Revista Logos Ciencia & Tecnología, 17(3), 10-23 | septiembre-diciembre, 2025
https://revistalogos.policia.edu.co:8443/index.php/rlct

Revista Logos Ciencia & Tecnología
ISSN 2422-4200 (en línea)

Artículos de Investigación

Determinants of Technology-Based University Entrepreneurship in Colombia: A Discriminant Analysis Approach

Determinantes del Emprendimiento Universitario con Base Tecnológica en Colombia: Un Enfoque de Análisis Discriminante

Sandra Patricia Rojas-Berrio*
Andres Isaias Ramirez-Barrera**
Jorge Eliecer Camargo Mendoza***
Oscar Fernando Castellanos Dominguez****

Fecha de recepción: 2025-07-21
Fecha concepto de evaluación: 2025-09-18
Fecha de aprobación: 2025-10-05

https://doi.org/10.22335/rlct.v17i2.2168

Para citar este artículo/To reference this article/Para citar este artigo: Rojas-Berrio, S. P.; Ramirez-Barrera, A.I.; Camargo Mendoza, J.E. & Castellanos Dominguez O. F. (2025). Determinants of Technology-Based University Entrepreneurship in Colombia: A Discriminant Analysis Approach. *Revista Logos Ciencia & Tecnología, 17*(3), 10-23. https://doi.org/10.22335/rlct.v17i2.2168.

Nota de autor: El presente artículo se deriva del proyecto de investigación titulado Revisión Sistemática de Literatura y Meta-Análisis Para las Prioridades de Investigación en Marketing y ha sido financiado por la Universidad Nacional de Colombia.

Author's Note: This article is derived from the research project entitled Revisión Sistemática de Literatura y Meta-Análisis Para las Prioridades de Investigación en Marketing and has been funded by the Universidad Nacional de Colombia.

ABSTRACT

This study identifies and analyzes the determinants of technology-based university entrepreneurship (TBUE) in Colombia, focusing on the factors that differentiate universities actively engaging in entrepreneurial initiatives from those with limited participation. Using a discriminant analysis approach, the research examines a sample of Colombian higher education institutions (HEIs) that have implemented technology transfer, innovation, and entrepreneurship programs. The study incorporates institutional indicators such as research capacity, innovation output, industry collaboration, and academic orientation.

The findings reveal that variables related to research and innovation capacity, including the number of patents, research groups, and collaboration agreements with the private sector, are the strongest discriminants between universities with high and low TBUE performance. The model correctly classified 84% of the universities, confirming its robustness and explanatory power. Furthermore, the results highlight the importance of organizational culture, strategic orientation, and institutional policy in fostering entrepreneurship ecosystems within universities.

These findings provide valuable insights for policymakers, university administrators, and stakeholders seeking to strengthen the role of HEIs in Colombia's innovation

* Autor de correspondencia.
Universidad Nacional de Colombia. Bogotá, D.C., Colombia.
sprojasb@unal.edu.co
https://orcid.org/0000-0002-1148-3779

** Universidad Nacional de Colombia. Bogotá, D.C., Colombia.
anramirezb@unal.edu.co
https://orcid.org/0000-0003-2558-7541

*** Universidad Nacional de Colombia. Bogotá, D.C., Colombia.
jecamargom@unal.edu.co
https://orcid.org/0000-0002-3562-4441

**** Universidad Nacional de Colombia. Bogotá, D.C., Colombia.
ofcastellanosd@unal.edu.co
https://orcid.org/0000-0001-6604-6368

system. By identifying the main determinants of TBUE, the study contributes to the design of targeted strategies that enhance the country's capacity for technology-based entrepreneurship and sustainable economic development.

Keywords: university entrepreneurship, technology transfer, innovation, discriminant analysis, Colombia

1. Introduction

Universities play a key role in innovation ecosystems by articulating the functions of teaching, research, and extension. The third university mission —extension— has evolved towards a logic of knowledge transfer and collaboration with the socio-economic environment (Etzkowitz & Leydesdorff, 2000). This connection is key to the emergence of TBEs, as it allows the transfer of research results to the productive sector. However, the success of this articulation depends on institutional structures that promote market-oriented innovation, interdisciplinary collaboration, and linkages with external actors (Benneworth & Jongbloed, 2010).

In these ecosystems, an essential condition for the generation of TBEs in universities is the existence of a critical mass of researchers and scientific capabilities. Thus, universities with a larger number of researchers, publications and patents are more likely to translate knowledge into marketable innovations (Cunningham & Link, 2015). In addition, evidence indicates that critical mass not only allows for subject specialisation, but also for internal collaboration, facilitating the emergence of innovative ideas that can become entrepreneurial initiatives (Mowery et al., 2001).

In the Colombian ecosystem, research groups are the structural nucleus from which a large part of scientific and technological production originates. This assumes that, in the university context, consolidated groups allow the formation of knowledge networks, access to funding and the involvement of students in R&D processes (Organisation for Economic Co-operation and Development [OECD], 2013). Likewise, the existence of categorised groups with ongoing projects has been a facilitating factor for the emergence of TBEs (González-Pernía et al., 2012).

In this context, the presence of researchers with doctoral training, international experience and high-impact publications also influences the emergence of TBEs. These researchers tend to be better able to identify technological opportunities, manage international networks and attract investment (Audretsch et al., 2006). In addition, their academic leadership is key to inspiring young researchers and students with an entrepreneurial profile (Bercovitz & Feldman, 2008).

Scientific publications, patents, software, prototypes, and utility models are products that can become the basis for new ventures. Applied or market transferable research results are strategic inputs for TBEs (Siegel et al., 2003). Intellectual protection and subsequent commercialisation require support structures such as technology transfer offices (TTOs), university spin-offs and mentoring networks (Wright et al., 2008).

In this context, incentive systems that exclusively reward academic publication limit the emergence of TBEs. In contrast, models that recognise technology transfer, participation in spin-offs or patenting can foster an entrepreneurial culture among researchers (Goethner et al., 2012). The creation of favourable institutional conditions —such as flexible licensing or royalty sharing— are key to stimulating entrepreneurial activity (Link et al., 2007).

In addition, TBEs often emerge within communities of practice and collaborative networks. Access to resources, collective peer support and membership in entrepreneurial university ecosystems increase the chances of success (Clarysse et al., 2005). Universities that foster incubators, collaborative spaces and partnerships with companies often facilitate these processes, allowing entrepreneurs to access mentoring, funding, and markets (Fini et al., 2011).

Also, entrepreneurial intentions in students and researchers depend on individual factors (such as self-efficacy) and institutional factors (such as the learning environment). University entrepreneurship education has been shown to increase the likelihood of students starting businesses, especially if it is linked to real projects or practical skills (Fayolle & Gailly, 2015). However, TBEs performance also requires continuous mentoring, management skills and access to business networks (Walter et al., 2013).

Despite regulatory advances and the growth of scientific capacities, there are still barriers to the consolidation of technology-based ventures in Colombian universities.

The weak articulation between research and transfer, the scarcity of specific incentive policies and the limitations in entrepreneurial training make it difficult for scientific results to translate into economic impact. Against this backdrop, the question arises: What conditions determine the success of technology-based entrepreneurship in universities in Colombia? This research seeks to contribute to the understanding of these factors, proposing recommendations to improve the institutional environment and university capacities for entrepreneurial innovation.

2. Method

This study adopts a quantitative, cross-sectional design based on secondary data collected from Colombian higher education institutions (HEIs). The objective is to identify the factors that discriminate between universities with high and low levels of technology-based university entrepreneurship (TBUE) through a discriminant analysis approach.

Linear discriminant analysis (LDA) is a controlling supervised dimensionality reduction method for the analysis of high-dimensional data (Wan et al., 2023). Namely, while Fisher's discriminant analysis (FDA) is a descriptive method used to evaluate the discriminatory capacity of variables, LDA is used for class prediction (Graf et al., 2024). Discriminant function analysis is a technique that allows researchers to explore, examine and describe in parallel the differentiation between two or more mutually exclusive groups with respect to different continuous variables (Brown & Tinsley, 1983).

The main purpose of dimensionality reduction is to transform the high dimensional data into a low dimensional subspace and to preserve the discriminatory information present in the high dimensional data (Wan et al., 2023). LDA is a parametric method that requires the estimation of two parameters: class means and the covariance matrix (Graf et al., 2024). Additionally, this analysis assumes multivariate normality of the data, as well as homogeneity of the covariance matrix between classes (Graf et al., 2024). To perform the LDA, the following procedure was used as a guide, and the steps followed were as indicated below (Kavlakoglu, 2024):

- Step 1: Set up environment
- Step 2: Install and import relevant libraries
- Step 3: Read and load the data
- Step 4: Preprocess the data
- Step 5: Perform exploratory data analysis
- Step 6: Split the data set
- Step 7: Implement LDA
- Step 8: Visualize the data
- Step 9: Classify the data with random forest
- Step 10: Evaluate the LDA model

For initial steps was performed using the programming language Python and included the generation of pair plots, histograms, and correlation heatmaps. The programming language R was used for the LDA.

2.1 Data

This section presents the main findings from the discriminant analysis conducted to identify the variables that differentiate Colombian universities with high and low levels of technology-based entrepreneurship (TBUE). The results are organized into three subsections: (1) descriptive statistics, (2) discriminant function results, and (3) validation of the discriminant model.

The data for this research work come from the following sources: Ministerio de Ciencia Tecnología e Innovación (Minciencias, n.d.), Ministerio de Educación Nacional (MEN, 2023a, 2023b), and Ministerio de Tecnologías de la Información y las Comunicaciones (MinTIC, 2024). Table 1 presents data specification and sources of information for the independent variables used in the LDA. The final number of observations of the data set corresponds to 4900 as of the collection, integration, pre-processing and clear up from the diverse sources.

The basic unit of observation corresponds to the dichotomous variable TBEs for the research groups of the 86 HEIs in Colombia registered in the profiles of the Sistema Nacional de Información de la Educación Superior (SNIES) (MEN, 2024).

Table 1.

Variables.

Variable	Data specification	Source
Profile of members	The profile of members variable represents the total score of the indicator by type of member defined by Minciencias for the research groups: ▪ Emeritus researcher ▪ Senior researcher ▪ Research associate ▪ Junior researcher ▪ Doctoral student ▪ Master's or clinical specialty student ▪ Young researcher ▪ Undergraduate student ▪ Member linked to doctorate ▪ Member linked to master's or clinical specialty ▪ Member linked to undergraduate ▪ Member linked to specialization ▪ Member linked	Minciencias (2024)
Number of students	Total quantity of students enrolled HEI as of the cut-off date of December 2023.	MEN (2023b)
Number of teachers	Total quantity of professors joined HEI as of the cut-off date of December 2023.	MEN (2023b)
Number of research groups	Total quantity of research groups per HEI as of the cut-off date of June 2024.	Minciencias (2024)
Patents granted	Total quantity of patents granted per HEI as of the cut-off date of December 2023.	MinTIC (2024)
TBEs	Total quantity of TBEs per HEI as of the cut-off date of June 2024.	Minciencias (2024)

Source: Own elaboration.

Machine learning (ML) seeks to find a relationship between dependent and independent variables (Kapse et al., 2024). The dependent variable of this study is the TBEs with two classes (0 = Negative; 1 = Positive), while the independent variables are the following: profile of members, number of students, number of teachers, number of research groups, and patents granted.

2.2 Sample Bias

This analysis included only data from 86 HEIs registered in the SNIES profiles. Information on TBEs was limited to those registered and validated by Minciencias (2024) in the profiles of research groups. The patents granted were limited to those officially recognised by MinTIC (2024).

2.3 Data Time Period

The data covers the period from December 2023 to June 2024.

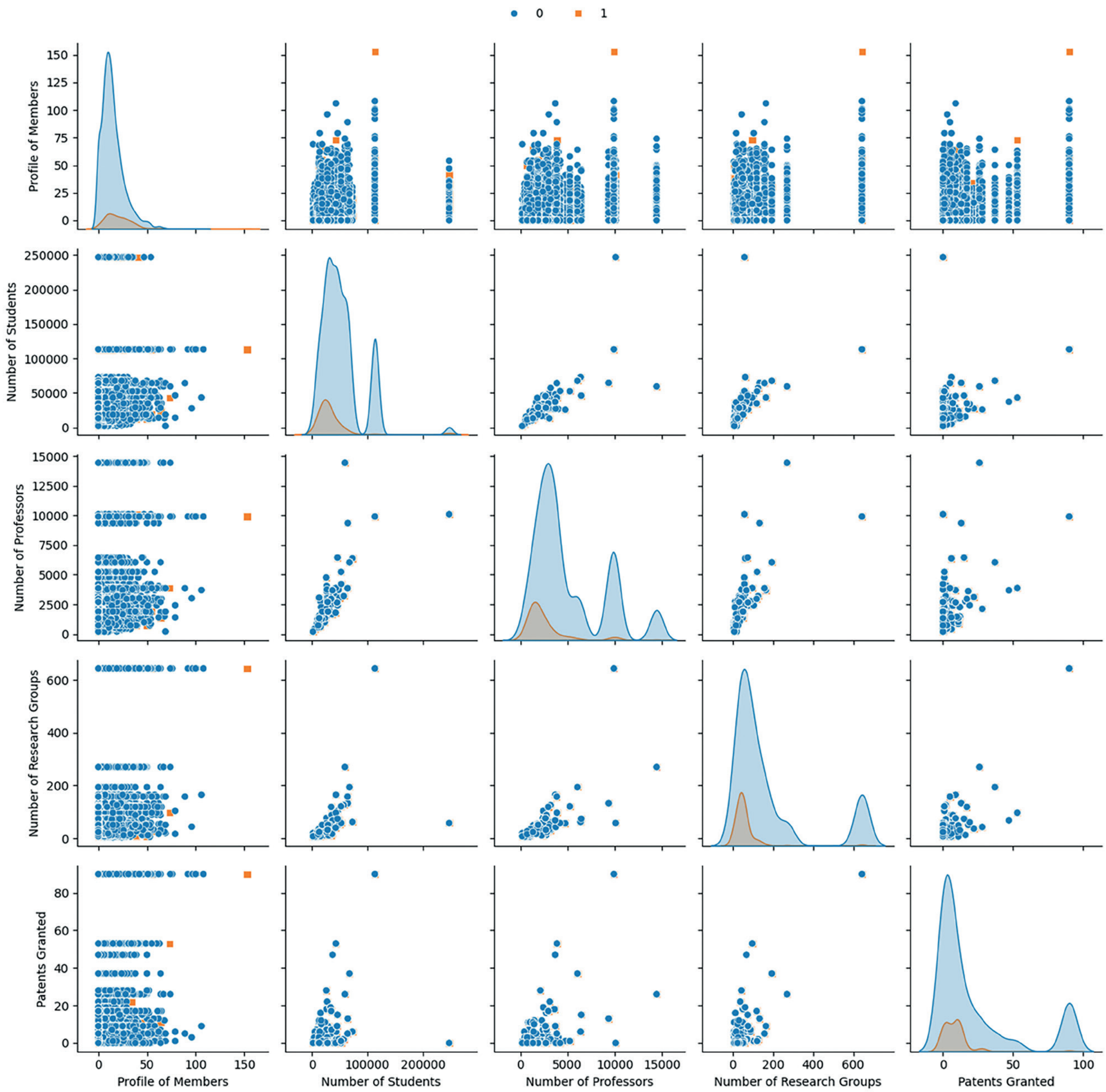
3. Results

3.1 Exploratory Data Analysis

Prior to conducting the LDA, an exploratory data analysis was carried out to assess variable distributions, detect potential outliers, and understand inter-variable relationships (Kavlakoglu, 2024). Figure 1 represents the relationships of the variables by a pair plot. The diagram illustrates how the variables: profile of members, number of students, number of professors, number of research groups, and patents granted, relate with the dichotomy of the variable TBEs. The diagonal plot elements stand for the distribution of each variable, while the off-diagonal plot elements stand for the scatter plots for each pair of variables (Kavlakoglu, 2024). With respect to profile of members, there is no correlation with the other variables.

Figure 1.

Pair plot of TBEs dataset.

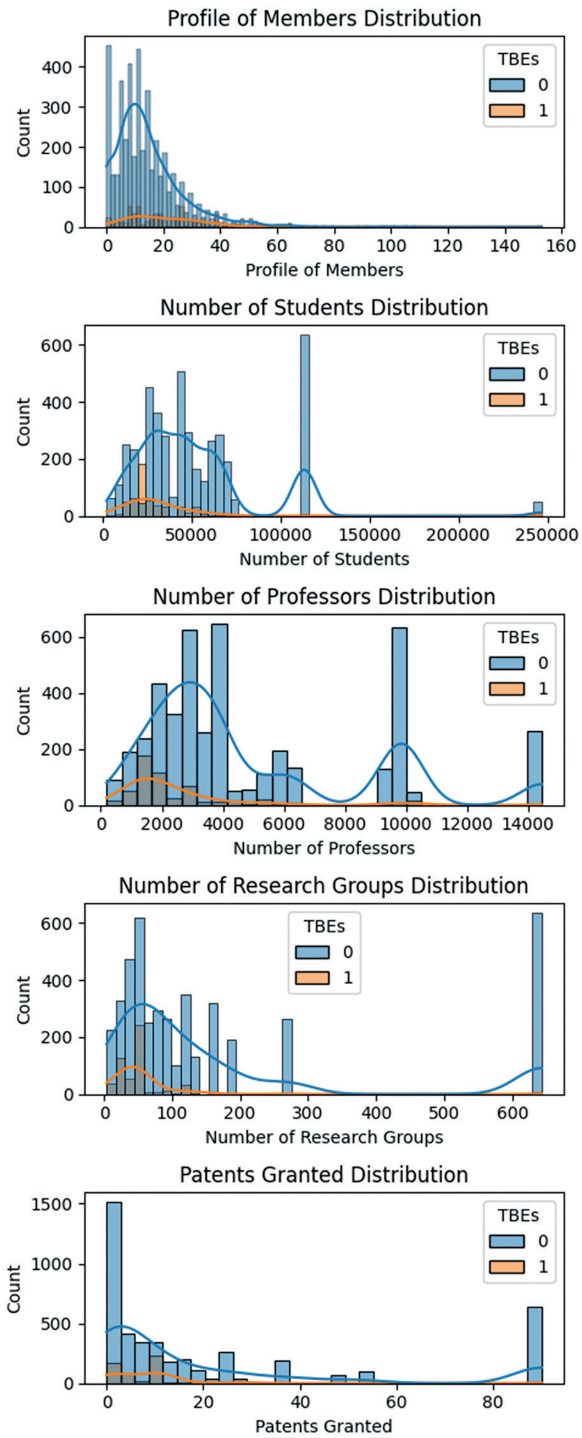


Source: Own elaboration.

Figure 2 represents the histograms of the variables. This graph is composed of five histograms that illustrate the distribution of the data set for the dichotomy of the variable TBEs. The histograms reveal an imbalanced dataset, highlighting differences between 0 and 1 (TBEs) in relation to profile of members, number of students, number of professors, number of research groups, and patents granted.

Figure 2.

Variables distribution.



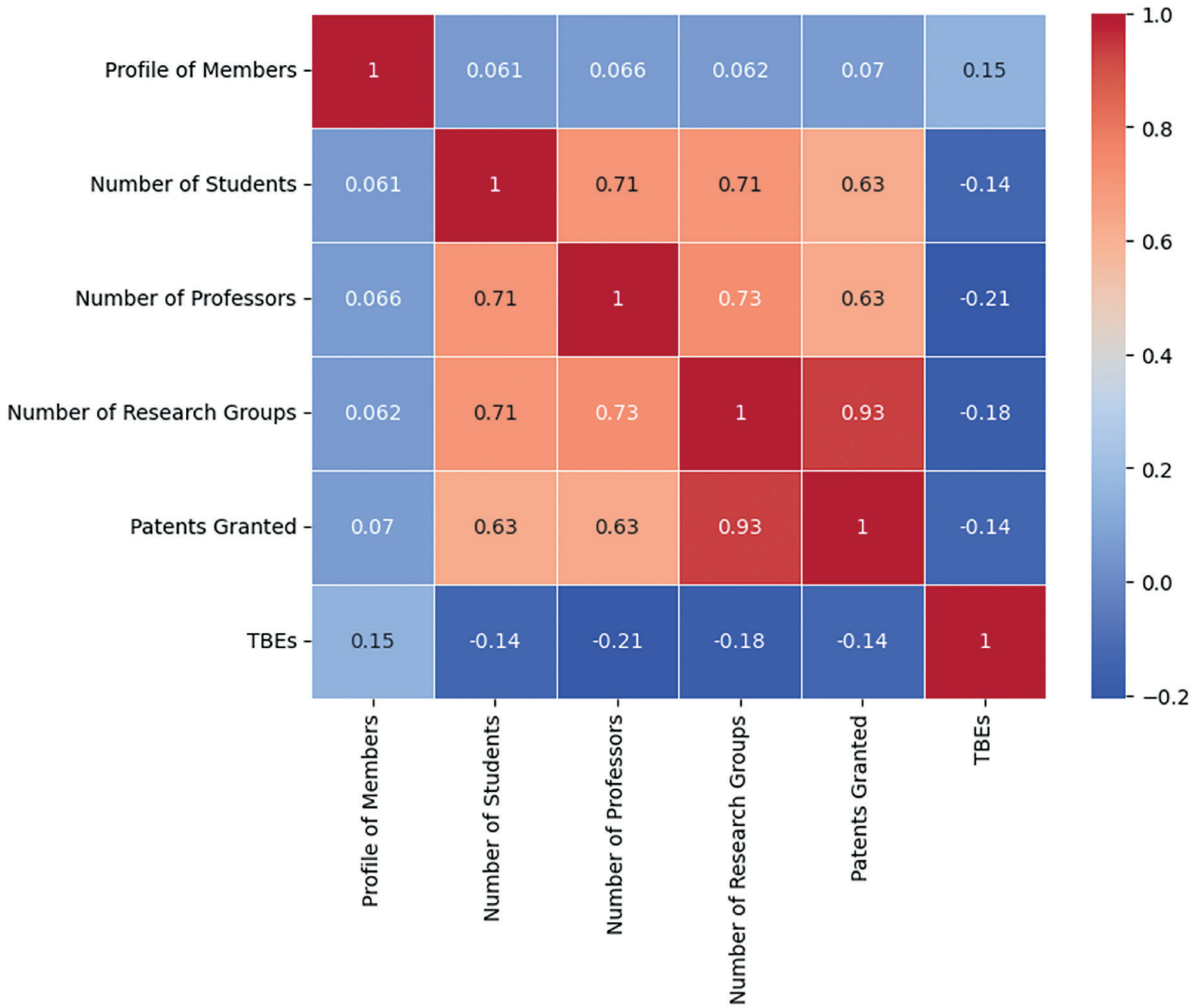
Source: Own elaboration.

Figure 3 represents the correlation heatmap on the relationships of the data set. The variables include profile of members, number of students, number of professors, number of research groups, patents granted, and TBEs. The heatmap values range from 0.21 to 1. Values closer to 1 signify a strong positive correlation and vice versa (Kavlakoglu, 2024).

About the positive correlations, the highest are as follows: number of research groups/patents granted (0.93), number of research groups/number of professors (0.73), and number of professors/number of students (0.71). On the other side, TBEs have negative correlations with number of professors (-0.21), number of research groups (-0.18), number of students (-0.14), and patents granted (-0.14).

Figure 3.

Correlation heatmap.



Source: Own elaboration.

3.2 LDA

Regarding the calculation of the discriminant function, the results of the a priori probabilities of the groups were as follows. Only 11.0% of the data set is positive and 89.0% is negative with respect to TBE. Table 2 below shows the GROUP means for the following variables: profile of members, number of students, number of professors, number of research groups, and patents granted. Therefore, for the negative group (0) it should be noted that the means are higher with respect to the positive group (1) for the variables: number of students (52401.68), number of professors (4995.999), number of research groups (172.0221), and patents granted (21.876999). On the other side, profile of members (20.60617) has a higher mean in the positive group (1).

Table 2.

Group means.

	Profile of members	Number of students	Number of professors	Number of research groups	Patents granted
0	14.55528	52401.68	4995.999	172.0221	21.876999
1	20.60617	36213.85	2569.670	59.5118	8.949183

Source: Own elaboration.

On the coefficients of linear discriminants (Table 3), their interpretation helps in understanding the contribution of each of the variables: profile of members, number of students, number of professors, number of research groups, and patents granted to the classification. Thus, for a dichotomous variable with only two classes, the result of its single linear discriminant 1 (LD1) is presented in Table 3. The variables that award the greatest contribution to the TBEs variable are profile of members (4.848090e-02), patents granted (1.974332e-02), and number of students (5.444515e-06).

Table 3.

Coefficients of linear discriminant.

Variable	LD1
Profile of members	4.848090e-02
Number of students	5.444515e-06
Number of professors	-1.780759e-04
Number of research groups	-4.694758e-03
Patents granted	1.974332e-02

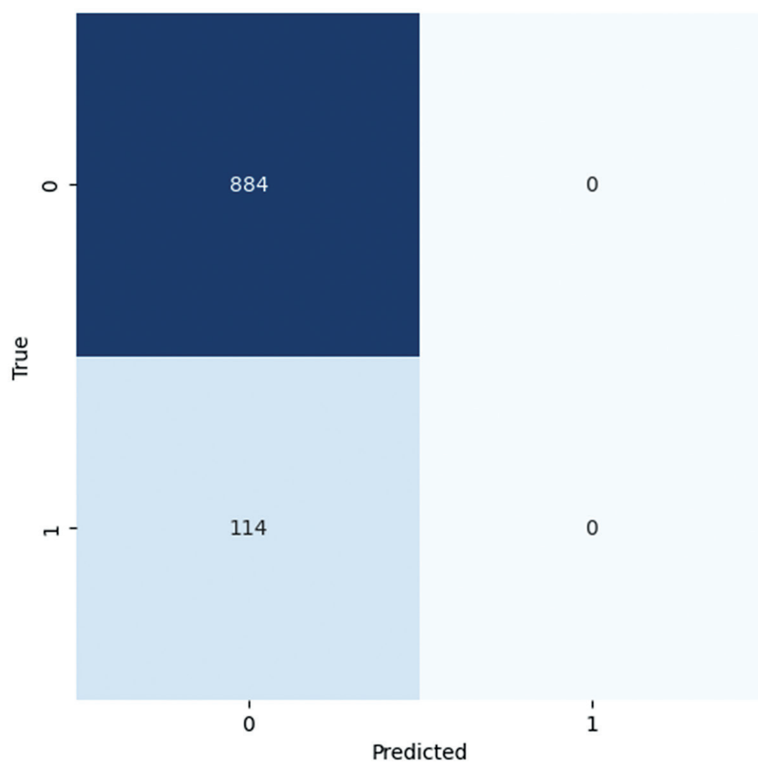
Source: Own elaboration.

These coefficients suggest that profile of members is the most influential predictor in the classification of TBEs, reinforcing the idea that the composition and quality of human capital in research groups is more determinant than structural size alone. Notably, the negative coefficients for number of professors and number of research groups may imply that, in some HEIs, larger structures do not necessarily promote entrepreneurship unless coupled with effective knowledge transfer mechanisms.

Finally, to evaluate the LDA model, a confusion matrix was used (Figure 4). The results indicate an accuracy: 0.89 with respect to model performance.

Figure 4.

Confusion matrix.



Source: Own elaboration.

4. Discussion

This section presents the main findings from the discriminant analysis conducted to identify the variables that differentiate Colombian universities with high and low levels of technology-based entrepreneurship (TBUE). The results are organized into three subsections: (1) descriptive statistics, (2) discriminant function results, and (3) validation of the discriminant model. The analysis underscores the pivotal role of research groups and scientific capabilities in fostering TBEs within universities. The data reveal that universities with larger research units, more faculty members, and a higher number of patents tend to have an increased likelihood of generating

TBEs, aligning with previous studies (Cunningham & Link, 2015).

Interestingly, the descriptive statistics indicate that the non-TBE universities generally have higher average numbers in the variables of research groups, professors, and students, suggesting that size or volume of activity alone may be insufficient for TBE emergence. This points towards other qualitative factors, such as the nature of research or institutional support, influencing entrepreneurship development.

The correlation analysis provides valuable insights, the strong positive relationships between Research groups and patents, as well as between the number of professors and research groups, suggest that institutional research infrastructure significantly impacts the potential for innovation output. Conversely, negative correlations involving TBEs indicate that, in this dataset, larger academic structures do not always directly translate into entrepreneurial activity, hinting at complex underlying dynamics.

Additionally, the low negative correlation between TBEs and variables such as number of students, professors, and patents granted suggests that other factors, possibly institutional policies, cultural aspects, or external collaborations, may mediate these relationships. This underscores the multifaceted nature of entrepreneurial success within universities.

The LDA results reveal that only about 11.0% of the universities are classified as positive TBEs, indicating a significant imbalance in the dataset and possibly reflecting the nascent stage of entrepreneurial activity in Colombian universities. This imbalance must be considered when designing policy interventions.

Additionally, the mean comparisons between the negative and positive groups show that universities with TBEs, although fewer in number, tend to have a higher average profile of members, indicating that human capital, particularly researcher diversity and leadership, plays a crucial role in fostering enterprise creation.

The variables with the most substantial contribution to the LDA —profile of members, patents granted, and number of students— highlight key areas for strategic focus. Enhancing researcher diversity, patenting activities, and student engagement may be essential pathways to stimulate TBE formation. It is noteworthy that the variable ‘profile of members’ has a higher mean in universities classified as TBEs, suggesting that faculty profile, especially the presence of doctoral-level researchers with international experience, might be a determinant factor, consistent with previous literature (Audretsch et al., 2006).

The model’s high accuracy, with an 89% correct classification rate, demonstrates that the selected variables are relevant predictors for TBE emergence. However, the moderate class imbalance suggests further model refinement or inclusion of additional variables could improve predictive power and robustness.

These findings emphasize the importance of institutional policies aimed at talent retention, internationalization, patenting incentives, and fostering collaborative research environments. Such measures could increase the likelihood of university-based start-ups, addressing gaps identified in the Colombian context. Additionally, the results also underscore that merely increasing research activity or infrastructure without concurrent entrepreneurial support mechanisms may not suffice. Comprehensive strategies involving mentorship, networking, and institutional culture shifts are essential to convert scientific research into viable enterprises.

Finally, the integration of qualitative factors such as organizational culture, entrepreneurial mindset, and external collaboration networks, although not directly captured in the quantitative data, are crucial to fully understand and promote TBE development in Colombian universities.

5. Conclusions

In conclusion, this study highlights the complex interplay between institutional research capacity, human capital, and entrepreneurial outputs within Colombian universities. The significant variables identified —profile of members, patents, and students— emphasize areas for targeted policy interventions. The findings support the hypothesis that larger and more research-active universities have a higher potential for TBE generation, but size alone does not guarantee entrepreneurial success, indicating the importance of quality, support, and strategic focus.

The correlation analysis reveals that the structural components of university research, especially research groups and faculty quality, are strongly linked with innovation outputs like patents, which serve as crucial inputs for new ventures. Moreover, the negative associations between TBEs and variables like research groups or faculty numbers suggest that scale alone may not translate into entrepreneurship; instead, specific institutional supports and entrepreneurial cultures are necessary catalysts.

The discriminant analysis confirms that individual and institutional characteristics, particularly the profile of members and patenting activity, are critical in predicting TBE emergence. This insight can guide universities and policymakers to prioritize talent development and intellectual property management. The high model accuracy indicates the effectiveness of these variables as predictors, providing a foundation for developing data-driven policies to foster entrepreneurial universities in Colombia. The results advocate for an integrated approach that combines strengthening research infrastructure, incentivizing patenting… and cultivating an entrepreneurial mindset among faculty and students.

Future research should consider incorporating qualitative dimensions such as institutional culture, leadership styles, and the role of informal networks in fostering academic entrepreneurship. Likewise, longitudinal studies could help track the evolution of TBEs in response to policy changes or institutional reforms, offering a dynamic perspective on entrepreneurial development in higher education (HE).

6. References

Aldana-Bermúdez, J., Rojas-Romero, J., & Cortés, G. (2020). University entrepreneurship and innovation ecosystems in Latin America: Challenges and perspectives. Journal of Entrepreneurship in Emerging Economies, 12(4), 567–586. https://doi.org/10.1108/JEEE-01-2020-0021

Audretsch, D. B. (2014). From the entrepreneurial university to the university for the entrepreneurial society. Journal of Technology Transfer, 39(3), 313–321. https://doi.org/10.1007/s10961-012-9288-1

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Clark, B. R. (1998). Creating entrepreneurial universities: Organizational pathways of transformation. Pergamon.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101

Etzkowitz, H. (2008). The triple helix: University–industry–government innovation in action. Routledge.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and "Mode 2" to a triple helix of university–industry–government relations. Research Policy, 29(2), 109–123. https://doi.org/10.1016/S0048-7333(99)00055-4

Guerrero, M., & Urbano, D. (2012). The development of an entrepreneurial university. Journal of Technology Transfer, 37(1), 43–74. https://doi.org/10.1007/s10961-010-9171-x

Guerrero, M., & Urbano, D. (2016). The impact of Triple Helix agents on entrepreneurial innovations' performance: An inside look at enterprises located in an emerging economy. Technological Forecasting and Social Change, 112(1), 107–118. https://doi.org/10.1016/j.techfore.2016.08.003

Londoño-Pineda, C., Cardona, D., & Cano, C. (2021). University entrepreneurship in Colombia: The influence of institutional policies and regional contexts. International Journal of Entrepreneurial Behavior & Research, 27(4), 925–944. https://doi.org/10.1108/IJEBR-07-2020-0501

Mungaray, A., Ramírez, S., & Fuentes, C. (2019). Entrepreneurial universities and innovation ecosystems in Latin America: Empirical evidence from Mexico and Colombia. Revista de Innovación y Desarrollo, 8(2), 145–164.

Röpke, J. (1998). The entrepreneurial university: Innovation, academic knowledge creation, and regional development in a globalized economy. Working Papers on Innovation Studies, 12(4), 1–32.

Rothaermel, F. T., Agung, S. D., & Jiang, L. (2007). University entrepreneurship: A taxonomy of the literature. Industrial and Corporate Change, 16(4), 691–791. https://doi.org/10.1093/icc/dtm023

Scott, W. R. (2008). Institutions and organizations: Ideas and interests (3rd ed.). SAGE Publications.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171–180. https://doi.org/10.1002/smj.4250050207

World Medical Association. (2013). World Medical Association Declaration of Helsinki: Ethical principles for medical research involving human subjects. JAMA, 310(20), 2191–2194. https://doi.org/10.1001/jama.2013.281053