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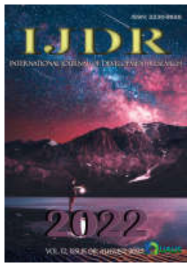

RESEARCH ARTICLE OPEN ACCESS

INDUSTRY 4.0 MATURITY: A CASE STUDY OF A MATURITY MODEL APPLIED TO THE MANAUS FREE TRADE ZONE COMPANY

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ABSTRACT

Considering the fourth industrial revolution underway in the first quarter of this century, with industry 4.0 and all related technologies as its main brand, its implementation is seen as a matter of maintaining the competitiveness and survival of manufacturing companies, becoming government, academia, and entrepreneurs' goals. Understanding Industry 4.0 maturity is the first step in developing strategies for industrial digitalization. The Manaus Free Trade Zone region, as it has an economy based on industry, is the focus of this work, which aims to obtain a diagnosis from a case study of a beneficiary company of the Informatics Law which obliges companies that benefit from tax benefits to investing in RD&I. For this work, the following will be carried out: (i) a systematic review of the scientific literature; (ii) choosing a model for measuring maturity levels; (iii) application of the model in a company benefiting from the Informatics Law; and (iv) validation of the model.

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INTRODUCTION

Industry 4.0 is, according to several authors, the symbol of the fourth industrial revolution (SCHUH *et al* ., 2020; GTAI, 2014; SCHUMACHER *et al* ., 2016; GHOBAKHLOO, 2018; CASTELO-BRANCO *et al* ., 2019), is marked by the application of cyber-physical systems (CPS) which, according to GTAI (2014), unite the virtual and real worlds into a single one, in which, from the application of artificial intelligence, it serves as a basis for technologies exemplified by Azevedo and Santiago (2019) as the internet of things (IoT), Big Data, cloud computing, additive manufacturing. Considered the state of the art in manufacturing, Schumacher *et al* . (2016) assess that the integration of technologies related to Industry 4.0 must take place throughout the value chain (horizontal level), covering suppliers and customers, as well as in all stages of production (vertical level), forcing internal and external involvement in the purpose of digital transformation. Although Industry 4.0 is already a reality in some sectors of developed countries, in Brazil there is still much to be done in several dimensions. The Manaus Free Trade Zone (MFTZ) is an exceptional area in Brazil, given that, it encourages the establishment of factories in the region covered by the Western Amazon and the State of Amapa, which are geographically isolated due to the preservation of the Amazon Forest, the Federal and State Governments grant tax benefits, making it possible for companies to remain in this area. Such a condition (the use of tax benefits) cannot be considered sufficient for the sustainability of the industrial hub located in Manaus, which, due to a global movement, must be inserted into the level of digitalized industrial systems, capable of carrying out predictive analysis to promote optimization to produce more and better. Successful companies tend to be those that will have physical products with innovative embedded digital services, having as a principle means of production that are also digital and interconnected throughout the value chain (DE CAROLIS, 2017) and that according to Zaoui and Souissi (2020), measuring the stage at which the company is in terms of industry 4.0 is the first step that precedes the definition of strategies to be admitted for digital transformation, it is understood that it is necessary to know the status to define financial, human and time resources for the implementation of technologies related to the fourth industrial revolution. One of MFTZ's main industrial segments is the computer goods manufacturer whose operation is part of the Informatics Law, which, in exchange for tax benefits, requires beneficiary companies to invest a percentage of their annual revenue in RD & I. It is important to note that according to Daemmrich (2017), industrial revolutions are supported by science, technology, and innovation, thus, in this work, a case study on a beneficiary company of the Informatics Law located in the MFTZ was performed from the perspective of industry 4.0 metrics.

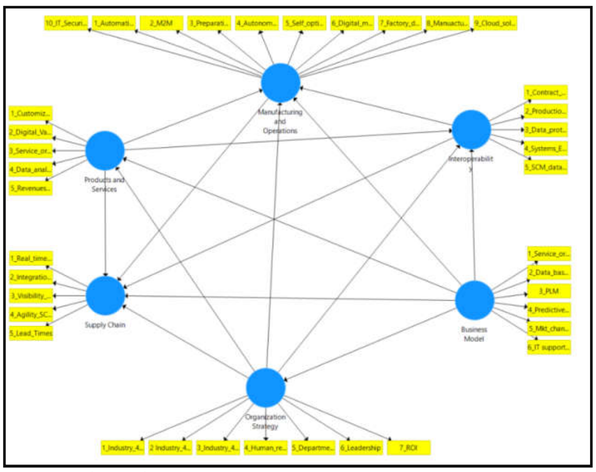
LITERATURE REVIEW

Due to the fact that the 4th industrial revolution has been explored for more than a decade, the scientific literature around maturity assessment models under Industry 4.0 measurements is very voluminous. Thus, this work used the research carried out by Itikawa and Santiago (2021) on the subject that, through a methodology explained by Ensslin *et al*. (2015) called Process Knowledge – Constructivist (ProKnow-C) the most relevant works were found. Maturity indicates whether something is complete, perfect, or ready, that is, maturity indicators are used to identify the current status within a development process and readiness indicators give indications prior to maturity, however, both are used to measure industry 4.0 metrics as synonyms (SCHUMACHER *et al*., 2016), thus, several widely used indicators were developed, exemplified by the Technological Readiness Level (TRL), which measures technological maturity from a commercial point of view (innovation) or the Manufacturing Readiness Level (MRL), which indicates the technological maturity of a production process, not being possible, through these, a broad diagnosis of Industry 4.0 (JUNG *et al* ., 2016). Having as a pillar the implementation of technologies in production processes, it is important to understand how the fact that industry 4.0 does not only address the application of innovations in companies, Buhr (2015) understands that the fourth industrial revolution does not only affect production processes through disruptions caused by value creation but involving the way it is produced, it affects people in companies and has effects even on society.

It is not possible to conceive smart manufacturing only by applying emerging technologies such as artificial intelligence, augmented reality, cloud computing, IoT, and 3D printing, among others, which have a direct relationship with products, manufacturing, and logistics, without other aspects such as the culture of the company, people qualified to work with data and flexibly, and customers and suppliers adept at constituting an interconnected value chain (PWC, 2021; WEYER *et al* ., 2015; BUHR, 2015; AZEVEDO E SANTIAGO, 2019). In this sense, the portfolio obtained identified maturity or readiness models that deal with industry 4.0 under several metrics commonly called dimensions. In the study carried out by De Carolis *et al*. (2017), maturity in digital transformation is measured in 4 dimensions and 5 variables, however, without a statement of results regarding the audit carried out using the model developed. Based on a detailed flow of steps for the definition of a maturity measurement model, Schumacher *et al* . (2019), built a system composed of 8 axes evaluated in 65 measurement variables through questionnaires structured by four levels of maturity. The final value of each analyzed variable corresponds to the average of the responses and that of the analyzed axis is the result of the weighted average, considering the weight of each variable. The results are displayed on a radar chart. The model presented by Schumacher *et al*. (2019) is an update of another formulated by Schumacher *et al* . (2019), on which occasion an analysis of models of important institutions/companies such as IMPULS, Pricewaterhouse Coop. and Rockwell Automation, from which the one developed by the authors came, either as references not to be used due to the lack of depth regarding the evaluation of variables or as a well-founded reference, as mentioned regarding the IMPULS model. In the work carried out for ACATECH, Schuh *et al.* (2020) developed a model structured in four major pillars that structure the degree of maturity in industry 4.0, namely: resources, information systems, organizational structure, and culture. This maturity model is the reference used in the elaboration of the ordinance that regulates the execution of projects for the implementation of technologies related to industry 4.0 in the sphere of compulsory investments in RD&I in the MFTZ under the Informatics Law (BRASIL, 2018).

Pimm4.0 Maturity Model: Considering the existence of countless models for measuring maturity level in industry 4.0 available in the literature, it is not the objective of this work to develop another model, but to use an existing one, demonstrating its scientific validity from a case study. In this context, the chosen model had as a prerequisite to be of local authorship and easy to apply in companies located in the MFTZ in terms of language, data collection, and connection of variables to production processes, enabling a more accurate diagnosis. The PIMM4.0 tool was developed by Azevedo and Santiago (2019) and registered by Santiago (2019), to diagnose the industry 4.0 maturity of Brazilian companies and was built on a platform that considers six dimensions obtained from the measurement of 38 variables. It is observed that the structure presented in the model by Azevedo and Santiago (2019) has a multivariate structure similar to that presented by the model by Schumacher *et al*. (2019) and variables equivalent to Schuh *et al*. (2020). These two models were then used as comparison parameters for the theoretical validation of Azevedo and Santiago (2019) through a spreadsheet in which the equivalences of each variable were verified. An example of the variable M2M is depicted in table 1. For this work, a questionnaire was formulated with one question for each PIMM4.0 variable and submitted to a company located in the MFTZ. Each question has 4-level Likert scale answers. A manufacturer of IT goods with annual sales of approximately R$ 500 million was chosen. As for the sample to which the research was submitted, it is important to verify that the universe to be considered in the company is not equivalent to the total number of employees, since the implementation of industry 4.0 involves knowledge with a strategic view of the business, but in general, the jobs occupied by operational workers dispense with an improved qualification in understanding the process and work dynamics (DE OLIVEIRA E CORREA, 2019). In this sense, the universe to be considered by the research will include management positions, engineers, and supply chain key workers. Since the total population is 31, the questionnaire was submitted to all, with a response of 27 (87.1% of the total population). According to Miott (2011), this amount is statistically valid, considering $Z_{\alpha/2}$ = 1.96 (confidence level of 95%) and standard error of 5% amplitude (E = 0.2) and standard deviation obtained in the survey, resulting on a minimum sample size of 23.

Structural Equation Modeling (SEM): The mathematical verification dealt with in this work is related to the verification of construct validity, which in this work can also be called latent variable (LV) or dimension, in which observable variables converge. The technique to be adopted is confirmatory factor analysis (LAROS, 2010). According to Neves (2018), structural equation modeling (SEM) statistically treats confirmatory analyzes to obtain approval for a model through the observation of covariances of independent variables on a dependent variable. This work makes use of SmartPLS 3 software to perform SEM. The model presented by Azevedo and Santiago (2019) shows the list of observable variables, whose values are obtained from the perception of the respondents of the questionnaire. It appears, however, that the authors themselves indicate that the dimensions (LV) to which the variables converge to have a relationship of dependence on each other. The model is input on Smart PLS according to Figure 1.



Source: The authors using SmartPLS 3.

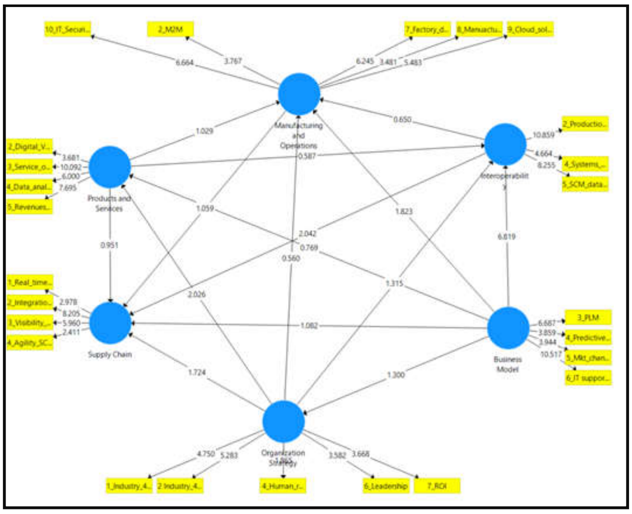
Figure 1. Azevedo e Santiago (2019) on Smart PLS 3

Henseler *et al*. (2019) define that the model verification takes place in two steps: (i) by evaluating the so-called external model, which deals with the validation of the construct formation and the reliability and validity of the reflexive constructs, and (ii) validation of the internal model, which deals with the relationship between the constructs. The first step starts by running PLS Algorithm from where it is possible to obtain quality indicators from the model (table 2). The first indicator to be evaluated is the AVE, which expresses the convergent validities from the average variances extracted, which according to Henseler *et al* . (2019), having at least the value of 0.5, expresses that there is sufficient convergence validation (RINGLE *et al*., 2014), that is, the LV can explain more than half of the variance of the observed variables. In the model under study, only interoperability reached the minimum value established by the literature. In this case, Ringle *et al*. (2014) recommend that the variables with the lowest factor loadings be observed, so that, by eliminating them, AVE coefficients ≥ 0.5 are reached. The following variables (marked in black in table 4) were eliminated after six iterations of evaluating the AVE values for each dimension of the model:

Excluding the variables listed in table 3, the quality indicators get the values in table 4: According to Matthiensen (2011), the analysis continues with the verification of Cronbach's α values, which indicates the internal consistency of the questionnaires and should have a value of 0.7 as a lower limit, which can be reduced to 0.6 in exploratory research. However, a more recent study by Hensler *et al* . (2019), reveals that this measure tends to severely underestimate the internal consistency of LV in partial least squares (PLS) regression models, and it is more appropriate to use the composite reliability coefficient (ρ_c), which must be above 0.7 to demonstrate that there are no biases in the LV. It is observed that in table 4, all dimensions have this indicator scored above 0.8. Next, the discriminant validity (DV)is analyzed. It verifies if the dimensions are independent (LV), being carried out in two ways (RINGLE *et al* ., 2014):

- Check whether the factor loadings of the observable variable are greater in the dimension to which it was linked when compared to other dimensions (Table 6): SmartPLS removes each observable variable from the respective LV and transfers it to another LV by recalculating the factor loadings.
- Considering that the factor loading calculated in "Interoperability - 1 Contract standard" was higher for another LV than for the one to which it was linked, this variable was also excluded.
- Comparison of AVE square roots of each LV with the correlations between them. The AVE square roots must always be greater than the correlations (see table 6) to determine the discriminant validity, implying that the LV is unique and does not capture characteristics from the others (NASCIMENTO and MACEDO, 2016). The values displayed on the diagonals are the AVE square roots (marked in green).

It is observed that the correlation between Business Model and Interoperability is higher than the values of the square roots of the respective AVE. In this case, Ringle *et al* . (2014) define that variables with the highest correlation values in both LV simultaneously should be removed, re-testing the model for each variable. With the removal of Interoperability – Data Protection, the following indicators are obtained (table 7): The correlation between Business Model and Interoperability is still higher than the values of the square roots of the respective AVE at 1.07%, however, Ringle et. al. (2014) consider that values below 2.5% are admissible, and in this case, it is possible to keep the model as it is. Next, the SmartPLS 3 bootstrapping module allows obtaining the t student tests values of the links between the LV (dimensions), or internal model, and these with the observable variables (external model), on which values of at least 1.96 mean a significance level of 5% (NASCIMENTO and MACEDO, 2016). From Figure 2, it can be seen that the connections of the external model, except the variable "4_Human Resources Training" linked to the "Organization Strategy" in its entirety, have significant values of connection between the observable variables and the LV. This variable was excluded from the model. On the other hand, from the connections of the internal model, only those located between (i) "Organization Strategy" and "Products and Services"; (ii) "Interoperability" and "Supply Chain"; and (iii) "Business Model" and "Interoperability" with t values equivalent to 2.026, 2.026 and 6.819 respectively are significant. This result reveals that the case study company does not have transversality between the characteristics represented by the LV, that is, these are, in the current company format, treated in isolation.



Source: The authors using SmartPLS 3.

Figure 2. SmartPLS 3 Bootstrapping model result.

Finally, according to Ringle *et al* (2014) and Nascimento and Macedo (2016), values of Q^2 (relevance or predictive validity), which indicates the accuracy of the adjusted model, and f^2 (effect size or Cohen's indicator), which determines whether the connections between variables are significant, are obtained. These authors clarify that, according to the literature, Q^2 must be greater than zero, and f^2 with values of 0.02, 0.15, and 0.35 are judged as small, medium, and large, respectively. Tables 8 and 9 depict the values of Q^2 and f^2 respectively. Q^2 above zero reveals that the model meets its purpose and the different values of f^2 below 0.15 identify a characteristic similar to that observed in the analysis of t Student values of the links between LV, that is, the dimensions analyzed, in the current form of the analyzed company, are isolated.

The PIMM 4.0 Model: The model by Azevedo and Santiago (2019) with calculations in Santiago (2019) makes use of SEM to determine the maturity level in industry 4.0, having as a reference the factor loadings of each observable variable on the LV attached to it. As the result of the model within data collected by the questionnaire application, PIMM4.0 output was (Figure 3): Maturity 2.6 indicates that there is a transition between levels 2-Technological (Part of the organization has automation and relative interconnection of processes, however without visibility of the 4.0 model) and 3-Transition (There is high integration between systems that allow the overview of the business, as well as the organization, has automation initiatives for capacity gain, transparency and predictive intelligence). Table 10 presents the variables listed as of low significance by SEM, which are repeated on the right side and marked in black those chosen by PIMM4.0 as being subject to possible improvement. Such a result is expected, since the SEM is more embracing than the PIMM4.0 model, and the fact that it selected fewer variables than that of low significance for the system cannot be considered an abnormality. SEM was performed as an iteration procedure by which the variables "3 Preparation for Ind.4.0", "5 Self-optimization", "3 Industry 4.0 Investment", "5 Lead Times" and "1 Service orientation" were excluded. Although the methodology considers AVE ≥ 0.5 as an acceptance parameter, all these variables were rejected with a factorial load above 0.5. It is important to mention that PIMM4.0 is interactive, which means that, being a registered software, throughout the roadmap for improving the company towards industry 4.0, new variables will be selected as important to be considered for improvement.

Table 1. Variables equivalences verification

Azevedo e Santiago (2019)	Schumacher *et al* . (2019)	Schuh *et al* . (2020)	Analysis
M2M	- Technology for information exchange - Integrated computers in machines; - Integrated computers in tools - Information exchange between machines;	- Efficient communication - Deliver contextualized information	Machines and tools are provided with sensors and actuators that generate data collected by integrated computers that perform pre-processing and deliver contextualized data for decision making

Source: The authors.

Table 2. Construct Reliability and Validity

Dimension (LV)	Cronbach's Alpha	Rho_A	Composite Reliability	AVE
Supply Chain	0,687	0,733	0,797	0,446
Organization Strategy	0,799	0,806	0,854	0,462
Interoperability	0,772	0,803	0,844	0,527
Manufacturing and Operations	0,716	0,743	0,785	0,292
Business Model	0,703	0,765	0,800	0,410
Products and Services	0,746	0,688	0,827	0,495

Source: The authors using Smart PLS 3.

Table 3. Excluded variables (in black)- SEM Methodology

Dimension (LV)	Observed Variable	Factorial load
1 Products and Services	1 Customization (R3)	
	2 Digital Values	0,726
	3 Service orientation	0,908
	4 Data analysis and treatment	0,806
	5 Revenues sources	0,864
2 Manufacturing and operations	1 Automation and Control (R3)	
	2 M2M	0,711
	3 Preparation for Ind.4.0 (R5)	
	4 Autonomous Transportation (R2)	
	5 Self-optimization	
	6 Digital model (R4)	
	7 Factory data collection	0,807
	8 Manufacturing data use	0,658
	9 Cloud solutions	0,816
	10 IT Security	0,881
3 Organization Strategy	1 Industry 4.0 roadmap	0,808
	2 Industry 4.0 KPI	0,835
	3 Industry 4.0 Investment (R2)	
	4 Human resources training	0,585
	5 Departmental collaboration (R4)	
	6 Leadership	0,766
	7 ROI	0,727
4 Supply chain	1 Real-time stock	0,648
	2 Integration SCM	0,82
	3 Visibility SCM	0,763
	4 Agility SCM	0,603
	5 Lead Times (R2)	
5 Business model	1 Service orientation (R3)	
	2 Data-based decision (R2)	
	3 PLM	0,766
	4 Predictive maintenance	0,662
	5 Mkt channel	0,642
	6 IT support to the business	0,844
6 Interoperability	1 Contract standard	0,669
	2 Production line feed	0,739
	3 Data protection	0,843
	4 Systems ERP, EDI, WMS, VMI	0,538
	5 SCM data share	0,81

Source: The authors, based on Ringle *et al* . (2014).

Table 4. Construct Reliability and Validity after variables exclusion

Dimension (LV)	**Cronbach's Alpha**	**Rho_A**	**Composite Reliability**	**AVE**
Supply Chain	0,688	0,719	0,804	0,510
Organization Strategy	0,802	0,789	0,863	0,561
Interoperability	0,772	0,791	0,846	0,630
Manufacturing and Operations	0,842	0,959	0,884	0,606
Business Model	0,710	0,728	0,821	0,538
Products and Services	0,853	0,981	0,897	0,687

Source: The authors using SmartPLS 3.

Table 5. Crossloading test

Variáveis	Supply chain	Organization Strategy	Interoperability	Manufacturing and operations	Business model	Products and Services
1 Customization (R3)						
2 Digital Values	0,224	0,181	0,142	0,140	0,196	0,726
3 Service orientation	0,336	0,525	0,032	0,023	-0,036	0,908
4 Data analysis and treatment	0,146	0,287	0,059	0,220	0,027	0,806
5 Revenues sources	0,088	0,233	-0,086	0,016	-0,155	0,864
1 Automation and Control (R3)						
2 M2M	0,058	-0,002	0,213	0,711	0,357	0,027
3 Preparation for Ind.4.0 (R5) 4 Autonomous Transportation (R2) 5 Self-optimization 6 Digital model (R4)						
7 Factory data collection	0,289	-0,019	0,285	0,807	0,444	0,193
8 Manufacturing data use	0,089	0,051	0,126	0,658	0,402	0,196
9 Cloud solutions	0,025	0,078	0,292	0,816	0,430	0,076
10 IT Security	0,475	0,260	0,625	0,881	0,620	0,013
1 Industry 4.0 roadmap	0,252	0,808	0,025	0,081	0,100	0,388
2 Industry 4.0 KPI	0,314	0,835	0,112	0,056	0,152	0,461
3 Industry 4.0 Investment (R2)						
4 Human resources training	0,475	0,585	0,430	0,436	0,310	0,216
5 Departmental collaboration (R4)						
6 Leadership	0,455	0,766	0,328	0,055	0,371	0,095
7 ROI	0,441	0,727	0,233	-0,209	0,314	0,434
1 Real-time stock	0,648	0,183	0,505	0,34	0,508	-0,020
2 Integration SCM	0,820	0,533	0,588	0,076	0,462	0,171
3 Visibility SCM	0,763	0,485	0,670	0,383	0,630	0,294
4 Agility SCM	0,603	0,319	0,295	-0,021	0,236	0,356
5 Lead Times (R2) 1 Service orientation (R3) 2 Data-based decision (R2)						
3 PLM	0,561	0,412	0,672	0,362	0,766	0,294
4 Predictive maintenance	0,279	0,027	0,421	0,451	0,662	-0,282
5 Mkt channel	0,568	0,387	0,542	0,402	0,642	-0,053
6 IT support to the business	0,518	0,178	0,745	0,567	0,844	-0,038
1 Contract standard	0,697	0,673	0,669	0,177	0,514	0,123
2 Production line feed	0,487	0,01	0,739	0,608	0,666	-0,129
3 Data protection	0,535	0,312	0,843	0,256	0,779	0,085
4 Systems ERP, EDI, WMS, VMI	0,350	-0,072	0,538	0,286	0,462	-0,171
5 SCM data share	0,628	0,201	0,810	0,370	0,585	0,194

Source: The authors, based on Ringle et al. (2014).

Table 6. LV correlations and AVE square roots

Dimension (LV)	AVE	Supply chain	Organization Strategy	Interoperability	Manufacturing and operations	Business model	Products and Services
Supply chain	0,510	0,714					
Organization Strategy	0,563	0,547	0,750				
Interoperability	0,597	0,657	0,161	0,773			
Manufacturing and operations	0,608	0,304	0,122	0,494	0,780		
Business model	0,539	0,674	0,354	0,819	0,604	0,734	
Products and Services	0,687	0,274	0,427	0,009	0,110	0,005	0,829

Source: The authors, based on Ringle et al. (2014).

Table 7. LV correlations and AVE square roots after adjustment

Dimension (LV)	AVE	Supply chain	Organization Strategy	Interoperability	Manufacturing and operations	Business model	Products and Services
Supply chain	0,512	0,716					
Organization Strategy	0,565	0,540	0,752				
Interoperability	0,616	0,635	0,058	0,785			
Manufacturing and operations	0,608	0,300	0,119	0,556	0,780		
Business model	0,539	0,671	0,347	0,742	0,605	0,734	
Products and Services	0,687	0,272	0,430	-0,036	0,107	-0,006	0,829

Source: The authors, based on Ringle et al. (2014).

Table 8. Predictive Validity (Q^2)

	Supply Chain	Organization Strategy	Interoperability	Manufacturing and Operations	Business Model	Products and Services
Q^2	0,18	0,335	0,241	0,388	0,272	0,456

Source: The authors using SmartPLS 3.

Table 9. Cohen Indicator (f^2)

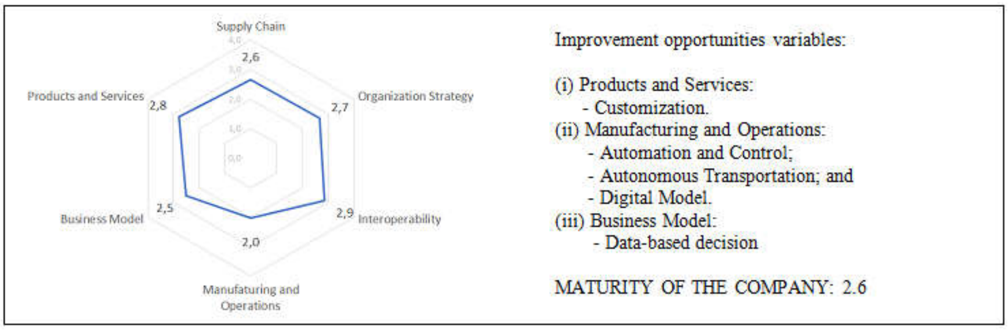
LV Link	f^2
Organization Strategy - Supply Chain	0,275
Organization Strategy - Interoperability	0,125
Organization Strategy - Manufacturing and Operations	0,024
Organization Strategy - Products and Services	0,270
Interoperability - Supply Chain	0,376
Interoperability - Manufacturing and Operations	0,024
Manufacturing and Operations - Supply Chain	0,105
Business Model - Supply Chain	0,083
Business Model - Organization Strategy	0,137
Business Model - Interoperability	1,486
Business Model - Manufacturing and Operations	0,160
Business Model - Products and Services	0,035
Products and Services - Supply Chain	0,064
Products and Services - Interoperability	0,014
Products and Services - Manufacturing and Operations	0,044

Source: The authors using Smart PLS 3.

Table 10. SEM excluded variables and PIMM4.0 improvement variables

SEM		PIMM 4.0	
Dimension (LV)	**Observable Variable**	**Dimension (LV)**	**Observable Variable**
1 Products and Services	1 Customization	1 Products and Services	1 Customization
2 Manufacturing and Operations	1 Automation and Control	2 Manufacturing and Operations	1 Automation and Control
	3 Preparation for Ind.4.0		3 Preparation for Ind.4.0
	4 Autonomous Transportation		4 Autonomous Transportation
	5 Self-optimization		5 Self-optimization
	6 Digital model		6 Digital model
3 Organization Strategy	3 Industry 4.0 Investment	3 Organization Strategy	3 Industry 4.0 Investment
	4 Human resources training		4 Human resources training
	5 Departmental collaboration		5 Departmental collaboration
4 Supply Chain	5 Lead Times	4 Supply Chain	5 Lead Times
5 Business Model	1 Service orientation	5 Business Model	1 Service orientation
	2 Data-based decision		2 Data-based decision
6 Interoperability	1 Contract standard	6 Interoperability	1 Contract standard
	3 Data protection		3 Data protection

Source: The authors.



Source: PIMM4.0

Figure 3. PIMM4.0 outputs (case study data)

Nevertheless, departmental collaboration is not directly linked to the connections among the LV in the studied model, the result obtained on Smart PLS 3 bootstrapping module would present better results on t student values if there were no isolation among LV. The variable "5 Departmental collaboration", according to this analysis should be selected as a concern, however, the conclusion is a result of the context interpretation which is difficult to get direct from a machine without human help. Variable "4 Human resources training" was excluded from the model because it had a t student value of 1.865, as shown in Figure 2, whose target parameter is at least 1.96 for a 5% The Discriminant Validity test, through which "1 Contract standard" and "3 Data protection" were eliminated, does not deal directly with the significance of the variable to the model, but with the greater correlation of the variable to the other LV. In this sense, it cannot be interpreted that the exclusion establishes a need to implement improvement.

CONCLUSION

Through the literary review of Itikawa and Santiago (2021), this work identified two scientifically relevant models elaborated by

Schumacher *et al* (2019) and Schuh *et al*. 2020. Bearing in mind that it was not the purpose to develop a new maturity measurement model in industry 4.0, one whose authors are local and which is easy to apply and interpret was chosen. The PIMM4.0, a model designed by Azevedo and Santiago (2019), before being applied as a case study, was evaluated from the perspectives of the models by Schumacher *et al*. (2019) and Schuh *et al* (2020) resulting in practically integral alignment at the level of observable variables. For the case study, a company located in the MFTZ was chosen and that is a beneficiary of the Informatics Law, given the legal obligation to apply annually in RD&I, noting that RD&I corresponds to the basic requirement for the development of the industry towards digital transformation (DAEMMRICH, 2019). Through the application of SEM, this work delved into the evaluation of PIMM4.0, seeking to demonstrate mathematically through the methodology presented by Ringle *et al* . (2019) by the use of the software Smart PLS 3 that there is statistical validity in the outputs of the model under study. The differences between the result obtained following the methodology of Ringle *et al* . (2019) and the outputs of PIMM 4.0 were individually analyzed, and cannot be considered as invalidating the model, which was previously identified as aligned with those pointed out by It ikawa and Santiago (2022) as the state of the art in the subject at hand. Finally, it is worth noting that the result obtained as the company's maturity under the metrics of industry 4.0 can only be evaluated from a strategic perspective, that is, the company must establish the objective of its business and understand the needs for its transformation. Being a beneficiary of the Informatics Law, it is expected that there will be both intention and resources to achieve the objective, since the initial step has already been taken, which is to know its level of maturity.

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