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Research article

Determination of key resource variables for a model of technological capability management in the alternative electricity generation industry of Colombia and Mexico, through a decision tree

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A R T I C L E I N F O

Keywords:
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Management
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Resources

A B S T R A C T

The study focuses on identifying key variables to develop a model for managing technological capabilities in the alternative energy generation industry in Colombia and Mexico. The objective is to identify critical factors that influence strategic decisions in this sector. Researchers MsC Neider Duan Barbosa Castro, PhD PD Fabiola Sáenz Blanco, Dr. Francisco Zorrilla Briones, and MsC Evy Fernanda Tapias Forero contribute their expertise in technological capability management and university-industry collaboration.

Advanced data mining techniques were used, integrating simulations and algorithms such as decision trees, to extract pertinent information and determine the most influential variables. Detailed Likert scale surveys were conducted in various power generation organizations in Colombia and Mexico, providing a comprehensive data set for analysis.

The paper discusses the need for effective management of technological capabilities. It emphasizes strategic collaboration between internal and external stakeholders. The importance of adopting innovative strategies and using a multi-level analytical approach to managing technology in the power generation industry is highlighted. This iterative and cyclical approach enables dynamic adaptability to technological and market changes. It continuously identifies areas for improvement and new opportunities.

The study's conclusions highlight the critical importance of innovation and market adaptation, as well as university-industry collaboration in the management of technological capabilities. The need for strategic and dynamic management to maintain a sustainable competitive advantage in the energy sector is evident. The integration of emerging technologies and operational flexibility are emphasized. In addition, the utility of data mining techniques in identifying and prioritizing key variables is highlighted. This provides a solid foundation for informed decision making in managing technological capabilities.

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1. Introduction

Acquiring true technological capability involves much more than simply purchasing specific technology. It requires an ongoing commitment to internal research, development, and innovation, as well as the strategic management of collaborative networks with multiple internal and external stakeholders (see Tables 1–7, Fig 1and 2).

This includes basic skills such as effective communication and interaction with both internal and external stakeholders to promote their active participation and contribution to innovation processes. Moreover, it is crucial to recognize that strengthening stakeholder relationships in terms of capacity development strengthens the identity of organizations [1].

Fig 3 and 4 As a result, the term "technology capability management" is often narrowly defined to focus on the selection, evaluation, and negotiation of technology based solely on supplier proposals, prices, and warranties. However, this approach focuses only on the short-term economic management of resources and overlooks critical aspects for optimal technology utilization [2].

Based on the foregoing, this paper aims to identify the variables that influence the management of technological capabilities focused on the network axis, responding to a management model proposed by two Colombian researchers and adopted by an international study that seeks to create software to strengthen competitiveness processes in the electric power generation industry through technological knowledge.Fig 5 and 6

2. Theoretical references

2.1. Technological capabilities

Fig 7 and 8 The conceptual framework underlying this research is based on the definition of technological capability proposed by Kim [3,4]. This perspective goes beyond the mere acquisition of technology and offers a more holistic and comprehensive view. Thus, Kim's vision, adopted by Rangel, defines technological capability as:

> "The effective use of technological knowledge for the purpose of maintaining competitiveness in price and quality. This capability allows the organization to assimilate, employ, adapt, and modify existing technologies, as well as create new technologies and develop new products and manufacturing methods, all to respond to environmental changes." [5,6].

In the context of an organization, technological capabilities are conceptualized as the set of skills and knowledge necessary to identify, acquire, adapt, develop, and apply technologies effectively in production processes and to foster innovation and competitiveness. These capabilities include the ability to select, assimilate, adapt and improve existing technologies, as well as the ability to generate new technologies based on pre-existing technological knowledge [7].

Therefore, it is important to refer to technological capabilities as an organization's ability to acquire, develop, and use technologies effectively and strategically. This includes not only the creation of proprietary technologies, but also the management and maintenance of technological supply chains and the training of specialized personnel in the use and development of these technologies. Investment in research, development, and innovation (I + D + i) is fundamental to strengthening these capabilities and reducing dependence on external technologies [8].

2.2. Technological capability management

In fact, technological capabilities can be divided into two basic processes [7].

- First, the acquisition of capabilities, which involves exploring and selecting available technologies that may be useful to the organization.
- Second, the adaptive capability, which involves modifying and adapting selected technologies to fit and function efficiently within the specific conditions of the organization's production processes.

These two approaches challenge the concept of technological capability management. This concept should encompass the acquisition of technology and the development of a robust set of organizational capabilities. These capabilities will enable the effective and strategic use of technological knowledge to drive sustainable competitiveness. Of course, it is necessary to evaluate the above two elements in terms of their impact on stakeholders. This academic work is entitled The Network Axis.Fig 9 and 10

Given this discussion, in 2017, after the postdoctoral immersion of researcher Fabiola Sáenz, she decided to propose, together with

Table 1
Expert opinions on internal stakeholder networks.

How relevant do you consider the following aspects given their impact on the development of projects within your organization? (Where 1 is irrelevant and 7 is relevant)

Variable	Name	Question
Communication	V1	Internal Communication Capacity
Participation	V2	Internal Participation Capacity
Administration	V3	Internal Network Management Capacity

Table 2
Expert opinions on the external stakeholder network.

How relevant do you consider the following aspects given their impact on the development of research within your organization? (Where 1 is irrelevant and 7 is relevant)		
Variable	**Name**	**Question**
Communication	V4	External Communication Capacity
Participation	V5	External Participation Capacity
Administration	V6	External Network Management Capacity

Table 3
Comparative goodness-of-fit tests using chi-square and Poisson statistics.

Variable	Chi-Squared Statistic	p-value (Chi-Squared)	Poisson Statistic	p-value (Poisson)
V1	7.33	0.06	6.67	0.08
V2	3.33	0.34	2.49	0.48
V3	3.83	0.43	3.81	0.43
V4	11.33	0.02	8.82	0.07
V5	6.33	0.18	3.37	0.50
V6	6.00	0.31	5.13	0.40

Note: Results obtained using SPSS software [19].

Table 4
Comparative correlation test result.

Variable 1	Variable 2	Pearson Correlation	Kendall's Tau Correlation
V1	V1	1	1
V1	V2	0.395	0.33
V1	V3	−0.199	−0.06
V1	V4	0.307	0.2
V1	V5	0.345	0.28
V1	V6	0.678	0.61
V2	V1	0.395	0.33
V2	V2	1	1
V2	V3	−0.117	0.06
V2	V4	−0.028	0.01
V2	V5	0.067	−0.02
V2	V6	0.116	0.15
V3	V1	−0.199	−0.06
V3	V2	−0.117	0.06
V3	V3	1	1
V3	V4	0.435	0.44
V3	V5	−0.102	−0.09
V3	V6	−0.039	−0.07
V4	V1	0.307	0.2
V4	V2	−0.028	0.01
V4	V3	0.435	0.45
V4	V4	1	1
V4	V5	−0.219	−0.28
V4	V6	0.525	0.39
V5	V1	0.345	0.28
V5	V2	0.067	−0.02
V5	V3	−0.102	−0.09
V5	V4	−0.219	−0.28
V5	V5	1	1
V5	V6	−0.034	0.04
V6	V1	0.678	0.61
V6	V2	0.116	0.15
V6	V3	−0.039	−0.07
V6	V4	0.525	0.39
V6	V5	−0.034	0.04
V6	V6	1	1

Note: Results obtained using SPSS software [19].

Table 5
Distribution density functions of the selected variables.

Variable	Distribution	Statistics	Chart
V1	**Binomial**	**n = 7** **p = 0.857**	Fig. 3
V2	**Binomial**	**n = 9** **p = 0.63**	Fig. 4
V3	**Binomial**	**n = 7** **p = 0.81**	Fig. 5
V4	**Binomial**	**n = 7** **p = 0.762**	Fig. 6
V5	**Binomial**	**n = 7** **p = 0.726**	Fig. 7
V6	**Poisson**	**4.92**	Fig. 8

Table 6
Experts opinions about networks with external stakeholders.

Colombia	
Type of Generation	Market Share Percentage in Colombia's Electric Market
Hydraulic	67.3 %
Photovoltaic	0.9 %
Wind	0.1 %
México	
Type of Generation	Market Share Percentage in Mexico's Electric Market
Hydraulic	14.6 %
Photovoltaic	6.9 %
Wind	8 %

Note: This table illustrates the experts' views on networking with external stakeholders.

Table 7
Consistency data by variable.

Distribution	Mode	Median	Dispersion	Min.	Max.	Missing	Error
Participation	0.19298	0.673	0.08	130,283	0.001	0.673	0 (0 %)
Generation		Hydraulic		1.08			0 (0 %)
COUNTRY		MEXICO		0.693			0 (0 %)
V1		High		1.24			0 (0 %)
V2		High		1.52			93 (9 %)
V3		High		1.39			0 (0 %)
V4		High		1.51			0 (0 %)
V5		Medium High		1.55			0 (0 %)
V6		Medium		1.86			136 (14 %

Note: This table illustrates the consistency by variable; data was obtained using Orange software.

master's student Neider Barbosa, a model for managing technological capabilities summarized in three main axes: knowledge, resources and networks. These axes represent the fundamental areas on which they focus the management of technological capabilities.

- **Knowledge:** This axis refers to the ability to manage knowledge within the organization to drive development, transformation, adaptation, and continuous improvement. The goal is to generate technological competence through effective knowledge management.
- **Resources:** This axis addresses the importance of having adequate physical and technological resources to support the organization's activities. It emphasizes the need for strategic investments in infrastructure and cutting-edge technology to strengthen the organization's processes.
- **Networks:** The ability to build and manage collaborative networks and alliances, both internal and external, is critical to managing technological capabilities. The goal is to promote effective communication among members of an organization and with other relevant stakeholders to share knowledge, resources, and experiences that drive innovation.

In summary, the model proposed by Sáenz and Barbosa focuses on improving knowledge management, optimizing technological resources, and strengthening collaborative networks as fundamental pillars to improve the technological capability of an organization [9].

This model was initially developed for research groups. However, some studies have been carried out in the textile industry [10], in

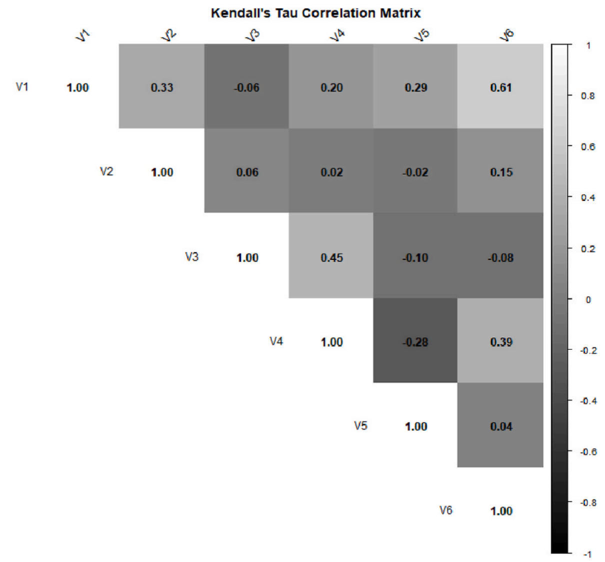

Fig. 1. Pearson correlation Heatmap for evaluating variable Interdependencies.
Note: Results obtained using R software [22].

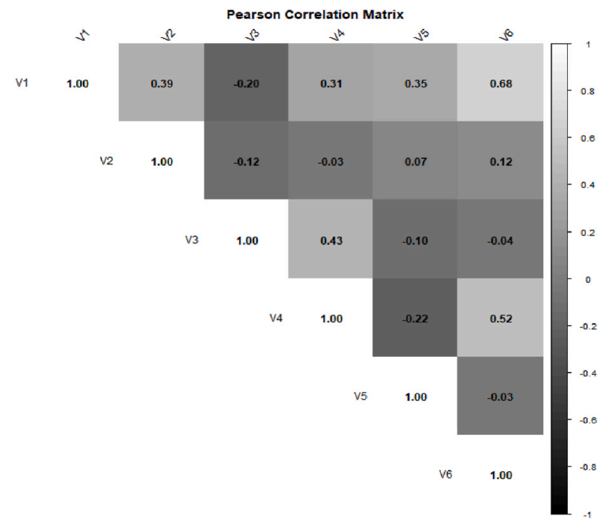

Fig. 2. Kendall's Tau correlation Heatmap for assessing ordinal variable relationships.
Note: Results obtained using R software [22].

the calibration industry [11], and in the characterization of research groups. The most recent research aims to integrate the model in the electric power generation industry in Colombia and Mexico [12,13].

In this sense, this article focuses on the most recent research, as the idea is to analyze the last axis of the model, which is networks, to determine which of the variables already studied and identified are essential in this context.

3. Methodology

In order to determine the variables involved in the process of managing technological capabilities focused on the organization of knowledge in organizations, given the objectives of this article, the methodology used is based on data mining techniques.

From the previously explained perspective, the first step is to determine large amounts of data through data simulation techniques, since the necessary amount of data is not available [14]. The second step is the use of data mining algorithms, in this case the use of trees as a tool to determine [15] which of the variables entered in step 1 are the most relevant. The final step is an analysis by experts to determine which of the variables studied should be considered for the analysis of the management of technological capabilities focused on knowledge, all respecting the model proposed by researchers Sáenz and Barbosa [16].

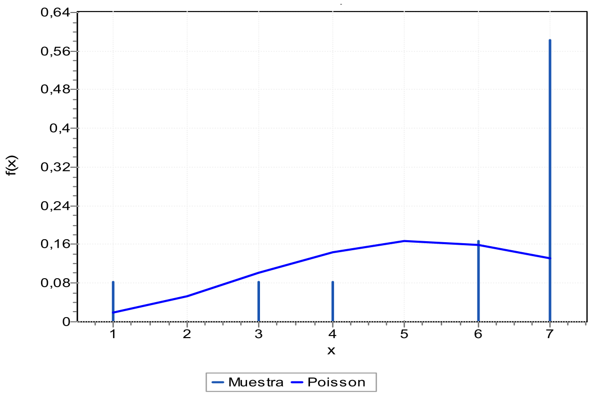

Fig. 3. Statistical behavior of V1.
Note: Generated by EasyFit Software.

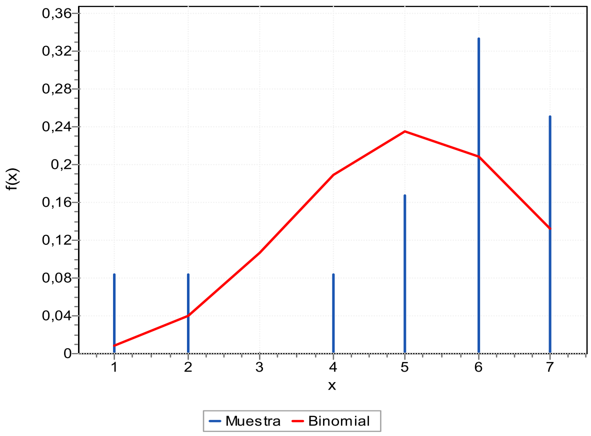

Fig. 4. Statistical behavior of V2.
Note: Generated by EasyFit Software.

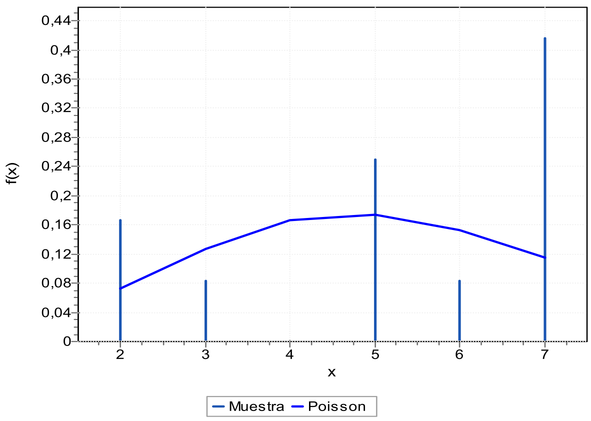

Fig. 5. Statistical behavior of V3.
Note: Generated by EasyFit Software.

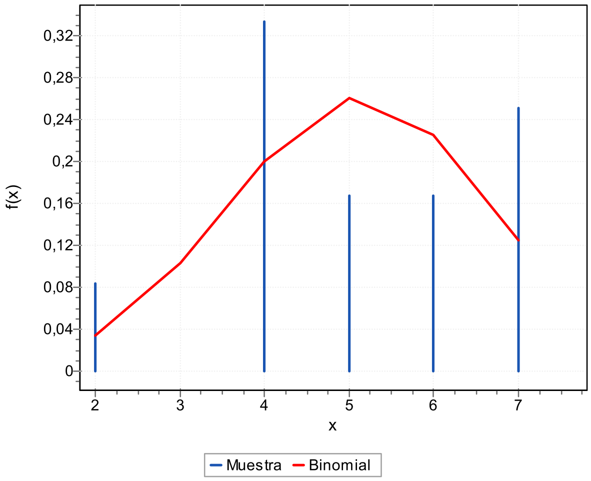

Fig. 6. Statistical behavior of V4.
Note: Generated by EasyFit Software.

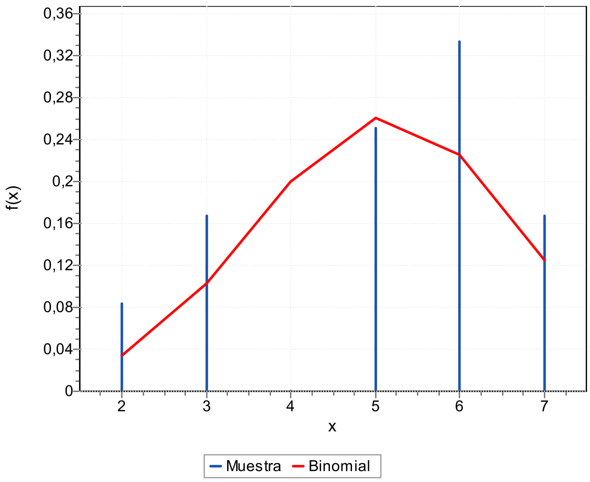

Fig. 7. Statistical behavior of V5.
Note: Generated by EasyFit Software.

4. Materials and methods

The development of this article begins with a fundamental step: the identification of the variables to be analyzed. This process was carried out through Likert scale surveys applied to organizations responsible for electricity generation in Colombia and Mexico. As previously mentioned, due to the difficulty of obtaining information in Mexico and the centralization of data in Colombia, a total of approximately 12 responses were obtained.

Given the limited sample size, the first step was to simulate a thousand data points to study the statistical behavior of the variables. This preliminary analysis is crucial for understanding the dynamics and trends presented by the responses obtained, despite the small sample size. This information is presented in the following tables.

The data simulation process has two main phases. The first is to determine the data distribution and the necessary estimation statistics; the second is to use computational and mathematical techniques to simulate the required amount of data, in this case 1000 data points. For this purpose, the software EasyFit [17] and Stafit [18] were used, assuming that the data follow a normal distribution.

There are two primary phases to the data simulation process. The first phase involves determining the underlying data distribution and the necessary estimation statistics; the second phase uses computational and mathematical techniques to simulate the required data set, in this case 1000 data points. The software used for this was EasyFit and Stafit. While data simulations often assume a normal distribution, it is important to note that the data in question are categorical and therefore exhibit discrete rather than continuous behavior, making them unsuitable for treatment as normally distributed data. Nevertheless, it is possible to fit these data to a discrete distribution that more accurately reflects their inherent behavior. Therefore, Chi-Square and Poisson tests are presented below to

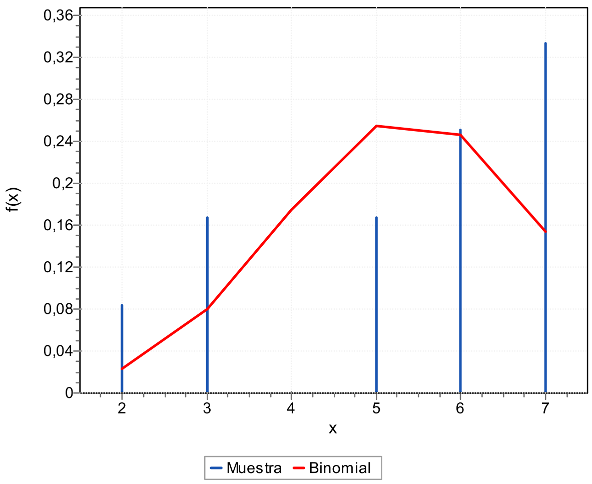

Fig. 8. Statistical behavior of V6.
Note: Generated by EasyFit Software.
Note: This table shows the distribution density functions of the selected variables.

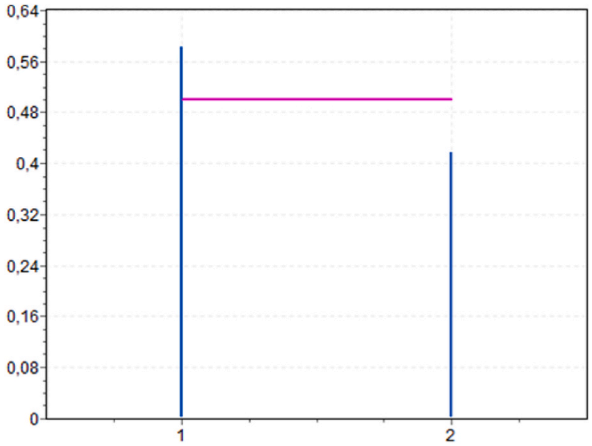

Fig. 9. Statistical behavior of country of origin transformation.
Note: Generated by EasyFit Software.

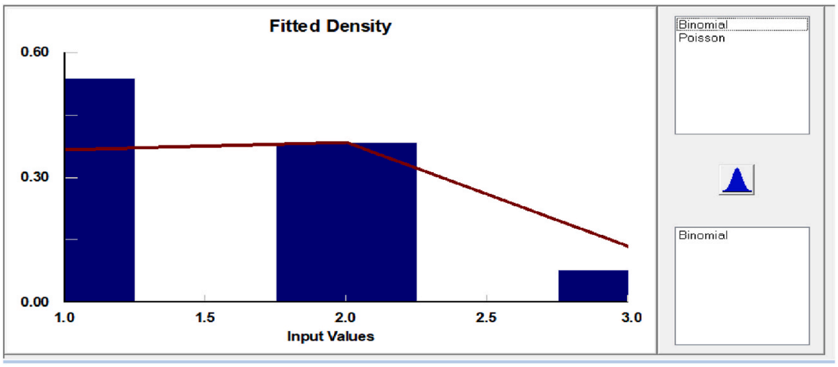

Fig. 10. Statistical behavior of the transformation of the type of creation.
Note. Generated by EasyFit Software.

evaluate the goodness of fit of the data.

As shown in the previous table, the results of the Chi-square and Poisson statistical tests indicate that variables V2, V3, V5, and V6 show a good fit in both tests, with p-values greater than 0.05. This indicates that these variables are consistent with the proposed theoretical distributions, which is statistically significant. Variable V4, while not passing the Chi-square test ($p = 0.023$), shows a good fit in the Poisson test ($p = 0.065$), indicating that its behavior follows a uniform pattern under the discrete Poisson distribution. Regarding variable V1, although its chi-squared test result ($p = 0.062$) is close to the significance threshold, the Poisson test ($p = 0.083$) shows a statistically acceptable fit. These results confirm the validity of the data simulation procedure used, as the majority of the variables show an adequate fit in at least one of the tests used. This provides a solid foundation for the subsequent interpretations and conclusions discussed later in the article.

One of the key factors in statistical data simulation is to ensure independence between variables. To this end, R software was used to perform various statistical analyses. Specifically, variable dependence was assessed using both Pearson and Kendall tests. The choice between these tests depends on the characteristics of the data and the underlying assumptions. For example, Pearson's test is appropriate for normally distributed data with expected linear relationships, whereas Kendall's coefficient is preferred for ordinal or non-parametric data, providing a robust alternative for assessing variable dependence [20].

Given the nature of the data in this study, it was deemed crucial to conduct both tests to ensure valid and reliable results. In particular, the use of both Pearson's test and Kendall's coefficient provided a comprehensive view of the relationships present in the data. This dual approach to assessing variable dependence increases the validity and reliability of the results within the research context [21].

The results of these tests, presented below, illustrate the correlations and associated levels of significance for each variable. Consequently, these results confirm the necessary independence to proceed with the data simulation, demonstrate the robustness of the methodology employed, and provide a solid foundation for subsequent analyses.

As shown in the correlation results, the variables show varying degrees of correlation in both the Pearson and Kendall tests. The strongest correlations are observed between certain variables, such as V1 and V6, while other relationships show weaker or near-zero correlations. These results indicate variability in the dependencies between the variables, while confirming the independence between them necessary for the validity of the data simulation. To facilitate a more comprehensive interpretation of these relationships, heat maps have been generated and are presented below. These visual representations provide a clear and intuitive means of understanding the complex interplay between variables, allowing for a more nuanced analysis of the correlation structures within the dataset.

The graphs presented provide a clear visualization of the correlation relationships between the variables, evaluated using the Pearson and Kendall coefficients. In the Pearson graph, a moderate positive correlation is observed between V1 and V6 (0.68), indicating a stronger relationship between these variables under the assumptions of normality and linearity. It is important to note that these tests were performed on discrete, not continuous, variables. Although Pearson is traditionally used for continuous data, in this case it was applied to observe how these relationships can be interpreted under the assumption of an almost linear distribution, revealing some weaker correlations, such as that between V1 and V3 (-0.20), which suggests a minimal dependence between certain variables.

On the other hand, the Kendall's correlation chart, designed to evaluate ordinal or non-parametric data, shows a similar trend, but with more adjusted coefficients, as in the case of V1 and V6 (0.61). This approach is better suited to the discrete characteristics of the data and provides a more robust and realistic view of the relationships. Kendall's results confirm the general independence between the variables, despite some slight dependencies, thus validating the data simulation methodology in the context of discrete variables.

Thus, both Pearson and Kendall plots show consistent correlations between variables, but with approaches that highlight key aspects of discrete data differently. While Pearson allows visualization of moderate relationships such as that between V1 and V6, the Kendall coefficient is better adapted to the discrete and ordinal nature of the data, providing more adjusted and robust results. Together, both approaches confirm that the variables, despite some slight dependencies, maintain the independence necessary to validate the data simulation process. This dual perspective reinforces the methodological soundness of the research and demonstrates the relevance of using both coefficients to obtain a comprehensive view of the interrelationships in the dataset.

After verifying that the original data meet the assumptions of normality and independence, which are essential to ensure the validity of the simulation, the distribution of the data and the descriptive statistics generated using EasyFit software [17] are presented below. These results are critical for generating a simulated data set that accurately reflects the characteristics of the source data.

Regarding the countries of origin of the energy generating companies, the categorical variable was transformed into a numerical variable, where 1 represents Mexico and 2 represents Colombia. The discrete probability distribution of this variable was then calculated, as shown in the following figure, before returning to the original values.

For the variable to be improved, which corresponds to the percentage market share of each type of energy generation in the electricity market, the analysis starts with the type of generation used. During the simulation process, the categorical variable was transformed by coding "photovoltaic" as 1, "hydraulic" as 2, and "wind" as 3. The results showed that these variables follow a binomial distribution with $n = 3$ n = 3 and a probability of success of 0.513.

Secondly, it is important to associate each country with the type of generation to determine the specific participation percentage. For Colombia, the participation is 67.3 % for hydraulic energy, 0.9 % for photovoltaic and 0.1 % for wind [23]. In Mexico, the participation percentages are 14.6 % for hydro, 6.9 % for photovoltaic, and 8 % for wind [24].

Based on the above, a simulated dataset of 1000 observations was created for evaluation. It is important to emphasize that for decision tree analysis it is necessary to define the behavior of large amounts of data. Therefore, a dataset was created to determine which variables in the study are key to the management of technological capabilities in the alternative electricity generation industry in Colombia and Mexico. Attribute selection is a powerful method for knowledge discovery and data mining because it encompasses a

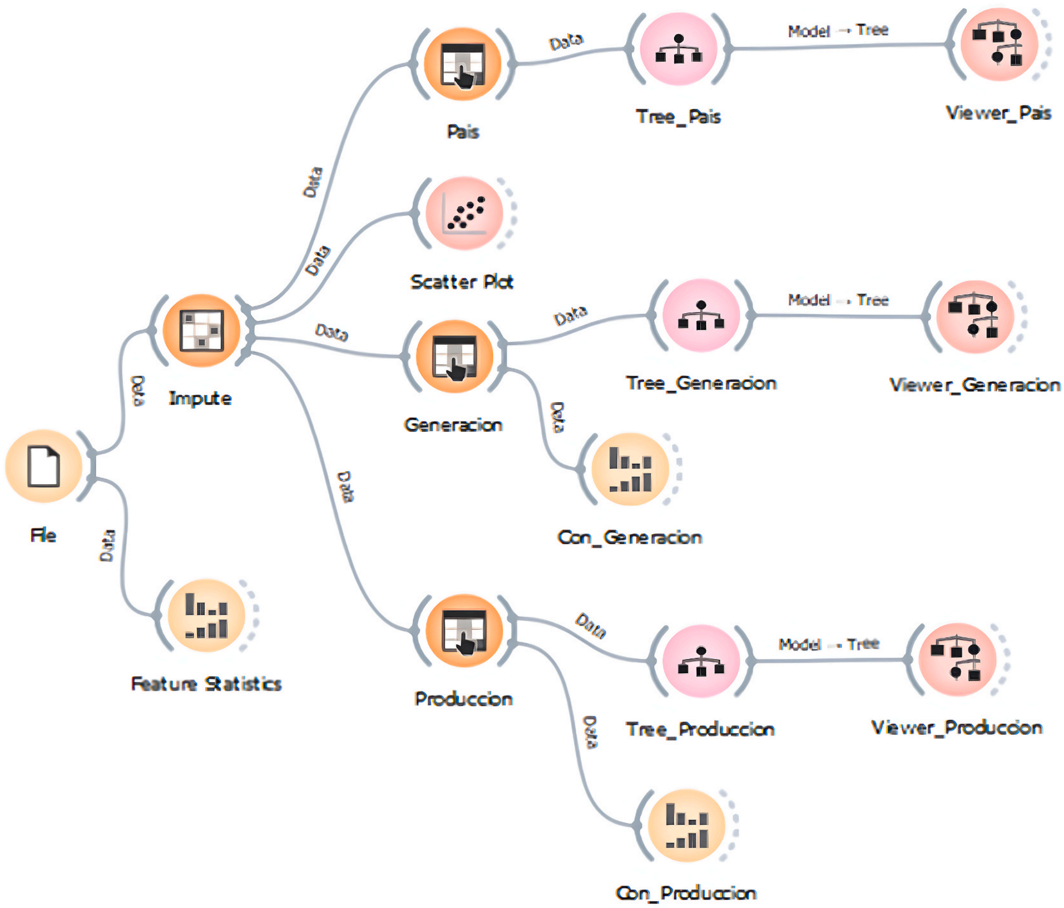

Fig. 11. Proposed data mining model for Orange software.
Note: Prepared by the authors for Orange Software.

wide range of complex data exploration techniques to discover useful patterns [25] This approach allows modeling and extracting knowledge from most of the available data, in this case, as it comprises a wide range of complex data research techniques to discover useful patterns. This approach allows for modeling and extracting knowledge from most of the available data, in this case, the simulated data.

It is worth noting that for the purposes of the study, the variables should return to their original qualitative format. In this sense, the values from 1 to 7 were categorized as low (1), low (2), medium-low (3), medium (4), medium-high (5), high (6), and high (7). For the country and generation method variables, they were simply returned to their original categories. These categories give rise to the objective variable, which is to maximize energy production using non-fossil methods. This is achieved by associating the values of the simulated data according to the following table.

For this study, the Orange software was used, an open-source data mining suite that includes a wide variety of data mining techniques [26]. In particular, decision trees were used, a supervised learning technique widely used in classification and regression tasks.

Decision trees are predictive models that map observations about an item to inferences about the value of the target variable. They build logical construction diagrams, similar to rule-based systems, but where the specific conditions for deriving a conclusion are structurally represented.These techniques are highly valued for their ability to generate interpretable models that scale to large amounts of data.

For this academic work, an integral model was developed. The selection of variables was based on three main criteria: 1) country differentiation, 2) generation method, and 3) production goals.

5. Results

As a first step, an analysis of data consistency was performed. The results show variations in consistency, with variable V2 showing 9 % inconsistency and variable V6 showing 14 % inconsistency, as detailed in the table below.

Eliminating data from a dataset is a critical step in ensuring the integrity of studies. First, there may be erroneous or incomplete

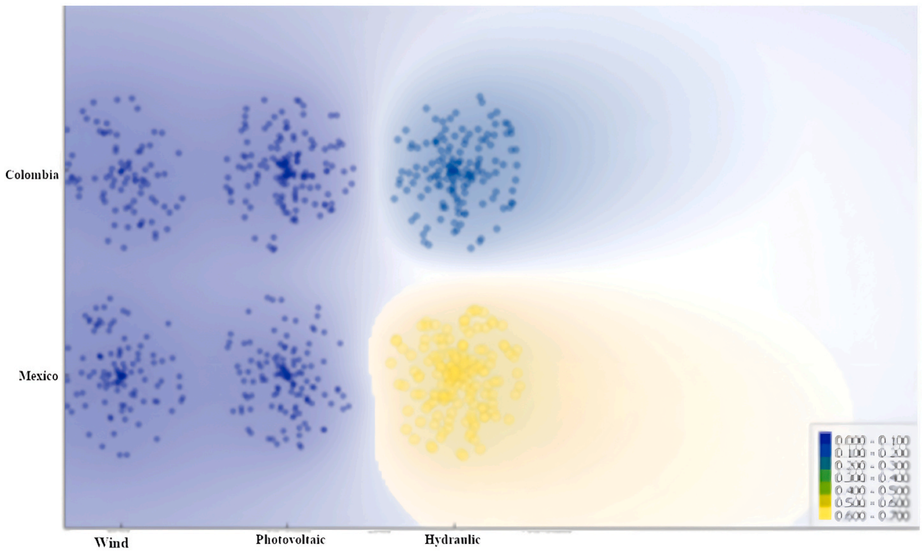

Fig. 12. Electric generation methods in the countries studied.
Note: Analysis conducted using Orange Software.

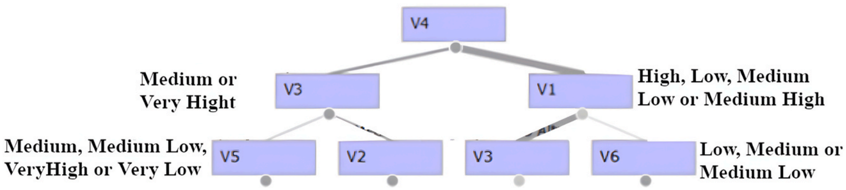

Fig. 13. Decision tree by electricity market share.
Note: Analysis conducted using Orange Software.

data that affect the accuracy of analyses. Eliminating them prevents the inclusion of erroneous information that could bias the results. In addition, some data may be considered outliers, which could affect the normality of the distribution and the validity of statistical models. For these reasons, it was decided to conduct a thorough analysis that would affect the entire data set. Although 21.3 % of the sample was lost, the authors believe that the remaining 787 consistent data points are more than sufficient to conduct a rigorous and reliable study (see Fig. 11).

This allows analyzing the electric generation methods using simulated data, as shown in Fig. 12. There are notable differences between Colombia and Mexico. In Colombia, there is a predominance of hydroelectric generation, as evidenced by a dense cluster of points in the yellow sector, indicating a higher concentration and consistency in this technology. On the other hand, Mexico presents a more balanced distribution among the three technologies analyzed: wind, photovoltaic and hydroelectric, as evidenced by the uniform distribution of points among the three categories. Despite the geographical and resource differences, both countries have made efforts to implement the three generation modalities studied. However, Colombia has a clear focus on hydroelectricity, possibly due to its robust hydrographic potential (see Fig. 9) (see Fig. 13) (see Fig. 2).

Now, in the context of this study, decision trees allowed the identification of key variables and their interactions to maximize energy production through non-fossil methods. It should be noted that only three levels of the different trees were considered for the equivalence of the study. For this purpose, three main perspectives were taken.

5.1. By market share in the electric market

When analyzing the need to manage technological capabilities focused on networks in power generation categorized by market share, the prominence of variable V4, located at the root of the decision tree, stands out. This strategic position gives V4 a primary role in the process, suggesting that its attributes significantly influence the determination of technological development strategies.

Further down the tree, variable V1 emerges as the second significant decision node. Despite the dispersion observed in the simulated data ('high', 'low', 'medium-high', or 'medium-low'), its influence is crucial in guiding decisions along specific paths, acting as a fine-tuning mechanism in the management process. The importance of V1 lies in its ability to diversify the decision-making process, leading to different potential technological trajectories.

At the end of the critical path tree, variable V3 defines the final step in this decision model. The bifurcation resulting from V1 leads

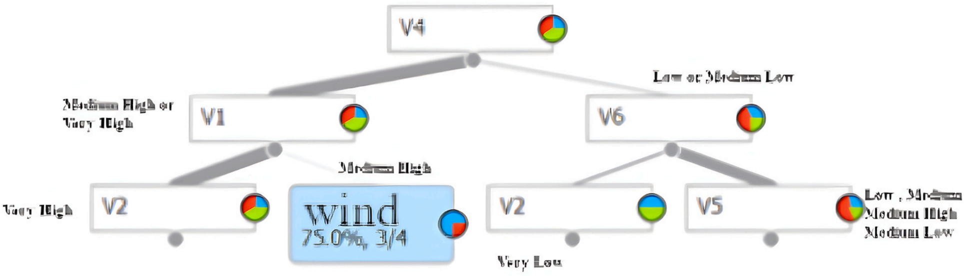

Fig. 14. Decision tree by electricity generation Type*W*.
Note: Analysis conducted using Orange Software.

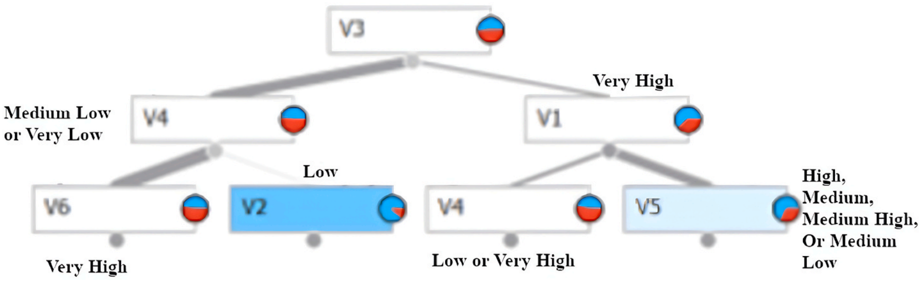

Fig. 15. Decision tree by electricity generation type.
Note: Analysis conducted using Orange Software.

to V3, solidifying it as the third key variable in this scheme. This final node is critical in determining the specific outcome of technological capability, underscoring the importance of V3 in completing the management analysis.

A deep understanding of this sequence of variables in the decision tree underscores the need for a methodical and strategic approach to technology management. This path not only reflects the hierarchy and complexity of technology decisions, but also guides managers to optimize resources and strengthen strategic impact. Implementing this critical structure allows managers to focus on the most influential variables to drive innovation and performance in power generation.Fig 14 and 15

In other words, the study highlights communication with external stakeholders as the primary factor affecting the effective management of technological capabilities according to their market share in the electrical sector. This communication is influenced by the same technological capability, but at an internal level. However, there is also a link between the ability to manage communication with internal stakeholders.

The effectiveness of technology management depends largely on the ability to interact and collaborate with external stakeholders such as customers, suppliers, partners, and government agencies. Poor communication with these groups can make it difficult to acquire resources, understand market needs, and adapt to regulatory changes.

Similarly, technology management is affected by internal communication within the organization. Smooth communication between different departments, teams, and hierarchical levels is critical for aligning goals, sharing information, and effectively coordinating efforts.

The study suggests that the ability to manage internal communication may be related to the ability to manage external communication. This means that companies that develop effective internal communication skills will be better positioned to build strong relationships with external stakeholders.

5.2. By generation method

In this case, the structure of the decision tree focuses its analysis on the critical variables for the management of energy production, highlighting the centrality of certain determining factors.

First, variable V4 is established as the root of the tree, occupying a strategic position and emphasizing the importance of V4 as the primary filter in the decision process, influencing subsequent analysis paths.

Following the path to superior performance, V1 is identified as a node that maintains the same performance segmentation as V4. Under this branch, V2 emerges as a key variable. The relevance of V2 is reinforced when both V4 and V1 show consistently high performance, positioning V2 as a critical factor in strategic decision making. In particular, the sequence V4 - V1 - V2 determines a clear inflection point towards the generation method "wind", which is reflected in a probability of 75 %. These data indicate that V2 is a critical determinant in high performance scenarios, suggesting a direct link to generation efficiency and feasibility.

This decision tree analysis shows that effective management of technological capabilities for energy generation must consider not only the hierarchy of variables, but also their impact on technological focus. V4 and V1 act as high-level indicators leading to V2, which is identified as an essential factor in optimizing wind power generation.

An organization's technological ability to communicate effectively with its stakeholders, both internal and external, is fundamental to its success. In this case, while the technological capability to communicate with external stakeholders is important, it should not be viewed as an isolated element.

The real strength lies in the organization's ability to foster smooth and transparent internal communications. This allows internal stakeholders to feel valued and involved in decision making, which in turn leads to greater engagement and support for the organization.

One example of how a power generation organization can strengthen its internal communications is by implementing digital platforms that facilitate information sharing and collaboration among employees.

In this context, wind power generation is a relevant case study. As a relatively new and complex technology, the organization needs effective mechanisms to communicate its benefits and challenges to both internal and external stakeholders.

Effective management of technological capabilities in this area requires solid communication at all levels of the organization.

5.3. *By country*

In the country-specific analysis, the V3 variable is identified as the central focus. Positioned at the root of the tree, V3's distinction highlights its pivotal role in the initial performance assessment and in determining subsequent analysis paths.

Variable V4 emerges as a key node, providing another level of differentiation for decision making. Here, V4 continues the classification with the same evaluation categories from the simulated data, demonstrating its iterative role in managing technological capabilities.

Following a similar dynamic, this node leads to variable V6 as an additional decision point. The branches leading to V6, which are "low or high," illustrate its critical function in determining outcomes in highly variable contexts for technological capability management.

The tree design reveals a systematic and cyclical approach to managing technological capabilities, where the analysis is not linear but allows for iteration through the V3 - V4 - V6 route. This approach underscores the need for continuous management of technological capabilities, exploiting opportunities for improvement and adapting strategies to changing conditions.

While internal communications management is critical to an organization's success, it should not be viewed in isolation from external communications. Both dimensions are closely related and influence each other.

An organization that neglects to communicate with its external stakeholders, even if it has impeccable internal management, could face serious challenges. For example, it could lose the trust of its customers, suppliers, or investors, negatively impacting its reputation and financial results.

In this context, managing communications with external stakeholders becomes particularly important. The organization needs to establish effective communication channels to keep its external stakeholders informed about its activities, strategies, and results.

In addition, it is essential for the organization to listen carefully to the needs and expectations of its external stakeholders and to take their input into account when making decisions.

6. Discussion

The previous results indicate that, as highlighted in 2 of the 3 trees studied, the variable V4, "Communication with external stakeholders", seems to be one of the most important factors in the decision making regarding the management of technological capabilities in the electricity generation industry. This variable, which refers to the involvement of external stakeholders in organizational processes, suggests that it is a crucial factor to consider. Therefore, engaging and maintaining effective communication with external stakeholders is key to the proper management of technological capabilities in these organizations.

It is probably not surprising that the iteration of internal and external stakeholders is important in Technological Innovation Hubs (TIH), especially in Higher Education Institutions (HEI), as it significantly affects the outcomes and social impact of the innovations developed by these hubs [27].

In particular, external stakeholders play a critical role in the social acceptance of innovations. If external stakeholders perceive innovations as beneficial and reliable, they are more likely to adopt and use them.

On the other hand, some authors emphasize the importance of developing the capacity to absorb knowledge through well-organized networks and knowledge management practices to foster a culture of organizational learning that enables the adoption of new digital and data-based competencies [28]. This absorptive capacity, also known as knowledge absorption capacity, stems precisely from communication with external stakeholders or interest groups.

In the context of real industries, organizational agility becomes a critical success factor for companies. This ability to adapt to changes in the environment, including political, economic, social, technological, environmental and legal aspects, as well as the threat of new competitors and rivalry among existing ones, is crucial for long-term survival and growth [29]. In essence, organizational agility becomes a continuous process of learning and adaptation. It is driven by effective communication with external stakeholders and the ability to respond promptly to environmental changes.

In the area of power generation, which is the focus of this study, it is important to note that external stakeholders play an important role in the value chain of the power generation industry. For the rapid growth of this industry, coordination among various stakeholders, such as manufacturers, customers, power producers, and the government, is crucial. In the early stages of expansion, these stakeholders often come together to form consortia and share risks and costs, facilitating the realization of larger projects [30].

In addition, it is mentioned that governments can influence the power generation value chain through incentive policies, such as subsidies or carbon taxes, which affect competitiveness. The government, as a stakeholder, requires constant communication with power generation companies to ensure an adequate supply of electricity, which is crucial for the successful implementation of governance [31].

To conclude this key variable, interaction with external stakeholders in the power generation industry is crucial to promote transparency, operational efficiency and informed decision making. This in turn enhances security, stability and competitiveness in the energy market [32].

On the other hand, the proposed results highlight the importance of a multifaceted and cyclical evaluation in the management of technological capabilities at the country level. This effect, demonstrated by the decision tree model that identifies variable V3 as the root, indicates that technological management must manage internal networks within the electricity generation organization to meet the country's needs, according to this case study.

In this case, the collaboration and commitment of internal stakeholders are fundamental for the development, implementation and optimal use of technological capabilities in a company. Their active participation and support are crucial for the success of technological innovation and the continuous improvement of the business environment [33]. This results from a continuous process that requires a multifaceted and cyclical evaluation of different factors, i.e. the effective management of internal stakeholder networks.

This variable has been identified as the root or main factor influencing the country's ability to meet its energy needs. At the firm level, the literature highlights the importance of technological capabilities and their relationship with stakeholders. It is emphasized that firms must effectively manage their technological capabilities to meet the demands and expectations of their various stakeholders, as the interaction between these technological capabilities and stakeholders can influence the firm's ability to innovate, adapt to market changes, and maintain a sustainable competitive advantage [34]. Furthermore, the importance of innovating in the power generation industry by adopting new, cleaner, and more flexible fossil fuel sources as a transitional measure while developing clean energy infrastructure is emphasized. These innovative strategies are critical to reducing emissions and pollution, enhancing national security and environmental protection, and increasing the energy sector's responsiveness to changing market conditions [35].

Therefore, organizations in this sector need to implement efficient technological management of their internal networks to optimize their operations and ensure adequate power supply for the country.

Variable V6, the ability to manage external networks, derived from the branches of V4, emerges as an additional critical point in the model. This variable emphasizes the importance of considering multiple levels of analysis in the management of technological capabilities, recognizing the complexity and interconnectedness of the factors involved in this process.

In this context, it is clear that a contextual perspective is offered on the collaboration processes between universities and industry [36], focusing on the barriers and facilitators that influence the establishment of successful collaborations [37]. This perspective is relevant for understanding how the management of external networks and technological capabilities affect these collaborations.

With regard to technological capabilities and their relationship to firms, in the current era of digital transformation, firms must effectively use technology to improve their operational efficiency, develop new products and services, reach new markets, and remain competitive [38].The adoption of emerging technologies such as artificial intelligence, data analytics, automation, and cloud computing can provide businesses with a significant competitive advantage.

To conclude the discussion on technological capability management with a focus on networks, it is important to highlight that, in light of the academic analysis conducted, the representation of the process as cyclical, as opposed to a linear approach, suggests an iterative methodology that allows for continuous review and strategic adaptation. This approach is fundamental in environments characterized by constantly changing technological conditions, where organizations must be agile in order to capitalize on improvement opportunities [39]. Adopting an iterative and cyclical approach to technological capability analysis enables organizations to respond quickly to environmental changes and continuously adapt their strategies and processes to maintain a sustainable competitive advantage.

Consequently, this iterative outcome recognizes the dynamic nature of the technological landscape and the need for constant review and adaptation. By adopting a cyclical rather than a linear approach, organizations can continuously evaluate and refine their technological capabilities, identify areas for improvement, and take advantage of new opportunities as they arise. This agility and adaptability is critical to business success in an increasingly technology-driven and frequently disrupted environment.

7. Conclusions

This study highlights the importance of effective technological capability management as a critical factor for innovation, market adaptation, and maintaining a sustainable competitive advantage in the power generation industry. It also emphasizes the adoption of iterative and cyclical approaches to technological capability management, which allows organizations to be agile in adapting to technological changes, identifying areas for improvement, and capitalizing on new opportunities.

The study found that the most influential variables in the technological capability management model were the ability to manage networks with internal and external stakeholders, including communication and effective demonstration of these capabilities. This shows that these variables are responsive to the technological capability management model.

Another relevant aspect is the collaboration between universities and industry, which plays a fundamental role in the development of technological capabilities. Effective management of external networks is essential for establishing successful collaborations and promoting knowledge and technology transfer between these sectors.

In addition, the study highlights the implementation of innovative strategies in the energy sector, such as the use of cleaner and more flexible energy sources. These strategies are critical to reducing emissions, improving environmental safety, and increasing the energy sector's responsiveness to changing market conditions.

The use of data mining techniques, such as decision trees, has provided a solid foundation for efficient technology capability management, enabling the prioritization of the most influential variables and focusing on those that maximize technological and operational performance. In addition, data simulation and analysis with expert participation validated the results, ensuring the robustness and relevance of the identified variables.

In conclusion, the study highlights the importance of efficient technological management, the use of advanced data analysis techniques, and strategic collaboration between sectors to optimize operations in the alternative power generation industry in Colombia and Mexico.

CRediT authorship contribution statement

Neider Duan Barbosa Castro: Writing – review & editing, Writing – original draft, Software, Project administration, Investigation. **Fabiola Sáenz Blanco:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Francisco Zorrilla Briones:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Evy Fernanda Tapias Forero:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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