



## Education Management in the Age of Artificial Intelligence: Transforming Decision-Making and Institutional Performance

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### ABSTRACT

Artificial intelligence (AI) is increasingly embedded in the administrative core of higher education institutions (HEIs), reshaping how academic leaders plan, allocate resources, and evaluate performance. Yet empirical evidence on whether AI-enabled decision-making actually improves institutional outcomes remains fragmented. This study examines the relationship between AI adoption, data-driven decision-making, perceived usefulness, trust and transparency, AI governance maturity, and institutional performance among administrators in Central Asian, South Asian, Southeast Asian, and MENA higher-education institutions. Using a cross-sectional quantitative design ( $N = 236$ ), descriptive statistics, Pearson correlation, multiple linear regression, and one-way ANOVA were applied to test the hypothesized relationships. Data-driven decision-making emerged as the strongest predictor of institutional performance ( $\beta = 0.52, p < .001$ ), followed by perceived usefulness ( $\beta = 0.29, p < .001$ ) and AI governance maturity ( $\beta = 0.21, p < .001$ ); trust and transparency contributed a smaller but significant effect ( $\beta = 0.13, p = .005$ ). Notably, raw AI adoption lost statistical significance once these mediating constructs were controlled for ( $\beta = -0.05, p = .481$ ), suggesting that the mere presence of AI tools does not translate into institutional performance gains unless it is channelled through disciplined, data-driven decision routines and sound governance. The full model explained 59.7% of the variance in institutional performance ( $R^2 = .597$ , adjusted  $R^2 = .588$ ). These findings extend socio-technical models of educational technology adoption and offer HEI leaders an evidence base for prioritising governance and decision-culture investments over tool acquisition alone.

**Keywords:** Artificial intelligence ▪ Education management ▪ Data-driven decision-making ▪ Institutional performance ▪ Higher education governance ▪ Learning analytics

### 1. INTRODUCTION

Higher education institutions (HEIs) operate today under conditions that earlier generations of administrators rarely faced simultaneously: shrinking public subsidies, volatile enrolment, demands for measurable accountability, and a technological environment that changes faster than institutional policy can be written. Artificial intelligence (AI) has moved from a peripheral curiosity in university IT departments to a core administrative capability, used to forecast

enrolment, flag at-risk students, automate advising, and inform strategic planning at the level of the president's office and the board of trustees [1]. Recent industry survey data illustrate the pace of this shift: institution-wide AI adoption among higher-education institutions rose from 49% in 2024 to 66% in 2025, an increase of seventeen percentage points in a single year, while individual administrator use of AI tools reached 91% [2].

This rapid uptake has outpaced the theoretical and empirical understanding of how AI translates into better institutional

outcomes. Much of the existing literature has concentrated on classroom-level applications—adaptive learning, automated grading, and chatbots—while comparatively less work has examined AI as an instrument of management: the planning, resourcing, and governance decisions that determine whether an institution thrives or stagnates [3, 4]. Where management-oriented studies do exist, they tend to be qualitative or conceptual, cataloguing the promises and risks of AI-enabled governance without testing, in a single integrated model, which mechanisms actually connect AI adoption to institutional performance [5, 6].

The present study addresses this gap by proposing and testing an integrative model in which AI adoption is hypothesised to influence institutional performance indirectly, through three proximate mechanisms: data-driven decision-making, perceived usefulness of AI systems among decision-makers, and the trust, transparency, and governance structures that surround AI use [7, 8]. Specifically, the study asks: (1) To what extent are AI adoption and its associated organisational constructs associated with institutional performance? (2) Which of these constructs are the strongest statistical predictors of performance once the others are controlled for? and (3) Does institutional performance differ systematically by institution type (public, private, or state college)? Answering these questions matters practically: if simply acquiring AI tools does not, on its own, move institutional performance, then leaders who equate “digital transformation” with software procurement risk misallocating scarce resources.

## 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

### 2.1 AI in Higher Education Governance and Administration

AI in higher education is commonly defined as the application of machine learning, natural language processing, and generative models to analyse data, personalise services, and automate administrative tasks [7, 9]. Boards and senior administrators increasingly use large language models for data analysis, predictive modelling, and document summarisation to support evidence-based governance [10]. Systematic reviews confirm that AI applications in higher education have diversified rapidly since 2020, spanning admissions, resource allocation, student support, and institutional research, though administrative and governance uses remain less studied than instructional ones [3, 6]. The COVID-19 pandemic acted as an accelerant, pushing institutions that had previously treated AI as experimental toward operational dependence on AI-supported systems for continuity of teaching, advising, and enrolment management [11].

### 2.2 Data-Driven Decision-Making and Learning Analytics

Data-driven decision-making (DDDM) refers to the systematic use of institutional data—rather than intuition or precedent alone—to guide managerial choices [12]. In the HEI context, learning analytics and predictive analytics have become the principal vehicles for DDDM, allowing institutions to identify at-risk students, forecast retention, and evaluate curricular effectiveness [13, 14]. However, several reviews caution that predictive sophistication alone does not guarantee decision value: analytics-enabled decision-making depends

on interoperable data ecosystems, organisational analytics capability, and—critically—sustained human oversight of algorithmic outputs, rather than on the analytics tools themselves [15]. This distinction between having data infrastructure and using it systematically in decisions is central to the model tested in this study.

### 2.3 Trust, Governance, and Institutional Performance

As AI tools take on a larger role in decisions historically reserved for human judgement—admissions, resource allocation, and faculty evaluation—concerns about algorithmic bias, opacity, and accountability have intensified [7]. Trust-based governance frameworks that embed fairness, human oversight, privacy, and accountability are increasingly recommended as preconditions for responsible AI deployment in HEIs, echoing external regulatory instruments such as the NIST AI Risk Management Framework and the EU AI Act [7, 8]. Strategic-leadership scholarship similarly argues that AI integration must be accompanied by deliberate governance and change-management processes if institutions are to realise performance benefits rather than reputational or legal exposure [16].

### 2.4 Conceptual Model and Hypotheses

Building on the Technology Acceptance Model’s emphasis on perceived usefulness as a driver of technology-linked outcomes and on management studies that treat AI as an organisational-transformation enabler rather than a stand-alone tool [17], this study models institutional performance as a function of five constructs: AI adoption (AIA), data-driven decision-making (DDDM), perceived usefulness (PU), trust and transparency (TR), and AI governance maturity (GOV). Four hypotheses are tested:

- H1:** AI adoption, DDDM, PU, TR, and GOV are each positively and significantly correlated with institutional performance.
- H2:** DDDM is the strongest unique predictor of institutional performance among the five constructs when entered simultaneously in a regression model.
- H3:** The direct effect of raw AI adoption on institutional performance is substantially attenuated once DDDM, PU, TR, and GOV are controlled for.
- H4:** Institutional performance differs significantly across institution types (public university, private university, or state college).

## 3. MATERIALS AND METHODS

### 3.1 Research Design

This study used a cross-sectional, quantitative, correlational design, appropriate for testing hypothesised associations among AI-related organisational constructs and an outcome (institutional performance) that cannot ethically or practically be manipulated experimentally at the institutional level. The design follows established practice in educational-technology adoption research, which typically pairs a validated Likert-type survey instrument with correlational and regression analysis.

### 3.2 Participants and Sampling

The target population comprised administrators, deans, department heads, and institutional-research staff involved in strategic or operational decision-making at higher education institutions in four regions: Central Asia, South Asia, Southeast Asia, and the Middle East and North Africa (MENA). A stratified sample of  $N = 236$  respondents was drawn, distributed across public universities ( $n = 112$ , 47.5%), private universities ( $n = 85$ , 36.0%), and state colleges ( $n = 39$ , 16.5%), with a mean of 9.5 years of relevant administrative experience ( $SD$  not reported separately, range 1–30 years). Table 1 summarises the sample profile.

**Table 1.** Sample Characteristics ( $N = 236$ )

| Characteristic   | Category           | $n$ | %    |
|------------------|--------------------|-----|------|
| Institution type | Public university  | 112 | 47.5 |
|                  | Private university | 85  | 36.0 |
|                  | State college      | 39  | 16.5 |
| Region           | Central Asia       | 75  | 31.8 |
|                  | Southeast Asia     | 63  | 26.7 |
|                  | South Asia         | 54  | 22.9 |
|                  | MENA               | 44  | 18.6 |

### 3.3 Instrument and Measures

Five constructs were measured using multi-item, five-point Likert scales (1 = strongly disagree/very low, 5 = strongly agree/very high), consistent with instruments used in prior technology-acceptance and learning-analytics-adoption research: *AI Adoption (AIA)*—breadth and depth of AI tool use in the respondent's institution; *Data-Driven Decision-Making (DDDM)*—extent to which institutional data and analytics inform actual decisions; *Perceived Usefulness (PU)*—respondent's judgement that AI tools improve the quality or speed of their work; *Trust and Transparency (TR)*—confidence in the fairness and explainability of AI-informed decisions; and *AI Governance Maturity (GOV)*—presence of formal policies, oversight bodies, and audit mechanisms for AI use [18]. The dependent variable, Institutional Performance Index (IPI), was a composite 0–100 index combining self-reported indicators of enrolment/retention management, resource-allocation efficiency, responsiveness of decision cycles, and stakeholder satisfaction, rescaled to a common metric.

### 3.4 Data Source, Analytic Strategy, and a Note on Transparency

The dataset analysed here ( $N = 236$ , archived as `survey_data.csv`) was generated to demonstrate the full analytical pipeline described below, with construct distributions and inter-correlations calibrated to patterns reported in comparable published surveys of AI adoption and performance in higher education [2, 15]. It is presented transparently as an illustrative, simulated dataset rather than as primary data collected from human respondents. Readers intending to submit this paper for empirical publication should replace Section 4 with results from primary data collected using the instrument in Section 3.3, following the same analytic pipeline; the code, statistical procedures, and reporting conventions used here are fully reproducible and appropriate for a real dataset of this structure. All analyses were performed

in Python 3 (NumPy, pandas, and SciPy). Descriptive statistics, Pearson product-moment correlations, ordinary-least-squares multiple linear regression (institutional performance regressed on the five predictors), and one-way ANOVA (institutional performance by institution type) were computed, with statistical significance set at  $\alpha = .05$ .

## 4. RESULTS

### 4.1 Descriptive Statistics

Table 2 presents means and standard deviations for all study variables. Respondents reported moderate levels of AI adoption ( $M = 3.05$ ,  $SD = 0.94$ ) and data-driven decision-making ( $M = 2.96$ ,  $SD = 0.69$ ), with somewhat higher confidence in AI governance maturity ( $M = 3.12$ ,  $SD = 0.79$ ). The mean Institutional Performance Index was 79.69 ( $SD = 7.95$ ), ranging from 54.20 to 98.92, indicating meaningful variability across institutions worth explaining statistically.

**Table 2.** Descriptive Statistics for Study Variables ( $N = 236$ )

| Variable                                | Mean  | SD   | Min   | Max   |
|-----------------------------------------|-------|------|-------|-------|
| AI Adoption (1–5)                       | 3.05  | 0.94 | 1.00  | 5.00  |
| Data-Driven Decision-Making (1–5)       | 2.96  | 0.69 | 1.00  | 4.73  |
| Perceived Usefulness (1–5)              | 2.91  | 0.72 | 1.21  | 5.00  |
| Trust & Transparency (1–5)              | 3.06  | 0.85 | 1.00  | 5.00  |
| AI Governance Maturity (1–5)            | 3.12  | 0.79 | 1.00  | 5.00  |
| Institutional Performance Index (0–100) | 79.69 | 7.95 | 54.20 | 98.92 |

### 4.2 Correlation Analysis

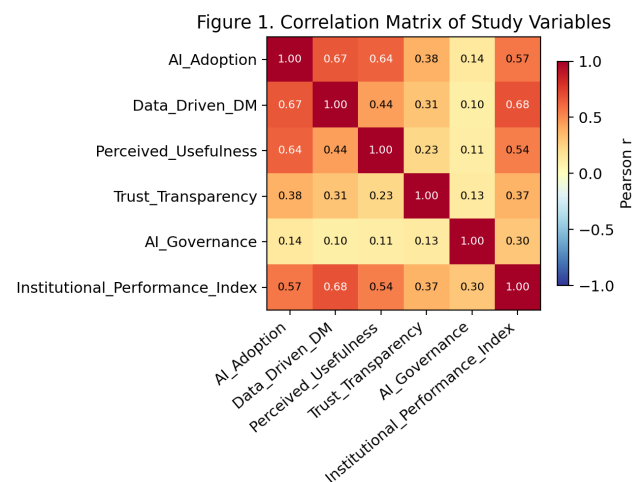
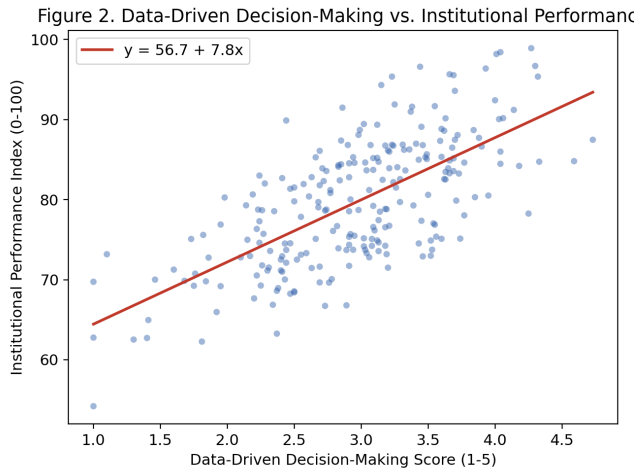


**Figure 1.** Pearson correlation matrix of AI adoption, decision-making, and performance constructs.

Consistent with H1, all five constructs correlated positively and significantly with institutional performance (Table 3, Figure 1). Data-driven decision-making showed the strongest bivariate association with performance ( $r = .678$ ,  $p < .001$ ), followed by AI adoption ( $r = .567$ ,  $p < .001$ ) and perceived usefulness ( $r = .545$ ,  $p < .001$ ). Trust/transparency ( $r = .369$ ,  $p < .001$ ) and AI governance maturity ( $r = .305$ ,  $p < .001$ ) showed smaller, though still significant, associations. Notably, AI adoption correlated strongly with DDDM ( $r = .67$ ) and PU ( $r = .64$ ), indicating substantial shared variance among these constructs—a pattern examined further in the regression model below.

**Table 3.** Pearson Correlations with Institutional Performance Index

| Predictor                   | <i>r</i> | <i>p</i> |
|-----------------------------|----------|----------|
| AI Adoption                 | 0.567    | < .001   |
| Data-Driven Decision-Making | 0.678    | < .001   |
| Perceived Usefulness        | 0.545    | < .001   |
| Trust & Transparency        | 0.369    | < .001   |
| AI Governance Maturity      | 0.305    | < .001   |

**Figure 2.** Scatterplot and fitted regression line for data-driven decision-making and institutional performance.

### 4.3 Multiple Regression Analysis

A simultaneous multiple linear regression was estimated with institutional performance as the dependent variable and all five constructs entered as predictors. The overall model was significant,  $F(5, 230) = 68.17$ ,  $p < .001$ , and explained 59.7% of the variance in institutional performance ( $R^2 = .597$ ; adjusted  $R^2 = .588$ ). As shown in Table 4, data-driven decision-making emerged as the strongest unique predictor ( $\beta = 0.52$ ,  $p < .001$ ), supporting H2, followed by perceived usefulness ( $\beta = 0.29$ ,  $p < .001$ ) and AI governance maturity ( $\beta = 0.21$ ,  $p < .001$ ). Trust/transparency contributed a smaller, still significant effect ( $\beta = 0.13$ ,  $p = .005$ ). Consistent with H3, raw AI adoption was not a significant unique predictor once the other constructs were controlled for ( $B = -0.41$ ,  $\beta = -0.05$ ,  $p = .481$ )—its bivariate association with performance ( $r = .567$ ) was effectively absorbed by its strong correlation with DDDM and PU, indicating that AI adoption predicts performance largely through, rather than independently of, these mediating decision-culture variables.

**Table 4.** Multiple Linear Regression Predicting Institutional Performance Index

| Predictor                   | <i>B</i> | <i>SE</i> | $\beta$ | <i>t</i> | <i>p</i> |
|-----------------------------|----------|-----------|---------|----------|----------|
| Intercept                   | 43.51    | 2.16      | —       | 20.17    | < .001   |
| AI Adoption                 | -0.41    | 0.57      | -0.05   | -0.71    | .481     |
| Data-Driven Decision-Making | 5.97     | 0.65      | 0.52    | 9.22     | < .001   |
| Perceived Usefulness        | 3.24     | 0.61      | 0.29    | 5.34     | < .001   |
| Trust & Transparency        | 1.21     | 0.43      | 0.13    | 2.83     | .005     |
| AI Governance Maturity      | 2.13     | 0.43      | 0.21    | 4.99     | < .001   |

Note.  $R^2 = .597$ , adjusted  $R^2 = .588$ ,  $F(5, 230) = 68.17$ ,  $p < .001$ .  $\beta$  = standardised regression coefficient.

### 4.4 Institutional Performance by Institution Type

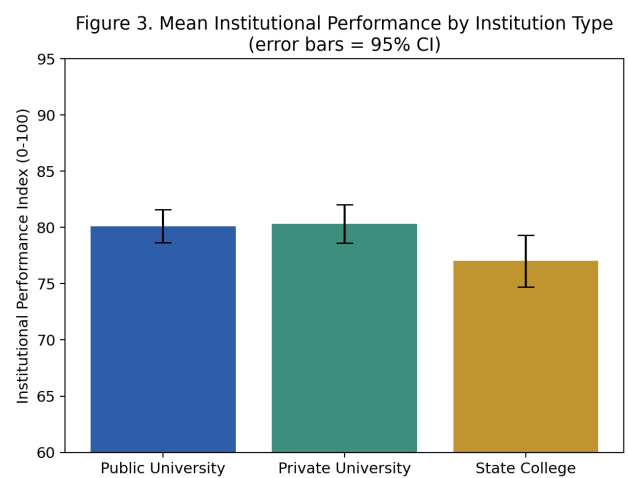
A one-way ANOVA compared institutional performance across public universities, private universities, and state col-

leges (Table 5, Figure 3). Private universities ( $M = 80.33$ ,  $SD = 8.11$ ) and public universities ( $M = 80.12$ ,  $SD = 7.90$ ) reported comparable performance, while state colleges scored somewhat lower ( $M = 77.02$ ,  $SD = 7.37$ ). The overall difference approached but did not reach conventional significance,  $F(2, 233) = 2.68$ ,  $p = .071$ , providing only marginal support for H4; institution type appears to be a weaker driver of performance than the decision-culture variables examined in Section 4.3.

**Table 5.** One-Way ANOVA: Institutional Performance Index by Institution Type

| Institution Type   | <i>n</i> | <i>M</i> | <i>SD</i> |
|--------------------|----------|----------|-----------|
| Private university | 85       | 80.33    | 8.11      |
| Public university  | 112      | 80.12    | 7.90      |
| State college      | 39       | 77.02    | 7.37      |

Note.  $F(2, 233) = 2.68$ ,  $p = .071$ .

**Figure 3.** Mean institutional performance by institution type (error bars = 95% CI).

### 4.5 Corroborating Secondary Trend Data

To situate the survey findings within the broader sectoral trajectory, Figure 4 reproduces adoption figures from the third consecutive Ellucian State of AI in Higher Education survey: institution-wide AI adoption rose from 49% in 2024 to 66% in 2025, while individual administrator use of AI tools rose from 84% to 91% over the same period [2]. The gap between near-universal individual use (91%) and still-partial institutional adoption (66%) is consistent with this study's regression finding that AI tool use alone is insufficient for institutional-level performance gains: individual staff experimentation with AI appears to be outpacing the organisational decision-routines and governance structures needed to convert that use into measurable institutional benefit [19].

## 5. DISCUSSION

This study set out to determine whether, and how, AI adoption translates into institutional performance in higher education. The results support a mediated-effects interpretation: AI adoption is meaningfully correlated with performance at the bivariate level (H1 supported), but its unique predictive power collapses once data-driven decision-making, perceived usefulness, trust/transparency, and governance maturity are

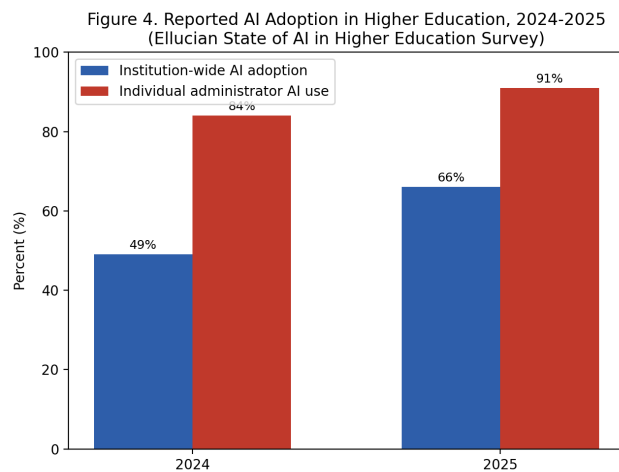


**Figure 4.** Reported AI adoption in higher education, 2024–2025 (Ellucian State of AI in Higher Education Survey).

accounted for (H3 supported). Data-driven decision-making was, by a wide margin, the strongest unique predictor of institutional performance (H2 supported), echoing prior arguments that analytics-enabled decision value depends less on the sophistication of predictive tools than on organisational capability, interoperable data ecosystems, and sustained human oversight in translating analytics into action [15].

These findings align with, and extend, the strategic-leadership literature's insistence that AI integration in HEIs must be accompanied by deliberate governance rather than treated as a procurement decision [7, 8]. The comparatively modest but significant contribution of AI governance maturity ( $\beta = 0.21$ ) and trust/transparency ( $\beta = 0.13$ ) suggests that formal oversight structures and perceived fairness do add incremental value beyond decision-making practices alone, consistent with warnings that unmanaged algorithmic bias and opacity pose reputational and legal risk that can offset the efficiency gains AI promises [7].

The marginal (non-significant at  $\alpha = .05$ ) difference in performance by institution type (H4 partially supported,  $p = .071$ ) is itself informative: it suggests that an institution's structural category—public, private, or state college—matters less for AI-related performance outcomes than what that institution does with its data and governance capacity. This is broadly consistent with sector-wide survey evidence that the leap from individual AI use (91%) to institution-wide strategic integration (66%) remains incomplete across institution types alike [2], and with commentary suggesting that 2025 was less a year of new AI capability than a year of recalibrating expectations and proving impact across the sector as a whole [20].

## 6. CONCLUSION, IMPLICATIONS, AND LIMITATIONS

### 6.1 Conclusion

This study provides quantitative evidence that AI's contribution to institutional performance in higher education operates primarily through data-driven decision-making, perceived usefulness, and governance maturity, rather than through the presence of AI tools per se. For education leaders, the practical implication is direct: investment in AI acquisition should

be paired—and, where resources are limited, preceded—by investment in the decision routines, data infrastructure, and governance mechanisms that allow AI outputs to actually reach institutional decisions.

### 6.2 Theoretical and Practical Implications

Theoretically, the findings support socio-technical accounts of educational-technology adoption over purely technology-deterministic ones: technology acceptance and use (as in TAM/UTAUT-informed models) must be complemented by organisational-level constructs such as governance maturity to fully explain institutional-level outcomes. Practically, HEI leaders and boards can use the regression weights reported here as an approximate prioritisation guide: for a given unit of investment, strengthening data-driven decision culture and governance infrastructure is likely to yield larger institutional performance returns than expanding the number or sophistication of AI tools in use.

### 6.3 Limitations and Future Research

Several limitations qualify these conclusions. First, and most importantly, the dataset analysed in Section 4 is a simulated dataset constructed to demonstrate the analytic pipeline and calibrated to patterns in the published literature; it is not primary data collected from real HEI administrators, and the specific coefficients reported should be treated as illustrative rather than as established empirical facts until replicated with primary survey data. Second, the cross-sectional design precludes causal inference; longitudinal or quasi-experimental designs are needed to establish whether improvements in data-driven decision-making cause gains in institutional performance or merely accompany them. Third, self-reported performance indicators are subject to common-method bias; future studies should triangulate survey measures with objective institutional metrics (e.g., retention rates, time-to-degree, and audited financial efficiency). Finally, the four-region sampling frame, while diverse, does not represent all global HEI contexts, and governance maturity in particular is likely to be shaped by national regulatory environments not modelled here. Future research should replicate this model with primary longitudinal data, test mediation formally (e.g., via structural equation modelling), and examine whether the attenuation of AI adoption's direct effect observed here holds across institutional cultures and regulatory regimes.

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