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Intellectual capital and organizational climate as predictors of scientific production in a Peruvian university: An analysis based on the Neutrosophic 2-Tuple Linguistic Model and PLS-SEM

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Abstract. Scientific production is a key performance indicator in higher education, which has motivated the search for factors that may influence its development. This study aims to analyze the impact of intellectual capital and organizational climate on scientific production at the National Intercultural University of the Amazon in Peru. Partial Least Squares Structural Equation Modeling (PLS-SEM) is used, with a sample consisting of 90 professors. Professors were surveyed using the neutrosophic 2-tuple linguistics model. The neutrosophic 2-tuple linguistic method allows teachers to express their opinions linguistically, which is more appropriate in complex decision-making situations. This method maintains accuracy in aggregations. Furthermore, accuracy is maintained because the calculations contain values of truth, indeterminacy, and falsity. This tool of Computing with Words is hybridized with PLS-SEM, which is a novelty.

Keywords: Intellectual capital, organizational climate, scientific production, higher education, PLS-SEM, 2-tuple linguistics model, Neutrosophic 2-tuple linguistic model, Computing with Words (CWW).

1. Introduction

Scientific production in higher education institutions is a key indicator of academic and social development. Recent studies show an increase in scientific output at Latin American universities, albeit with persistent challenges. Scientific production is a key component for the academic, technological, and social development of countries. At the university level, its promotion not only enables the generation of new knowledge but also improves institutional positioning, influences public policies, and strengthens educational processes. In this context, intellectual capital and organizational climate have been identified as relevant factors influencing scientific productivity.

Intellectual capital, comprised of human, structural, and relational capital, represents the set of intangible assets possessed by an organization that facilitates innovation and knowledge. Recent evidence further reinforces these results: intellectual capital significantly influences organizational performance in universities, with this effect being enhanced by intrinsic motivation. Furthermore, a specific scale has been proposed to measure intellectual capital in academic contexts, highlighting that the human, social, and organizational dimensions have a direct impact on scientific productivity. In turn, structural capital, related to knowledge management systems and institutional support, allows for the optimization of research processes. Finally, relational capital—links with academic networks, industries, or other universities—enhances knowledge transfer and scientific collaboration. Scientific production, which encompasses the generation and dissemination of knowledge, social impact, and academic recognition, is significantly influenced by the organizational climate, as it affects the commitment and satisfaction of university staff.

In parallel, the organizational climate, understood as the shared perceptions of an institution's members about their work environment, has also been shown to be a decisive factor in motivation, commitment, and academic performance. A favorable institutional climate encourages mentoring, collaboration, and leadership, all of which positively impact scientific production. Recent studies also highlight that the organizational climate can enhance the effect of intellectual capital by strengthening faculty members' intrinsic motivation. Thus, the interaction between intellectual capital and the organizational climate becomes a relevant area of study for understanding how universities can improve their research performance.

The growing competition among universities to excel in national and international rankings has led to increased attention paid to improving scientific output. Institutions that manage to establish a favorable research environment not only increase their visibility but also attract high-caliber students and scholars. In this context, universities need to understand the interrelationship between intellectual capital and organizational climate, and how these factors can be managed to maximize their impact on scientific output. In the higher education sector, universities should focus on developing intellectual capital and fostering a positive organizational climate to improve scientific output.

Although numerous studies explore the influence of intellectual capital and organizational climate on scientific production, most of this research is conducted in international contexts, with little attention paid to the specific characteristics of Peruvian universities. Many of our country's institutions face structural challenges such as limited investment in research, insufficient infrastructure, and gender inequalities in academic production, which could significantly alter these relationships. Therefore, universities must identify and address these limitations to create a more favorable environment for research and innovation.

Although a growing body of research has examined the impact of intellectual capital on university performance, the integration of organizational climate as a complementary predictor remains limited. By offering empirical evidence in an underexplored academic context, this research aims not only to contribute to scientific knowledge in the area but also to provide practical recommendations for strengthening institutional research capacities.

Structural Equation Modeling (SEM) has gained popularity in social science research, particularly for analyzing complex relationships between constructs and scientific output [1]. SEM, including Partial Least Squares (PLS) techniques, is useful for exploratory and predictive assessments of causal relationships between variables in theoretical models [2, 3]. This methodology has been applied in various fields, including library and information science, consumer behavior, and psychological and educational research [4-15]. While SEM offers significant benefits, its application requires a rigorous process to ensure the reliability of the study's conclusions.

In this paper, we combine the SEM method with the 2-tuples linguistic method [16]. The linguistic 2-tuple method is a technique in Computing with Words (CWW) that allows linguistic information to be represented and manipulated without loss of precision. CWW is an information-processing approach that uses linguistic terms instead of numerical values [17]. Rather than saying "temperature = 37.5 °C," we say "high temperature." This is useful when the information is vague, imprecise, or subjective, as in human evaluations, medical decisions, or social judgments.

Specifically, we use the neutrosophic 2-tuples linguistic model, where the fuzziness is extended to a neutrosophic model [18]. Neutrosophy is the theory that extends classical and fuzzy logic by considering three independent components: Truth (T), Falsehood (F), and Indeterminacy (I). Instead of saying that something is "70% true", one can say that it is "70% true, 20% false, and 10% indeterminate". This is very useful when there is contradictory or incomplete information. The neutrosophic 2-tuple method combines the advantages of both methods: the linguistic expressiveness of 2-tuples and the uncertainty-handling capability of neutrosophy.

This approach has begun to expand to areas where uncertainty, ambiguity, and subjectivity are part of everyday life. These include ([19-25]): group decision making, to evaluate gender equitable policies from the perspective of Latin American professor's, multiple attribute group decision making, typhoon vulnerability assessment of civil engineering structures, feasibility assessment in industrial projects, core competencies evaluation of track and field students in sports colleges, among others.

In short, any field where nuanced human judgment needs to be modeled can benefit from this approach. Therefore, a group of 90 faculty members at the National Intercultural University of the Amazon (UNIA) were surveyed during the 2023-2024 academic year. They were asked to provide their opinions based on a linguistic scale containing triplets of linguistic values, as part of the neutrosophic 2-tuple method. These data allow respondents to express themselves naturally, while also capturing the uncertainty and indeterminacy inherent modeled by neutrosophy. The data are then transformed into equivalent real values, which are used to study the influence of intellectual capital and organizational climate on scientific output at the National Intercultural University of the Amazon. In this final step, Partial Least Squares Structural Equation Modeling (PLS-SEM) is applied. Although SEM has been hybridized with other methods [4, 8-12], this is the first time it has been combined with a neutrosophic 2-tuple linguistics model, to the best of the authors' knowledge.

The article is divided into a Materials and Methods section, where the neutrosophic 2-tuple linguistic model and the PLS-SEM method are recalled. The following section contains the results obtained, next, there is a Discussion, and the article finishes with a Conclusion.

2. Materials and Methods

This section contains the basic components of the Neutrosophic2-Tuple Linguistic Model and the PLS-SEM method.

2.1 Neutrosophic 2-Tuple Linguistic Model

Definition 1 ([17]). $S = \{s_0, s_1, \dots, s_g\}$ is a set of linguistic terms, $\beta \epsilon [0, g]$ is a real value that represents the result of a symbolic operation. The linguistic 2-tuple which expresses the information equivalent to β is calculated using the function Δ:

$$\Delta: [0, g] \rightarrow S \times [-0.5, 0.5)$$

$$\Delta(\beta) = (s_i, \alpha) \quad (1)$$

Here s_i satisfies $i = \text{round}(\beta)$ and $\alpha = \beta - i, \alpha \in [-0.5, 0.5)$, "round" is the usual rounding operator. s_i is the index label closest to β and α is the value of the symbolic translation.

Let us note that $\Delta^{-1}: \langle S \rangle \rightarrow [0, g]$ is defined as $\Delta^{-1}(s_i, \alpha) = i + \alpha$. So, a linguistic 2-tuple $\langle S \rangle$ is identified with its numerical value in $[0, g]$.

Let us suppose that $S = \{s_0, \dots, s_g\}$ is a *2-Tuple Linguistic Set* (2TLS) with odd cardinality g+1. It is defined for $(s_T, a), (s_I, b), (s_F, c) \in L$ and a, b, c $\in [0, g]$, where $(s_T, a), (s_I, b), (s_F, c) \in L$ individually express the degree of truthfulness, indeterminacy, and falsehood by 2TLS. A *2-tuple Linguistic Neutrosophic Number* (2TLNN) is defined with Equation 2:

$$l_j = \left\{(s_{T_j}, a), (s_{I_j}, b), (s_{F_j}, c)\right\} \quad (2)$$

Where $0 \le \Delta^{-1}(s_{T_j}, a) \le g$, $0 \le \Delta^{-1}(s_{I_j}, b) \le g$, $0 \le \Delta^{-1}(s_{F_j}, c) \le g$, and $0 \le \Delta^{-1}\left(s_{T_j}, a\right) + \Delta^{-1}\left(s_{I_j}, b\right) + \Delta^{-1}(s_{F_j}, c) \le 3g$.

The scoring and accuracy functions allow us to rank 2TLNN.

Let $l_1 = \left\{(s_{T_1}, a), (s_{I_1}, b), (s_{F_1}, c)\right\}$ be a 2TLNN in L, the scoring and accuracy functions in l_1 are defined in Equations 3 and 4, respectively:

$$S(l_1) = \Delta\left\{\frac{2g + \Delta^{-1}\left(s_{T_1}, a\right) - \Delta^{-1}\left(s_{I_1}, b\right) - \Delta^{-1}\left(s_{F_1}, c\right)}{3}\right\}, \Delta^{-1}(S(l_1)) \in [0, g] \quad (3)$$

$$H(l_1) = \Delta\left\{\frac{g + \Delta^{-1}\left(s_{T_1}, a\right) - \Delta^{-1}\left(s_{F_1}, c\right)}{2}\right\}, \Delta^{-1}(H(l_1)) \in [0, g] \quad (4)$$

2.2 Basic Notions of the PLS-SEM Model

Structural Equation Modeling (SEM) is a very powerful multivariate statistical tool that allows the analysis of complex relationships between variables, both observed and latent [1-3]. It can directly measure observed variables (age, income, item responses). Latent variables are not directly measured but are inferred from observed variables (e.g., self-esteem measured through several questions).

SEM models causal or correlational relationships between variables. It allows for the measurement of unobservable constructs (such as motivation, stress, or intelligence) through observable indicators. It assesses direct, indirect, and total effects between variables. It combines techniques such as confirmatory factor analysis and regression analysis in a single framework.

The main objective of SEM is to test theoretical models of how different variables relate to each other. It is very useful in social sciences, psychology, education, health, and marketing, where the phenomena studied are often complex and not directly observable. The graphical representation of variables is part of the method. Observed variables are drawn as squares and latent variables as circles. Relationships are indicated by arrows (a single one for direct effects and, a double one for correlations).

There are mainly two types of models in SEM:

1. Path Analysis
   a. Only includes observed variables.
   b. It resembles multiple regression but allows for estimating direct, indirect, and total effects between variables. It is useful for exploring simple causal relationships.
2. Models with Latent Variables.
   a. They include both observed and latent variables (constructs not directly measurable, such as motivation or anxiety).
   b. They are subdivided into:
      - Confirmatory Factor Analysis (CFA): Evaluates how observed variables reflect latent constructs.
      - Structural Model: Estimates the relationships between latent constructs.

As we explained earlier, graphical representation in SEM is key to visualizing relationships. The following symbols are used:

- Squares or rectangles: Observed variables.
- Circles or ovals: Latent variables.
- One-way arrows (→): Indicate causal relationships or direct effects.

- Bidirectional arrows (↔): Represent correlations between variables.

The following example shows a model that can show how a latent variable such as "stress" (oval) influences observed variables such as "insomnia" or "irritability" (squares), and how these, in turn, relate to another latent variable such as "academic performance."

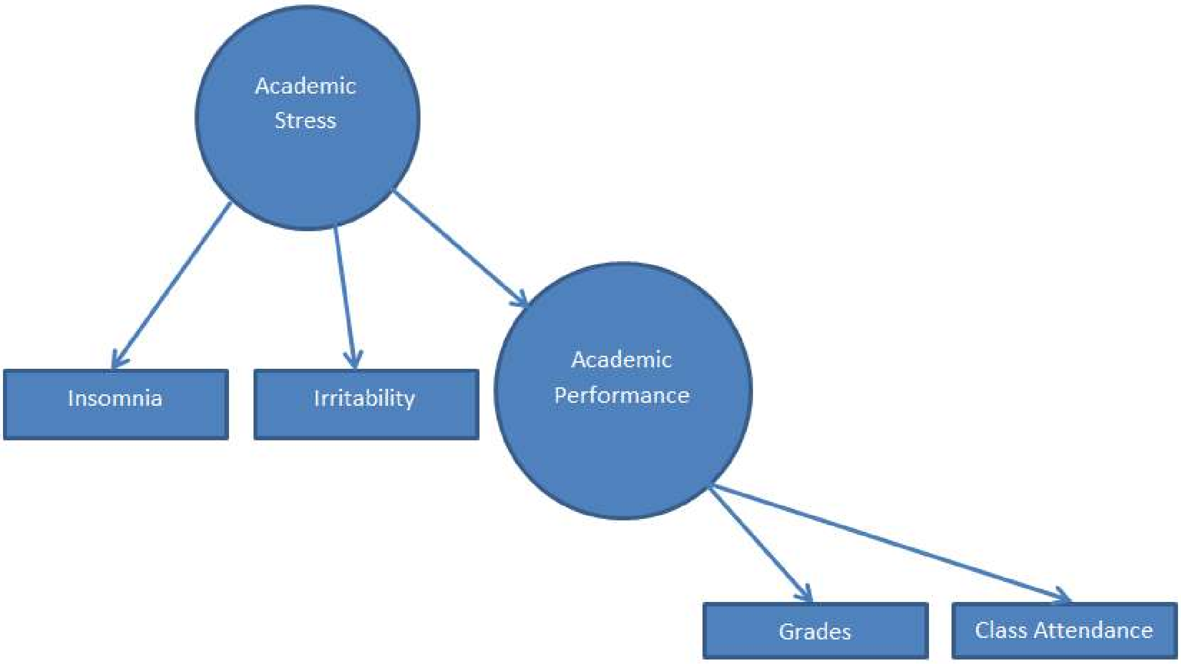

Figure 1: Graphical representation of the variables studied in the example.

The main hypothesis for model estimation is that the population variance-covariance matrix (Σ) is equal to the variance-covariance matrix associated with the theoretical model ($\Sigma[\theta]$). This condition is very difficult to satisfy, so estimation methods are used to find the parameter vector $\hat{\theta}$, such that Σ is close to $\Sigma[\hat{\theta}]$. Σ is not known, therefore it is estimated through the sample variance-covariance matrix (S).

To estimate the discrepancy between what is observed through the data and the estimates obtained through the model, the difference of matrices S- $\Sigma[\theta]$, called the residual, is used. On the other hand, to estimate the models, methods such as Maximum Likelihood (ML), Ordinary Least Squares (OLS), Generalized Least Squares (GLS), and Unweighted or Asymptotically Distribution-Free Least Squares (ULS or ADF) are used. All of them are based on the principle of iteratively minimizing a fitting function.

PLS-SEM stands for Partial Least Squares Structural Equation Modeling. It is a widely used technique in social sciences, marketing, psychology, and management. Unlike other methods such as covariance-based SEM, PLS-SEM is more flexible because:

- It does not require the data to follow a normal distribution.
- Works well with small samples.
- It is oriented towards prediction rather than confirmation of theories.

It is composed of two main parts:

1. Measurement model: relates latent variables with their observable indicators.
2. Structural model: shows the relationships between latent variables.

It is especially useful when exploring new theories or working with complex and less-than-clean data.

Once the model parameters are estimated, the fit must be assessed. One of the best-known tests is the χ^2 test, which is used to check the main hypothesis:

$H_0: S = \Sigma[\hat{\theta}]$ against $H_1: S \neq \Sigma[\hat{\theta}]$.

The statistic is distributed as a chi2 with $\frac{t(t+1)}{2} - p$ degrees of freedom, where t represents the number of estimated parameters and p is the number of observed variables.

3. Results

The target population consists of 117 faculty members from the National Intercultural University of the Amazon (UNIA) during the 2023-2024 academic year. The final sample consists of 90 faculty members. A structured survey is administered, consisting of 39 items distributed across three scales: intellectual capital (13 items), organizational climate (19 items), and scientific production (7 items). The scale used is based on the linguistic values belonging to the set $LS = \{s_0, s_1, s_2, s_4\}$ where:

s_0: Very bad,

s_1: Bad,

s_2: Neither Good Nor Bad,

s_3: Good,

s_4: Very good.

Respondents were asked to mark with a check, for each question based on the previous scale, in which position they consider the item a_i (i = 1, 2,…, 39) must be in terms of truthfulness, indeterminacy, and falsity, as shown in Figure 2.

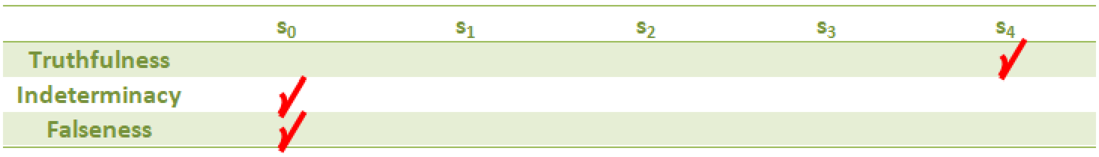

Figure 2: Figure showing the responses requested from each respondent for each survey item. Source: authors.

Figure 2 shows an example where the item is evaluated using checks with the triple (s_4, s_0, s_0). This is interpreted as meaning the item is "Very Good," there is no uncertainty, and it is not evaluated as "Very bad." The following procedure is explained:

1. Each jth respondent answers on a scale like the one shown in Figure 2, for each of the ith item asked. Let us denote this by v_{ij} (i = 1, 2,…, 39; j = 1,…, 90).

   Here $v_{ij} = \left(s_{k_{ij}}, s_{l_{ij}}, s_{m_{ij}}\right)$, where $k_{ij}, l_{ij}, m_{ij} \in \{0, 1, 2, 4\}$ are the indices of the LS set according to the opinion of the jth respondent, regarding the ith item.

2. The values v_{ij} are converted into a single value using Equation 3 and are denoted by $\tilde{v}_{ij} = S(v_{ij})$. In this case, the indices of $\tilde{v}_{ij}$ are taken as inputs to the PLS-SEM model.

3. The PLS-SEM model is applied, yielding causal relationships between variables. The details of the results are shown below.

Once the data were collected, they were initially processed in SPSS v26 software to perform the descriptive analysis. Subsequently, SmartPLS v4.0 software was used to estimate the structural and measurement models. Path coefficients (β), T values (calculated using a bootstrap with 3,000 samples), and p values were evaluated, with a significance level of 0.05. In addition, the coefficient of determination (R^2) and indirect effects were examined to assess the mediating role of intellectual capital.

Table 1 presents the key psychometric indicators for assessing the quality of the constructs.

Table 1. Descriptive statistics and construct reliability. Note: CR = Composite reliability; AVE = Average variance extracted. Source: Authors.

Construct	Number of Items	Alpha Cronbach	Rho_A	CR	AVE
Intellectual Capital	13	0.95	0.96	0.96	0.72
Organizational Climate	19	0.92	0.93	0.93	0.58
Scientific Production	7	0.97	0.97	0.97	0.85

The results show that both Intellectual Capital and Scientific Output achieve excellent levels of reliability, with Cronbach's alpha coefficients larger than 0.95 and composite reliability (CR) larger than 0.96. The Average Variance Extracted (AVE) for these constructs also meets the established criteria (0.72 and 0.85 respectively). However, the Organizational Climate construct, although showing acceptable reliability (α = 0.92, CR = 0.93), presents an AVE slightly lower than the recommended value (0.58), which suggests that some of its items may not fully capture the essence of the theoretical construct.

Table 2 provides strong evidence of the discriminant validity of the constructs, assessed using the correlation matrix and the square root of the AVE, according to the Fornell-Larcker criterion. The results indicate that each construct shares greater variance with its indicators than with those of the others, meeting the standards established in the methodological literature on structural models with PLS-SEM.

Table 2. Correlation matrix and square root of the AVE (discriminant validity). Source: Authors.

	1	2	3
1. Intellectual Capital	**0.85**	-	-
2. Organizational Climate	0.54	**0.76**	-
3. Scientific Production	0.85	-0.08	**0.92**

Table 3 presents the results of the path coefficients of the proposed structural model.

Table 3. Results of the path coefficients (hypothesis). *** p < 0.001. Source: Authors.

Hypothesis	Path Coef.	t-value	p-value	Confidence Interval (95%)	Result
H_1: Intellectual Capital→Organizational Climate	0.538***	4.310	<0.0001	[0.312, 0.781]	Supported
H_2: Intellectual Capital→Scientific Production	0.848***	15.478	<0.0001	[0.725, 0.942]	Supported
H_3: Organizational Climate→Scientific Production	-0.081	1,039	0.299	[-0.234, 0.052]	Not supported

It is observed that Intellectual Capital exerts a positive and highly significant effect on both Organizational Climate (β = 0.538, p < 0.0001) and Scientific Output (β = 0.848, p < 0.0001). The 95% confidence intervals exclude the value zero in both cases, which reinforces the statistical robustness of these relationships and allows empirically confirming hypotheses H_1 and H_2. In contrast, Organizational Climate did not show a significant relationship with Scientific Production (β = –0.081, p = 0.299), and its confidence interval includes zero (95% CI = [–0.234, 0.052]), which is why hypothesis H_3 was not supported.

The model (Figure 3) obtained an R^2 of 0.652 for Scientific Output (PC abbreviation in Spanish), which stands out visually within the structural diagram as a key indicator of explanatory power. This value indicates that Intellectual Capital (CI abbreviation in Spanish) and Organizational Climate (CO abbreviation in Spanish) explain 65.2% of the variance observed in scientific output. This reinforces the robustness of the proposed theoretical model and its predictive capacity in the context of Peruvian universities.

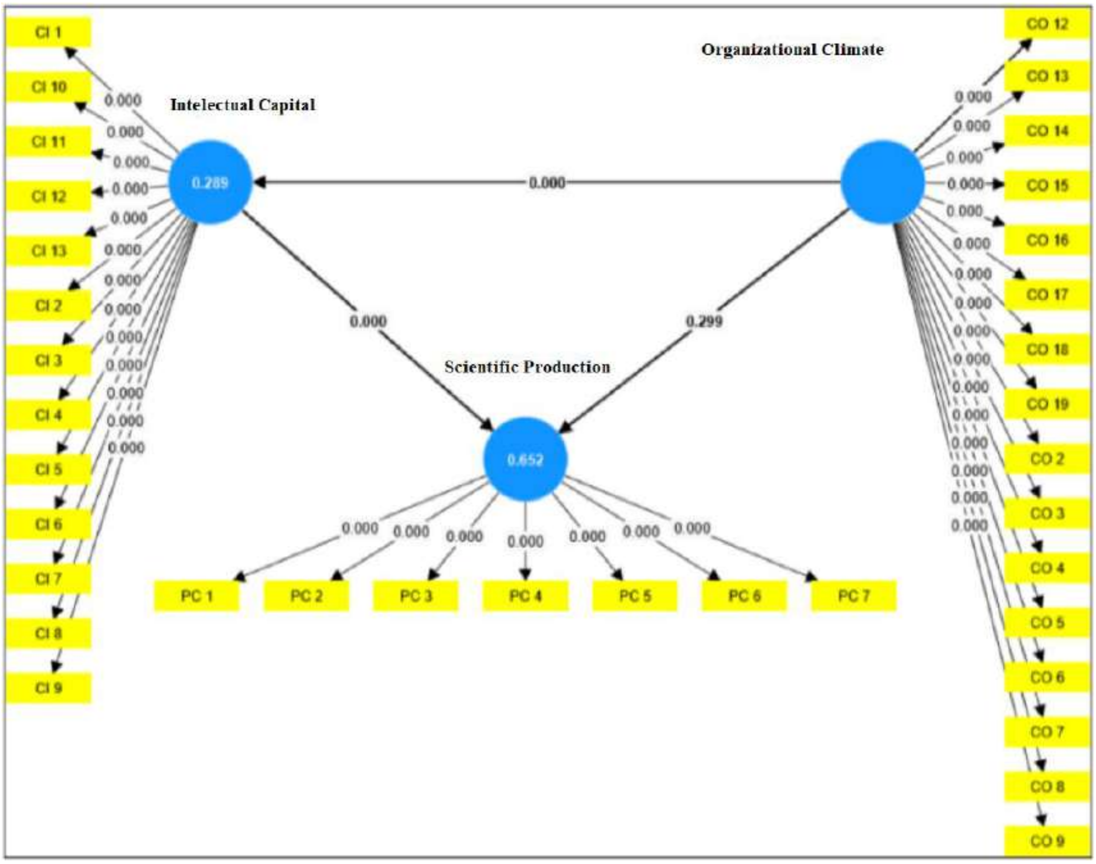

Figure 3: Results of the analysis model on the General Hypothesis. Source: Authors.

Table 4 shows that the indirect effect of Intellectual Capital on Scientific Production, mediated by the Organizational Climate, does not reach statistical significance (β = –0.044, p = 0.327).

Table 4. Indirect and total effects. Source: Authors.

Relationship	Effect	t-value	p-value	Confidence Interval (95%)
Indirect: Intellectual Capital → Organizational Climate. → Scientific Production	-0.044	0.981	0.327	[-0.148, 0.030]
Total: Intellectual Capital → Scientific Production	0.805***	12.257	<0.0001	[0.663, 0.914]

This suggests that the influence of intellectual capital on scientific productivity is primarily direct, with no evidence of mediation by the organizational environment.

Table 5 shows that the proposed structural model presents a satisfactory overall fit, according to the criteria commonly accepted in the PLS-SEM literature.

Table 5. Model fit. Source: Authors.

Metrics	Value	Acceptance criteria
SRMR (Standardized Root Mean Square Residual)	0.065	< 0.08 (good fit)
NFI (Normed Fit Index)	0.91	> 0.90 (acceptable)

The value of the Standardized Root Mean Square Residual (SRMR) obtained was 0.065, which is below the threshold of 0.08 considered to indicate a good fit. Likewise, the NFI (Normed Fit Index) reached a value of 0.91, exceeding the minimum threshold of 0.90 recommended for models with adequate global fit.

4. Discussion

The results presented in Table 1 demonstrate solid levels of internal consistency for the three constructs in the model. Cronbach's alpha and composite reliability (CR) values far exceed the threshold of 0.90 in all cases, indicating strong internal cohesion among the items comprising each construct. These findings are in line with the methodological recommendations of the PLS-SEM approach, which establishes a CR above 0.70 as the minimum acceptable criterion to ensure internal reliability.

Regarding convergent validity, the average variance extracted (AVE) values were also adequate for the constructs of Intellectual Capital (AVE = 0.72) and Scientific Production (AVE = 0.85), exceeding the recommended threshold of 0.50. These values indicate that a substantial portion of the total variance is explained by the items corresponding to their latent constructs, thus confirming the theoretical convergence of the proposed model.

However, the Organizational Climate construct presented a marginal AVE (0.58). Although this value exceeds the minimum required, its proximity to the lower limit may indicate a certain weakness in the homogeneity of its indicators. This situation has been reported in studies applied to educational and social contexts, where the measurement of organizational climate faces validity challenges due to contextual and cultural variability in the interpretation of its items.

Recent studies agree that these indicators (CR> 0.70 and AVE >0.50) represent robust standards of measurement quality in structural models with PLS-SEM, especially in research on intellectual capital, organizational innovation, and academic environments.

Overall, the reliability and convergent validity results support the robustness of the proposed measurement model, although it is recommended to review and refine the operationalization of the Organizational Climate construct in future research.

According to Table 2, the strong positive correlation between Intellectual Capital and Scientific Output (r = 0.85) is particularly noteworthy, reinforcing the theoretical coherence of the model. This relationship is consistent with previous findings in knowledge-based organizations and with classic studies, which also reported strong associations between intellectual capital and performance. However, more recent research has reported moderate correlations (r ≈ 0.40–0.60), attributed to corporate contexts other than academia.

On the other hand, the correlation between Organizational Climate and Scientific Output was low and negative (r = –0.08), suggesting a weak connection between these dimensions in the university environment analyzed. This finding contrasts with studies conducted in school and business contexts where organizational climate has shown positive effects on performance, especially when moderating variables such as leadership or institutional commitment are included.

Additionally, applied research in the banking sector has found evidence of adequate discriminant validity between intellectual capital and other variables such as ethical climate or job satisfaction, confirming that these constructs can be kept theoretically separate even in complex organizational environments. Similarly, the discriminant structure of intellectual capital has been validated in multiple industries, where its three dimensions (human, structural, and relational) maintain conceptual independence despite their operational interdependence.

Taken together, these correlation patterns anticipate the effects subsequently observed in the path coefficients, where intellectual capital is consolidated as the main predictor of scientific production, while organizational climate shows a marginal role in this process.

Analyzing Figure 3, the findings shown are consistent with previous studies that highlight the role of intellectual capital as a direct driver of organizational performance, particularly in knowledge- and innovation-based contexts. For example, intellectual capital has been shown to significantly influence organizational effectiveness in technology companies, educational institutions, and strategic industrial sectors. The effect observed in our study ($\beta = 0.848$) even exceeds that reported in technological innovation contexts ($\beta \approx 0.62$), possibly due to the scientific-academic nature of our object of study.

On the other hand, the absence of a significant effect of organizational climate on scientific production contrasts with studies in organizations with structured institutional cultures and formal performance incentives, as well as with research in corporate contexts where climate acts as a driving variable for work engagement and innovation. The difference could be explained by the absence of formal incentive or recognition mechanisms in the academic environment evaluated, thus limiting the role of climate as a direct facilitator of scientific productivity.

Likewise, some authors identify that a motivating organizational culture ($\beta= 0.231$, $p <0.001$), knowledge outsourcing ($\beta = 0.181$, $p < 0.01$), and technological capital measured as time dedicated to research ($\beta = 0.382$, $p < 0.001$) have significant positive effects on scientific production.

Overall, the results confirm that Intellectual Capital is a key predictor in the model's structure, while Organizational Climate does not play a mediating or direct role in scientific outcomes in the context analyzed.

This pattern has been replicated in multiple studies, highlighting that intangible resources linked to knowledge—such as individual skills, tacit experience, and organizational capabilities—exert a more immediate effect on performance than contextual conditions such as organizational climate.

For example, in the Pakistani banking sector, intellectual capital was found to directly influence performance, without significant mediation by other organizational variables. Additionally, in the technological field, it has been suggested that productivity can act as a moderator—rather than a mediator—in the relationship between intellectual capital and performance, suggesting a more complex dynamic of influence. Furthermore, the fact that our study focused on researchers and academics introduces a possible theoretical explanation: professional autonomy, intrinsic motivation, and tacit knowledge could play a more determining role in scientific production than the immediate institutional environment. This interpretation is in line with approaches to self-determined motivation in academic contexts, where personal factors often outweigh organizational ones.

However, our findings contrast with studies that have found partial mediation effects of organizational climate, such as the model proposed by some authors in companies with formal incentive systems and a collaborative innovation culture. This divergence could be explained by contextual differences: while those studies address highly structured corporate sectors, ours focuses on the academic environment, characterized by greater dispersion in institutional policies and greater individual autonomy. Overall, the absence of mediation by the organizational climate in this study reinforces the thesis that intellectual capital acts as a direct driver of scientific performance, while the work environment, although relevant, does not significantly mediate this relationship in academic contexts without clear incentive structures.

Most of the indicators of the constructs evaluated present factor loadings above the recommended threshold of 0.70, which indicates adequate convergence between the items and their respective latent constructs.

The pattern shown in Table 4 is especially evident in the constructs of Intellectual Capital and Scientific Production, whose indicators show loadings ranging from 0.76 to 0.88. These values are comparable with those reported in previous studies that used measurements of scientific productivity based on objective and bibliometric criteria.

However, the Organizational Climate indicator presents some weaknesses in its quality. In particular, items CO1 ($\lambda = 0.492$) and CO19 ($\lambda = 0.470$) show factor loadings below the acceptable standard, which may be influencing the reduction in the AVE value observed for this construct. Although all indicators are statistically significant ($p < 0.0001$), items with loadings below 0.60 are commonly considered for elimination or revision in studies using a PLS-SEM approach.

This type of behavior has been widely documented in research where imported instruments are not fully adapted to local contexts, such as universities or public sectors. In these cases, redesigning or adapting low-performing items has been recommended to ensure a valid and culturally relevant measurement.

The need to revise the instrument used to measure organizational climate has also been discussed by authors who suggest that the items should be specifically aligned with the scientific research environment to capture relevant aspects such as autonomy, intellectual collaboration, and publication culture. This recommendation becomes even more relevant in studies focused on researchers and academics, where organizational climate manifests itself differently than in traditional corporate or school contexts. In summary, although the measurement model presents satisfactory overall performance, the presence of low loadings on some Organizational Climate items suggests the need for contextual adjustments or methodological refinements in future research.

The results in Table 5 provide evidence that the specified model adequately represents the underlying relationships between the theoretical constructs and the observed data. In particular, the magnitude of the SRMR suggests that the differences between the empirical covariance matrix and the matrix estimated by the model are minimal, indicating parsimony and consistency in the structural specification.

Compared to recent studies, these values are within the ranges typically reported for well-fitting models in contexts of high knowledge and intangible capital. For example, research in the field of organizational innovation has reported similar or even less favorable values: SRMR < 0.08 and NFI ≈ 0.90 have been reported as acceptable fit standards in intellectual capital-intensive sectors. Likewise, in the context of national innovation, the use of these indices as key evaluation criteria for PLS models in complex macroeconomic scenarios is ratified.

Furthermore, our model performs better than other published models, where an SRMR of 0.083 has been reported for a similar intellectual capital model. Similarly, our model's NFI (0.91) falls within the average range (0.89–0.92) identified in a meta-analysis of studies on intellectual capital models.

However, despite the acceptable overall fit, it should be noted that there are opportunities for improvement, particularly in the specification of the Organizational Climate construct, which showed certain weaknesses in convergent validity and factor loading in previous analyses. Refining the measurement of this construct could contribute to further optimizing the overall fit of the model in future research.

Taken together, the SRMR and NFI indices support the robustness of the proposed model and place it within the accepted methodological standards for structural studies focusing on intellectual capital and academic productivity.

The results of this study confirm that intellectual capital and organizational climate are determining factors in university scientific production. Intellectual capital, in particular, showed a direct and significant influence, also acting as a mediator in the relationship between organizational climate and academic productivity.

5. Conclusion

This study provides significant empirical evidence on the influence of intellectual capital and organizational climate on scientific production at the National Intercultural University of the Amazon. Through a rigorous structural equation analysis, intellectual capital was determined to be the most influential factor in scientific production ($p < 0.001$), demonstrating a direct and significant relationship. It was also revealed that organizational climate exerts an indirect effect on scientific production, mediated by intellectual capital ($p < 0.001$), revealing a complex interaction between these variables. They suggest that institutional policies should prioritize the development of strategies that promote a favorable work environment and investment in the development of faculty members ' intellectual capital.

It is important to note that, to the authors' knowledge, this is the first time that the PLS-SEM method has been applied to data originally obtained using the neutrosophic 2-tuple linguistic method as an input. Since the information to be obtained is subjective, it was shown that it is convenient to use this CWW model to represent imprecise and vague knowledge. This was made easier by using linguistic values and considering the triplet of values of truthfulness, indeterminacy, and falseness.

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