AI Governance and Strategic Management as Factors Associated with the Performance of Automated IT Processes in Firms in San Pedro Sula, Honduras

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Abstract*— The adoption of artificial intelligence (AI) in organizations depends not only on technological availability but also on governance structures, leadership, infrastructure, and data management. This study examined how AI governance and strategic management relate to the performance of automated information technology (IT) processes in firms in San Pedro Sula, Honduras. A quantitative, non-experimental, cross-sectional, descriptive-correlational design was applied through a five-point Likert questionnaire administered to IT-related participants from these firms. After data cleaning (110 records, 4 duplicates removed) and excluding 19 records showing a constant-response pattern across all 28 Likert items, the analytical sample comprised 87 cases, with no missing or out-of-range values. The scales showed excellent internal consistency (Cronbach's alpha between 0.888 and 0.964). Because the composite indices were non-normally distributed (Shapiro–Wilk, $p < .001$), Spearman correlations were used as the primary association test, complemented by linear regression with HC3 robust standard errors. Results showed a strong, positive relationship between AI governance and strategic management and IT-automation performance ($\rho=0.613$; $p<.001$; $R^2=0.418$), which remained significant, and somewhat stronger, in a robustness check that reincorporated the 19 excluded cases ($n=106$; $\rho=0.695$; $p<.001$; $R^2=0.520$). General hypothesis H1 and specific hypotheses H1a–H1d were all supported. The findings show that stronger AI governance and strategic management are associated with higher perceived IT-automation performance in San Pedro Sula firms. However, the cross-sectional design precludes causal inference. The results offer practical implications for IT managers in emerging Latin American economies.

Keywords*— AI governance; AI strategic management; IT process automation; organizational performance; digital transformation.

I. Introduction

Digital transformation has become a key driver of growth and performance across industries and regions [1]. Evidence links the intensity of digital transformation to improvements in operational performance and, more gradually, financial performance [2], as well as gains in enterprise technological innovation efficiency [3]. Within this broader process, however, artificial intelligence (AI) poses a distinct challenge: adoption alone does not guarantee reliable operational outcomes. Converting AI into organizational value requires governance structures, committed leadership, adequate technological infrastructure, and data management mechanisms capable of sustaining its integration into business processes.

Academic interest in AI governance—the policies, oversight structures, accountability mechanisms, and ethical practices that guide the responsible and strategic use of this technology—has grown markedly in recent years [4], [5]. AI governance is a critical factor for managing AI-related risks, aligning AI with corporate strategy, and ensuring responsible decision-making [6], [7]. Countries and industries have also begun institutionalizing public and corporate algorithmic governance policies [8], and specialized roles—such as the Chief Data Officer—have emerged to operationalize these mechanisms, even as AI becomes more autonomous through agentic systems [9].

AI governance does not operate in isolation: it requires strategic management and organizational leadership. Integrating AI systematically into business strategy is a first-order managerial challenge [10], and AI adoption often creates tensions around cross-functional coordination, organizational culture, and technological absorptive capacity [11], [12]. Executive leadership and AI-specific managerial competencies enable effective adoption [11], [13], [14], while the absence of ethical, people-centered leadership can erode organizational trust in these technologies [13], [15]. AI has, in turn, become a tool that supports corporate governance and more efficient executive decision-making [16], [17]–[19].

A third body of research examines how AI relates to the performance of automated IT processes, measured in terms of efficiency, productivity, control, continuity, quality, and internal-user satisfaction. Intelligent process automation—including robotic process automation combined with AI—is linked to efficiency gains, cost reductions, and better operational decisions [20]–[29], [30], and organizational AI capability explains a substantial share of the variation in firm performance [25], [26], [31]. Recent systematic reviews confirm AI's influence on business operational efficiency [32], reinforcing the relevance of this line of inquiry for the entrepreneurship, innovation, and digital transformation research community.

Despite this evidence, most studies on AI governance, strategic management, and automation performance come from advanced economies or large Asian and Latin American economies; empirical evidence from small Central American economies remains scarce [33]–[35]. The existing literature provides limited empirical evidence on how AI governance relates to automated-process performance in Central American firms, particularly in Honduras. No prior studies were identified that jointly examine AI governance and strategic management alongside IT-automation performance in Honduran companies. This study addresses this gap by providing contextual business

evidence from firms in San Pedro Sula, without extending conclusions beyond the sample studied.

Accordingly, the general objective of this study was to analyze the relationship between AI governance and strategic management and the performance of automated IT processes in firms in San Pedro Sula, Honduras. The specific objectives were to characterize AI governance, leadership, evaluation, infrastructure, data, and technology management in the firms studied; describe the performance of automated IT processes in terms of efficiency, control, continuity, quality, compliance, and satisfaction; examine the relationships between the AI governance and strategic management dimensions and the automation performance dimensions; and identify which governance dimensions show the strongest association with that performance, without inferring causality.

This study contributes to the literature in three ways. Theoretically, it integrates four bodies of literature rarely examined jointly in small-firm settings: AI governance, strategic management and leadership, infrastructure and data, and IT-automation performance. Empirically, it provides robust quantitative evidence—including reliability checks, a full-sample robustness check, and robust-error regression—from a Central American business context that is largely absent from the literature. Practically, it offers IT managers in the region concrete guidance on which governance mechanisms to prioritize to support higher perceived automation performance. The study contributes to the broader discussion of digital transformation and artificial intelligence from the standpoint of organizational capabilities and governance in emerging economies.

The remainder of the paper is organized as follows. Section II reviews the literature and presents the conceptual model; Section III describes the methodology, including the study's scope and methodological considerations; Section IV reports the results; Section V discusses the findings; and Section VI presents the conclusions.

II. Literature Review and Conceptual Model

A. AI Governance in Organizations

AI governance is the system of policies, roles, oversight processes, and accountability mechanisms that guide the development, acquisition, and use of artificial intelligence within an organization [5], [6]. A recent conceptual review of strategic AI oversight in global corporations finds that effective governance combines formal structures—committees, policies, audits—with informal organizational learning mechanisms [4]. Corporate responsibility, in turn, needs to be redefined for the AI era to explicitly incorporate ethical considerations into algorithmic management [7], and social institutions and national public policy significantly shape how organizations govern AI [8].

A central component of AI governance is the periodic evaluation of AI performance and value return, together with explicit policies on ethical and responsible use [6], [17], [18]. AI-assisted corporate governance research suggests that these evaluation and accountability mechanisms not only mitigate risk but also strengthen organizations' capacity to sustain automation over the long term [17]–[19]. Agentic AI adds a further layer of complexity to governance, requiring dynamic oversight mechanisms that go beyond traditional IT controls [9].

B. Strategic Management, Leadership, and Organizational Capabilities for AI

Strategic AI management means systematically integrating self-learning technologies into corporate strategy, which requires revisiting classical strategy-formulation models [10]. AI adoption faces intertwined cultural, technical, and organizational challenges that hinder smooth integration into operations [12], and significant barriers persist for scaling AI-driven transformation in firms, including gaps in data governance and executive sponsorship [20], [21]. These barriers also surface when integrating AI within knowledge management systems, where unclear processes limit organizational uptake [22].

Executive leadership plays an enabling role. Managers need new competencies to lead effectively in AI-driven contexts [11], and ethical, people-centered leadership is essential to sustaining internal trust in these technologies [13]. A recent systematic review concludes that AI can strengthen top-management leadership when formal adoption and training processes are in place [14]. In Brazilian organizations, C-level executives' trust in AI was linked to the maturity of available governance mechanisms [15], while other studies show that AI can improve decision-making efficiency when paired with robust corporate governance frameworks [16].

C. IT Process Automation and Organizational Performance

Process automation—including robotic process automation (RPA), intelligent automation, and its combination with AI—is consistently linked to improvements in productivity, efficiency, and service quality [23], [24], [28]. Evidence shows that an organization's AI capability predicts its financial and operational performance [26], [31], and that AI-driven innovation improves business performance metrics, particularly when organizational innovation capability mediates that relationship [25]. Additional studies document efficiency gains and cost reductions from AI-driven business processes [27], [36], [30], [37], [38], as well as the role of integrating AI with knowledge management in sustaining competitive advantage [39].

In business intelligence and decision-making, integrating AI and machine learning improves operational efficiency and the quality of managerial decisions [29], and AI-supported strategic performance measures strengthen organizational control [31]. A recent systematic review found that AI significantly influences firms' operational efficiency, while cautioning about the heterogeneity of the contexts studied [32]. A quantitative assessment of AI's impact on process automation documented measurable gains in productivity and service quality [40], and a

recent bibliometric analysis showed the accelerated growth of the literature on AI applied to management control [41].

D. Evidence from Emerging Economies and Latin America

Evidence on AI governance and performance in emerging economies remains limited compared with Asia, Europe, and North America. A recent study applied a DEMATEL approach to examine how small and medium-sized enterprises are leveraging AI, identifying the lack of formal governance as a critical barrier [33]. A systematic review of AI applications for sustainable practices in Latin American SMEs found that adoption tends to be incipient and poorly structured in governance terms [34]. From a macroeconomic perspective, AI exposure is reshaping labor markets across Latin America unevenly across countries [35]. Together, this evidence suggests that Latin American firms—including Central American ones—face particular challenges institutionalizing AI governance, reinforcing the value of localized business evidence such as that provided by this study for San Pedro Sula, Honduras.

E. Conceptual Model and Hypotheses

Based on the literature reviewed, this study proposes a conceptual model linking AI governance and strategic management (independent variable) to the performance of automated IT processes (dependent variable). The independent variable was operationalized into two dimensions: D1) governance, leadership, and strategic evaluation; and D2) infrastructure, data, and technology management. The dependent variable was operationalized into D1) efficiency, control, and operational continuity; and D2) quality, auditing, and satisfaction. Fig. 1 summarizes this model.

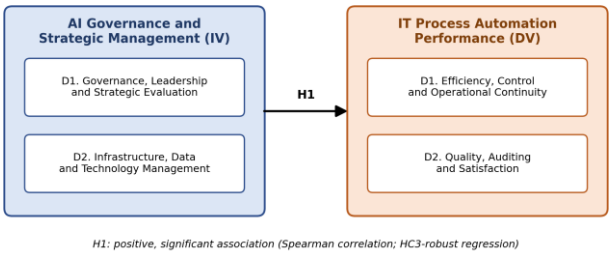


Fig. 1. Conceptual model of the relationship between AI governance and strategic management and IT-automation performance.

Based on this model, the following research hypotheses were formulated, consistent with specific objectives (c) and (d):

H1. AI governance and strategic management are positively and significantly related to the performance of automated IT processes.

H1a. AI governance, leadership, and strategic evaluation are positively and significantly associated with efficiency, control, and operational continuity.

H1b. AI governance, leadership, and strategic evaluation are positively and significantly linked to quality, auditing, and satisfaction.

H1c. AI-related infrastructure, data, and technology management are positively and significantly associated with efficiency, control, and operational continuity.

H1d. AI-related infrastructure, data, and technology management are positively and significantly related to quality, auditing, and satisfaction.

H0. There is no statistically significant relationship between AI governance and strategic management and the performance of automated IT processes among the participating firms.

III. Methodology

A. Design and Context

The study followed a quantitative approach with a non-experimental, cross-sectional design and descriptive-correlational scope. The analysis focused on the statistical relationship between variables, without manipulating conditions or longitudinal follow-up. The business context corresponded to firms located in San Pedro Sula, Cortés Department, Honduras; interpretation of the results remains within this territorial scope and does not extend to Honduran firms as a whole.

B. Participants and Sample

The original database contained 110 records. A conservative cleaning procedure removed only 4 exact duplicate records, retaining the first occurrence of each case. The analytical sample comprised 106 participants from firms in San Pedro Sula working in information technology areas. No missing values or scores outside the expected 1–5 Likert range were identified.

A non-probabilistic convenience sample targeted participants linked to IT functions at firms in San Pedro Sula. Inclusion required participants to hold IT-related functions and to be familiar with their organization's technological or automated processes.

C. Instrument and Operationalization

The instrument was a structured questionnaire developed specifically for this study, using five-point Likert items (1 = strongly disagree/very low, 5 = strongly agree/very high) organized into two blocks: IV (AI governance and strategic management) and DV (automated IT-process performance). Each dimension was calculated as the mean of its items, and the global indices of each variable as the mean of the selected items. Table I summarizes the operationalization used; its internal consistency was assessed with Cronbach's alpha and is reported in Section IV.

TABLE I
Operationalization of Variables and Dimensions

Variable / Dimension	Instrument Items	Conceptual Content
IV–D1. Governance, Leadership and Strategic Evaluation	IV1, IV5, IV6, IV10, IV13	Strategic direction, top-management support, governance and ethics policies, and evaluation of AI value return.
IV–D2. Infrastructure, Data and Technology Management	IV9, IV11, IV12	Technological infrastructure, data availability and quality, and technical support for AI solutions.
DV–D1. Efficiency, Control and Operational Continuity	DV1, DV2, DV6, DV9, DV10, DV11, DV13	Time and error reduction, monitoring, productivity, continuity, and process control.
DV–D2. Quality, Auditing and Satisfaction	DV5, DV12, DV14	Service quality, compliance and auditing, and internal-user satisfaction.

The instrument content underwent expert review and a pilot test with approximately 30% of the target population before final administration. The full 14-item AI governance and strategic management block (IV) obtained a Cronbach's alpha of .978, and the full 14-item IT-automation-performance block (DV) obtained a Cronbach's alpha of .981; internal consistency was high in both blocks, consistent with the dimension-level coefficients reported in Section IV (Table III).

D. Procedure and Ethical Considerations

Data collection used a self-administered questionnaire directed at IT-related participants from firms in San Pedro Sula. Before responding, participants were informed of the study's academic purpose, the voluntary nature of participation, and the confidential, aggregated treatment of the information. Data were analyzed in anonymized, aggregated form, following standard research-ethics principles for survey-based organizational studies.

E. Statistical Analysis Plan

The analysis plan followed these stages: (1) data cleaning and quality checks (duplicates, missing values, response range); (2) identification and exclusion of records with a constant-response pattern across the 28 Likert items, yielding the analytical sample used throughout (n=87); (3) construction of dimensions and global indices; (4) reliability assessment via Cronbach's alpha; (5) descriptive statistics (mean, standard deviation, median); (6) Shapiro-Wilk normality testing to select the association test; (7) Spearman correlations among dimensions and global indices; (8) linear regression with HC3 robust standard errors, in both a global model and a simultaneous dimension-level model; (9) a robustness check reincorporating the 19 constant-response cases into the full sample (n=106); and (10) exploratory comparisons via the Kruskal-Wallis test across organizational and professional characteristics.

F. Scope and Methodological Considerations

Because the design is non-experimental and cross-sectional, the observed relationship between AI governance and strategic management and IT-automation performance does not establish temporal sequence or causal links between the two constructs. Because data were collected from a single self-report source for each case, common-method bias is also possible. Although the questionnaire used specific response anchors and clearly differentiated IV and DV blocks, common-method bias cannot be ruled out. In addition, participants were recruited through non-probabilistic convenience sampling, and automation performance was self-reported rather than measured through independent operational indicators; both features limit the generalizability of the findings and should be considered when interpreting the strength of the associations reported. Future studies could strengthen measurement validity by incorporating additional data sources, such as operational indicators recorded by IT systems, and could draw on probabilistic sampling where feasible.

The 19 cases showing a constant-response pattern across the 28 Likert items (about 18% of the analytical sample) were treated as indicative of low-quality response behavior, consistent with standard survey-methodology practice, and were excluded from the primary analytical sample (n=87) used to test the study's hypotheses. Because this exclusion criterion is a judgment call, the full sample (n=106, including these cases) was also analyzed as a robustness check, reported in Section IV-E: the main association remained significant when these cases were reincorporated, though somewhat stronger in magnitude (ρ=0.695; $p<.001$, versus ρ=0.613; $p<.001$ in the primary sample), and the drop of about ten points in explained variance (R^2=0.418 versus R^2=0.520) indicates that response quality is not immaterial to the results, reinforcing the decision to treat the cleaned sample as the primary basis for interpretation. The exploratory comparisons by organizational and professional characteristics (Section IV-G) are reported with a moderate sample size and unequal subgroup sizes, and are therefore presented as exploratory rather than confirmatory tests of heterogeneity.

IV. RESULTS

A. Data Cleaning and Sample Description

Of the 110 original records, 4 exact duplicates were removed, leaving 106 participants from firms in San Pedro Sula. No missing values or responses outside the 1–5 Likert range were detected. A second audit identified 19 records with constant responses across the 28 Likert items, about 18% of these 106 cases. Consistent with standard practice for identifying low-quality survey responses, these 19 records were excluded, yielding the primary analytical sample used for hypothesis testing (n=87). The full sample of 106 cases, including the constant-response records, is examined separately in Section IV-E as a robustness check.

B. Participant Characteristics

Table II summarizes the distribution of the 87 participants in the analytical sample by organization type, IT work area, academic degree, and years of experience. Most participants worked at private companies (65.5%), followed by educational institutions (9.2%) and public institutions (9.2%). Technical support (36.8%) and software development (19.5%) were the most common work areas. Regarding academic degree, 63.2% of participants reported university-level training (complete or incomplete bachelor's or engineering degree), and 11.5% held a master's degree. In terms of IT experience, 63.2% of

participants had three years or less, while 18.4% reported more than ten years.

TABLE II
Participant Characteristics (n = 87)

Characteristic	n	%
Organization type — Private company	57	65.5
Organization type — Educational institution	8	9.2
Organization type — Public institution	8	9.2
Organization type — Service company	7	8.0
Organization type — Technology company	7	8.0
IT work area — Technical support	32	36.8
IT work area — Software development	17	19.5
IT work area — Infrastructure and networks	9	10.3
IT work area — Technology project management	8	9.2
IT work area — Data analysis	8	9.2
IT work area — Databases	7	8.0
IT work area — Cybersecurity	6	6.9
Academic degree — Incomplete bachelor's/engineering	28	32.2
Academic degree — Complete bachelor's/engineering	27	31.0
Academic degree — High school	13	14.9
Academic degree — University technical degree	9	10.3
Academic degree — Master's degree	10	11.5
IT experience — Less than 1 year	25	28.7
IT experience — 1 to 3 years	30	34.5
IT experience — More than 10 years	16	18.4
IT experience — 4 to 6 years	14	16.1
IT experience — 7 to 10 years	2	2.3

C. Reliability and Descriptive Statistics

The six scales analyzed showed excellent internal consistency in the primary analytical sample (n=87), with Cronbach's alpha coefficients ranging from 0.888 to 0.964 (Table III). The global AI governance and strategic management index had a mean of 2.82 (SD=1.24; median=2.88), at a low-intermediate level, while the global automation-performance index reached a mean of 3.21 (SD=1.17; median=3.60), at an intermediate level. Fig. 2 illustrates these means by dimension.

TABLE III
Reliability and Descriptive Statistics of the Scales (n = 87)

Scale / Dimension	Cronbach's α	M	SD	Mdn
IV–D1 Governance, Leadership and Evaluation	0.917	2.789	1.248	2.8
IV–D2 Infrastructure and Data	0.905	2.870	1.298	3
IV Global (AI Governance and Management)	0.951	2.819	1.235	2.88
DV–D1 Efficiency, Control and Continuity	0.948	3.236	1.181	3.57
DV–D2 Quality, Auditing and Satisfaction	0.888	3.161	1.213	3.67
DV Global (Automation Performance)	0.964	3.214	1.172	3.6

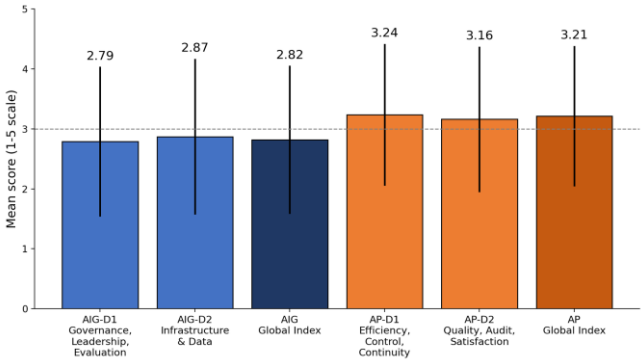


Fig. 2. Means of the dimensions analyzed (1–5 scale); bars indicate ±1 SD.

Among the AI governance and strategic management items, the lowest-scoring were periodic evaluation of AI-solution performance (M=2.64), active top-management support (M=2.77), and measurement of AI return on investment (M=2.80), pointing to opportunities for improvement in formal governance mechanisms. Among automation-performance items, time reduction through automation (M=3.34), reduction of human errors (M=3.32), and internal-user satisfaction (M=3.31) received the most favorable scores.

D. Normality and Spearman Correlations

Shapiro-Wilk tests for the main indices were significant ($p<.001$), indicating a departure from normality; Spearman correlation was therefore used as the primary association test. As shown in Table IV, the relationship between the global AI governance and strategic management index and the global automation-performance index was positive and strong ($\rho=0.613$; $p<.001$), supporting H1. All correlations between specific dimensions were also positive and statistically significant, ranging from 0.538 to 0.615, supporting H1a–H1d. A robustness check on the full sample (n=106), reported in Section IV-E, confirmed the same pattern with a somewhat larger magnitude (global $\rho=0.695$; dimension-level correlations ranging from 0.629 to 0.689).

TABLE IV
Spearman Correlations Among Dimensions and Global Indices (Primary Sample, n=87)

Relationship	ρ	p	Interpretation
IV global, DV global (H1)	0.613	<.001	Strong positive
Gov., leadership, eval. w/ Efficiency, control (H1a)	0.615	<.001	Strong positive
Gov., leadership, eval. w/ Quality, satisfaction (H1b)	0.582	<.001	Moderate positive
Infrastructure, data w/ Efficiency, control (H1c)	0.538	<.001	Moderate positive
Infrastructure, data w/ Quality, satisfaction (H1d)	0.570	<.001	Moderate positive

E. Robustness Check: Full Sample

As a robustness check on the primary result obtained in the cleaned sample (Section IV-D; n=87, $\rho=0.613$; $p<.001$), the analysis was repeated on the full sample, reincorporating the 19 records with constant responses (n=106). The association remained significant and, if anything, somewhat stronger in this full sample ($\rho=0.695$; $p<.001$; Table V), which supports the

presence of the relationship regardless of how constant-response cases are handled. At the same time, the corresponding drop in explained variance in the regression model (R^2=0.418 in the primary n=87 sample versus R^2=0.520 in the full sample, Section IV-F) is more than marginal, indicating that the two samples are not fully interchangeable and reinforcing the decision to treat the cleaned sample as the primary basis for interpretation.

TABLE V
Primary (Cleaned) Sample versus Full-Sample Robustness Check

Analysis	N	ρ	p	R^2 (simple regr.)
Full sample, robustness check (constant responses retained)	106	0.695	<.001	0.52
Primary sample (19 constant responses excluded)	87	0.613	<.001	0.418

F. Robust Regression Model

As a complementary analysis, a linear regression with HC3 robust standard errors was estimated on the primary sample (n=87). In the global model, AI governance and strategic management explained a substantial proportion of the observed variance in automation performance (R^2=0.418; adjusted R^2=0.411; B=0.613; p<.001). In a simultaneous model with both dimensions of the independent variable as predictors, only the governance, leadership, and evaluation dimension retained a significant independent contribution (B=0.473; β=0.503; p=.003); the infrastructure and data dimension lost significance once the former was controlled for (B=0.142; β=0.157; p=.385), owing to its high correlation with that dimension (Spearman ρ≈0.891; VIF≈5.1). This does not mean infrastructure and data are irrelevant: in separate univariate models, both dimensions significantly predicted performance (governance, leadership, and evaluation: R^2=0.415, B=0.605, p<.001; infrastructure and data: R^2=0.370, B=0.549, p<.001), confirming their individual relevance—though not their joint statistical independence—and consistent with the conceptual overlap between governance, leadership, infrastructure, and data discussed in Section II. A robustness check on the full sample (n=106, Section IV-E) reproduced the same pattern with somewhat larger coefficients (R^2=0.520; B=0.707; simultaneous model: governance, leadership, and evaluation B=0.515, β=0.529, p=.001; infrastructure and data B=0.192, β=0.205, p=.236, n.s.; Spearman ρ≈0.913; VIF≈6.3), confirming that the multicollinearity pattern is not an artifact of sample cleaning. This pattern of very high inter-dimension correlation, combined with the very high Cronbach's alpha obtained for both blocks (0.888–0.964; Table III), also admits an alternative reading to organizational AI immaturity: it may reflect item redundancy or insufficient discriminant validity between the two theoretical dimensions of the independent variable, a possibility that cannot be ruled out with the reliability evidence available and that, combined with the common-method-bias risk acknowledged in Section III-F, could be inflating the strength of the reported relationship. Distinguishing between these explanations would require construct-validity evidence beyond Cronbach's alpha, such as a confirmatory factor analysis with discriminant-validity indices (e.g., the heterotrait-monotrait ratio), which the present dataset does not support given its sample size and is therefore identified as a priority for future validation of the instrument.

TABLE VI
Robust Regression Model (HC3 Standard Errors, Primary Sample, n=87)

Model / Predictor	B	β	p	R^2
Global model: IV global on DV global	0.613	—	<.001	0.418 (adj.=0.411)
Simultaneous: Gov., leadership, eval.	0.473	0.503	0.003	—
Simultaneous: Infrastructure, data	0.142	0.157	0.385 (n.s.)	—

G. Exploratory Comparisons

Exploratory comparisons using the Kruskal-Wallis test were conducted, in the primary sample (n=87), by organization type (p=.213 for IV; p=.074 for DV), years of experience (p=.977; p=.460), academic degree (p=.622; p=.886), and IT work area (p=.999; p=.715). None of these variables showed statistically significant differences in the global AI governance and strategic management or automation-performance indices. These results should be considered exploratory, given the reduced size of some subgroups.

H. Hypothesis Evaluation

Table VII summarizes the evaluation of the study's hypotheses in the primary sample (n=87). General hypothesis H1 and the four specific hypotheses H1a–H1d were supported by the empirical evidence, with positive, significant relationships between the AI governance and strategic management dimensions and the IT-automation performance dimensions. All five relationships were also confirmed in the full-sample robustness check (n=106, Section IV-E), with a somewhat larger magnitude. Consequently, the general null hypothesis (H0) is rejected.

TABLE VII
Hypothesis Evaluation

Hypothesis	Decision	Evidence
H1	Supported	ρ=0.613; p<.001
H1a	Supported	ρ=0.615; p<.001
H1b	Supported	ρ=0.582; p<.001
H1c	Supported	ρ=0.538; p<.001
H1d	Supported	ρ=0.570; p<.001

V. Discussion

The main finding of this study—a strong, positive relationship between AI governance and strategic management and the performance of automated IT processes, observed in the primary, cleaned sample (n=87; ρ=0.613; p<.001)—is consistent with literature identifying governance as a relevant organizational mechanism linking technology adoption to better operational outcomes [4]–[6], [9]. The relationship remained significant, and somewhat stronger in magnitude, when the 19 constant-response cases were reincorporated in the full-sample check (n=106; ρ=0.695; p<.001), suggesting that the link does not depend on the specific criterion used to handle these cases; at the same time, the accompanying reduction in explained variance in the cleaned sample (R^2=0.418 versus R^2=0.520 in the full sample) indicates that response quality is

not immaterial to the strength of the association, which is why the cleaned sample is treated as the primary basis for interpretation throughout this study. General hypothesis H1 and the four specific hypotheses H1a–H1d were all supported in the primary sample and confirmed, with somewhat larger magnitudes, in the full-sample robustness check, indicating that the relationship between AI governance and automation performance is not concentrated in a single dimension but manifests across the different facets of the model.

The variance accounted for by the robust regression model—substantial in both the primary sample (R^2=0.418) and, more markedly, in the full-sample check (R^2=0.520)—is consistent with prior studies linking organizational AI capability to firm performance [26] and AI-supported strategic performance measures [31]. This result also aligns with evidence that AI-driven innovation is associated with better business performance metrics, particularly when organizational capabilities mediate that relationship [25]. Together, these findings suggest that, even in a Central American emerging-economy context, the strength of AI governance and strategic management practices explains a considerable share of the observed variance in perceived automation performance—a pattern previously documented mainly in larger economies. As detailed in Section IV-F, the global AI governance and strategic management index remained the central result of the analysis, while the dimension-level associations (H1a–H1d) are interpreted as complementary evidence, given the high correlation between the two dimensions of the independent variable and the alternative measurement-artifact explanation discussed above.

A. Organizational Interpretation

Examining specific items, the lowest-scoring aspects—periodic evaluation of AI-solution performance, active top-management support, and measurement of return on investment—coincide with the governance mechanisms the literature identifies as hardest to institutionalize, particularly in organizations at early stages of AI maturity [6], [21], [22], [17]. This suggests that, although participants reported tangible operational benefits from automation (reduced time and errors, higher internal-user satisfaction), a lag remains in formalizing the governance and strategic-evaluation mechanisms behind those benefits. This pattern is consistent with evidence for Latin American SMEs, where AI adoption tends to precede the formalization of its governance [33], [34], reinforcing the practical value of distinguishing between technology adoption and its institutionalized governance.

The high intercorrelation between the two dimensions of the independent variable (Spearman $\rho \approx 0.891$; VIF≈5.1 in the primary sample; $\rho \approx 0.913$; VIF≈6.3 in the full-sample check), and the loss of significance of the infrastructure and data dimension in the joint model, should not be read as evidence that this dimension is irrelevant: evaluated separately, it also showed a significant relationship with automation performance. This pattern matches studies describing the intertwined nature of organizational AI capabilities—governance, leadership, data, and infrastructure tend to develop jointly and in a correlated manner within organizations [12], [22]—and suggests that, at early stages of organizational AI maturity, governance and infrastructure and data may behave as a single general factor rather than fully differentiated capabilities. However, this organizational-immaturity reading is not the only plausible explanation. Given the very high Cronbach's alpha obtained for both blocks (0.888–0.964) together with the very high inter-dimension correlation, item redundancy or insufficient discriminant validity between the two theoretical dimensions cannot be ruled out with the evidence available; combined with the common-method-bias risk acknowledged in Section III-F, these two possibilities could jointly be inflating the strength of the reported relationship rather than reflecting a genuine single underlying factor. Adjudicating between a substantive organizational-immaturity interpretation and a measurement artifact would require construct-validity evidence beyond internal-consistency coefficients—for instance, confirmatory factor analysis with discriminant-validity indices such as the heterotrait-monotrait ratio—which the present sample size does not support. This distinction likely becomes both empirically sharper and easier to test with a larger sample and a longer trajectory of AI institutionalization in the organizations studied.

B. Regional Contribution

These results extend the scarce business evidence available on AI governance and automation performance in Central America, complementing prior studies focused on larger regional economies such as Brazil [15] and Peru [32], [40], as well as regional studies on AI adoption in Latin American SMEs [33]–[35]. The study responds to recent calls in the literature to geographically diversify empirical evidence on AI governance beyond advanced economies and large Latin American economies [33], [34].

C. Practical Implications

The results suggest that strengthening the periodic evaluation of AI initiatives, measuring their value, and securing top-management support are organizational priorities linked to higher perceived performance of automated processes—consistent with the literature on AI leadership and governance [11], [13], [14], [16], [42]—before pursuing larger-scale technology investments. Infrastructure and data governance, repeatedly identified in the literature on intelligent process automation as an enabling condition [23], [24], [28], [29], also showed a significant relationship of its own when evaluated independently, even though it proved statistically redundant with governance and leadership in the joint model.

VI. Conclusions

This study examined the relationship between AI governance and strategic management and the performance of automated IT processes among participants from firms in San Pedro Sula, Honduras. In the primary, cleaned sample (n=87, excluding 19 constant-response cases), results showed a positive, strong, and statistically significant relationship between both constructs

(ρ=0.613; p<.001; R^2=0.418), a relationship that remained significant, and somewhat stronger, in a full-sample robustness check (n=106; ρ=0.695; p<.001; R^2=0.520). General hypothesis H1 and the four specific hypotheses H1a–H1d were all supported in the primary sample and confirmed in the robustness check, underscoring the theoretical and practical relevance of AI governance and strategic management as a factor linked to higher perceived performance of automated IT processes in the study context.

This study contributes to the literature in three ways. Theoretically, it integrates four bodies of literature—AI governance, strategic management and leadership, infrastructure and data, and IT-automation performance—rarely examined jointly in small emerging-economy firms. Empirically, it provides robust quantitative evidence, with reliability checks, a full-sample robustness check, and regression with robust standard errors, from a Central American business context largely absent from the literature. Practically, the findings suggest that strengthening periodic evaluation mechanisms, measuring AI value return, and securing explicit top-management support are priority organizational steps—ahead of larger-scale technology investments—for achieving higher perceived automation performance.

Consistent with the methodological scope described in Section III-F, these results should not be generalized to Honduran firms as a whole nor interpreted causally; the convenience sample and self-reported performance measure further limit this generalization. Future research could extend the sample to other cities in Honduras and the wider Central American region, ideally through probabilistic sampling; incorporate a longitudinal design to track the evolution of AI-governance maturity over time; and conduct confirmatory factor analysis with discriminant-validity indices (e.g., the heterotrait-monotrait ratio) on a larger sample, so that the conceptual separation between governance and leadership and infrastructure and data—and the alternative possibility of item redundancy discussed in Section V—can be tested with construct-validity evidence beyond Cronbach's alpha.

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