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FULL LENGTH ARTICLE

AI-Enabled Strategic Planning for Educational Institutions: An Education Technology Readiness Framework for Transformation

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ABSTRACT

Educational institutions are under growing pressure to integrate artificial intelligence (AI) and education technology (EdTech) in ways that improve teaching, governance, and service delivery rather than merely expand digital procurement. Strategic planning is therefore a core institutional capability: it aligns infrastructure, teacher readiness, student access, digital learning resources, and governance routines into a coherent transformation agenda. This study develops an AI-enabled strategic planning framework using the public 2023 World Bank EdTech Readiness Index (ETRI) pilot evidence. The framework converts traffic-light dashboard indicators into pillar-level maturity scores, strategic gaps, and a multi-criteria readiness benchmark. Empirical analysis of the Ho Chi Minh City and Dominican Republic pilot dashboards shows that school management is the strongest readiness domain in both settings, whereas connectivity and digital education resources remain more constrained. The paper contributes a managerial decision model that translates readiness evidence into institutional priorities, implementation roadmaps, and governance checkpoints. Unlike tool-centred studies, the analysis treats AI as a decision-support capability for educational planning. The framework offers a transparent and reproducible approach for organising EdTech strategy while keeping final decisions anchored in professional judgement and educational value.

Keywords: Artificial intelligence in education ▪ Education technology ▪ Strategic planning ▪ Institutional transformation ▪ EdTech readiness ▪ Decision support ▪ TOPSIS

1. INTRODUCTION

The expansion of AI and digital learning tools has reshaped the strategic agenda of educational institutions. The central question is no longer whether schools and universities should adopt technology, but how they should sequence capabilities, govern risks, and connect digital initiatives to educational value. Recent scholarship shows that AI in education has moved well beyond intelligent tutoring and automated assessment toward broader institutional concerns involving governance, implementation, and leadership [1, 2, 3, 4]. In this context, strategic planning becomes a practical governance problem: leaders must decide which capabilities are foundational, which are developmental, and which should be postponed until institutional readiness improves.

This challenge is especially visible in systems attempting to scale AI-supported teaching, analytics, and digital services while still dealing with uneven connectivity, weak support structures, and inconsistent access to digital resources. The concern is not simply one of infrastructure. Decisions about AI and EdTech also involve teacher capability, student participation, implementation support, data use, and policy alignment [5, 6, 7]. Fragmented adoption can produce isolated pilots, short-lived enthusiasm, or technology investments that do not materially improve educational quality.

This study addresses a practical research question: how can public readiness evidence be translated into a strategic planning framework for AI and EdTech transformation in educational institutions? To answer this question, the paper analyses the 2023 pilot evidence of the World Bank EdTech Readiness Index (ETRI) and uses it to build a decision model for institutional planning. The paper makes four contributions. First, it provides a reproducible readiness-scoring procedure based on public evidence. Second, it formalises a strategic planning model that links readiness gaps with institutional priorities. Third, it presents an interpretable readiness benchmark using TOPSIS. Fourth, it frames the results in managerial language that is useful for ministries, school systems, and higher education institutions.

2. RELATED WORK

2.1 AI in education as an institutional rather than tool-level issue

The contemporary AI-in-education literature increasingly emphasises institutional adoption rather than isolated technical applications. Early syntheses published in 2020 identified both the rapid growth of AI applications in education and a substantial gap between technical experimentation and theory-driven implementation [1, 2]. The field has since been reframed around three broad paradigms: AI-directed, AI-supported, and AI-empowered learning [3]. This shift is significant for institutional planning because it suggests that educational organisations need coordinated capability building rather than ad hoc acquisition of tools.

The same pattern is evident in higher education. A recent state-of-the-field review shows that AI applications now span prediction, recommendation, content support, assessment, and academic services, but also notes the need for clearer institutional strategies, governance routines, and evaluation criteria [4]. A systematic review focused on Latin America reaches a similar conclusion and argues that AI adoption in higher education remains uneven across institutional contexts, making readiness and leadership critical planning concerns [8]. These findings support the view that AI should be examined through an organisational lens rather than only through the performance of individual tools.

2.2 Leadership, governance, and strategic decision-making

Strategic planning in educational institutions depends on the interaction between analytics and human judgement. Research in educational leadership argues that AI can function as an analytical partner in decision-making, but not as an autonomous substitute for professional judgement [5]. A related cautionary perspective shows that AI-assisted decision systems can distort educational priorities if leaders over-rely on technically generated outputs without sufficient contextual interpretation [6]. These studies are directly relevant to institutional planning because they define the conditions under which AI can support strategic analysis responsibly.

The governance challenge became sharper with the rise of generative AI. Recent work highlights both the opportunities of large language models for feedback, support, and content generation, and the associated risks involving assessment integrity, privacy, and transparency [9]. In parallel, research on the strategic transformation of higher education shows that AI adoption is reshaping both academic and administrative processes and therefore requires coordinated institutional leadership rather than isolated technical deployment [10]. Ethics research reinforces the same message by proposing a community-wide framework for trustworthy AI in education, with explicit attention to fairness, accountability, transparency, and human oversight [7].

2.3 Strategic planning for EdTech adoption

The literature on strategic EdTech decision-making is smaller than the literature on classroom technology use, but it is particularly relevant to this study. A qualitative investigation of five leading-edge K–12 districts found that EdTech decisions are shaped by leadership routines, local evidence, implementation constraints, and the need to reconcile innovation with system-wide goals [11]. Complementing this perspective, a case-based study of Hong Kong schools identified organisational barriers to AI adoption, including limited expertise, weak alignment, and competing interpretations of implementation priorities [12]. These findings indicate that strategic planning in education is not merely a technical selection problem; it is a capability sequencing problem.

Readiness frameworks offer a practical bridge between institutional strategy and implementation. The World Bank ETRI was designed to identify enabling conditions for effective EdTech integration and to support policy and investment choices [13]. Likewise, the OECD's PISA 2022 evidence shows that digital resources and learning opportunities remain closely tied to educational equity [14]. Taken together, these studies suggest that a useful planning framework must integrate access, institutional capability, and governance rather than focus on innovation rhetoric alone.

3. DATA AND RESEARCH DESIGN

The empirical base of the study is the public pilot evidence reported in the 2023 World Bank ETRI compilation note [13]. The analysis uses the dashboard-level indicators for Ho Chi Minh City and the Dominican Republic because these two pilot cases expose comparable pillar structures and traffic-light readiness judgements. The extracted dataset includes six readiness domains: school management, teachers, students, devices, connectivity, and digital education resources. It also distinguishes policy-oriented and practice-oriented indicators where the public dashboard provides this differentiation.

Each indicator is coded from its published traffic-light status. Following the ETRI interpretation bands, red is mapped to the midpoint value 2.00, yellow to 3.50, and green to 4.50. These values do not claim fine-grained measurement precision; they serve as conservative ordinal-to-cardinal transformations suitable for strategic comparison. This coding rule enables the construction of comparable pillar-level maturity scores while remaining faithful to the source dashboard structure.

The study is positioned as a managerial analytics exercise rather than a causal effectiveness study. The unit of analysis is the readiness domain, and the outputs are planning priorities, not treatment effects. The purpose is to provide a transparent planning model that can be adapted when richer institutional microdata become available.

4. PROPOSED MODEL

4.1 Readiness encoding and pillar maturity

Let s_{ij} denote the encoded score of indicator j in case i. The traffic-light transformation is defined as

$$s_{ij} = \begin{cases} 2.00, & \text{if the indicator is red,} \\ 3.50, & \text{if the indicator is yellow,} \\ 4.50, & \text{if the indicator is green.} \end{cases} \quad (1)$$

For each case i and pillar p, the pillar maturity score is the arithmetic mean of the n_{ip} indicators associated with that pillar:

$$M_{ip} = \frac{1}{n_{ip}} \sum_{j=1}^{n_{ip}} s_{ij}. \quad (2)$$

The maturity score is designed to be interpretable. A value close to 5 indicates a strong enabling condition; a lower value indicates a strategic bottleneck.

4.2 Strategic gap and baseline priority

The baseline planning logic is expressed as a gap-to-target measure:

$$G_{ip} = T - M_{ip}, \quad (3)$$

where $T = 5$ is the target maturity level. The baseline strategic priority index is

$$P_{ip} = w_p G_{ip}, \qquad w_p > 0, \quad (4)$$

where w_p represents the managerial importance of pillar p. In this study, the weights are set to reflect implementation leverage: teachers (1.25), students (1.20), school management (1.15), digital education resources (1.10), connectivity (1.05), and devices (1.00). The weighting scheme is transparent and can be adjusted by decision-makers.

4.3 Extended model for institutional deployment

To make the framework more useful for institutional planning, the baseline gap model can be extended in two directions. First, a red-exposure term captures the share of severe weaknesses inside each pillar:

$$R_{ip} = \frac{n_{ip}^{\text{red}}}{n_{ip}}. \quad (5)$$

Second, a policy–practice alignment coefficient captures whether institutional rules and observed practices move in the same direction:

$$A_i = 1 - \frac{\left|\bar{s}_i^{\text{pol}} - \bar{s}_i^{\text{prac}}\right|}{3}, \qquad 0 \le A_i \le 1. \quad (6)$$

Here, $\bar{s}_i^{\text{pol}}$ and $\bar{s}_i^{\text{prac}}$ denote the average policy and practice scores of case i. A value of A_i close to 1 indicates strong alignment. Using these components, institutions can extend the baseline model to a composite strategic urgency score:

$$U_{ip} = w_p \left(\alpha \frac{G_{ip}}{3} + \beta R_{ip} + \gamma (1 - A_i) \right), \quad (7)$$

where $\alpha + \beta + \gamma = 1$ and the weights express local planning preferences. This extension is not required for the baseline empirical results reported here, but it strengthens the framework by showing how readiness, severity, and governance misalignment can be integrated in future institutional deployments.

4.4 TOPSIS readiness benchmark

To summarise system-level readiness, the model uses TOPSIS. The column-normalised value is

$$r_{ip} = \frac{M_{ip}}{\sqrt{\sum_i M_{ip}^2}}, \quad (8)$$

and the weighted normalised value is $v_{ip} = w_p r_{ip}$. The positive and negative ideal solutions are given by

$$A_p^+ = \max_i (v_{ip}), \qquad A_p^- = \min_i (v_{ip}). \quad (9)$$

The Euclidean distances to the ideal and anti-ideal profiles are

$$D_i^+ = \sqrt{\sum_p (v_{ip} - A_p^+)^2}, \qquad D_i^- = \sqrt{\sum_p (v_{ip} - A_p^-)^2}, \quad (10)$$

and the closeness coefficient is

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}. \quad (11)$$

A higher C_i indicates greater relative readiness across the six pillars.

5. RESULTS

5.1 Strategic evidence map

Figure 2 synthesises the readiness evidence from four complementary perspectives. In both cases, school management appears as the strongest pillar, suggesting that leadership and planning structures are not the primary bottleneck. By contrast, connectivity and digital education resources remain more constrained, particularly in the Dominican Republic. The evidence map also shows a practical distinction between policy readiness and practice readiness. Where policy scores exceed practice scores, the system appears to need implementation support rather than additional formal rules.

5.2 Priority structure and indicator patterns

The priority quadrant in Figure 3 separates domains into managerial action zones. Domains with both high strategic gaps and high leverage deserve early attention because they are likely to influence the performance of other elements in the institutional system. The figure shows that domains linked to teaching capability, student use, and digital resources occupy the most consequential positions in the planning space.

Figure 4 provides a more granular interpretation of the same evidence. The pattern suggests that strategic weakness is not

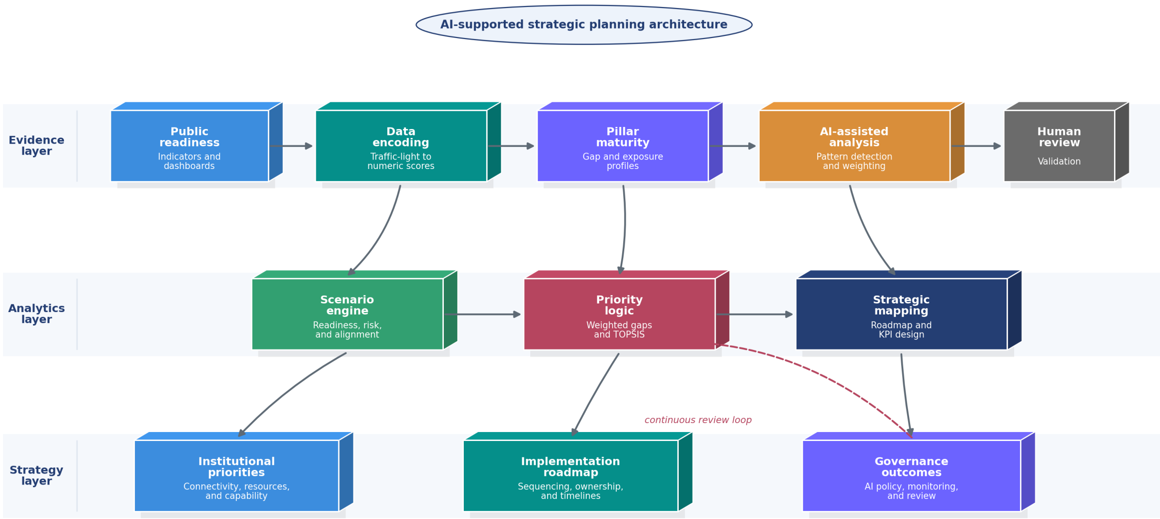

Figure 1. AI-supported strategic planning architecture for EdTech transformation. The baseline empirical results reported in this paper use the readiness-scoring and priority logic layers, while the scenario engine and governance loop show how the framework can be extended in institutional applications.

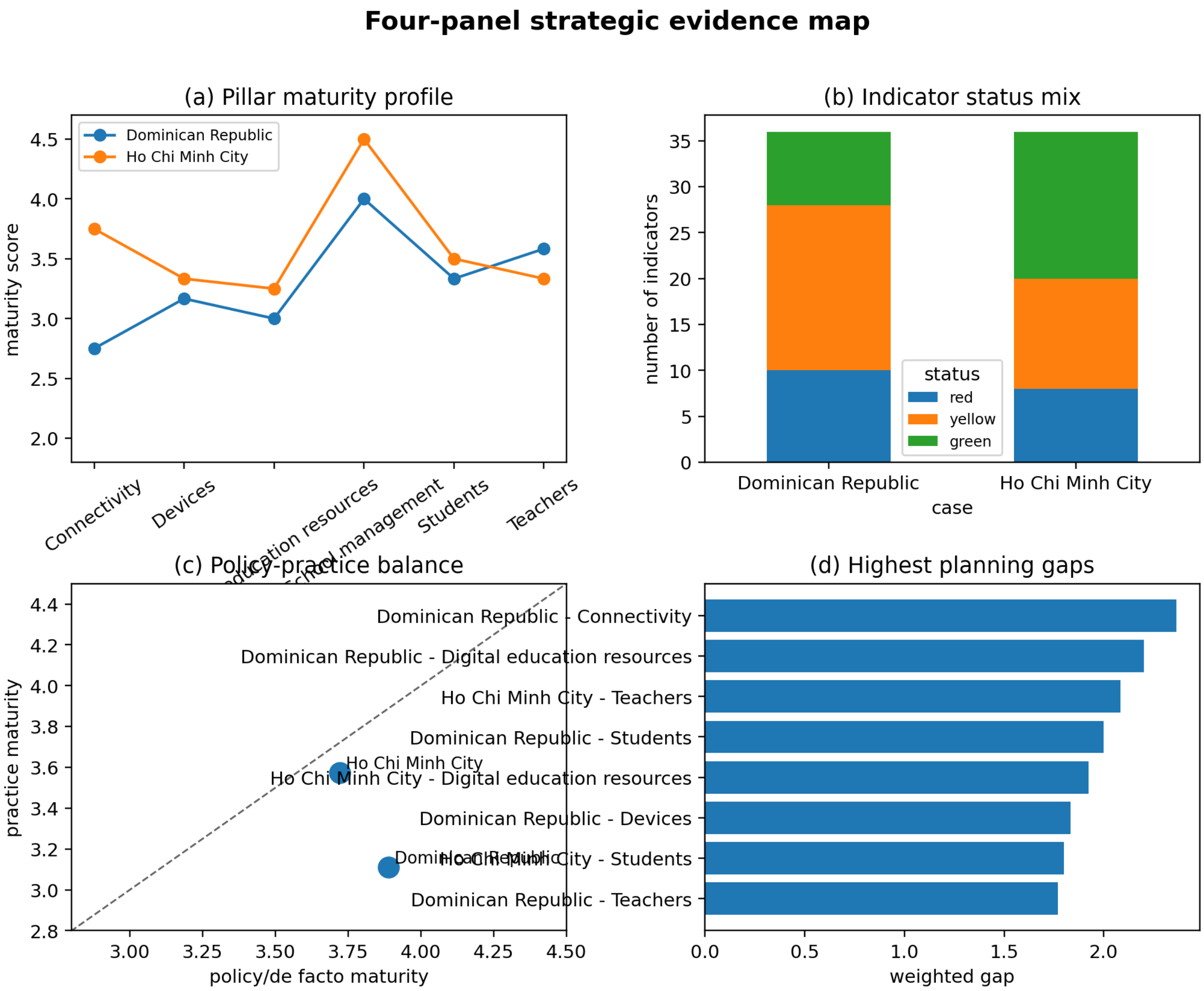

Figure 2. Four-panel evidence map derived from the public ETRI dashboard extract.

explained by hardware availability alone. Rather, the more persistent gaps concern effective use, support structures, and the quality of digital resources. This finding is important because it redirects planning away from procurement-only responses.

Table 1 confirms the visual interpretation of the evidence. Ho Chi Minh City records the highest score in school management (4.50), whereas the Dominican Republic reaches its strongest value in the same domain (3.92). The weakest scores occur in connectivity and digital education resources for the Dominican Republic (2.75 in each case), while Ho Chi Minh City shows more moderate but still meaningful constraints in teachers (3.08), devices (3.08), and digital edu-

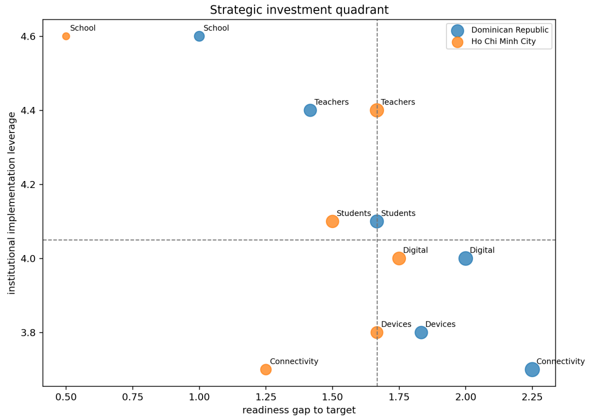

Figure 3. Priority quadrant based on readiness gap and implementation leverage.

Figure 4. Indicator-level maturity heatmap.

Table 1. Pillar maturity scores from the ETRI dashboard extract.

Pillar	HCMC	Dominican Rep.
School management	4.50	3.92
Teachers	3.08	3.33
Students	3.25	3.25
Devices	3.08	3.00
Connectivity	3.50	2.75
Digital education resources	3.25	2.75

cation resources (3.25).

5.3 Portfolio ranking and system benchmark

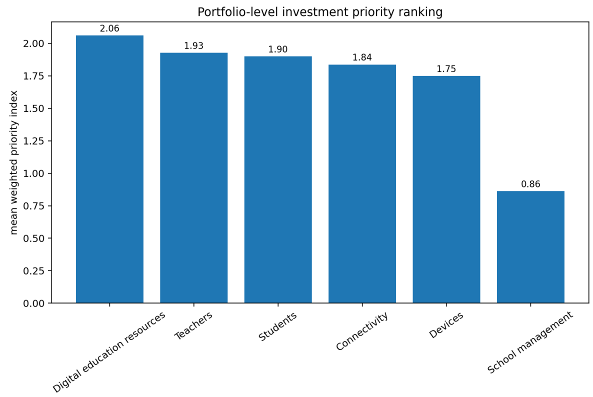

Figure 5. Baseline portfolio priority ranking under the managerial weighting scheme.

The baseline portfolio ranking in Figure 5 identifies the domains that require the most sustained strategic attention across the two pilot cases. Digital education resources and connectivity emerge as the strongest cross-case priorities, followed by students and teachers. The result is consistent with the underlying indicator evidence: educational institutions cannot rely on AI-enhanced learning or digital service models if digital content quality, support structures, and access conditions remain weak.

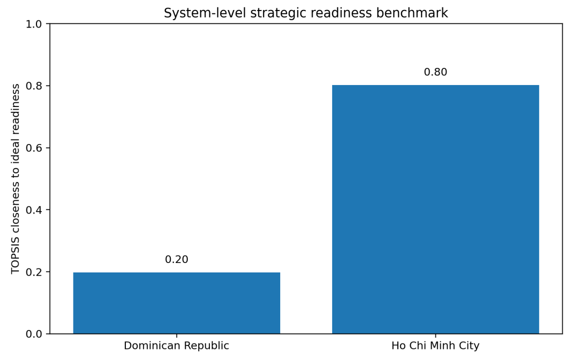

Figure 6. TOPSIS readiness benchmark.

The TOPSIS benchmark in Figure 6 summarises overall readiness. Ho Chi Minh City records a closeness coefficient of 0.802, while the Dominican Republic records 0.198. This result should not be interpreted as a league table. Its main value lies in providing a concise comparative signal for strategic communication while preserving the richer pillar-level evidence for implementation planning.

6. DISCUSSION

The results point to a clear planning lesson: educational transformation should be managed as a coordinated capability-building process rather than as a sequence of technology purchases. In both pilot cases, school management is relatively strong, but the more fragile elements concern connectivity, digital learning resources, and the translation of policy into classroom or school-level practice. This implies that leadership intent alone is insufficient to support AI-enabled transformation.

A second insight concerns the role of teachers and students in the strategic model. The evidence suggests that formal structures can coexist with uneven classroom use and uneven learner experience. This matters because many AI applications in education assume a degree of pedagogical integration and digital fluency that institutions may not yet possess. Strategic planning should therefore treat teacher capability and student use as dynamic readiness domains, not as residual outcomes of infrastructure investment.

A third insight concerns governance. The proposed framework treats AI as a decision-support layer rather than a decision-maker. This is consistent with the educational leadership literature, which argues that AI can improve evidence handling, but that final judgement must remain human-led [5, 6]. The extended model further shows that institutional priorities can be interpreted not only in terms of gaps, but also in terms of severity and policy–practice misalignment.

Finally, the findings reinforce the equity dimension of EdTech strategy. Public readiness evidence shows that access and effective use are not interchangeable. Institutions may make progress on devices or nominal digital provision while still failing to ensure high-quality use, support, and inclusive access. Strategic planning must therefore link AI and EdTech decisions to the broader educational mission rather than to symbolic digital modernisation.

7. IMPLICATIONS FOR INSTITUTIONAL STRATEGY

The framework can be used as a practical planning tool in annual or multi-year strategy cycles. First, leaders can code readiness evidence using the same red–yellow–green structure found in many dashboards. Second, they can calculate pillar maturity scores and interpret gaps using the baseline priority model. Third, where richer institutional evidence is available, they can activate the extended model to include severity and policy–practice alignment. Fourth, they can translate the results into a roadmap with owners, milestones, and key performance indicators.

For school networks and ministries, the framework offers a common language for comparing units without collapsing them into simplistic league tables. For higher education institutions, the same structure can be adapted to AI governance by reframing the pillars around academic management, faculty capability, student readiness, AI platforms, data infrastructure, and digital learning resources. In both settings, the model helps leaders justify sequencing decisions in a way that is analytically transparent and educationally defensible.

8. CONCLUSION

This paper developed an AI-enabled framework for strategic planning in educational institutions using public 2023 EdTech readiness evidence. The contribution is methodological and managerial. Methodologically, the paper provides a transparent readiness-scoring and benchmarking model. Managerially, it shows how AI can support planning by converting diffuse readiness evidence into coherent institutional priorities.

The results suggest that the most important planning bottlenecks are not located in leadership structures alone, but in the conditions that determine whether digital transformation can be enacted in practice: connectivity, digital resources, support systems, and meaningful pedagogical use. Future work can extend the framework by incorporating cost data, longitudinal indicators, and institution-level microdata, allowing planning models to move from comparative readiness analysis toward scenario-based strategic simulation.

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