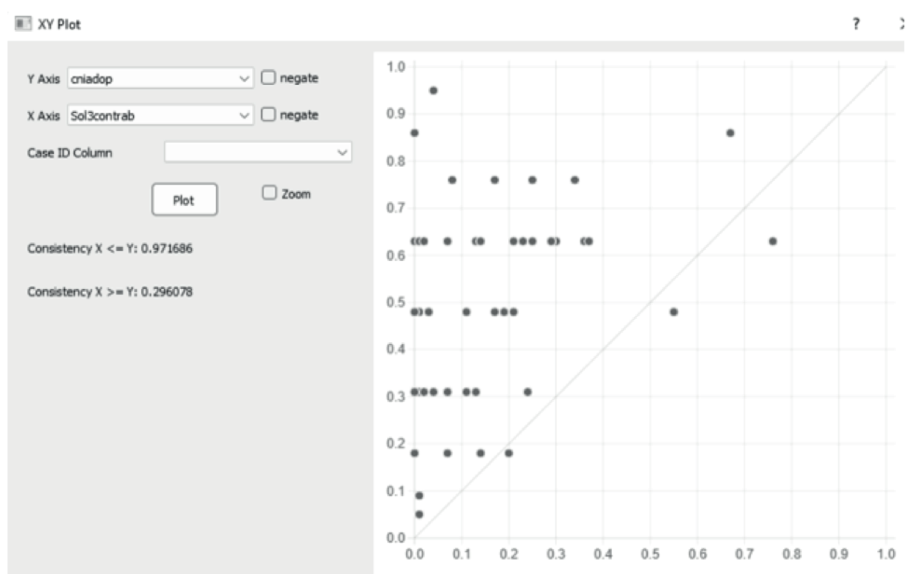
In this model, organizational culture and technological knowledge appear as peripheral variables, which contrasts with the first model, where they played a central role.

In contrast, the presence of ICT professionals remains a central variable in both models, appearing in configurations 3, 4 and 5, which demonstrates a strong consistency in the results.

Among the configurations identified in the second model, configuration 3 again provides the best explanation of the adoption process, with a raw coverage of 0.54, unique coverage of 0.11, and consistency of 0.91.

This configuration suggests that the combination of leadership motivation, access to ICT professionals, technological knowledge, and the absence of a large workforce explains the depth of digital technology adoption.

Figure 3: XY Plot.
Adoption Rate Calibration and Solution 3 Chosen.
Model 2: cniadop = f(cmotvb, cprotic, ccultu, cconoc, ctrab)
C. 3: cmotvb*cprotic*cconoc*~ctrab



Source: elaboration using FSQCA software

Figure 3 presents the XY Plot for configuration 3 of the second model. In this case, the observed adoption level is located on the X-axis and the configuration on the Y-axis.

The dispersion of the points around the diagonal line is greater than in the first model, indicating a lower explanatory quality. This is confirmed by the correlation coefficients (Rho = 0.39; Kendall Tau = 0.30), which are lower than those obtained in the first model.

Overall, the results highlight the importance of internal organizational capabilities in explaining the depth of digital technology adoption. In particular, access to ICT professionals and technological knowledge appear as the most consistent explanatory conditions across the models.

6. Discussion of results

This section is divided into two parts. First, the main findings are discussed in light of the theoretical framework and previous literature. Second, the implications of the results for public policy are examined.

6.1. On the main results.

If the two most relevant configurations are selected, based on consistency and coverage, the following results emerge for each model.

- In the first model, the central variables explaining the depth of adoption of Industry 4.0 technologies are access to ICT professionals, organizational culture, and technological knowledge. Leadership motivation appears as a peripheral condition within this configuration.

- In the second model, the configuration that best explains the level of technological adoption includes leadership motivation, access to ICT professionals, and technological knowledge.

This finding is consistent with Marrucci et al. (2025), who show that Industry 4.0 implementation in European SMEs depends on the interaction between technological and organizational dimensions rather than on isolated factors. Similarly, Wang et al. (2023) identify multiple configurations combining technological and organizational conditions, suggesting that digital transformation emerges from complementarities among internal capabilities rather than from single drivers.

These findings reinforce the configurational perspective of digital transformation. Similar to previous TOE–fsQCA studies, no single condition was sufficient to explain advanced levels of digital technology adoption. Instead, digital transformation emerges from the interaction of complementary technological and organizational capabilities operating simultaneously within firms.

The variables that appear to determine the technological scaling process according to the qualitative comparative analysis are the following:

• Access to ICT professionals. Firms with ICT specialists are better positioned to experience technological scaling, confirming the findings of Almeida et al., (2020), Cabrera-Sánchez et al., (2019), and Gatica et al., (2022). The presence of this type of qualified workforce facilitates technological scouting, decision-making, system integration, and maintenance processes.

• Technological knowledge. The level of technological knowledge is fundamental in the adoption process, as highlighted by Marrucci et al. (2025). Considering that the firms analysed already show some sensitivity toward digital technologies, knowledge enables them to develop stronger technological synergies.

• Organizational culture. A culture supportive of digital innovation positively influences technological scaling. This finding is consistent with previous studies (Gatica et al., 2024; Horváth et al., 2019; Chauhan et al., 2021; Marrucci et al., 2025. In particular, agile organizations capable of adapting quickly to technological change appear to have an advantage in digital transformation processes (Li et al., 2023).

• Leadership motivation. The motivation of business leaders emerges as an important element for technological adoption processes, reaffirming the findings of Motta et al., (2019) and Maggi et al., (2020). In this regard, Xu (2025) argues that it is essential to raise digital awareness and improve strategic planning among senior management, by focusing on key areas and fostering enthusiasm among employees to drive digital transformation.

Internet quality—measured in terms of service speed and stability—appeared as relevant in the Necessary Condition Analysis (Table 6), but it did not prove significant within the configurations identified in the first model. This component of technological infrastructure may function as an initial enabling condition during the early stages of digital adoption. However, once certain technologies have already been implemented, its relevance for further technological scaling appears to diminish, contradicting the findings of Wang et al., (2023).

The innovation rate, the age of the business leader, and the number of employees were not significant in explaining the depth of technological adoption. In the case of firm size our findings do not allow us to conclude that company size is a key factor – a variable traditionally used to determine the adoption of Industry 4.0 technologies – thereby contradicting the conclusions reached by Ingaldi et al., (2020) and Kiraz et al., (2020). It should be noted that the analysis focuses exclusively on small and medium-sized enterprises, which represent a relatively homogeneous segment. Therefore, the effect of operational scale on the adoption process cannot be clearly observed within this sample. It is likely that this relationship would differ if large firms were included in the analysis, which falls outside the scope of the present study.

Regarding the innovation rate and leader age variables, elements related to organizational culture and leadership motivation may partly offset their potential effects. This result differs from some expectations derived from the theoretical framework and may be explained by the fact that the firms analysed have already reached a minimum level of digital adoption, which reduces the influence of these factors.

These results reveal the predominance of technological and organizational variables, which appears to be a characteristic of the manufacturing firms analysed (Wang et al., 2023; Li et al., 2023). In the technological dimension, the availability of ICT professionals and the level of technological knowledge emerge as fundamental conditions. In the organizational dimension, the presence of a culture supportive of technological change and the motivation of business leaders play a decisive role. Our findings are consistent with those of Codara et al., (2023), who suggest that alignment between senior management's strategic definitions and new organisational conditions in areas such as work redesign, new roles and new business opportunities can ensure organisational resilience in the context of new technologies.

Among the selected factors, none of the environmental conditions analysed remained in the final configurational models. This finding had already been suggested in the Necessary Condition Analysis (Table 6), where variables such as the sectoral diversification of customers, the number of public actors interacting with the firm, and the possibility of selling to large exporting firms were not significant in explaining adoption levels amongst manufacturing SMEs. This finding is consistent with the observations of Zhang et al. (2024), where the most explanatory model focuses on a combination of technological and organisational variables, with environmental variables (market competition and public policy support) playing a more pe-

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ripheral role. Therefore, our findings suggest that the environmental conditions analysed play a more limited role than technological and organisational conditions in explaining the adoption of digital technology in the firms studied.

6.2. Regarding public policies.

The results suggest that direct public support mechanisms, by themselves, may be insufficient to promote substantial digital transformation processes in manufacturing SMEs. Rather, successful adoption appears to depend on the development of internal technological and organizational capabilities. This finding is consistent with the configurations identified in the analysis, where technological knowledge, access to ICT professionals, organizational culture, and leadership motivation emerged as the most relevant conditions. Consequently, public policies should focus not only on facilitating access to technologies, but also on strengthening the internal capabilities that enable firms to absorb, integrate, and scale digital innovations over time.

The results highlight the importance of strengthening strategic capabilities within firms in order to accelerate the adoption of digital technologies among manufacturing SMEs. Increasing technological knowledge, expanding the number of professionals with expertise in digital technologies, having leaders motivated to face technological challenges, and developing a flexible organizational culture are key elements. However, these internal capabilities are difficult to address through current public policy instruments.

The policy orientations presented in Table 9 are based on the main conditions identified in the configurational analysis. They do not correspond to a single configuration but reflect the combination of the central conditions identified across the different configurations. Since technological knowledge, access to ICT professionals, leadership motivation, and organizational culture emerged as the main conditions explaining the depth of digital technology adoption, public policies should focus on strengthening these capabilities rather than only facilitating access to digital technologies. Table 9 summarises the main policy orientations derived from these findings.

Table 9. Public policies based on the core elements of the various configurations

Technology-Organisation Dimension	Environment	
	Public policy	Offer
Leadership	To place an emphasis on industries that can adopt new technologies and which, at the same time, have a high capacity to disseminate these technologies within the local productive fabric (Fiorini et al., 2022). These companies can act as 'bridges' to revitalise regions that are lagging behind technologically.	Working in this area involves strengthening regional programs that encourage collaboration with key business leaders who can serve as role models for other companies.
ICT specialists	To work on the regional human capital training system to train workers who can contribute to Industry 4.0 work systems (Margherita et al., 2021). There is a shift from manual tasks to roles requiring advanced knowledge, and workers must be trained locally at colleges and universities..	This implies a rethinking of the educational provision offered by universities and technical colleges, but it also means that current employees in companies will need to retrain in the new technologies
Technological knowledge	It is essential to develop a base of supplier companies specializing in new technologies, particularly in regions that are lagging behind technologically (Bogliacino et al., 2016). This industrial base enables support to be provided to manufacturing SMEs to help them adopt new technologies, and plays a fundamental role in the identification, adaptation and maintenance of new digital technologies within SMEs.	It is essential to have sector-specific or cross-sector technology centers that facilitate the creation and incubation of a range of technology-based companies across the regions.
Organisational culture	Our research highlighted the limited role played by procurement from large firms in driving digital transformation within SMEs. Public policy could therefore foster new production linkages and learning networks between large firms – typically exporters – and supporting SMEs to facilitate the adoption of new technologies (Hietala et al., 2019).	Working groups are needed to strengthen the suppliers of major exporting companies in key inputs. This mentoring mechanism requires a long-term vision and must be supported by public policies that facilitate the uptake of new technologies.

Identifying hubs capable of disseminating technologies (Fiorini et al. 2022), developing new human capital suited to the challenges of digitalisation (Margherita et al., 2021), building a new base of specialised suppliers (Bogliacino et al., 2016) and fostering the development of supply chain linkages between large firms and SMEs (Hietala et al., 2019); all require public policy interventions to be more complex, given that there are different combinations of factors involved in achieving digital transformation in manufacturing SMEs. The high degree of heterogeneity across different situations precludes a 'one-size-fits-all' policy (Capello et al., 2023).

7. Final conclusions

The results show that higher levels of digital technology adoption among manufacturing SMEs are explained by combinations of technological and organizational capabilities, particularly technological knowledge, access to ICT professionals, organizational culture, and leadership motivation.

Consistent with previous studies applying the TOE framework and fsQCA (Li et al., 2023; Wang et al., 2023; Zhang et al., 2024; Xu, 2025; Marrucci et al., 2025), our findings confirm that fuzzy-set qualitative comparative analysis is a useful methodological approach for studying digital transformation in SMEs. This type of analysis allows researchers to identify combinations of factors that are not mutually exclusive, providing a closer representation of the organizational complexity involved in the adoption of new technologies.

Given the limitations of our research, future studies should deepen the understanding of the interactions between the factors identified in this study. In particular, it would be valuable to carry out dynamic analyses comparing different patterns of technology adoption over time (Song et al., 2023). Similarly, the present study was based on a relatively small sample of 52 firms belonging to two trade associations. Future research could expand the analysis to other industrial sectors, firms of different sizes, and additional Latin American regions with mature industrial bases facing technological challenges.

Finally, it is important to highlight the strategic role of motivated business leaders in initiating what may be described as a "virtuous cycle of digital transformation." Such a cycle may involve the incorporation of professionals specialized in digital technologies, the development of deeper organizational knowledge of emerging technologies, and the strengthening of an organizational culture oriented toward digital innovation.

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