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Key Factors in the Sustainable Growth of MSMEs in Ibero-America: An Empirical Study Based on Machine Learning

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Abstract

Micro, small and medium-sized enterprises (MSMEs) play a fundamental role in the socio-economic development of Ibero-America. However, they face structural and contextual challenges that constrain their sustainable growth. This study analyses the key determinants of MSMEs' growth in the region using a quantitative approach based on a Random Forest model applied to a dataset of 1796 observations collected by a team of researchers from different universities affiliated with the Foundation for Strategic Analysis and Development of Small and Medium-Sized Enterprises (FAEDPYME). The results reveal that sound corporate governance, effective human talent management supported by strong organisational communication, the development of skills to reduce the digital divide, innovation, and environmental perception constitute hierarchically significant factors for business development and sustainability. Relevant patterns that enable business sustainability are discussed, and a basis for the formulation of public policies aimed at strengthening the productive fabric is provided. This study offers empirical evidence that contributes to the ongoing discussion on innovation and sustainability among MSMEs in Ibero-America.

Keywords: MSMEs; sustainability; innovation; human talent; Random Forest; Ibero-America

1. Introduction

Micro, small and medium-sized enterprises (MSMEs) account for more than 95% of the business sector in Ibero-America and are an essential pillar for job creation [1,2], innovation, and social cohesion [3,4]. Their role transcends the economic sphere by contributing directly to the achievement of the Sustainable Development Goals (SDGs) in terms of inclusive economic growth, poverty reduction, and the promotion of innovation [3,5,6]. However, despite their importance, MSMEs face persistent structural barriers, such as limited access to financing [5,7], insufficient digitalisation [6,8], and political instability. These conditions undermine their competitiveness and jeopardise their long-term sustainability.

Recent literature has advanced in the study of determinants such as sustainable innovation [9], financial education [10], and gender equality in business leadership [11,12], providing evidence of their influence on business competitiveness. However, most of this research adopts descriptive approaches or focuses on national cases, which limits the comparative understanding of the factors that influence the sustainable growth of MSMEs in broad regional contexts such as Ibero-America. Furthermore, the use of traditional methodologies, such as linear regressions or descriptive analyses, constrains the ability to model non-linear and complex relationships among organisational variables [13,14].



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In this context, a research gap is identified related to the limited availability of empirical analyses that integrate machine learning approaches to explain the sustainable growth of MSMEs in Ibero-America. Although academic interest in business sustainability has increased, the literature remains fragmented and presents significant methodological gaps, as most studies use descriptive approaches or linear models that do not capture the complexity or the non-linear interactions of organisational behaviour. In particular, there is a lack of multinational studies applying Random Forest models to large cross-country business databases such as FAEDPYME, nor has their potential been systematically explored for identifying strategic paths derived from representative trees that explain differences in growth or sustainability between business profiles.

The available evidence is also concentrated on descriptive approaches or linear models that assume simple relationships between variables, which limits the identification of non-linear and dynamic patterns characteristic of organisational behaviour in complex contexts [9,14]. Even the few studies that use Random Forest in the MSME field focus mainly on credit risk analysis [15,16], on a single isolated factor such as innovation [17], or on specific dimensions such as work performance [18] within the same predictive model, and do not address sustainability and competitive growth from a multivariate perspective.

The objective of this study is to identify the characteristics of sales management that explain the sustainable growth of MSMEs in Ibero-America, by applying the Random Forest model to a database of 1796 observations provided by FAEDPYME. The aim is to answer the following research question: What factors in sales management enable greater sustainability and competitive growth of MSMEs in Ibero-America? To address this question, the following hypotheses are proposed:

- H1.** *Innovation has a predominant effect on the performance and sustainable growth of MSMEs.*
- H2.** *Human talent acts as an enabler of organisational development and contributes significantly to business performance.*
- H3.** *Strong corporate governance provides strategic support that promotes growth and improves the performance of MSMEs.*
- H4.** *In MSMEs, a strong internal environment (climate, agility, cohesion) can offset the adverse effects of an unfavourable external environment on business performance.*

Additionally, the study incorporates the Random Forest model due to its ability to model non-linear relationships and to rank predictive variables with greater precision than traditional econometric models, which is particularly relevant given the multivariable complexity of MSME growth.

The Random Forest choice is based on several methodological advantages over traditional econometric models and other machine learning algorithms. Unlike linear, logit, or probit regressions, which impose strict parametric assumptions (linearity, independence between predictors, and absence of multicollinearity), Random Forest does not require these conditions and is capable of capturing non-linear relationships and complex interactions between organisational and contextual variables, which are common features in multi-block business surveys such as FAEDPYME [13,19]. This flexibility is essential given the coexistence of categorical, ordinal, and numerical variables that define sustainability factors in MSMEs.

From a comparative perspective, multiple studies have shown that Random Forest offers greater stability and predictive accuracy than econometric models. Pioneering studies by Breiman [20] and exhaustive analyses by Fernández-Delgado et al. [21] show that its

structure based on multiple decision trees significantly reduces the risk of overfitting and improves generalisation capacity, even in high-dimensional contexts. Added to this is the contribution of Probst et al. [14], who also highlight that hyperparameter tuning (number of trees, depth, partitioning criteria) allows for significant performance optimisation without loss of interpretability. Likewise, Ma and Fan [22] demonstrate that Random Forest is particularly robust to noise and outliers, offering lower sensitivity to disturbances in the dataset compared to methods such as SVM or neural networks, which is essential in social databases where subjective perceptions and ordinal measures can coexist. Complementarily, Boubaker et al. [23] show in their study that integrating innovative methods such as CSW–RA–DEA and ML, especially RF, significantly improves the evaluation and prediction of MSME performance in developing countries.

The article makes three main contributions. On a theoretical level, it broadens the understanding of sustainable growth in MSMEs from the perspective of dynamic capabilities, showing how organisational and contextual factors interact in a non-linear way. On an empirical level, it offers unprecedented regional evidence based on advanced predictive analysis techniques that overcome the limitations of traditional models. Finally, on a practical level, it formulates recommendations for the design of public policies and business strategies that strengthen human capital, innovation and the reduction in the digital divide as drivers of sustainability.

2. Literature Review

2.1. Corporate Sustainability in MSMEs

Corporate sustainability is understood as the ability of organisations to maintain balanced growth in the long term, simultaneously generating economic, social and environmental value [24]. In the case of micro, small and medium-sized enterprises (MSMEs), this concept transcends financial performance, as it implies resilience, adaptability and capacity for innovation in changing contexts [25]. Due to their resource constraints, MSMEs face greater challenges in achieving sustainability, especially in emerging economies such as those in Ibero-America.

2.2. Key Concepts in the Literature

Various studies have addressed the factors that affect the sustainability of micro, small and medium-sized enterprises (MSMEs), highlighting the interaction between internal dimensions such as innovation, human capital and financial management, and external variables such as the political, institutional and technological context. The main approaches identified in the recent literature are summarised below.

Innovation is an essential pillar for the sustainability and competitiveness of MSMEs, enabling the creation of new products, services and processes that strengthen their economic performance and their commitment to long-term environmental responsibility [9,26]. In this context, entrepreneurs are increasingly open to dialogue and cooperation with their stakeholders, such as customers, employees and strategic partners, promoting co-creation spaces aimed at designing sustainable solutions that enhance their adaptability and strengthen organisational competitiveness [27–29]. Similarly, the development of innovation capacities has become a priority challenge, especially in relation to the acquisition of entrepreneurial and technological skills that foster sustainable innovation [30–32].

Consequently, innovation not only drives organisational sustainability but also generates a positive impact on financial and environmental results, strengthening corporate reputation and generating new market niches [9,33].

Human capital is another essential component for business sustainability and organisational competitiveness [34], as it improves organisational adaptability to the environ-

ment [35]. In MSMEs, the lack of technical skills limits their development [25], while higher qualifications and investment in human capital are linked to better business decisions [36], greater innovation [37], increased labour productivity [38] and business economic growth [39].

Likewise, financial education is becoming established as a key dimension of human capital, as it influences the strategic decision-making of MSMEs. A higher level of financial literacy improves financial performance [40], investment decision-making [41], risk management [42–44] and business sustainability [45]. In addition, the financial behaviour of entrepreneurs has a significant influence on organisational performance [10].

However, financial education remains a structural weakness in the sector, limiting its ability to cope with changing environments [46]. Hence the need to strengthen the technical and financial skills of human talent as a basis for sustainable and innovative management.

Access to finance constitutes another critical determinant of MSMEs growth, as it strengthens their operational efficiency and competitive capacity [47]. However, structural barriers persist, such as the lack of collateral and the stringent requirements of financial institutions, which hinder their inclusion in the formal financial system [48,49].

These limitations are exacerbated by poor financial literacy and low credit availability, which restricts innovation and hinders the execution of planned investments [50,51]. Despite the benefits of available financial products, their adoption remains limited among MSMEs [52].

Given this scenario, sound financial management and strategic planning improve access to credit and efficiency in the use of resources [53,54]. In addition, self-financing and digital transformation have been shown to have a positive impact on financial performance by reducing dependence on external financing and optimising internal processes [55].

MSMEs face obstacles in accessing formal financing. Alternatives such as fintech lending and crowdfunding are presented as viable solutions, provided that adequate regulatory frameworks are in place.

Political stability and legal certainty are also key conditions for creating environments conducive to private investment and business growth, especially in MSMEs, which tend to interpret stable political scenarios as a sign of confidence to invest, hire and expand their operations [56,57]. Conversely, political uncertainty creates an environment of risk aversion, inhibits innovation and reduces the competitiveness of the sector [58,59]. This climate of uncertainty particularly limits investment in research and development (R&D), mainly in companies without political ties, which face greater financial constraints and levels of risk [60].

Furthermore, various forms of insecurity hinder commercial operations and discourage domestic and foreign investment, restricting business growth [61]. In this context, companies that do not have comprehensive risk management systems are more vulnerable to these effects, compromising their sustainability [62]. Moreover, digital transformation is also affected by barriers linked to IT insecurity and a shortage of specialised talent, limiting technological modernisation processes and the ability to adapt to the digital environment [63].

Finally, the literature mentions the importance of the digital divide and gender perspective are interrelated dimensions that condition the competitive development of MSMEs, as reducing them is linked to greater business resilience, long-term sustainability, and organisational well-being [64]. In crisis contexts, a preference for female leadership has been observed due to more ethical and socially responsible approaches [11,12].

Furthermore, studies in Chile and Spain show that companies led by women achieve better financial performance and higher survival rates, demonstrating that gender and

leadership styles have an impact on business results and reinforcing the need for public policies that promote equity in the business sphere [65,66].

On the other hand, in a digitalised environment, the use of ICT, the development of collaborative networks and marketing strategies such as SEO are becoming established as tools for improving the management, visibility and positioning of MSMEs; however, these opportunities require reducing the digital divide and ensuring inclusive access to technology [67,68].

Overall, the literature reveals that the sustainability of MSMEs has been explained using four theoretical approaches that do not always converge. The first approach, which is structural in nature, argues that the main determinants of sustainable performance are access to finance, institutional stability and macroeconomic conditions, although empirical evidence shows mixed results regarding the actual magnitude of these effects. A second approach, focused on internal capabilities, proposes that human capital, job satisfaction, and organisational culture are more stable drivers of competitiveness, but debate persists about the causal direction between these variables and performance. A third technological approach emphasises innovation and digitalisation as critical factors, showing that technology adoption does not always translate into productivity improvements, especially in small firms with low absorptive capacity. Finally, an institutional-relational approach highlights the role of networks, corporate governance, and stakeholders, although the literature does not agree on whether these factors act as enablers or moderators of sustainable performance.

The coexistence of divergent results confirms the absence of an integrated model that simultaneously captures the non-linear relationships between internal, external, technological, and institutional variables. This lack of theoretical and empirical integration reinforces the need to apply advanced methodologies, such as Random Forest, which allow for the prioritisation of predictors and the understanding of complex patterns of business sustainability in MSMEs in Ibero-America.

2.3. Theoretical Basis

This study is based on the theory of dynamic capabilities [69], which posits that competitive companies are those capable of integrating, building and reconfiguring internal and external resources in highly uncertain environments. In the case of MSMEs, sustainability is explained through three interrelated processes:

- Identify: recognise opportunities and threats in the environment.
- Leverage: mobilise resources to respond quickly to market changes.
- Transform: reconfigure organisational structures and routines to sustain competitiveness over time.

The results of this research are interpreted within this theoretical framework, which allows for an understanding of how MSMEs combine internal factors (human capital, innovation, corporate governance) and external factors (financing, political context, digitalisation, gender) to drive their sustainable growth.

3. Methodology

The study adopts a predictive, non-experimental quantitative approach based on supervised machine learning techniques, specifically the Random Forest (RF) algorithm, implemented in Python (version 3.11) using the scikit-learn package. RF is recognised for its ability to handle large volumes of data and model complex relationships, reduce overfitting, manage categorical, ordinal and continuous variables, capture non-linear relationships and higher-order interactions, and provide interpretable results through variable importance measures [14,20,21,70].

This type of model effectively handles heterogeneous variables, as the algorithm supports categorical and Likert-type ordinal variables without requiring strict transformations, thereby facilitating the processing of multi-block business surveys [13,19,71]. The model is particularly suitable for contexts characterised by high dimensionality and potential non-linear relationships between predictor variables and the target variable, features observed in the FAEDPYME 2024 database.

The RF's ability to estimate the relative importance of variables is also useful for identifying the factors that contribute most to the categorisation of business performance. It allows representative trees to be visualised and interpretable decision paths to be generated using `plot_tree` and `export_graphviz`, enabling a transparent explanation of predictions [72]. The model is also aligned with previous studies applying machine learning techniques to the analysis of micro and small enterprises to forecast success, growth or risk [73].

The structured survey from the FAEDPYME 2024 network was used, consisting of 18 blocks of questions aimed at evaluating factors related to corporate governance, human talent, environment, innovation and business performance. The questionnaire includes variables of different types:

- Categorical variables such as manager gender, family business, company size by employee range, type of economic sector, etc.
- Likert-type ordinal variables rated on scales from 1 to 5 to measure perceptions of the environment, job skills, difficulty in hiring, level of innovation, importance of talent-attraction strategies, among other aspects.
- Continuous variables, such as number of employees, percentage of international sales, percentage of women in management.

These variables were carefully preprocessed and encoded in Python using `pandas` and `scikit-learn`, ensuring their appropriate transformation for supervised modelling. Likert-type responses were treated as ordinal, preserving their structure for predictive analysis.

In line with the literature on organisational growth in changing environments, the dynamic capabilities approach is adopted as the conceptual framework to structure and justify the thematic blocks considered in the analysis. This approach makes it possible to align the survey variables with key strategic components.

3.1. Dynamic Capabilities and Empirical Operationalisation

The study adopts the dynamic capabilities framework as the conceptual basis for analysing the factors that influence the business growth of MSMEs. This framework holds that organisations must possess three key capabilities to sustain competitive advantages in changing environments:

- Opportunity detection: identifying changes in the environment, new technologies or emerging customer needs.
- Exploitation: mobilising resources to exploit these opportunities through innovation, investment or organisational development.
- Transformation: reconfiguring assets and internal structures to adapt flexibly to such changes.

Based on this framework, a supervised model was constructed using variables from the FAEDPYME survey, whose thematic dimensions allow these capabilities to be empirically operationalised, as summarised in the following Table 1:

Table 1. Relationship between dynamic capabilities and the FAEDPYME survey.

Dynamic Capability Construct	Survey Block	Component Description
Opportunity detection	Competitive environment and perception	P11_1 to P11_5 P12_1 to P12_7 P13_3#0/1
	Internationalisation	P10_1, P10_2
	Innovation	P13_1#0/1 to P13_9#0/1
Utilisation	Human Talent	P14_1 to P18_5
	Corporate Governance	P4 to P8_5
	Innovation and Improvement Strategies	P13_1#0/1 to P13_9#0/1
Reconfiguration	Organisational Change and Investment	P9_1#0/1 to P9_3#0/1 P17_1#0/1 to P17_10#0/1
	Strategic Alliances	P13_4#0/1

Note: The symbol #0/1 is used to refer to affirmative responses that describe the level of importance of each selected option.

3.2. Details of the Empirical Model and Implementation

A pipeline was built for the pre-processing, training, and validation of the Random Forest model. The target variable corresponds to the perception of overall business performance (p12_5_mod), recoded into four ordinal classes (2, 3, 4, 5). This recoding was empirically justified to improve class distribution and facilitate classification, as classes 1 and 2 were under-represented and were grouped together to avoid severe class imbalance.

Two versions of the model were constructed to determine which one best satisfied the principle of parsimony. The first version used the original dataset without major modifications to the data processing, while the second incorporated the SMOTE technique to over-sample the less frequent classes and mitigate the bias towards the majority classes. The application of SMOTE is widely recognised in machine learning for datasets with class imbalance, as it generates synthetic instances of the minority class, improving the predictive performance of the models [74,75].

Although SMOTE is a technique that can introduce noise in boundary regions, in this study its relevance was verified by direct comparison with standard alternatives for treating imbalance (Random Forest without over-sampling and Random Forest with class balancing). These alternative models achieved approximately 50% performance, demonstrating a limited ability to learn minority-class patterns. In contrast, the incorporation of SMOTE allowed the model to reach 96%, showing a substantial improvement in stability and predictive accuracy. Therefore, the choice of SMOTE is empirically justified, as it is the only strategy capable of effectively correcting the imbalance present in the data and allowing more representative learning for the target class.

The Random Forest model was optimised through a systematic hyperparameter search (GridSearchCV), evaluating combinations of depth, number of trees, minimum split, and number of predictors per split. This procedure was integrated into a pipeline that incorporates SMOTE only in the training set, preventing information leakage. The optimisation was performed under five-fold stratified cross-validation, ensuring stable estimates and reducing sensitivity to predetermined configurations. The optimal model was selected by maximising the weighted F1-score.

The ratio of 70% for training and 30% for testing follows the recommendations of recent literature in machine learning, as it provides an appropriate balance between robust

training and sufficiently informative external validation. This allows the model to learn general patterns without memorising the data, while reserving a suitable proportion to evaluate its generalisation capacity [76,77].

To ensure the reproducibility of the results, the parameter `random_state = 42` was set. This practice ensures that, in future executions of the model, the training and test sets remain consistent, allowing valid comparisons between alternative configurations or models. The choice of the number 42 has become popular as a neutral standard value for random seed initialisation, although any fixed value could serve this purpose [78].

3.3. Model Interpretability

The entire workflow was reproducible through the construction of supervised pipelines that integrate cleaning, coding, modelling, and validation. Subsequently, the importance of each predictor variable in the prediction was calculated, highlighting the main factors associated with performance. As an interpretative decision rule, the most representative tree within the forest was identified by calculating Euclidean distances between the importance vectors of the individual trees and the complete set**, and from this tree**, explicit decision paths were visualised, showing how certain combinations of variables lead to specific predictions, thus contributing to the interpretability of the model [79].

3.4. Model Performance Evaluation

The model evaluation process was carried out using ordinal classification metrics: overall accuracy, macro- and weighted-average F1-scores, Cohen's kappa, and the confusion matrix. These metrics provide a comprehensive and balanced evaluation of the model's performance in ordinal classification settings and class-imbalanced scenarios [72,80], as summarised in the following Table 2.

Table 2. Validation by category.

Class	Precision	Recall	F1-Score	Observations
2	1.000	0.867	0.929	45
3	0.952	0.987	0.969	159
4	0.981	0.987	0.984	157
5	1.000	0.989	0.994	88
Accuracy			0.976	449
Macro avg	0.983	0.957	0.969	449
Weighted avg	0.976	0.976	0.975	449
Cohen's kappa	0.965			

To avoid technical overload, the operational details of the pre-processing (coding, libraries, and computational procedures) have been summarised and moved to the methodological Appendix (Appendix A). Only the conceptual structure of the pipeline is retained in the main text: initial cleaning, coding, partitioning, stratification, balancing, and model optimisation through cross-validation.

4. Results

The empirical analysis was based on the implementation of the Random Forest algorithm, trained with class balancing using the SMOTE technique (Synthetic Minority Over-sampling Technique), with the aim of identifying patterns associated with the perceived level of growth in the sales of MSMEs in Ibero-America. This section presents the most representative results of the trained and validated model, including performance metrics, decision paths generated by the most representative tree, and their contextual

interpretation, thereby enabling the empirical findings to be linked to the thematic blocks of the conceptual framework.

It was decided to include only the results of the model with SMOTE, as it showed a significant improvement in predictive capacity compared to the model without class balancing. After applying this technique, the model achieved satisfactory performance, outperforming the model without SMOTE in terms of overall accuracy and class balance.

To contextualise this performance, the final model was compared with simpler alternatives (Table 3), such as logistic regression and Random Forest without SMOTE. Logistic regression displayed limited performance due to its inherent characteristics, while the Random Forest without SMOTE exhibited difficulties associated with class imbalance, mainly affecting recall in minority categories. By contrast, the SMOTE-enhanced Random Forest model achieved significantly higher metrics, demonstrating that synthetic balancing provides substantial improvements in class discrimination and model stability.

Table 3. Performance comparison table.

Model	Accuracy	F1 Weighted	Recall	Comment
Logistic Regression	0.695	0.691	0.695	Limited ability to capture non-linear patterns
RF (without SMOTE)	0.651	0.648	0.651	Imbalance affects recall; poor performance in class 2
RF (SMOTE)	0.976	0.975	0.976	Improved performance; better class balance

4.1. Representative Decision Tree

After optimisation using GridSearchCv, the final model corresponded to a Random Forest of 500 trees. For interpretative purposes, the most representative tree in the forest was selected using a quantitative criterion. The Euclidean distance between the variable-importance vectors of all trees was calculated, and the tree with the lowest average distance from the set was chosen, ensuring that its relevance pattern is closest to the overall behaviour of the model. Under this procedure, Tree 51 (Figure 1) was selected, which provides a concise visualisation of the decision paths associated with classification into class 5, the category linked to the highest perceived sales growth.

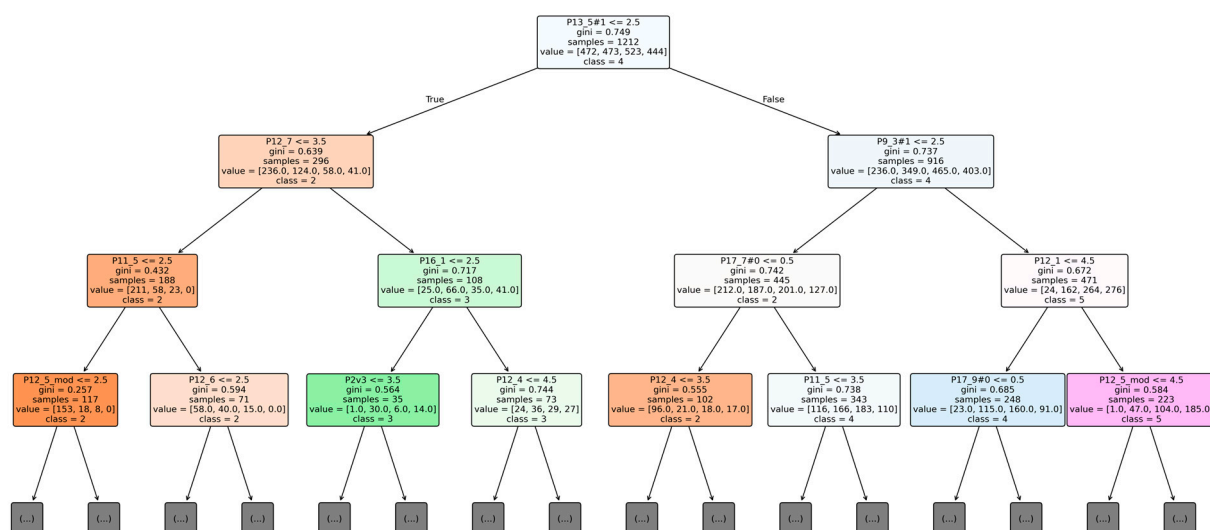


Figure 1. Representative Tree SMOTE index 51.

Class 5 represents micro, small and medium-sized enterprises (MSMEs) that perceive high sales growth, which may be associated with greater competitive dynamism, operational efficiency, or adaptability to the environment. The analysis of the paths leading to this class within the representative tree of the RF model reveals patterns in the combination of categorical and Likert-type ordinal variables that characterise firms with high perceived performance.

4.1.1. Main Routes to Class 5

The following routes (successive node conditions) help to clarify the business profiles that lead to class 5 (Table 4). Key variables are highlighted by thematic block.

Table 4. The five main routes of the tree.

Route	Detail	Interpretation
Route 1		
P13_5#1 $\leq$ 2.5	(Processes with little innovation in 2024)	Young companies with satisfied teams, which do not excel in process innovation but perform well in product innovation and external training. Companies with little difficulty attracting talent are more likely to be classified at the highest levels of perceived growth by the model.
P12_7 $>$ 3.5	(High job satisfaction)	
P16_1 $\leq$ 2.5	(Little training in strategy)	
P2v3 $\leq$ 3.5	(Young company)	
P12_4 $\leq$ 4.5	(Moderate organisational agility)	
P15_10 $>$ 2.5	(High participation in external training)	
P15_9 $\leq$ 2.5	(Little difficulty in attracting talent)	
P13_1#1 $>$ 4.5	(High level of product innovation 2024)	
Route 2		
P13_5#1 $\leq$ 2.5	(Processes with little innovation in 2024)	This profile suggests that, even with human capital difficulties and limited use of digital tools, investment in innovative infrastructure and acceptable internal labour relations increases the likelihood of being classified at higher levels of perceived growth.
P12_7 $>$ 3.5	(High job satisfaction)	
P16_1 $\leq$ 2.5	(Little training in strategy)	
P2v3 $\leq$ 3.5	(Young company)	
P12_4 $\leq$ 4.5	(Moderate organisational agility)	
P15_10 $>$ 2.5	(High participation in external training)	
P15_9 $>$ 2.5	(They do have talent difficulties)	
P17_5#1 $\leq$ 3.5	(Moderate internal labour relations)	
P17_2#1 $\leq$ 1.5	(Low use of digital tools)	
P13_6#1 $>$ 2.5	(Innovation in facilities and equipment)	
Route 3		
P13_5#1 $\leq$ 2.5	(Processes with little innovation in 2024)	Companies with strong labour relations stand out. Despite difficulties attracting talent, high job satisfaction and well-valued internal strategies enhance their potential for classification in high-growth levels.
P12_7 $>$ 3.5	(High job satisfaction)	
P16_1 $\leq$ 2.5	(Little training in strategy)	
P2v3 $\leq$ 3.5	(Young company)	
P12_4 $\leq$ 4.5	(Moderate organisational agility)	
P15_10 $>$ 2.5	(High participation in external training)	
P15_9 $>$ 2.5	(They do have talent difficulties)	
P17_5#1 $>$ 3.5	(Moderate internal labour relations)	
Route 4		
P13_5#1 $\leq$ 2.5	(Processes with little innovation in 2024)	Adaptable companies with satisfied employees and no immediate plans for generational transition may be experiencing internal consolidation that favours growth.
P12_7 $>$ 3.5	(High job satisfaction)	
P16_1 $\leq$ 2.5	(Little training in strategy)	
P2v3 $\leq$ 3.5	(Young company)	
P12_4 $>$ 4.5	(High adaptability to change)	
P8_3 $\leq$ 2.5	(Generational transition not yet considered)	

Table 4. *Cont.*

Route	Detail	Interpretation
Route 5		
P13_5#1 $\leq$ 2.5	(Processes with little innovation in 2024)	More mature companies that invest in training and have satisfied employees align with a growth pattern, even without significant process innovation.
P12_7 $>$ 3.5	(High job satisfaction)	
P16_1 $\leq$ 2.5	(Little training in strategy)	
P2v3 $>$ 3.5	(Company with more years of experience)	
P15_7 $\leq$ 2.5	(Low difficulty in investing in training)	

Note: The symbol #1 refers to the level of importance of each selected option.

4.1.2. Summary of Relevant Patterns

Table 5 provides a synthesis of the common patterns identified in the paths that lead to class 5 (highest sales growth). This classification integrates the most influential variables, grouped by strategic block, derived from the representative tree of the Random Forest model, thereby revealing recurring configurations of innovation, human talent, corporate governance and the internal environment. Identifying these blocks provides a structured view of the mechanisms that distinguish firms with relatively better performance, facilitating their linkage with the principles of dynamic capabilities and their interpretation within the strategic framework of the study.

Table 5. Summary of patterns.

Block	Predominant Variables	Role in Growth	Link to the Theory of Dynamic Capabilities
Innovation	P13_1#1 (product innovation), P13_6#1 (goods innovation), P13_5#1 (process innovation)	Direct growth catalyst	Sensing/perceiving + transforming/reconfiguring: these variables reflect the firm's ability to identify new opportunities through changes in products and processes, and to reconfigure resources and infrastructure accordingly.
Human Resources	P15_9, (Commitment to the company) P15_10 (External training), P12_7 (Job satisfaction)	Enabling condition	Leveraging staff capabilities (commitment, professionalism, and job satisfaction) allows identified opportunities to be exploited. The theory holds that without competent and motivated personnel, strategic decisions do not translate into results.
Corporate Governance	P8_3 (Generational transmission), P2v3 (age of the company), P16_1 (Qualification)	Strategic support	Transforming/reconfiguring: corporate governance provides the institutional structure required for reconfiguring organisational processes and allocating resources. Managerial training, professionalisation, and challenges linked to generational transition influence the organisation's capacity to transform itself.
Internal Environment	P12_4 (Speed of adaptation), P17_5#1 (labour relations), P17_2#1 (Digital tools)	Compensating factors	Leveraging + transforming/reconfiguring speed of adaptation (P12_4) reflects the ability to respond rapidly to changes in the environment. Internal actions such as improving labour relations or increasing the use of digital tools (P17_5#1, P17_2#1) signal reconfiguration capabilities within the organisation.

Note: The symbol #1 refers to the level of importance of each selected option.

The paths leading to class 5 (Table 5) show that growth cannot be explained by any single isolated factor but rather by synergistic combinations of different elements: individual satisfaction and flexibility, leadership training and professionalisation, the implementation of innovation strategies, and organisational adaptability. These configurations provide insight into how different strategic blocks interact in a complementary way to sustain superior performance, consistent with the principles of dynamic capabilities.

Of the 1796 companies analysed, 371 follow one of the 36 routes identified by the most representative tree (tree 51) that converge on category 5, indicating that around 21 percent of all firms fall into trajectories associated with the highest level of perceived growth. The internal distribution shows that the route with the largest number of firms includes 171 cases, followed by another route with 59 firms, while the remainder are distributed across less prevalent pathways. This characterisation makes it possible not only to identify the magnitude of firms that share these patterns but also to distinguish routes with substantial empirical weight from infrequent trajectories, thereby providing greater interpretative robustness to the analysis.

The contribution and specific content of each strategic block are detailed below (Table 5):

Strategic innovation

Within this block, the factors with the greatest predictive importance are product innovation (P13_1#1) and equipment innovation (P13_6#1), both associated with a higher probability of classification in the upper growth categories. This suggests that firms innovating in facilities, processes, or capital goods—beyond final products—tend to achieve better performance. Innovation acts as a catalyst even when limitations exist in human talent or the digital environment.

Human talent and working environment

Variables such as job satisfaction (P12_7), difficulties in attracting talent (P15_9), and participation in external training (P15_10) show high predictive relevance, indicating that human capital is a differentiating component in growth classification. Firms with satisfied teams and employees in continuous training are more likely to be classified at higher levels of perceived growth, even when their internal processes are not highly innovative.

Corporate governance

In this block, variables such as managerial training in strategy (P16_1), firm age (P2v3), and intention of family succession (P8_3) display high predictive relevance, suggesting that governance decisions play a key differentiating role in the model. Firms that have not yet initiated formal generational transition processes, have leadership with academic training in management, and are relatively young, show a higher probability of being classified in the upper perceived growth categories.

Digital environment

To a lesser extent, factors such as labour relations (P17_5#1), use of digital tools (P17_2#1), and organisational agility (P12_4) also appear as relevant. The model suggests that firms with cohesive working environments, even without advanced digitalisation levels, are more likely to receive favourable classification when they maintain adaptability to external changes or effectively manage internal human relationships.

5. Discussion

The findings obtained from the representative tree of the Random Forest model show that the sustainable growth of Ibero-American MSMEs does not depend on a single factor, but rather on a synergistic configuration of internal capabilities that interact in a non-linear and mutually reinforcing way. The hierarchical sequence identified—low process innovation, high job satisfaction, continuous training, and adaptable leadership—shows that

the companies with the highest perceived growth are not necessarily the most digitised or those with formal strategic structures, but rather those that effectively mobilise their human capital as a compensatory source of competitiveness. This result complements previous studies that highlight innovation as a determining factor in sustainable performance [9,33], by empirically demonstrating that job satisfaction and external training function as enabling preconditions for innovation to produce sustainable effects on performance.

Compared to the prevailing literature, which positions access to finance as the main structural obstacle for MSMEs in emerging economies [5,47], this factor did not emerge among the most hierarchically relevant predictors. This difference can be explained by two reasons: first, the FAEDPYME dataset includes surviving firms that have already overcome initial liquidity constraints, introducing a survival bias; and second, perceived sales growth responds more directly to internal transformation routines than to long-term structural financial conditions. In this sense, the results provide evidence that not all the structural factors described in the macroeconomic literature translate into predictive relevance at the micro-enterprise level, which invites us to differentiate between systemic constraints and actionable internal capabilities.

From the theoretical framework of dynamic capabilities [69], the results can be interpreted as empirical evidence of bundling or capability-packaging processes. MSMEs that achieve higher levels of sustainability are those that reconfigure limited resources such as training, internal cohesion and incremental innovation to respond quickly to environmental changes. The importance of job satisfaction in the upper nodes of the tree reinforces the notion that the social and behavioural dimensions of work are latent drivers of sustainability, particularly in contexts of resource scarcity. Thus, the empirical results support the hypothesis that companies can achieve sustainability through relational and human capital, even before reaching high levels of digitalisation or financial sophistication.

In relation to the hypotheses proposed, the findings of the Random Forest model allow us to state the following:

- H1 is supported, given that innovation, especially in products and equipment, consistently appears as one of the most important predictors and acts as a direct catalyst for sustainable growth.
- H2 is also confirmed, as variables such as job satisfaction, continuous training and staff commitment emerge as enabling conditions that enhance the firm's capacity to transform opportunities into results.
- H3 is supported, as manager qualifications, leadership professionalisation and corporate governance stability are positioned as structural elements that enable organisational reconfiguration and sustain competitive advantages.
- Finally, H4 is consistently validated, as a strong internal environment, characterised by labour cohesion, agility and adaptability, compensates for external constraints, showing that internal resilience can buffer political, economic and technological pressures.

Furthermore, when comparing our results with empirical evidence from other Latin American countries, consistent regional patterns emerge that reinforce the robustness of the model. Paredes-Chacín et al. [81] demonstrated in 13 Latin American countries that incremental innovation and organisational adaptability are central determinants of economic sustainability, which aligns with the importance of innovation in the representative tree of this study. Complementarily, Tegethoff et al. [82] show that in Colombian MSMEs, knowledge management and the strengthening of human talent condition the adoption of eco-innovations, reinforcing the enabling role of human capital. In turn, Valdés [83] shows that organisational cohesion and internal governance in companies from Argentina, Brazil and Chile mitigate the effects of adverse external environments, consistent with hypothesis H4. Finally, Almeida [84] shows that open innovation practices in Portuguese

SMEs enhance innovative capacity, suggesting that the patterns identified also extend to other Ibero-American contexts.

Although the results of this study are consistent with patterns identified in recent Latin American research, the novelty of this work lies in the use of a predictive, machine-learning-based approach that allows predictors to be characterised and non-linear configurations of internal capabilities to be revealed—something that previous studies have not addressed. Taken together, this comparative evidence shows that the relationships identified are not exclusive to our sample and that the approach adopted offers a more nuanced and comprehensive understanding of sustainable growth in MSMEs in the region.

In summary, the findings suggest a conceptual shift in understanding the sustainable growth of Ibero-American MSMEs: rather than depending on the availability of financial resources, growth depends on the sequential activation of people-centred internal capabilities. This positions human talent as a strategic lever for sustainability, and not merely as an operational component. Consequently, public policies should prioritise the creation of training ecosystems, management mentoring programmes and the strengthening of the working environment, given that these strategies generate immediate sustainable returns and contribute to achieving the Sustainable Development Goals, particularly SDG 8 (Decent work and economic growth) and SDG 9 (Industry, innovation and infrastructure).

6. Limitations and Future Lines of Research

A first limitation of the study relates to the cross-sectional nature of the FAEDPYME database. As the data covers a single time period, the patterns identified reflect static relationships between internal capabilities and perceived growth, without capturing evolutionary dynamics or lagged effects. Future research should incorporate longitudinal designs that allow for the analysis of causal trajectories and capacity maturation, especially in digitisation processes, where the impacts tend to manifest with time lags.

Secondly, the model is built on surviving companies, which introduces a selection bias towards firms that managed to withstand capital constraints, adverse environments or market failures. Consequently, the results cannot be automatically generalised to informal micro-enterprises or start-ups in pre-production phases. A natural next step is to replicate the model with samples stratified by type of company, level of formalisation and economic sector, allowing validation of whether the combinations of capabilities identified remain or whether different sustainability configurations emerge.

From a methodological point of view, although Random Forest offers predictive robustness and interpretability superior to linear methods, future studies could contrast these results with additional explainable AI (XAI) techniques (e.g., SHAP values or LIME) and with deep non-linear architectures (e.g., deep neural networks). This comparison would allow assessment of whether the routes identified here constitute stable patterns or whether alternative configurations could emerge under models capable of capturing higher-order interactions.

Although the model performed well in internal validation, no external dataset was available to assess its generalisation outside the analysed sample. This limitation suggests that future work should apply the model to independent databases or in real-world interventions, especially if the findings are to be used to guide public policy.

Finally, it is pertinent to incorporate institutional variables at the country level, such as regulatory frameworks, regional governance, political risks, and digital infrastructure, to estimate moderating effects of context and move towards multilevel models that simultaneously integrate internal capacities and structural constraints. This approach would strengthen the explanatory depth of the model and link public policy formulation more directly to the organisational pathways that effectively lead to competitive sustainability.

7. Conclusions

The study provides a renewed understanding of the sustainable growth of Ibero-American MSMEs by demonstrating that it does not depend on a single isolated factor, but on specific configurations of internal capabilities that interact in a non-linear manner. From a theoretical point of view, the results extend the scope of the dynamic capabilities approach by empirically showing that incremental innovation, job satisfaction, continuous training, and organisational adaptability function as compensatory mechanisms capable of counteracting structural limitations inherent in emerging markets. This offers a more nuanced reading of the traditional literature, which has tended to overemphasise macroeconomic constraints such as access to finance.

Methodologically, the use of Random Forest made it possible to reveal specific strategic paths, not only individual variables, which constitutes a significant contribution to organisational studies. The identification of the representative tree provides interpretative input that allows us to understand how particular combinations of internal capabilities lead to high levels of growth, overcoming the limitations of linear models used in previous research.

In the area of public policy, the findings suggest that the most effective interventions are not necessarily those aimed solely at expanding credit, but those that strengthen internal capacities that enhance business resilience and productivity. Based on the patterns detected, the following specific measures are proposed:

- Subsidised training programmes in digital and technological skills, focused particularly on rural MSMEs or those with low technological absorption capacity.
- Public–private initiatives for continuous training for workers and managers, prioritising skills in adaptive leadership, incremental innovation and change management.
- Corporate governance professionalisation plans, including executive mentoring, family succession support, and strategic management training for managers without formal education.
- Acceleration programmes that foster innovation in products and equipment, with access to microcredits aimed exclusively at incremental improvement and technological renewal projects.
- Strategies to strengthen the working environment through tax incentives for companies that invest in organisational well-being, work–life balance and talent retention practices.

Finally, this study shows that business sustainability in MSMEs should not be interpreted solely as a function of the environment, but as the result of the coordinated activation of internal capabilities that allow limitations to be transformed into opportunities. This perspective opens new lines of research aimed at comparing growth patterns between countries, evaluating the stability of the routes identified through longitudinal analyses, and exploring hybrid models of machine learning and explainability to deepen the understanding of organisational dynamics.

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Institutional Review Board Statement: In accordance with Ecuadorian regulations, this study is exempt from ethical review. This exemption is established under Ministerial Agreement MSP No. 00015-2021 and Ministerial Agreement MSP No. 00005-2022, which state that observational studies of this nature do not require approval from an Institutional Review Board.

Informed Consent Statement: Verbal consent was obtained instead of written consent because the survey was completely anonymous and only requested general information about the companies.

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Appendix A

This appendix summarises the essential computational structure used to implement the models with and without SMOTE. Operational details and ancillary elements are omitted in order to maintain clarity and focus reproducibility on the fundamental stages.

1. Libraries Used

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from sklearn.metrics import classification_report, confusion_matrix
```

2. Stratified division of the dataset (seed for reproducibility)

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size = 0.30,
    stratify = y,
    random_state = 42
)
```

3. Supervised pipeline with standardisation, SMOTE and RF

```
pipeline = Pipeline([
    ('scaler', StandardScaler()), # Estandarización de variables numéricas
    ('smote', SMOTE(random_state = 42)), # Balanceo interno
    ('rf', RandomForestClassifier(random_state = 42))
])
```

4. Model optimisation using grid search (GridSearchCV)

```
param_grid = {
    'rf__n_estimators': [100, 300, 500],
    'rf__max_depth': [10, 20, None],
    'rf__min_samples_leaf': [1, 2, 4],
    'rf__max_features': ['sqrt', 'log2']
}
Execution with cross-validation K = 5
grid = GridSearchCV(
    estimator = pipeline,
    param_grid = param_grid,
    scoring = 'f1_weighted',
```

- ```

cv = 5,
n_jobs = -1,
verbose = 1
)
grid.fit(X_train, y_train)

```
5. Selection of the optimal model

```

best_model = grid.best_estimator_
print("Mejores hiperparámetros:", grid.best_params_)

```
  6. Representative tree and paths to class 5

```

importancias = [tree.feature_importances_ for tree in best_model['rf'].estimators_]
dist = pairwise_distances(importancias)
arbol = best_model['rf'].estimators_[np.argmin(dist.mean(axis = 1))]

```
  7. Predominant decision paths towards class 5

```

print(export_text(arbol, feature_names = X.columns.tolist()))

```

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