Evaluation of the Level of Digital Transformation in MSMEs using Fuzzy Cognitive Maps based on Experts

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Abstract— the concept of digital transformation involves exploiting digital technologies to generate new ways of doing things in organizations, including the creation of new processes, models, and services that produce value based on the digitization of data and processes. The application of digital technologies enables organizations to develop capabilities for innovation, automation, etc., utilizing both established and emerging technologies, including the widespread use of artificial intelligence. In this paper is proposed the implementation of a fuzzy cognitive map based on experts for the evaluation of the level of digital transformation in MSMEs (Micro, Small & Medium Enterprises). The main variables of digital transformation used to define our fuzzy cognitive map were classified into five types: i) Organization and Culture variables related to strategies, way of working, and ecosystems, ii) Customer variables related to services and digital channels and products, iii) Operations and Internal Processes variables related to supply chain, suppliers, business model, iv) Information Technologies variables related to innovation, digitization, data and analytic. Finally, the fifth type of variable is the target, which indicates the level of digital transformation of the organization. Our model achieved an accuracy of 99.4% to determine the digital transformation level of an organization. Thus, our fuzzy cognitive map can predict and analyze the factors associated with digital transformation in MSMEs.

Keywords: Digital Transformation, Maturity models, Fuzzy cognitive maps, Artificial Intelligence

I. INTRODUCTION

Digital transformation is the process of integrating digital technologies in the business model, processes, and culture in an organization to improve its strategies, and performance, among other things [1]. Digital transformation is a long-term endeavor that entails determining how technology is employed within an organization to affect its behavior. Thus, digital transformation involves envisioning how digital technologies can improve service levels, reduce costs, and optimize inventory management, among other things, through the implementation of organizational changes using these technologies to achieve operational excellence.

Advanced technologies, such as artificial intelligence, data analytics, and the Internet of Things, are integrated into the digital transformation process to enable organizations to collect and analyze real-time data, automate processes, and improve the supply chain.

On the other hand, fuzzy cognitive maps (FCMs) are graph-based structures that support causal reasoning and enable the propagation of causality in both forward and backward directions [2]. They are particularly useful in domains where the concepts and relationships between them are inherently fuzzy, such as politics, military affairs, and historical events. They have been used in different areas where the modeling of the problem is very complex, such as health [3], analysis of social networks [4], or emerging processes [5], [21], among others.

A. *Related Works*

At the level of FCM in classification and prediction tasks, the approach described in [3] combines different indicators used in the standard diagnosis of dengue, such as clinical symptoms, laboratory tests, and physical findings to determine the severity of dengue. Also, to study the vulnerability factors to climate variability in Andean rural micro-watersheds, an FCM was employed in [4]. Another work based on an FCM, and a fuzzy linguistic methodology, called VIKOR, determines the vendor selection in the Industry 4.0 era [5].

The investigation carried out in [6] analyzes the effect of digital transformation on the performance of MSMEs in terms of competitive advantage. The study revealed that competitive advantage acted as a mediator in the association between digital transformation and the performance of MSMEs, and all proposed hypotheses were confirmed. In [7], the goal is to develop a holistic maturity model for digital transformation using a theory-based approach, known as DX-CMM. This model aims to help organizations assess their current level of capability and maturity in digital transformation, identify gaps, and create a standardized roadmap for enhancing their digital transformation efforts.

According to [6], technological advancements and digital information are expected to be utilized by traditional entrepreneurs. However, this study concluded that all proposed hypotheses were acceptable, and that competitive advantage partially mediated the relationship between digital transformation and MSMEs' performance. In [8], the authors propose a staged digital transformation capability maturity model framework that enables organizations to assess their present digital capability and establish a plan of improvements to move to a higher level. In [7] conducted a systematic literature review and found that none of the 18 existing maturity models in the field of digital transformation met all the criteria of appropriateness, completeness, clarity, and objectivity.

According to the literature review, there is no digital transformation approach that enables firms to evaluate their existing digital competencies and create a roadmap for improvement to reach a higher level. Thus, there is a lack of research and artifacts available for maturity models related to digital transformation.

B. Contributions

The main goal of this research is to utilize FCMs to evaluate the digital transformation levels in MSMEs. The FCM is responsible for analyzing the factors associated with digital transformation data and providing a diagnosis. The causal relationships between the digital transformation concepts are optimized to match the experts' opinions.

The study is based on five groups of concepts issued by the Governance and Management Objectives in COBIT [7]. The concepts are classified into five types and reflect the behavior of the company at all levels such as: i) Organization and Culture, ii) Customer, iii) Operations and Internal Processes, iv) Information Technology, and v) Objective, which indicates the digital transformation level of the organization. The main contributions of this paper are:

- Develop an FCM to determine the level of digital transformation in MSMEs.
- Analyze the behavior of factors associated with digital transformation in MSMEs.
- Carry out an explainability analysis for MSMEs about their current situation in digital transformation.

This paper is organized as follows: Section 2 discusses the theoretical framework employed, Section 3 defines our FCM for the evaluation of the digital transformation levels in MSMEs, Section 4 details the computational experiments conducted, Section 5 compares this research with previous studies, and Section 6 presents the conclusions and future works.

II. Theoretical background

This section presents a background of Digital Transformation in MSMEs. In addition, it provides the basic concepts of FCMs.

A. Digital Transformation

The application of digital technologies to generate significant changes in an organization with the goal of improving its operations is what defines digital transformation. [9]. Digital transformation is based on the adoption of digital technologies in an organization to transform its business processes. The interpretation of "digital technology" in the context of digital transformation differs across the literature. Some authors encompass new Information Technologies solutions [10], and others emphasize in cutting-edge technologies like big data, cloud computing, artificial intelligence, blockchain, and the Internet of Things [11]. Also, some authors include social media analytics, and embedded devices [12].

As described in [13], there are two possible strategies for companies to undertake digital transformation. The first is an offensive approach that involves investments in digital transformation portfolios, while the second is a defensive approach that focuses on cultivating new capabilities within the organization.

The COBIT model classifies the concepts into five types:

a) Organization and Culture: variables related to the culture and management of the organization. The concepts of this variable used in this work are:
   - *Strategy*, it refers to having an action plan for digital transformation and an understanding of the competitive environment,
   - *Culture and management* refers to good practices at work, in the management of organizational processes and in the development of leadership, promoting human talent in its different areas and levels, creating an agile and innovative culture,
   - *Way of working* refers to the type of face-to-face work and/or teleworking, and the practices and procedures implicit in them,
   - *Leadership* refers to the managerial activities that organizational leaders have to influence the work team, and
   - *Ecosystems* refers to the environment, not only internal, but also close external to the organization, which impacts the digital transformation process, to analyze its economic/social/cultural effect.

b) Customer: variables related to services (digital or not). The concepts of this variable used in this work are:
   - *Digital channels* are the distribution channels of the different organizational strategic messages sent to interested parties.
   - *Products*, services, and/or products offered by the organization as a result of its job or operation., and
   - *Digital services* refer to the use of digital tools to improve the customer experience, based on a deep understanding of the customer and its needs

c) Operations and Internal Processes: variables related to the organizational flow. The concepts of this variable used in this work are:
   - *Supply chain* are the supply chains of goods and services that an organization requires for its operation,
   - *Suppliers* refer to having providers of technological solutions, in addition to having advisors who

accompany the digital transformation process of the organization, and

- ○ *Business model* refers to the organizational capacity to explore new businesses based on technology, the development of new products that allow new markets to be captured, among other things.

d) Information Technology: variables related to the organization technology. The concepts of this variable used in this work are:

- ○ *Innovation* refers to the business strategy of organizational transformation and human resource management based on reengineering, optimization and process improvement,
- ○ *Digitization* is the process of transforming analog or intangible processes and physical or tangible elements into digital ones,
- ○ *Data and analytics* refer to the level of access to data that an organization has, the potential to monetize it by learning about its different uses, among other things, and
- ○ Utilization of *technological solutions* involves implementing methods, systems, or tools that aid in the execution of organizational tasks with greater efficiency, as well as automating certain processes.

B. Fundamentals of FCMs

In 1986, Kosko developed FCMs [14] from the cognitive maps of Axelrod's work in 1976 [25]. FCMs are a popular way of modeling complex systems because of their straightforward construction and interpretation. They consist of a network of concepts and their interrelationships [14], [15], [18].

1. **Basic definitions of an FCM**

In Figure 1, an FCM is shown, which consists of eight concepts (C1 to C8). Each concept denotes a specific system variable of the system to study. The impact of one concept on another is displayed by the weight in the directed edges among them [16]. Different strategies can be employed to establish these relationships within FCMs. In [18], [22] Aguilar et al. describe three ways to define the relationships in FCMs: using fuzzy rules, generic logical rules that describe the causal relationships, or mathematical models to describe the system under evaluation.

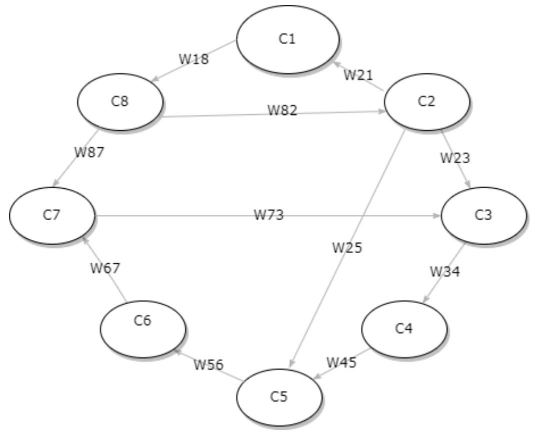

Figure 1. Example of an FCM.

The weight assignment in FCMs can be carried out using different methods, including those involving expert opinion or learning processes [18], [22]. The weights assigned represent the influence of one concept on another, with values ranging from -1 to +1 or 0 to 1, indicating either activating or inhibiting impacts [2]. Thus, different levels of causality are represented. An example of degrees of causality using linguistic terms can be found in Table 1. For example, if the value of the antecedent concept Ci is significantly low, and the value of the consequent concept Cj is substantially high, then the causal link between the two concepts can be categorized as negatively high. Mathematically, an FCM is represented as a tuple of four elements:

$$\Phi = \langle n, f(\cdot), r, W \rangle. \qquad (1)$$

where $n \in \mathbb{R}^m$ is the set of concepts $(n_1, ..., n_m)$, $f(\cdot)$ is the activation function that holds concept values in a determined range r, and $W \in \mathbb{R}^{m \times m}$ is the adjacency matrix employed to capture the connections among the concepts.

Table 1. Example of generic logic rules used to classify the causal relationships based on the values of concepts.

Linguistic term	Numerical value	Generic logic rule	
		Antecedent C_i	Consequent C_i
Positive complete	1	Very high	Very high
Positive high	0.75	High	High
Positive moderate	0.5	Medium	Medium
Positive low	0.25	Low	Low
Null	0	NA	NA

There are various activation functions that can be used to model the activation of each concept in an FCM (see Table 2). The selection of a specific activation function depends on the specific problem being addressed. For example, if the goal is to model disease symptoms, the sigmoid function may be more appropriate than the hyperbolic tangent function since the values of the concepts being modeled will typically range from 0 (absence of the symptom) to 1 (presence of the symptom), making negative values unnecessary [18], [19].

Table 2. Activation functions used in FCMs.

Activation function	Equation	Range
Bivalent	$f(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$	$f(x) \in \{0, 1\}$
Trivalent	$f(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases}$	$f(x) \in \{-1, 0, 1\}$
Sigmoid	$f(x) = \frac{1}{1+e^{-\lambda x}}$	$f(x) \in [0, 1]$
Hyperbolic tangent	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	$f(x) \in [-1, 1]$

W is used to store the relationships between the concepts in an FCM. For example, see the adjacency matrix for the FCM of Fig 1 in Fig. 2.

$$\mathbf{W} = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \\ C_8 \end{array} \begin{array}{c} \begin{matrix} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 \end{matrix} \\ \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{18} \\ w_{21} & 0 & w_{23} & 0 & w_{25} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{34} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{54} & 0 & w_{56} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{67} & 0 \\ 0 & 0 & w_{73} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{82} & 0 & 0 & 0 & 0 & w_{87} & 0 \end{pmatrix} \end{array}$$

Figure 2. Example of Adjacency Matrix.

2. Reasoning in FCMs

To mathematically define the inference process in an FCM, three key components are required: the weight matrix W, the activation function, and the current state vector of the FCM $a \in \mathbb{R}^m$, which indicates the current degree of activation of each concept. The activation degree of a concept determines if the concept is activated or stimulated in a particular iteration. Thus, in the case of the range [0, 1], a concept is "activated" when its value is 0 in one iteration (t) but becomes greater than 0 in the next iteration (t + 1).

To infer the output in an FCM, it is necessary a process that involves calculating the state vector through successive iterations of multiplying it with the weights matrix until the system reaches a steady state, as is defined by Equation 2 [14]:

$$a_j(t+1) = f\left(\sum_{i=1, i \neg j}^{m} W_{ij} a_i(t)\right) \qquad (2)$$

where $a_j(t + 1)$ is the value of concept C_j at iteration t + 1, m is the number of concepts, W_{ij} is the value for the relationship from concept C_i to concept C_j, and $a_j(t)$ is the value of concept C_j at iteration t. The point of equilibrium (steady state) is reached when $a_j(t) = a_j(t-1)$ or $a_j(t) - a_j(t-1) \leq 0.001\ \forall j$. Thus, the system is considered to have reached a steady state when the difference between the state vectors in consecutive iterations is less than or equal to 0.001.

This is the base of the reasoning mechanism of an FCM. FCMs are a crucial tool in simulation scenarios because they enable experts to analyze the system's performance from various starting points. An initial condition is defined by the set of concepts in the iteration (0) and is denoted as:

$$a(0) = \left[a_1(0), a_2(0), \ldots, a_m(0)\right] \qquad (3)$$

where $a_1(0)$ is the value of concept C_1 at iteration = 0.

III. Our FCM to Evaluate the Level of Digital Transformation in Companies.

This section details the process to construct our evaluation model about the level of digital transformation in organizations utilizing FCMs. Our FCM is based on experts in the field to assign the relationships. Thus, the construction of the FCM is based on a methodology that consists of six steps [20], [23], as depicted in Figure 3

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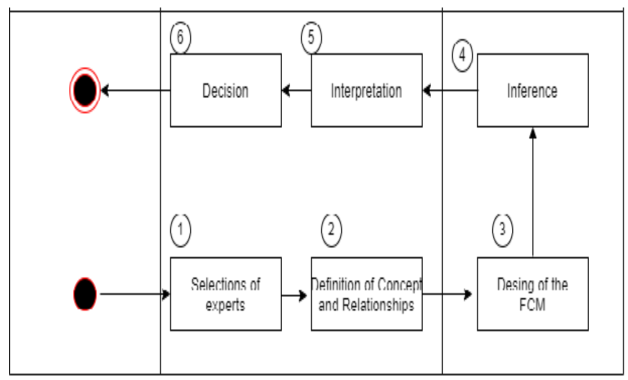

Figure 3. Methodology to build the FCM.

The rest of this section briefly describes these steps applied to our FCM.

A. Selection of experts

This study involved the participation of five experts with considerable expertise in the area of digital transformation.

B. Concepts and relationships

The initial phase of this process is carried out by experts in digital transformation. Based on the established concepts of the COBIT model (see Table 3), the experts constructed W with values ranging from 0 to 1 to indicate the relationships between the concepts. Table 3 shows an additional concept to those used in the COBIT model, which is the concept of the digital transformation level. This concept is the concept that is inferred using the FCM.

Using Table 1 as a guide, the experts selected the linguistic term that best represented the relationship between each concept, and then assigned numerical values to these terms to create the weight matrix. Table 1 allowed establishing the relationships of the concepts between each category and between categories. For example, digital services of the customer category were related to strategies and ecosystems of the organization, and culture category with product of the customer category, business model of the operations and internal processes category, among others.

Table 3. FCM Concepts for Digital Transformation.

Node	Name Concept
C1	Strategy
C2	Culture and Management
C3	Way of working
C4	Leadership
C5	Ecosystems
C6	Digital Services
C7	Products
C8	Digital Channels
C9	Suppliers and Supply Chain
C10	Business Model
C11	Processes
C12	Innovation
C13	Digitalization
C14	Technological Solutions
C15	Data and Analytics
End Node	**Digital Transformation**

C. FCM design

In our approach, the FCMs is developed by the experts, so their knowledge should be mixed into a single overall map to define the FCM. The process for producing a consolidated global map is described by the equation below [21], [22]:

$$E_{ij}^{G} = \sum_{e=1}^{NE} \frac{E_{ij}^{e}}{NE} \qquad (4)$$

This equation calculates the overall weight for the FCM, represented by E^G_{ij}. The opinion of expert e regarding the causal link between concepts C_i and C_j is represented by E^e_{ij} and NE indicates the total number of experts who participated. Finally, the overall FCMs are constructed. In our case, we have used the FCM Expert package (version 1.0.0) [2] but in the literature, there are others like [22], [24]. Figure 4 shows the final FCMs. The construction of the FCMs with the experts has an implicit bias due to their subjectivity in assigning causal relationships [16], [18], [22]. Addressing bias in FCMs is beyond the scope of our study, but it will be considered in future work.

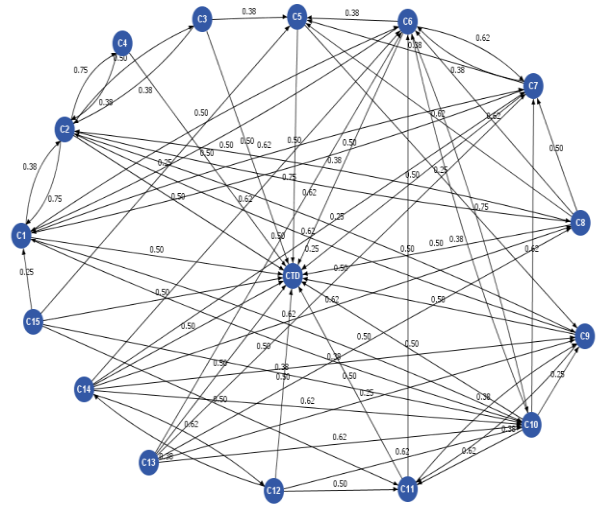

Figure 4. General FCM for evaluating the level of digital transformation in companies.

D. Inference

The fourth step involves the utilization of the FCM defined in the study to analyze different scenarios (for example, in our case, the level of digital transformation of different organizations) [18], [21]. In this step, the inference process is carried out for each case study, following the reasoning process outlined in section III-B-2. The experiment design and the results of this stage are shown in section 4.

E. Interpretation

The interpretation of FCM inference results for each case study is carried out in this step and is detailed in section 4.

F. Decision

The last stage is the decision that the user of our FCM makes to improve the digital transformation process in the organization. Since FCM is a method that provides an analysis of explainability based on causal relationships between concepts, this information can be used in the decision-making process to identify what to do.

IV. EXPERIMENTS

In this section, we explore the diagnostic capability of our FCM in different scenarios. We utilize the FCM to categorize digital transformation levels in several organizations. Particularly, we used two organizations as case studies. Specifically, the COBIT concepts in Table 3 are defined after an exhaustive evaluation of the respective concepts in each organization, so that from them, the FCM infers the concept of the level of digital transformation in that organization.

Case 1. For the company Chamber of Commerce.

The Chamber of Commerce is an organization formed by entrepreneurs, and owners of small, medium, or large companies. In order to support business efficiency, the Chambers of Commerce are expanding their portfolio to virtual services, which will allow their users greater agility in their procedures.

Table 4 shows the input values for concepts in a range of (0.0, 0.25, 0.50, 0.75, 1.0), where 0 is the absence of this concept and 1 is the maximum presence of this concept in the organization. Thus, in this organization, after an evaluation of the current state of each concept linked to the COBIT model of digital transformation, the following values were determined by the organizational experts: the concept of Strategy (C1) with a value of 0.7, Culture and Management (C2) of 0.7, Way of Working (C3) of 0.5, Leadership (C4) of 0.3, Ecosystems (C5) of 0.5, Digital Services (C6) of 0.7, Products (C7) of 0.6, Digital Channels (C8) of 0. 8, Suppliers and Supply Chain (C9) of 0.4, Business Model (C10) of 0.6, Processes (C11) of 0.4, Innovation (C12) of 0.8, Digitalization (C13) of 0.8, Technology Solutions (C14) of 0.9, and Data and Analytics (C15) of 0.4.

Table 4. Input values for case study 1.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
0.7	0.7	0.5	0.3	0.3	0.7	0.6	0.8	0.4	0.6	0.4	0.8	0.8	0.9	0.4

Table 5 shows the results of the inference process. Particularly, the initial vector of concepts (Table 4) is passed to the inference rule (Eq. 2) and the final vector can be seen in Table 5, where each iteration is the dynamic evolution of the concepts. In the final vector, the digital transformation concept (CTD) reached a value of 0.9954. Based on this result, we can see that the variables related to digitization (0.638) and data and analytics (0.659) are the ones that most need to be strengthened in this organization.

On the other hand, the causal relationships that affect the digitization variable are those of the customer and operation groups, while the variables that affect the data and analysis variable are those of the organization and culture and operation groups. It is necessary to determine which variables of these groups to improve in order to have a positive impact on these two variables. Now, these two variables, despite not having such high values, do not impact the perceived level of digital transformation in the organization, which means that the rest of the variables with values greater than 0.7 allow inferring in the organization a high level of digital transformation.

Table 5. Output vector for case study 1.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	CTD
0,936	0,8878	0,7417	0,7754	0,889	0,9532	0,9539	0,8336	0,9502	0,9502	0,8832	0,741	0,638	0,7129	0,659	0,9954

Case 2. Galavis Coffee Company.

It is a north Santander Company, founded in 1918, dedicated to the roasting and distribution of Colombian Coffee.

Table 6 shows the input values of the COBIT concepts for this company, after an evaluation of their current states by organizational experts. The concept of Strategy (C1) has a value of 0.5, Culture and Management (C2) of 0.4, Way of Working (C3) of 0.3, and so for the rest.

Table 6. Input table for case study 2.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
0,5	0,4	0,3	0,5	0.3	0,4	0,4	0,4	0,3	0,4	0,5	0,3	0,3	0,3	0,3

Table 7 shows the results of the inference process. The final vector of this organization can be seen in Table 7. In the final vector, the CTD decision concept reached a value of 0.9878. Also, in Table 7 we can see that variables related to innovation and technological solutions are the ones that most need to be enhanced in this organization.

As before, an explicability analysis could be done to determine for those two variables, which are the ones that affect them, and based on that, how to influence to improve them. But again, these two variables do not affect by themselves the high level of transformation inferred, since the rest of the variables have a value greater than 0.7, which contributes to that value of digital transformation

Table 7. Output vector for case study 2

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	CTD
0,963	0,8877	0,7417	0,7754	0,8891	0,9531	0,9539	0,8335	0,8718	0,9501	0,8831	0,657	0,741	0,652	0,7125	0,9878

Case 3. A Company with high technology.

In this case, we are going to suppose a company where all the Information Technology concepts have a value of 1 and the rest in 0. The results can see in Table 8.

Table 8. Output vector for case study 3

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	CTD
0,9723	0,9358	0,7761	0,8208	0,9358	0,9822	0,9829	0,8833	0,9185	0,9807	0,931	0,9148	0,9278	0,8964	0,937	0,975

In the final vector, the CTD variable (decision concept) reached a value of 0.975. Based on this result, we can determine that the variables of the information technology group have a high impact to achieve a high level of digital transformation. But also, we can see that the variable related to the way of working is the only that needs to be enhanced in this case

Case 4. A Company without technology.

In this case, we are going to suppose a company where all the Information Technology concepts have a value of 0 and the rest in 1. The results can see in Table 9.

Table 9. Output vector for case study 4.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	CTD
0.9723	0.9359	0.7763	0.821	0.9359	0.9822	0.9828	0.8832	0.9184	0.9807	0.9312	0,692	0.7745	0,689	0.7362	0.9271

In the final vector, the CTD variable (decision concept) reached a value of 0.9271. Based on this result, we can determine that the rest of the variables alone can contribute to a high digital transformation process. Also, the variables related to innovation and technological solutions (which belong to the group of information technology variables) are the ones that need to be promoted in this case..

V. Comparison with other works in digital transformation

To compare this study with other works, a set of four criteria were established, which are outlined below:

Cri1: It uses non-intrusive schemes for diagnosis.

Cri2: It uses machine learning in the diagnostic model.

Cri3: It explains the reason for the level of deduced digital transformation.

Table 8 presents a comparison of this study with previous works based on these criteria that are deemed pertinent in the context of agroindustrial MSMEs and their digital transformation. These criteria are significant as they pertain to the application of automated technologies in agroindustry and the utilization of machine learning to enhance the agroindustrial production process. By using machine learning in the diagnostic model, it allows identifying patterns among the data to make predictions. By explaining the reason for the level of digital transformation inferred, it will allow organizations to assess their current digital capability and establish an improvement plan to move to a higher level.

Table 8. Comparison with other works.

	Cri1	Cri2	Cri3
[3]	√	√	X
[4]	X	X	X
[5]	X	X	X
[6]	X	X	√
[7]	X	X	√
[8]	X	X	√
[9]	X	X	√
This work	√	√	√

The first criterion is met by the studies [3] and ours since both use computerized methods and models for diagnosis. The second criterion is met by [3] and our study, which uses machine learning for different purposes, such as information processing for dengue diagnosis [3]. The third criterion is met by studies [6], [7], [8], [9]. They explain the relationship between digital transformation and MSME performance, conduct digital transformation maturity assessments, and design a comprehensive understanding of digital transformation and its impact. and our study since it focuses on the digital transformation of agro-industrial MSMEs.

Our study meets all the requirements of a *diagnostic model* to analyze the digital transformation in an organization, in our case, based on FCMs. Our model is *not intrusive* because it uses organizational expertise to assess the current status of certain variables in the organization, and from there, it uses a computerized tool to make the diagnosis. It uses the FCM theory as the *machine learning technique*, which is an explanatory technique because an FCM allows *explaining the conclusions* that are reached through the causal relationships that exist between the concepts/variables, the basis of its inference process.

VI. Conclusión

The purpose of this study was to develop a FCM to determine the level of digital transformation in MSMEs. A computational tool is proposed to analyze the variables, which are divided into five specific types: i) Organization and Culture, ii) Customer, iii) Operations and Internal Processes, iv) Information Technologies, and v) Objective, which indicates the level of transformation digital in an organization according to the values in the previous variables in this organization.

The FCM allowed analyzing the behavior of factors associated with digital transformation in MSMEs. Our approach is an explicable and interpretive technique that permits the explanation of results based on the diverse concepts in the digital transformation of the COBIT model.

This approach is very useful because it allows detecting the concepts that need to be strengthened or improved in an organization to strengthen its digital transformation process to be more competitive. The developed model is easily customizable and flexible, making it simple to integrate additional concepts and relationships. For its use, only an initial vector of the current state of the variables related to the digital transformation and the weight matrix are required.

In the case studies of agroindustrial MSMEs, our FCM-based tool allowed determining the variables related to digital transformation to improve. It was found that the variables associated with digitization, data and analysis, innovation and technological solutions, were those that should be improved.

In turn, our model allowed determining for the MSMEs of the agro-industrial sector analyzed, the variables that should have a high value at the end because they influence the most to have a high level of digital transformation in companies. According to the results obtained, they are the variables of Strategy (C1), Digital Services (C6), Products (C7) and Business Model (C10). If these variables have a high value, they guarantee to reach a high level of digital transformation in said organizations.

The FCM developed in this study has limitations. Firstly, it did not consider the Digital Maturity Model, which identifies the level of digitization of processes, installed capabilities, and weaknesses in MSMEs. Secondly, FCM models based on human knowledge may result in a biased evaluation of the accuracy of these models. Particularly, both the FCM topology and the weights were defined by the experts.

Future research should focus on minimizing the bias of the digital transformation evaluation model in an organization through a learning process of the FCM topology (and its weights) based on learning techniques using organizational historical data linked to the COBIT model variables. Furthermore, since the dataset used in this study is from a single city in Colombia, distributed strategies such as federated learning should be considered to create a global model, in this case of a country, that includes data from different cities.

ACKNOWLEDGMENT

All the authors wish to thank the EAFIT University's Vice President for Discovery and Creation for their support in this research.

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