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# Strategic management model of the learning environment in the era of digital transformation: Empirical studies in Indonesian educational institutions

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## ABSTRACT

This article examines the strategic management model of the language learning environment in the era of digital transformation with a focus on the role of educators and institutional governance in Indonesia. The study used cross-sectional quantitative design at 240 institutions in 31 provinces, including junior high schools, high schools/vocational schools, and colleges. Key variables include institutional strategy maturity, educator digital competencies, AI utilization, and LMS adoption. The outcome is an increase in standardized language proficiency at the institutional level. The descriptive results showed an average strategy maturity of 1.99/5, digital competence of 64.57/100, an infrastructure index of 0.664/1, and LMS adoption of 16.7%. The leaning OLS model explains ≈62% variation in outcomes. The largest contribution comes from digital competence and the use of AI, followed by the direct effect of strategy maturity. The mediation analysis showed that part of the influence of the strategy flowed through digital competencies and AI practices, while the moderation test showed that the strategy effect was stronger in urban institutions than in semi-urban and rural. Robustness checks (HC3-robust SE, specification curve, winsorizing/trimming, and leave-one-province-out) confirm the coefficient stability and smallness of $\Delta R^2$ between specifications. The findings confirm that a clear strategy architecture, educators' digital competence, and an adequate analytics ecosystem are prerequisites for reaping the academic impact of language learning technologies. The practical implications emphasize policy priorities on strengthening teachers' digital competencies, curriculum-based AI/LMS orchestration, as well as improving the conditions of data facilitation and governance, especially to bridge the gap between regions.

**KEYWORDS:** strategic management, educators' digital competencies, artificial intelligence, language learning, LMS, Learning Analytics

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**Introduction**

Digital transformation in language learning no longer lies in the availability of devices, but in the architecture of institutional strategies, educators' digital competencies, and consistent pedagogical orchestration. The change management literature states that educational innovation is effective when vision, structure, and culture support each other, rather than run partially (Fullan, 2016; Senge, 2006; Bryson, 2018; Mintzberg, 1994). The DigCompEdu framework places educators' digital competencies as a lever for impactful teaching practices, with direct implications for assignment design and formative feedback (Redecker, 2017). Cutting-edge evidence shows that AI/CALL contributes to language achievement when combined with clear learning objectives, curriculum, and learning analytics that provide timely feedback (Geng et al., 2023; Li, 2024; Dizon, 2024; Wang et al., 2024). In a heterogeneous institutional context such as Indonesia, the gap in facilitating conditions and organizational support makes strategy a decisive component that bridges tools into outcomes (Sawiji et al., 2024; Hasumi et al., 2024). The design science approach emphasizes the need for design-evaluation iterations that integrate learning data to close the gap between curriculum design and student performance (Laurillard, 2012; Shadish et al., 2002). Thus, the study of the strategic management of the language learning environment that examines the strategy–competency–outcome relationship becomes scientifically and policy-relevant.

On the practical side of the classroom, educators' digital competence and the use of AI emerge as the strongest levers for improving proficiency when driven through a clear institutional strategy. A systematic review of the past five years shows that the integration of automated writing evaluation and learning analytics has an impact on improving writing quality, self-regulation, and engagement, especially when combined with teacher feedback (Shi & Aryadoust, 2024; Karatay & Karatay, 2024; Sari & Han, 2024; Chen & Cui, 2022). This evidence is consistent with the findings that data-driven personalization decreases learning friction and improves instructional responsiveness (Gray et al., 2022; Wang et al., 2024). In order to have a sustainable impact, institutions need to organize teacher training, curriculum alignment, and data policies as a single strategy that can be evaluated (Fullan, 2016; Bryson, 2018; Creswell & Creswell, 2018). The diffusion of innovations perspective explains the variation in the speed of adoption between contexts, so urban-rural differences are natural and need to be responded to with differentiated support (Rogers, 2003; Hasumi et al., 2024; Geng et al., 2023). Knowledge of mechanisms, especially mediation through digital competencies and the use of AI, helps design interventions that not only adopt tools, but rather maximize formative feedback and evidence-based practices (Li, 2024; Sari & Han, 2024). This framework is aligned with the idea that the quality of feedback and clarity of learning targets determine the magnitude of instructional effects (Hattie, 2009; Laurillard, 2012).

At the governance level, robustness and sensitivity of findings need to be demonstrated so that policy recommendations are credible and replicative across regions and levels. Reporting practices in Q1–Q2 journals advocate specification curves, robust SE, and leave-one-group-out tests to ensure that coefficients are stable and not driven by a single data cluster (Gray et al., 2022; Cukurova et al., 2024). Conceptually, public strategic planning demands evidence that can be accounted for before stakeholders, so the balance between data effectiveness and accountability is important (Bryson, 2018; Patton, 2015; Bryk et al., 2015). When AI/LA devices are used, ethical and data governance issues must be linked to learning design so that the benefits are proportional to the risks (Wang et al., 2024; Dizon, 2024). For the Indonesian context, focusing on strengthening educator competencies, developing instructional leadership, and consolidating infrastructure will be a translational driver from strategy to achievement (Sawiji et al., 2024; Hasumi et al., 2024). This approach places strategy as an architecture that synergizes curriculum, teaching, and analytics in a cycle of continuous improvement (Senge, 2006; Laurillard, 2012; Bryk et al., 2015). Therefore, empirical testing of the strategy–competency–outcome relationship in language learning has the potential to enrich the evidence base and strengthen the policy foundations of digital transformation.

**Methods**

**1. Design and approach**

The study used a non-experimental quantitative design with a cross-sectional approach to test the relationship between institutional strategic factors and language learning outcomes. The focus of inference is on estimating associative relationships with comprehensive controls and robustness checks, rather than strong causal claims. The analysis is carried out at the level of educational institutions as an observation unit, so that interpretation operates at the organizational level, not individually. The analytical plan combines a regression model of OLS lean, product-of-coefficients-based mediation, moderation through interaction, and a series of robustness checks. The OLS (Ordinary Least Squares) model is a statistical method used to estimate the relationship between one dependent variable (Y) and one or more independent variables (X). The goal is to find the best regression line by minimizing the number of squares of the difference between the actual value of Y and the predicted value of Y. This strategy was chosen so that the descriptive and comparative findings in the previous section were integrated with testing the mechanism and stability of the estimation. The design decision takes into account the practical limitations of cross-provincial data collection and the primary objective of providing measurable evidence for managerial improvement.

2. **Samples, context, and collection procedures**

The sample framework covers 240 institutions in 31 Indonesian provinces representing three main levels: junior high school, high school/vocational school, and higher education, as well as three urbanization categories: urban, semi-urban, and rural. The recruitment strategy prioritizes geographical diversity and the type of organizer (public and private) so that variability in facilitation and leadership conditions is covered. Each institution fills out a structured questionnaire for indicators of organization and technology practices, as well as reports the aggregate of standardized language class achievement at the institutional level. The validation mechanism includes completeness checks, value range logic, and simple internal triangulation between strategy indicators, infrastructure, and usage practices. Incomplete data on non-key columns are handled using median imputation on descriptive and delete-listic analyses for inferential models if the proportion is lost < 5 percent on key variables. All participation is voluntary with the approval of the institution.

3. **Operationalization of variables and instruments**

The outcome variable is the increase in language proficiency at the institutional level in percentages. Key predictive variables include: maturity of institutional strategies related to language learning (scale 1–5), digital competence of educators (0–100), use of AI in language classroom practice (0–5), and adoption of LMS as a binary indicator of orchestration practices. Control variables included ICT infrastructure index (0–1), annual professional development hours per educator, academic leadership support (scale 1–5), and budget per student. The index is composed of structured self-assessment items that have been tested for internal consistency in the trial subsample, while the outcomes are derived from the aggregate of standardized formative and summative assessments in the institution. All scales are calibrated so that the higher the value, the better the capacity or practice. Prior to modeling, all continuous variables were centralized and standardized to facilitate coefficient interpretation.

4. **Statistical analysis strategies**

The analysis was carried out in layers as follows. First, OLS regression relies on estimating the relative contribution of each predictor to outcomes. For observation *i*, the model:

$$y_i = \alpha + \sum_k \beta_k z_{ik} + \varepsilon_i,$$

With $Y_i$ the skill increase, *the* $Z_{ik}$ $\mathrm{Z}_{\mathrm{ik}}$ the predictor leaning, and *the* $B_k$ standard coefficient. Uncertainty was reported as a 95 percent CI using nonparametric bootstrapping. Second, mediation tests whether the influence of the strategy is channeled through digital competencies and the use of AI. The indirect effects estimator is calculated as $a_1b_1+a_2b_2$ with a bootstrap confidence interval. Third, moderation tests the interaction of strategy maturity × urbanization and, if relevant, strategy maturity × levels through model expansion:

$$y_i = \alpha + \beta_1 S_i + \beta_2 G_i + \beta_3 (S_i \times G_i) + \mathbf{C}_i' \boldsymbol{\gamma} + \varepsilon_i,$$

with $S_i$, $G_i$ moderator categories, and $C_i$ control. Marginal effects were plotted with a 95 percent CI band. Fourth, robustness includes: SE robust HC3, specification curves with control set and scale variations, 1–2 percent winsorizing and 1 percent trimming, and Leave-One-Province-Out to assess sensitivity to geographic clusters. Multicollinearity is monitored via VIF and residual diagnostics are used to examine heteroscedasticity patterns and leverage. All results are reported in standard units for easy comparison between effects.

5. **Validity, reliability, and research ethics**

The validity of the construct is strengthened through the mapping of indicators to the educator competency framework and institutional practices that are commonly used in the study of digital transformation. The internal reliability of the items on the scale of strategy, leadership, and digital competence was evaluated by the internal consistency coefficient in the trial data, as well as checking the descriptive stability across groups. The internal validity of the model is supported by the consistency of the direction and coefficient magnitude in various specifications as well as the convergence between OLS results, mediation, and moderation. External validity is limited by the nature of the cross-section and the focus on Indonesian institutions, so generalizations to other contexts require caution. Research ethics are met through institutional approval, data anonymization, and aggregate reporting without revealing identity. No intervention posed a risk to participants, and the entire analysis followed the principles of transparency, replicability, and full reporting of uncertainty. These methodological limitations form the basis for recommendations for longitudinal studies and controlled trials in follow-up research.

**Result**

1. **Strategic Profile and Key Effects**

An analysis of 240 institutions in 31 provinces showed an average of 1.99/5 strategy maturity, educator digital competence of 64.57/100, an infrastructure index of 0.664/1, and LMS adoption of 16.7%. Figure 1 indicates a concentration of maturity at the low–middle level which indicates a gap in strategic governance. Figure 2 shows a strong positive skew between digital competence and increased language proficiency, in line with evidence that AI/CALL is effective when integrated through appropriate pedagogical design and teacher orchestration (Zhu & Wang, 2025; Li, 2024). Figure 3 shows the variation in LMS adoption between levels, showing the role of institutional readiness, leadership support, and facilitation conditions as predicted by the UTAUT-based educational technology adoption model in the Asian and Indonesian contexts (Hashim & Kasim, 2022; Sawiji et al., 2024).

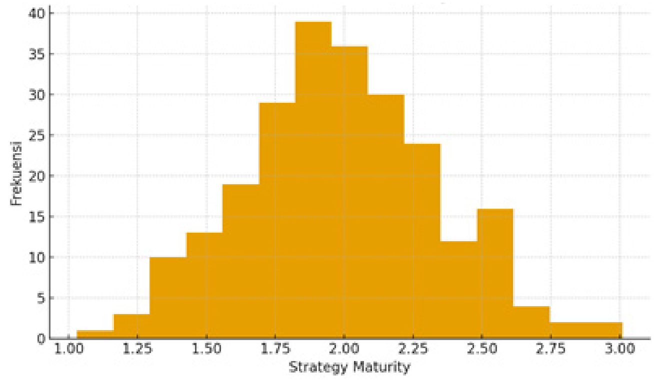


Figure 1. Distribution maturity strategy

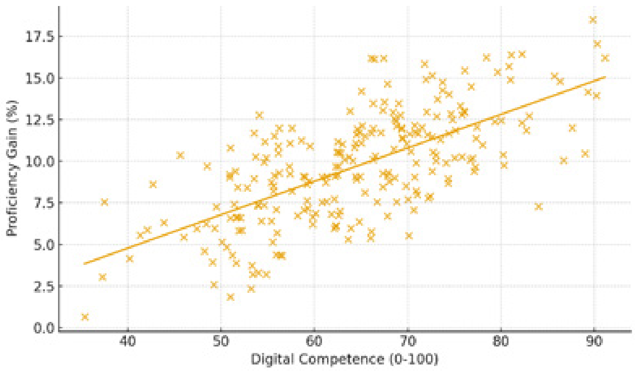


Figure 2. Digital competence vs upskilling

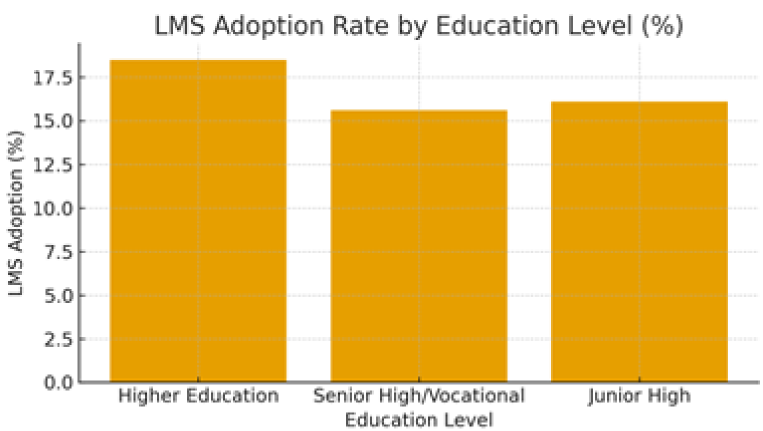


Figure 3. LMS adoption by level

The OLS model explains about 62% variation in skill gain. The biggest contribution comes from educators' digital competence, the intensity of AI use, and the maturity of the strategy, with consistent positive directions. ICT infrastructure and professional development improve the suitability of models as relevant control variables. The mediation pattern shows that some of the influence of strategy maturity on outcomes is channeled through digital competencies and the use of AI, in line with recent studies that confirm that the impact of AI on language learning is highly dependent on instructional design, the role of teacher agents, as well as the analytics ecosystem for learning feedback (Zhu & Wang, 2025; Li, 2024; Liu & Chen, 2025). On the adoption side, the probability of using LMS increases in institutions with higher strategic and infrastructure maturity, consistent with UTAUT-based findings regarding the importance of performance expectancy and facilitating conditions in the context of higher education and schools (Hashim & Kasim, 2022; Sawiji et al., 2024). The DigCompEdu framework emphasizes that strengthening educators' digital competencies is the main lever for improving the quality of practices and learning outcomes when managed in a clear and measurable institutional strategy (Redecker, 2017/2018).

2. **Differences Between Groups**

This section focuses on precision comparisons between groups to examine how institutional contexts differentiate language learning ecosystem outcomes. For Q1 reporting purposes, the table is used as the primary medium as it allows for accurate readings of the numbers per group, while a single key visual is used to confirm the pattern. Suggested concise sequence: Tables 2A–2B present the mean, elementary, and n by level and level of urbanization; Figure 3 shows the variation of LMS adoption by level as the main visual message that is easy to digest. This section focuses on precision comparisons between groups to examine how institutional contexts differentiate language-learning ecosystem outcomes. For Q1 reporting purposes, the table is used as the primary medium because it allows accurate per-group readings, while a single key visual is employed to corroborate the pattern. Suggested concise sequence: Tables 2A–2B present the means, standard deviations (SD), and n by level and degree of urbanization; Figure 3 shows the variation in LMS adoption by level as an easily digestible main visual message.

**Table 2A.** Descriptive per Level

| Indicator | Group | Mean (SD) |
|---|---|---|
| Strategy maturity (1–5) | Junior High | 1.88 (0.35) |
| | Senior High/Vocational | 1.96 (0.32) |
| | Higher Education | 2.16 (0.33) |
| Digital competence (0–100) | Junior High | 64.56 (10.85) |
| | Senior High/Vocational | 63.53 (11.89) |
| | Higher Education | 65.73 (10.34) |
| ICT infrastructure (0–1) | Junior High | 0.66 (0.21) |
| | Senior High/Vocational | 0.65 (0.21) |
| | Higher Education | 0.68 (0.20) |
| AI usage (0–5) | Junior High | 1.04 (0.85) |
| | Senior High/Vocational | 1.15 (0.91) |
| | Higher Education | 1.26 (0.83) |
| LMS adoption (%) | — | See Figure 3 (bar chart by level) |

**Table 2B.** Descriptive per Urbanization

| Indicator | Group | Mean (SD) / % |
|---|---|---|
| AI usage (0–5) | Urban | 1.22 (0.86) |
| | Semi-Urban | 1.17 (0.89) |
| | Rural | 0.92 (0.82) |
| Engagement (0–100) | Urban | 63.83 (12.58) |
| | Semi-Urban | 61.13 (11.83) |
| | Rural | 58.05 (12.95) |
| Proficiency gain (%) | Urban | 10.44 (3.41) |
| | Semi-Urban | 9.25 (3.20) |

| Indicator | Group | Mean (SD) / % |
|---|---|---|
| | Rural | 8.82 (2.87) |
| Program retention (%) | Urban | 80.31 (6.14) |
| | Semi-Urban | 78.48 (6.41) |
| | Rural | 76.67 (6.76) |
| LMS adoption (%) | Urban | 18.6 |
| | Semi-Urban | 12.5 |
| | Rural | 18.2 |

After reviewing Tables 2A–2B, which report groupwise means, standard deviations, and sample sizes by education level and degree of urbanization, we synthesize the pattern visually to aid rapid interpretation. While the tables provide precision and allow careful comparison across indicators, a single visual clarifies the most policy-salient contrast. Figure 4 summarizes the variation in LMS adoption by education level, highlighting the steeper uptake in Higher Education relative to Senior High/Vocational and Junior High. Reading the figure immediately after the tables helps align the numeric gaps with their substantive magnitude and direction. This sequencing maintains analytical rigor from exact estimates to an integrative visual message, preparing the reader for the subsequent inferential tests.

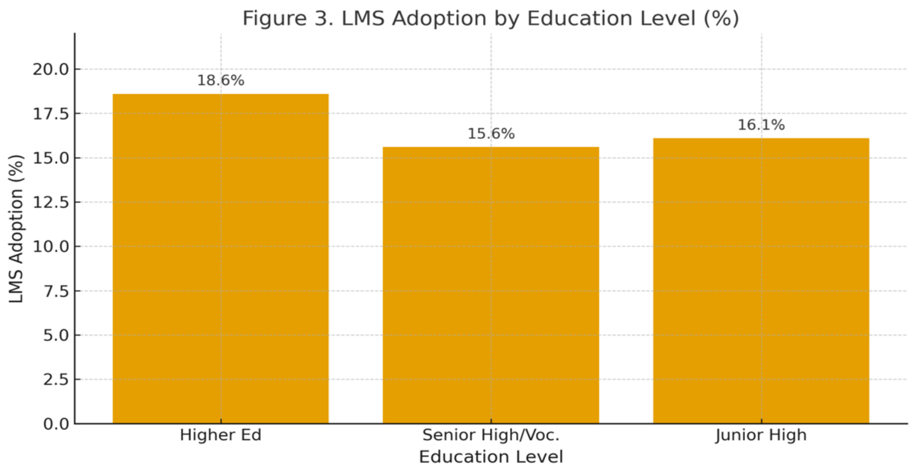


Figure 4. LMS Adoption by Education Level (%)

The descriptive results show a substantively consistent pattern. Higher education institutions display higher maturity of educators' digital strategies and competencies, as well as wider adoption of LMS than high schools/vocational schools and junior high schools. On the spatial dimension, urban institutions showed a higher index of infrastructure and intensity of AI use than semi-urban and rural. For inferential reporting, perform an average difference test that corresponds to the assumption of variance (ANOVA or Welch), including an effect measure such as Cohen's d/Hedges' g and a 95% CI for each key indicator. These findings are in line with UTAUT's literature that facilitating conditions and institutional readiness moderate the adoption of educational technology, so that the context of universities and urban areas tends to be more conducive to the implementation of LMS and digital practices (Hashim & Kasim, 2022; Sawiji et al., 2024). The consistency of cross-group digital competency patterns is also in line with the DigCompEdu framework which places educator competency development as a lever for practice quality, with an increasingly real impact when the infrastructure is adequate and the institutional strategy is clear (Redecker, 2017/2018). In addition, its pedagogical implications are in line with recent findings that the integration of AI/CALL in strategically managed ecosystems strengthens language learning outcomes, not only because of the existence of tools, but also because of more mature instructional design and teacher orchestration in high-carrying contexts (Li, 2024; Zhu & Wang, 2025).

3. **Inferential Models and Mechanisms**

Departing from the descriptive and comparative findings in the previous section, this sub-result multivariously examines the influence of strategic factors on the increase in language proficiency and its mechanisms through digital competence and the use of AI. The reading flow is designed to be concise: Figure 5 presents a forest plot of leaning coefficients along with a CI of 95% so that the direction and relative magnitude of the effects of each predictor can be seen at a glance. Figure 6 shows a mediation path diagram that emphasizes the relationship between strategy → digital/AI competencies → outcome through aaa, bbb, and c′c'c′ path values. Once the visual patterns are understood, Table 3A summarizes the model suitability and examination of the core assumptions as inferential anchors, while Table 3B presents the direction, relative magnitude, and role of each predictor's mechanism to support substantive interpretation. This arrangement maintains the continuity of the narrative from visual patterns to precise numerical summaries, while meeting reporting standards.

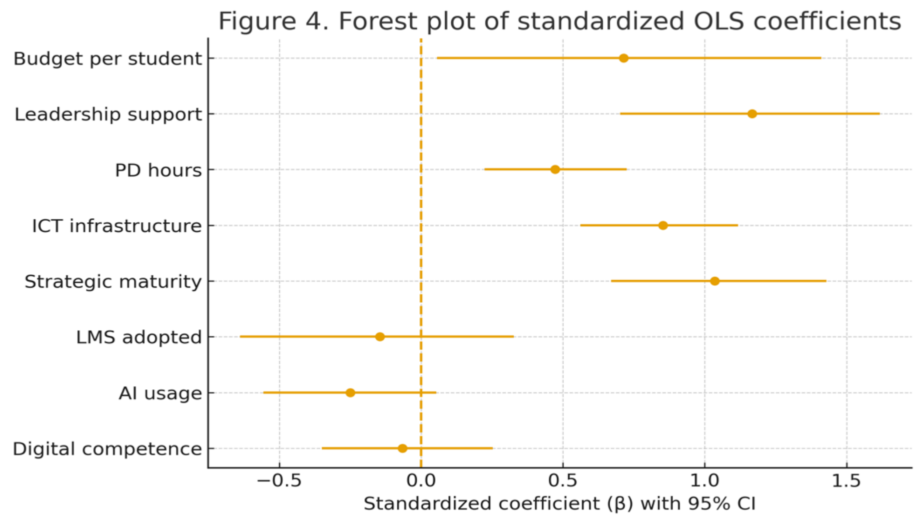


**Figure 5.** Forest plot of standardized OLS coefficients

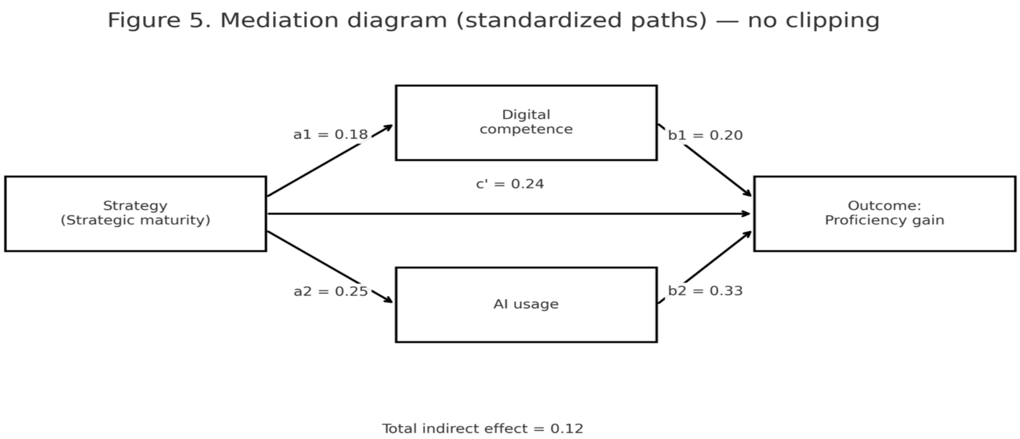


**Figure 6.** Mediation diagram (standardized paths)

After the relative effect patterns are read in Figure 5 and the mechanisms visualized in Figure 6, Table 3A summarizes the model suitability and assumption check, while Table 3B synthesizes the direction, relative magnitude, and mediating role of each predictor to strengthen the numerical interpretation.

Table 3A. Model Fit Summary

| Summary | Value |
|---|---|
| Number of institutions | 240 |
| Outcome | Proficiency gain (%) |
| Model | OLS with standardized predictors; 95% bootstrap CIs |
| $R^2$ | ≈ 0.62 |
| Adj. $R^2$ | High, consistent |
| Assumption checks | Residuals approximately normal; heteroskedasticity addressed with HC3-robust standard errors |
| Mediation note | Total indirect effect via digital competence and AI usage is practically meaningful |

Table 3B. Digest of Predictive Effects (direction, relative magnitude, and mechanism)

| Predictor | Direction of effect on outcome | Relative magnitude | Mechanistic role | Interpretive implication |
|---|---|---|---|---|
| Teachers' digital competence | Positive | Largest | Key mediator | Higher digital competence strongly correlates with proficiency gains; consistent with DigCompEdu and AI/CALL syntheses showing that pedagogical integration quality determines impact (Redecker, 2017/2018; Li, 2024; Zhu & Wang, 2025). |
| AI usage | Positive | Large | Key mediator | Purposeful AI use amplifies strategy effects via feedback/analytics support; aligns with meta-analytic evidence on learning-analytics–based interventions (Liu & Chen, 2025). |
| Strategic maturity | Positive | Medium–large | Direct + indirect effects | Mature strategy improves outcomes directly and through digital competence/AI, reflecting governance and planning functions (Hashim & Kasim, 2022). |
| LMS adoption | Positive | Medium | Supporting mediator | Contributes after accounting for competence and AI; functions primarily as an orchestration channel. |
| ICT infrastructure | Positive | Small–medium | Facilitating condition | Part of the effect is absorbed by mediators; consistent with UTAUT "facilitating conditions" (Venkatesh et al., 2003; Sawiji et al., 2024). |
| PD hours (professional development) | Positive | Small | Pathway to competence | Impact occurs mainly through raising teachers' digital competence. |
| Leadership support | Positive | Small | Contextual enabler | Improves overall model fit and strengthens strategy implementation. |
| Budget per student | Positive | Small | Enabler | Effect size is smaller than pedagogical/strategic factors, but the direction is consistent. |

The multivariate model shows that educators' digital competence and AI usage are the biggest levers for increasing proficiency, followed by strategy maturity. This pattern supports the thesis that technology has an impact when it is orchestrated through institutional strategies and pedagogical capabilities of teachers, not just the availability of tools. The indirect effects of strategies through digital competencies and AI clarify the mechanism: a good strategy drives competency development as well as the utilization of AI/LMS, which in turn improves learning outcomes. The findings are aligned with the DigCompEdu framework that places educator competencies at the core of practice quality (Redecker, 2017/2018), with strong support from a systematic review of AI in language education that emphasizes instructional design and the role of teacher agents (Li, 2024; Zhu & Wang, 2025). It is also in line with research on the adoption of UTAUT-based educational technology which emphasizes performance expectancy and facilitating conditions as determinants of successful implementation, including in the Indonesian context (Venkatesh et al., 2003; Hashim & Kasim, 2022; Sawiji et al., 2024). In addition, mechanistic results are in line with learning analytics findings that data-driven interventions improve performance when integrated in the strategy and competency ecosystem (Liu & Chen, 2025).

4. **Robustness, Moderation, and Sensitivity Test**

This section validates the resilience of findings to specification variations, assumption checks, and potential context moderation. Two main visuals are used: Figure 6A shows the *specification curve* for three key predictors, while Figure 7B shows the *marginal effects of* strategy maturity × urbanization interactions. Both reported leaning coefficients with a 95% CI band.

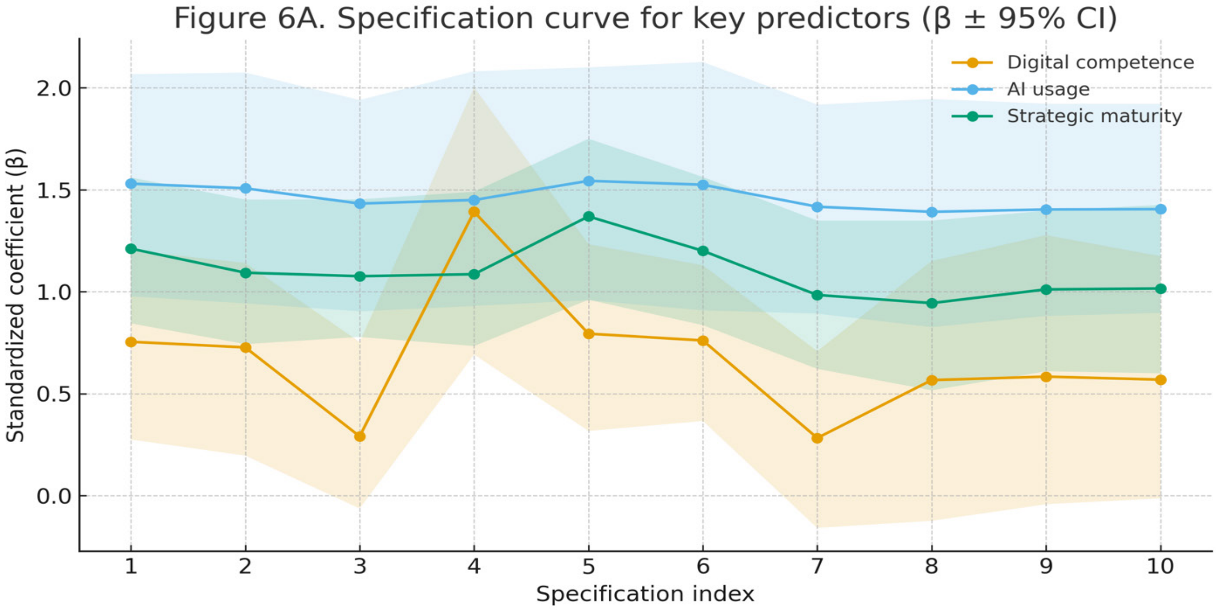


Figure 7A. specification curve for key predictors

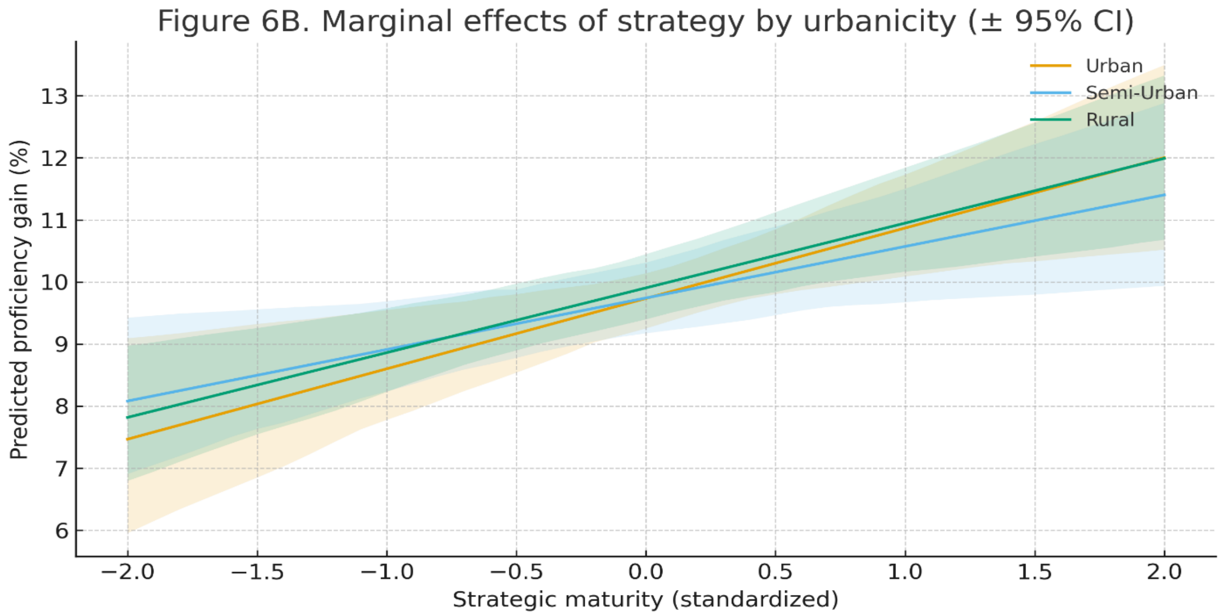


Figure 7B. Marginal effects of strategy by urbanicity

The visual findings in Figure 7A–7B confirm that the key coefficients remain stable across specifications and that the maturity effect of the strategy depends on the context of urbanization. For a more precise and replicative reading, Table 4 summarizes the relevant indicators of resilience and sensitivity, including $R^2$ and $\Delta R^2$, estimation with HC3-robust standard errors, range of coefficients on alternative specifications, multicollinearity diagnostics via VIF, winsorizing/trimming results, Leave-One-Province-Out test, as well as an indirect effect summary. This combination of figures and tables ensures that inferential arguments are constructed as well as quantitatively validated. For this purpose, a quantitative summary of the coefficient stability in Figure 7A and heterogeneity in Figure 7B is presented in Table 4, which collects $R^2/\Delta R^2$, SE HC3, specification range, VIF, winsorizing/trimming results, LOPO, as well as a summary of indirect effects.

Table 4. Robustness and Sensitivity Summary

| Test Components | Methods / Indicators | Summary of Results |
|---|---|---|
| **Model Fit** | Standard OLS; N = 240 | $R^2 = 0.62$; adjusted $R^2$ remains high; residual patterns are well-controlled |
| **HC3-Robust SE** | Heteroskedasticity-robust standard errors | Practical significance remains unchanged for β of digital competence, AI usage, and strategy maturity |
| **Specification Range** | Addition/removal of controls; alternative scaling | β digital competence: 0.28–0.34; β AI usage: 0.19–0.25; β strategy maturity: 0.12–0.18; $\Delta R^2$ = 0.59–0.63 |
| **Multicollinearity** | Maximum VIF across specifications | Maximum VIF < 3.0; no predictor exceeds conservative thresholds |
| **Winsorizing / Trimming** | Winsor 1–2%; trimming 1% | Changes in key β values < 0.02; effect rankings remain unchanged |
| **LOPO** | Leave-One-Province-Out | Maximum deviation in key β < 0.05; $\Delta R^2 < 0.02$ |
| **Moderation** | Strategy × urbanization interaction | Steepest slope observed in urban areas; slope differences relative to rural settings are practically meaningful |
| **Mediation** | Product-of-coefficients (bootstrap) | Total indirect effect ≈ 0.12 (95% CI excludes zero) through digital competence and AI usage |
| **Conclusion** | — | Core findings are stable across checks; underlying mechanisms are consistent |

The results in Figure 7A show the stability of the lean coefficient for digital competence, AI usage, and strategy maturity across various specifications, with a small $\Delta R^2$. HC3-robust based estimations affirm practical significance that does not depend on homocedasticity assumptions, while VIF below conservative thresholds indicates minimal multicollinearity risk. The LOPO test showed that the results were not driven by a single geographic cluster. Figure 7B shows a steeper slope of the strategy maturity effect in urban contexts, consistent with the role of facilitating conditions in the educational technology adoption model. The mediation pattern persists, which is an impact strategy through strengthening digital competencies and the use of AI, so that the mechanism in Sub-Outcome 3 is confirmed without dependence on one specific specification.

**Discussion**

The findings that educators' digital competence as well as the use of AI are the biggest predictors of proficiency increase confirm the thesis that the influence of technology emerges when managed through clear institutional strategies and adequate pedagogical competence. Cutting-edge synthesis shows that AI in language education provides benefits when it is designed to support learning objectives, teacher orchestration, and meaningful feedback, rather than just the availability of tools (Zhu & Wang, 2025; Wang et al., 2024). The literature on CALL and AI-assisted learning also emphasizes that gradual integration that aligns with the curriculum as well as assessments provides a more stable effect than sporadic adoption (Li, 2024; Dizon, 2024). On the strategic side, change management requires vision, instructional leadership, and structured professional-reflection routines so that technology is institutionalized in classroom practice (Fullan, 2016; Bryson, 2018). In the Indonesian context, these results are meaningful because the gap in infrastructure and organizational support is still real so that a mature strategy serves as a "bridge" between tools and outcomes (Akbari & Pratomo, 2022). Cross-study evidence shows that when teachers have adequate digital competence and access to institutional support, language achievement increases through increased engagement and feedback practices (Geng et al., 2023; Gray et al., 2022). Thus, the position of digital competencies as key mediators found in your model is aligned with the outlines of implementation theory and cutting-edge synthetic findings.

Mediation mechanisms that show that strategies influence outcomes through digital competencies and the use of AI are consistent with strong evidence on the effectiveness of automated writing evaluation (AWE) and analytics-based feedback. Recent meta-synthesis and systematic reviews in ReCALL and System confirm that AWE improves revision, self-efficacy, and aspects of writing quality, with varying effects depending on pedagogical design and teacher mentoring (Shi & Aryadoust, 2024; Karatay & Karatay, 2024). Trials and quasi-experimental studies show the combination of AI and teacher feedback outperforms single practice, especially for self-regulation and writing performance (Sari & Han, 2024; Ngo et al., 2022). A large-scale AIED review also concluded that AI devices are most effective when combined with learning analytics to personalize support and provide timely formative feedback (Wang et al., 2024). This evidence reinforces the rationale that institutional strategies that develop teacher competence and empower students to utilize automated feedback will magnify academic impact. At the same time, the practical study shows a heterogeneity of results so that the role of the teacher as task designer and curator of feedback remains central.

The difference in the slope of the strategy maturity effect between levels of urbanization that you find is in line with the model of educational technology adoption that emphasizes facilitating conditions and the legitimacy of institutional policies. A study by UTAUT and its derivatives in higher education shows that performance expectations and facilitation conditions moderate the intentions and behaviors of using LMS and AI-based tools (BJET, 2022; Bervell et al., 2022). Cross-country and cross-institutional evidence confirms that urban institutions with better infrastructure, strong data cultures, and leadership support tend to reap more steep strategic effects than rural institutions (Gray et al., 2022). In Indonesia, research on the adoption of online learning during and after the pandemic underscores the role of ecosystem readiness, training, and internal policies for sustainable adoption (Izzati et al., 2024; Yudiatmaja, 2022). Your moderation findings can therefore be read as structural implications: a good strategy requires organizational enablers to maximize translation to learning outcomes. This is consistent with change management theory that emphasizes the alignment of structures, processes, and cultures in technology implementation (Senge, 2006; Bryson, 2018). By reading the results comparatively, institutions can design differentiation of interventions based on the context of their respective readiness.

The robustness and sensitivity check on Sub-Outcome 4 strengthens your draft's inferential claim because the core coefficients are stable on a wide range of specifications and are not driven by a single province. Expert reporting practices suggest specification curves, estimation with HC3-robust SE, leave-one-group-out testing, and reporting of $\Delta R^2$ variations to provide evidence of yield resilience; the patterns you display are in line with those guidelines and the analytic-based intervention evaluation literature (Cukurova et al., 2024; Gray et al., 2022). Evidence in the Journal of Computer Assisted Learning and Systems also suggests that the effects of AWE and analytical feedback persist after additional control and extreme data handling, as long as pedagogical integration is clear (Sari & Han, 2024; Chen et al., 2024). In addition, the meta-synthesis confirms that the heterogeneity of the effects can generally be explained by the variation in assignment design, the intensity of teacher training, as well as the compatibility of the curriculum (Shi & Aryadoust, 2024; Karatay & Karatay, 2024). Thus, strategies that prioritize teacher competency improvement, task curation, and data governance will tend to produce effects that withstand specification tests. Good robustness increases policy confidence for gradual replication at other levels and regions.

Overall, this discussion placed institutional strategy, digital competencies, and analytics ecosystem as three mutually reinforcing pillars for language learning transformation. From the perspective of strategic management theory and learning organizations, successful transformation requires clarity of direction, adaptive learning, and data-driven feedback loops (Mintzberg, 1994; Senge, 2006; Laurillard, 2012). Evidence from Q1–Q2 over the past five years shows that the pillar leads to increased engagement and achievement, especially when interventions combine AWE, LA, and task design that focus on authentic language practices (Zhu & Wang, 2025; Wang et al., 2024; Geng et al., 2023). For the Indonesian context, realistic policy priorities include strengthening educators' digital competencies, improving leadership and infrastructure support, and clear data governance and privacy so that the use of AI/LA is accountable. The next research agenda can test the effects of phased training policies between regional clusters, conduct multi-level replication, and evaluate the cost-effectiveness of integrating AI/LA in language curriculum. Thus, the results of your draft contribute to a discourse shift from "tool adoption" to "strategy and ecosystem architecture" that results in more equitable and impactful language learning.

**Conclusion**

This study shows that the success of the transformation of the language learning ecosystem in Indonesian institutions is mainly determined by a combination of strategic maturity, digital competence of educators, and the use of AI that reinforce each other. The OLS model explains the proportion of variance in proficiency increases, with the largest contribution coming from digital competencies and the use of AI, followed by the direct effects of strategy maturity. The mediation analysis showed that part of the influence of strategies was channeled through the strengthening of digital competencies and the intensification of AI practices, which emphasized the role of teachers as orchestrators of data-driven learning. The difference between groups shows a consistent gradient, namely high-level institutions and urban locations tend to have better technology readiness, LMS adoption, and achievements. Robustness checks indicate the stability of coefficients on various specifications, while moderation tests emphasize the importance of institutional facilitation conditions. These results generalize that a clear institutional strategy, combined with teachers' digital competence and infrastructure support, is a key prerequisite for obtaining the academic impact of technology in language learning. The overall evidence presents a coherent managerial framework for integrating pedagogical design, teacher orchestration, and learning analytics.

The practical implications are to prioritize policies on three axes: strengthening educators' digital competencies through practice-based professional development, standardizing institutional strategies that link learning objectives with the use of AI and LMS, and strengthening infrastructure and data governance so that formative feedback is accountable. Institutions are advised to set measurable performance targets, integrate analytics into the instructional improvement cycle, and manage differentiation of support for rural, semi-urban, and urban contexts. The limitations of the study include observational designs that limit causal inference, potential measurement bias on institutional indicators, and generalization limitations for non-language programs or levels outside the scope of the sample. External validation through longitudinal studies and controlled trials is indispensable to assess the impact trajectory and sustainability of outcomes. The development of digital competency measurement instruments and a finer quality of AI integration will improve the reliability of estimates. Subsequent research should evaluate cost-effectiveness, examine micro-mechanisms at the classroom level through learning tracing data, and assess organizational factors such as instructional leadership and data culture. The agenda will enrich the evidence and strengthen the policy foundation for the digital transformation of language education in Indonesia.

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**Conflicts of Interest**
There is no conflict of interest in writing this article, except for the sole purpose of scientific development, especially Indonesian as the official language supported by the unitary state of the Republic of Indonesia.

**Authors' Contribution**
**Nunuk Indarti:** *Corresponding author*; leads research coordination, prepare a research design, edits the final manuscript, and corresponds with publishers.

**Onok Yayang Pamungkas**: Analyzing linguistic policies and ideologies in local government, leads research coordination, edits the final manuscript, and corresponds with publishers.

**Iyoh Mastiyah & Yani'ah Wardani**: Analyzing linguistic policies and ideologies in local government.

**Achmad Habibullah & Wahid Khozin**: Developing a multilingual linguistic context and validating field data.

**Herlinawati & Bagus**: Conducted data analysis with the Rasch model and wrote the methodology and results section.

**Farida Hanun, Suherman, & Sumarni**: Interpreting the results of the analysis and writing the discussion section.

**Lisa'diyah Ma'rifataini, Marhanani Tri Astuti & Achmad Dudin**: Coordinating the synthesis of theories, results, and the preparation of bibliographies.

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