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Evaluating the Interrelationships within the Technological Ecosystem: An SEM-PLS Approach to Innovation Management

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Abstract*– This study examines the influence of the technological ecosystem on innovation management within educational institutions through a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. A quantitative, non-experimental, cross-sectional, and explanatory research design was applied to a sample of 148 participants from institutions in southern Peru. The technological ecosystem was conceptualized as a multidimensional construct composed of technological infrastructure, resource availability, and accessibility. The measurement model demonstrated strong reliability and validity, with high composite reliability values (>0.89), adequate convergent validity (AVE > 0.50), and satisfactory discriminant validity according to Fornell-Larcker and HTMT criteria. The structural model explained 43.8% of the variance in innovation management (R^2 = 0.438), indicating moderate explanatory power. While the overall technological ecosystem construct showed a negative relationship with innovation management, its individual dimensions exhibited positive and statistically significant effects, suggesting that a lack of strategic alignment among ecosystem components may hinder overall innovation performance. Complementary analyses, including ordinal regression (Nagelkerke R^2 = 0.605) and Spearman correlation, confirmed the robustness and consistency of the findings. These results highlight the importance of strengthening digital infrastructure, improving accessibility, and ensuring effective resource allocation to enhance innovation capabilities. The study contributes to the literature by providing empirical evidence of the complex and multidimensional nature of technological ecosystems in emerging educational contexts.

Keywords--Technological Ecosystem, Innovation Management, PLS-SEM, Digital Infrastructure, Organizational Innovation, Educational Technology.

I. Introduction

Innovation management has become one of the main strategic priorities for organizations seeking sustainability, competitiveness, and long-term growth in increasingly digital and uncertain environments. Rapid technological change, globalization, and the constant emergence of disruptive business models have forced institutions to redesign their internal processes and strengthen their capacity to innovate continuously. In this scenario, technological ecosystems have gained relevance as dynamic environments that enable collaboration, knowledge exchange, technological integration, and value creation among multiple actors [1] [2].

A technological ecosystem can be understood as the set of interconnected technological resources, digital infrastructure, organizational capabilities, and stakeholders that collectively support innovation processes. Unlike isolated technology adoption approaches, ecosystem perspectives emphasize interdependence, complementarities, and coordinated development among institutions, users, platforms, and strategic partners [3]. This systemic view is particularly valuable because innovation rarely emerges from a single factor; rather, it results from interactions among infrastructure, talent, accessibility, governance, and resource availability.

In recent years, the acceleration of digital transformation has intensified the importance of technological ecosystems across productive sectors, especially in education. Universities and educational institutions increasingly depend on digital platforms, virtual learning systems, connectivity networks, data analytics tools, and collaborative technologies to improve teaching, research, administration, and innovation capacity. Furthermore, the COVID-19 pandemic exposed structural weaknesses in many organizations and highlighted the need for resilient ecosystems capable of adapting rapidly to unexpected disruptions [4].

Although the literature on innovation ecosystems has grown considerably, important conceptual and empirical gaps remain. Many previous studies have focused on industrial clusters, startups, or private-sector innovation networks, while fewer investigations have examined technological ecosystems within educational organizations in emerging economies. Likewise, several studies analyze technological factors independently, without considering the multidimensional interaction among infrastructure, accessibility, and resource availability as integrated determinants of innovation management [5] [6].

This issue is especially relevant in Latin American contexts, where institutions frequently face heterogeneous levels of digital maturity, budget restrictions, unequal access to technology, and diverse organizational cultures. In Peru, educational institutions have made progress in digitalization; however, challenges persist regarding strategic alignment, technology governance, modernization processes, and effective innovation management. Understanding how ecosystem dimensions influence innovation outcomes may provide useful evidence for institutional planning and policy design [7] [8].

From a theoretical perspective, examining the technological ecosystem contributes to expanding innovation management literature by incorporating a systemic and multidimensional approach. From a practical perspective, identifying the most influential components of the ecosystem can guide decision-makers in prioritizing investments, strengthening digital capabilities, and improving institutional competitiveness.

Therefore, the objective of this study is to evaluate the influence of the technological ecosystem on innovation management through a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. Specifically, the research analyzes the effects of technological infrastructure, resource availability, and accessibility as key dimensions of the ecosystem. The findings seek to provide empirical evidence from the educational sector in southern Peru and offer recommendations for strengthening innovation-oriented technological strategies.

II. METHODOLOGY

This research employs a quantitative approach, with a basic, non-experimental, and explanatory-level design, to assess the interrelationships within the technological ecosystem and their impact on innovation management. The quantitative approach facilitates the collection and analysis of numerical data, allowing for the identification of patterns and relationships among the variables of interest [6]. The study is structured to test specific hypotheses derived from the theoretical framework, using statistical methods to validate the findings [2].

Partial Least Squares Structural Equation Modeling (PLS-SEM) is used as the primary analytical technique in this study. PLS-SEM is particularly well-suited for exploratory research where the relationships between latent constructs are complex and not fully understood [13]. This method allows for the simultaneous estimation of multiple equations, accommodating both reflective and formative measurement models. The flexibility of PLS-SEM in handling small sample sizes and its ability to model non-normal data make it an appropriate choice for this research [14].

The target population of this research consists of staff from schools in southern Peru that operate within the institution's technological ecosystem, specifically those engaged in innovation management practices, totaling 215 at the time. A simple random sampling technique is used to select a sample of 148 respondents. The sample is stratified to ensure representation across different school sizes and types, which facilitates a comprehensive analysis of the impact of the technological ecosystem on innovation management [15].

Data collection is carried out through a structured questionnaire designed to measure the key variables associated with the technological ecosystem and innovation management, based on Moral-Pérez [16]. The questionnaire includes validated scales for the following constructs: technological infrastructure, resource availability, and accessibility. Each construct is operationalized using a series of Likert-scale items, allowing respondents to express their level of agreement or frequency of occurrence.

Data collection is conducted through an online survey distributed to the selected sample. The survey is administered using a secure platform to ensure the confidentiality and integrity of the data [17]. Prior to distribution, a pilot test is conducted with a small group of respondents to refine the questionnaire and ensure item clarity. The final survey is distributed via email, and follow-up reminders are sent to improve response rates [15]. The data collection period lasted four weeks, during which a total of 148 responses were obtained.

Los datos recopilados se analizan utilizando el software SEM-PLS específicamente SmartPLS versión 3.0. El análisis se desarrolla en dos etapas principales: el modelo de medición y el modelo estructural.

- Evaluation of the measurement model: The reliability and validity of the constructs are assessed through tests of composite reliability, average variance extracted (AVE), and discriminant validity [18]. Items with low loadings or poor reliability are removed to enhance the robustness of the model [19].

- Evaluation of the structural model: The structural model is assessed to test the hypothetical relationships between the constructs. Path coefficients are estimated, and the significance of these relationships is evaluated using bootstrapping techniques to generate t-values and p-values [20].

III. RESULTS

Reliability Analysis

The reliability of the independent variable Technological Ecosystem, measured using Cronbach's alpha, was 0.965, indicating a high level of internal consistency, as evidenced in the results presented.

TABLE 1
RELIABILITY OF THE INDEPENDENT VARIABLE

Cronbach's Alpha	Number of Items
,965	29

The second questionnaire, corresponding to the dependent variable Innovation Management, was analyzed using Cronbach's alpha statistic, yielding a result of 0.960. This is considered a high level of reliability for the dependent variable, as shown in Table 2.

TABLE 2
RELIABILITY OF THE DEPENDENT VARIABLE

Cronbach's Alpha	Number of Items
,960	18

Exploratory Factor Analysis

The result of the total variance explained for the Technological Ecosystem instrument reveals three main components that, together, account for 64.512% of the total variance. This percentage is considered adequate, as it reflects a good representation of the data variability. These results are presented in Table 3.

TABLE 3
TOTAL VARIANCE EXPLAINED OF THE INDEPENDENT VARIABLE

	Initial Eigenvalues			*Sum of Squared Loadings After Rotation*		
Compo-nent	Total	% of Variance	% Cumul-ative	Total	% of Variance	% Cumulative
1	14,692	50,662	50,662	8,058	27,787	27,787
2	2,417	8,334	58,996	5,354	18,462	46,248
3	1,600	5,516	64,512	5,296	18,264	64,512

According to Table 4, the result of the total variance explained for the Innovation Management instrument shows two components that account for a cumulative total of 66.691%, which indicates an adequate percentage and reflects the variability of the information.

TABLE 4
TOTAL VARIANCE EXPLAINED OF THE DEPENDENT VARIABLE

	Initial Eigenvalues			*Sum of Squared Loadings After Rotation*		
Compo-nent	Total	% of Variance	% Cumul-ative	Total	% of Variance	% Cumulative
1	10,811	60,062	60,062	6,121	34,005	34,005
2	1,193	6,629	66,691	5,883	32,686	66,691

During the exploratory factor analysis, no item was removed as all showed communalities greater than 0.5, thus remaining as originally included within the construct. The final model consists of three components for the independent variable and two components for the dependent variable, yielding a high Kaiser-Meyer-Olkin (KMO) measure and confirming that Bartlett's test of sphericity is significant.

Confirmatory Factor Analysis

According to Table 5, for the independent variable, the three-factor model shows a moderate fit in the confirmatory factor analysis, with incremental indices such as CFI (0.916) and TLI (0.908) exceeding the minimum acceptable threshold (>0.90), indicating a good ability of the model to reproduce the data structure. Although some absolute indices such as RMR (0.27), GFI (0.774), and AGFI (0.665) fall below the ideal values, these discrepancies are common in certain samples. Therefore, the model fit is considered acceptable to proceed with the study, which will be further supported by validity and reliability tests.

TABLE 5
CFA OF THE ADJUSTED MODEL FOR THE INDEPENDENT VARIABLE

Index	*Value*
Chi-cuadrado mínimo	642,380
RMR (Root Mean Square Residual)	0,27
GFI (Goodness of Fit Index)	0,774
AGFI (Adjusted GFI)	0,665
CFI (Comparative Fit Index)	0,916
TLI (Tucker-Lewis Index)	0,908
NFI (Normed Fit Index)	0,821

The results of the internal consistency analysis shown in Table 6 demonstrate excellent reliability for all evaluated variables and dimensions. The values for Cronbach's Alpha and rho_A significantly exceed the minimum recommended threshold of 0.70, indicating high stability and internal coherence among the items comprising each construct. Additionally, the composite reliability values range between 0.891 and 0.971, well above the acceptable minimum criterion, confirming that the constructs are solidly defined and that the measurements are consistent and reliable. These indicators support the strength of the instrument and ensure the internal consistency validity required to proceed with the structural model analysis.

TABLE 6
PLS MODEL CONSISTENCY VALIDITY

	Cronbach's Alpha	*rho_A*	*Composite Reliability*
VD	0.951	0.951	0.965
VI	0.956	0.961	0.971
VID1	0.940	0.943	0.947
VID2	0.870	0.872	0.899
VID3	0.846	0.848	0.891

Results of the model analysis, as shown in Table 7, indicate that the Average Variance Extracted (AVE) for all evaluated variables and dimensions meets the established criteria for adequate convergent validity. The dependent variable (DV) presents an AVE of 0.908, indicating that over 90% of the variance in its indicators is explained by the construct, demonstrating excellent convergent validity. The independent variable (IV) achieves an AVE of 0.776, well above the minimum threshold of 0.50. The specific dimensions VIF1, VIF2, and VIF3 show AVE values between 0.586 and 0.667, all within the acceptable range to validate the adequacy of the indicators to their respective constructs. These results confirm that the model possesses robust convergent validity, supporting the reliability and accuracy of the measurements used in the structural analysis.

TABLE 7
CONVERGENT VALIDITY OF THE MODEL

Variable	*Average Variance Extracted (AVE)*
VD (Variable Dependiente)	0.908
VI (Variable Independiente)	0.776
VIF1 (Factor 1)	0.586
VIF2 (Factor 2)	0.667
VIF3 (Factor 3)	0.667

According to Table 8, the discriminant validity assessed using the Fornell-Larcker criterion reveals that the square root of the Average Variance Extracted (AVE), represented on the diagonal, is greater for each construct than its correlations with other constructs in the model. For instance, the dependent variable (DV) shows a diagonal value of 0.953, which is higher than its correlations with the independent variable (0.643) and with the specific dimensions, ranging between 0.564 and 0.614. Similarly, the independent variable (IV) has a diagonal value of 0.881, exceeding its correlations with related dimensions (between 0.765 and 0.912). This configuration confirms that each construct explains more of its own variance than it shares with other constructs, thereby ensuring the model's discriminant validity. Consequently, it can be concluded that the constructs are conceptually distinct and that the measurements do not exhibit significant collinearity, reinforcing the reliability and validity of the structural analysi.

TABLE 8
DISCRIMINANT VALIDITY OF THE MODEL (FORNELL-LARCKER CRITERION)

	VD	*VI*	*VIF1*	*VIF2*	*VIF3*
VD	0.953				
VI	0.643	0.881			
VIF1	0.564	0.870	0.765		
VIF2	0.582	0.893	0.681	0.817	
VIF3	0.614	0.912	0.717	0.724	0.817

The assessment of discriminant validity using the HTMT (Heterotrait-Monotrait ratio) index in Table 9 shows that most values fall below the recommended threshold of 0.85, indicating an adequate distinction between constructs. Specifically, the relationships between the dependent variable (DV) and the other constructs present values ranging from 0.606 to 0.666, within the acceptable range. Overall, the model demonstrates acceptable discriminant validity.

TABLE 9
VALIDEZ DISCRIMINANTE DEL MODELO (CRITERIO HTMT)

	VD	*VI*	*VIF1*	*VIF2*	*VIF3*
VD					
VI	0.732				
VIF1	0.606	0.977			
VIF2	0.634	1.001	0.726		
VIF3	0.666	1.018	0.762	0.783	

Figure 1 presents the structural model estimated using SEM-PLS, analyzing the influence of the technological ecosystem (IV) on innovation management (DV). The IV construct consists of three dimensions (VIF1, VIF2, and VIF3), with high and consistent weights (ranging from 0.855 to 0.896), confirming its validity as a second-order variable. The model explains 43.8% of the variance in DV ($R^2 = 0.438$), a moderate value that reflects good explanatory power. A negative relationship is observed between IV and DV (-0.839), suggesting that certain aspects of the ecosystem may be interfering with effective innovation management, while VIF2 shows a direct positive effect (0.546) on DV. Most factor loadings exceed 0.70, supporting the convergent validity of the indicators. Overall, the model demonstrates significant relationships and adequate structural consistency.

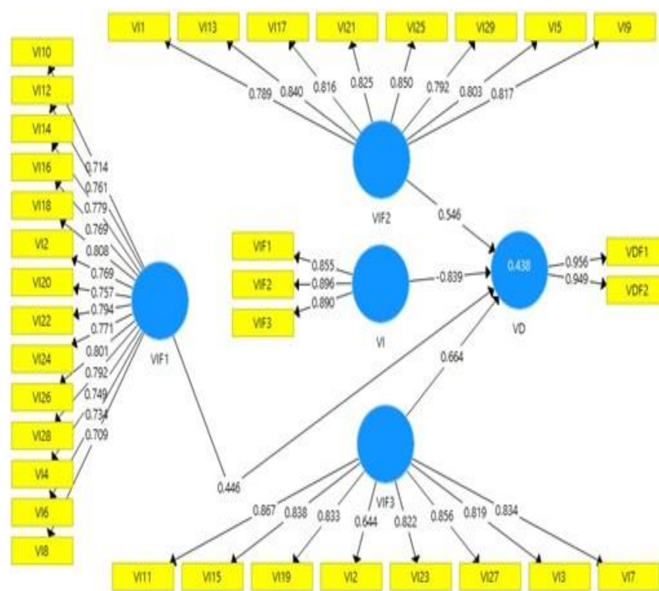

Figure 1 - Construct Validity of the Model

Hypothesis Testing

The results in Table 10 from the bootstrapping analysis show that all structural paths in the model are statistically significant, based on t-values greater than 1.96 and p-values less than 0.05, indicating that the proposed relationships are not due to chance. Specifically, the relationship between the technological ecosystem (IV) and innovation management (DV) presents a t-value of 2.291 and a p-value of 0.022, confirming its significance. Similarly, the dimensions VID1 (t

= 2.759, p = 0.006), VID2 (t = 2.221, p = 0.027), and VID3 (t = 2.279, p = 0.023) also show significant effects on DV. These results statistically support the proposed hypotheses, demonstrating that both the overall construct and its dimensions exert a significant influence on innovation management.

TABLE 10
ORIGINAL STRUCTURAL MODEL EVALUATION – BOOTSTRAPPING

Original Sample (O)		*Sample Mean (M)*	*Standard Deviation (STDEV)*	*T Statistics (|O/STDEV|)*	*P Values*
VI -> VD	-8.442	-7.806	3.685	2.291	0.022
VID1 -> VD	3.733	3.494	1.353	2.759	0.006
VID2 -> VD	2.810	2.603	1.265	2.221	0.027
VID3 -> VD	2.912	2.712	1.278	2.279	0.023

The results were validated through ordinal regression analysis. According to Table 11, the Nagelkerke pseudo R^2 values indicate that the technological ecosystem explains 60.5% of the variance in innovation management, reflecting a strong relationship. Technological infrastructure shows a similar impact, explaining 59.5% of the variance. Meanwhile, resource availability and accessibility also have a significant, though slightly lower, influence with values of 48.7% and 46.9%, respectively. These findings suggest that strengthening these dimensions can significantly enhance organizational innovation capacity.

TABLE 11
NAGELKERKE PSEUDO R-SQUARED FOR ORDINAL REGRESSIONS

Relationship	*Nagelkerke Pseudo R^2*
VI (Ecosistema tecnológico) → VD	0.605
VID1 (Infraestructura) → VD	0.595
VID2 (Disponibilidad de recursos) → VD	0.487
VID3 (Accesibilidad) → VD	0.469

The results in Table 12 show a strong, positive, and significant correlation between the technological ecosystem measured through its dimensions of infrastructure (0.675), accessibility (0.637), and availability (0.620) and the dependent variable, Innovation Management, where $p < 0.01$. Furthermore, infrastructure and accessibility exhibit high levels of interrelation with availability, evidencing an interconnected technological ecosystem. In particular, technological infrastructure stands out as a key factor which, together with accessibility and the availability of technological resources, significantly enhances organizations' capacity for innovation management.

TABLE 12
SPEARMAN CORRELATION BETWEEN THE DIMENSIONS OF THE INDEPENDENT VARIABLE (IV) AND THE DEPENDENT VARIABLE (DV)

	Infrastructure	*Availability*	*Accessibility*	*Technological Ecosystem*	*Innovation Management*
Infrastructure	1.000	0.871**	0.853**	0.973**	0.675**
Availability	0.871**	1.000	0.822**	0.934**	0.620**
Accessibility	0.853**	0.822**	1.000	0.912**	0.637**
Technological Ecosystem	0.973**	0.934**	0.912**	1.000	0.682**
Innovation Management	0.675**	0.620**	0.637**	0.682**	1.000

**Note: All correlations are significant at the 0.01 level (2-tailed).

DISCUSSION

The findings of this study provide relevant empirical evidence regarding the relationship between technological ecosystems and innovation management in educational institutions. Overall, the results confirm that the technological ecosystem constitutes a significant explanatory factor of innovation performance, supporting previous research that emphasizes the strategic role of digital capabilities, organizational resources, and collaborative environments in fostering innovation [21] [22].

One of the most notable findings is that the multidimensional components of the multidimensional components of the technological ecosystem technological infrastructure, resource availability, and accessibility showed positive and statistically significant effects on innovation management. This suggests that institutions with stronger digital infrastructure, better access to technological tools, and sufficient resource support are more likely to develop effective innovation practices. These results are consistent with studies indicating that innovation capacity depends not only on creativity or leadership, but also on the availability of enabling technological conditions [23] [24].

However, the structural model also revealed a negative relationship between the overall technological ecosystem construct and innovation management. Although this result may initially appear contradictory, it can be interpreted as evidence of ecosystem complexity rather than model inconsistency. In practice, organizations may possess valuable technological components individually while lacking strategic integration among them. Fragmented systems, duplicated platforms, insufficient interoperability, weak governance structures, or misalignment between technological investments and innovation objectives may reduce the positive impact of the ecosystem as a whole.

This interpretation is especially relevant in educational institutions, where digital transformation processes are often implemented progressively under budgetary, administrative, or cultural constraints. As a consequence, isolated technological improvements may coexist with systemic inefficiencies that limit innovation performance. Therefore, technological ecosystems should not be evaluated only by the presence of resources, but also by the degree of coordination, alignment, and institutional readiness that connects those resources.

From a methodological perspective, the study demonstrates the usefulness of PLS-SEM for modeling complex relationships among multidimensional constructs. High reliability coefficients, adequate convergent validity, and satisfactory discriminant validity indicators support the robustness of the proposed model. Complementary analyses through ordinal regression and Spearman correlation further reinforce the consistency of the findings.

From a practical standpoint, managers and policymakers should move beyond isolated technology acquisition strategies. Instead, they should prioritize integrated digital governance, strategic planning, staff capability development, interoperable systems, and equitable access mechanisms. Investments in infrastructure alone may be insufficient if institutions do not simultaneously strengthen organizational processes and innovation culture.

Theoretically, this research contributes to the innovation ecosystem literature by validating a multidimensional model in the context of educational institutions in an emerging economy. It also highlights that technological ecosystems are not homogeneous constructs. Their impact depends on the how effectively their internal dimensions interact. Future studies are encouraged to replicate the model in other sectors and countries, as well as to employ longitudinal designs to examine ecosystem evolution over time.

CONCLUSIONS

The study demonstrates that the technological ecosystem significantly influences innovation management, although this influence is not homogeneous. The SEM-PLS structural model explained 43.8% of the variance in innovation management ($R^2 = 0.438$), confirming the relevance of the technological ecosystem as a determining factor in organizational innovation processes.

The dimensions of the technological ecosystem showed positive and statistically significant effects on innovation management: technological infrastructure ($\beta = 0.446$; $p = 0.021$), resource availability ($\beta = 0.546$; $p = 0.027$), and accessibility ($\beta = 0.664$; $p = 0.023$). These findings indicate that each component contributes positively to strengthening innovation capacity when strategically coordinated.

Additionally, ordinal regression analysis confirmed that the technological ecosystem explains 60.5% of the variance in innovation management according to Nagelkerke's pseudo R^2. The individual dimensions also showed relevant impacts: technological infrastructure (59.5%), resource availability (48.7%), and accessibility (46.9%). Spearman correlation analysis revealed positive and significant associations between innovation management and ecosystem dimensions, with coefficients of 0.675 for infrastructure, 0.620 for availability, and 0.637 for accessibility ($p < 0.01$).

These findings emphasize the importance of understanding the technological ecosystem as a multidimensional construct. Strengthening infrastructure, improving accessibility, and ensuring adequate resource availability are key actions for enhancing innovation management in educational institutions. Future studies may incorporate longitudinal designs and broader samples to validate these relationships in other contexts.

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