A Decision-Support Model for Assessing Smart Education Infrastructure in Higher Education Institutions

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Abstract: This paper proposes a decision-support model for assessing smart education infrastructure in higher education institutions. The study transforms the concept of smart education infrastructure into a measurable institutional framework based on six key dimensions: interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance. To support institutional digital assessment, a weighted Smart Education Infrastructure Readiness Index (SEIRI) is introduced for evaluating implementation maturity, classifying readiness levels, and identifying priority areas for improvement. The proposed approach also includes a dashboard-oriented workflow that integrates data acquisition, score normalization, readiness calculation, and recommendation generation. A pilot expert-informed illustrative scenario involving three anonymized institutional units is used to demonstrate how the model computes readiness levels, ranks infrastructure deficits, and generates targeted recommendations for institutional development. The contribution of the study lies in the development of an applied IT artifact that combines a formalized readiness assessment algorithm with a deployable decision-support workflow for smart education infrastructure management.

1 INTRODUCTION

The rapid advancement of digital technologies has significantly transformed the mission, structure, and operational models of higher education institutions (HEIs). Universities are increasingly expected to provide flexible, learner-centered, and data-informed education while simultaneously improving administrative efficiency, resource management, and institutional competitiveness. In this context, digital transformation has become not merely a technological trend but a strategic imperative for higher education development [1]-[4].

One of the central concepts emerging from this transformation is smart education infrastructure, which refers to an integrated educational ecosystem that combines digital platforms, intelligent systems, network technologies, connected devices, and pedagogical innovations to support teaching, learning, and academic administration [4]-[8]. Unlike conventional infrastructure, smart education infrastructure is designed to enable interconnectivity, automation, adaptivity, and data-driven decision-making across multiple institutional processes. This includes the use of cloud-based learning management systems, smart classrooms, Internet of Things (IoT) devices, artificial intelligence (AI) tools, learning analytics, and secure digital services [4]-[9].

Recent studies show that the digital transformation of universities is closely associated with the development of smart campuses and intelligent learning environments that can enhance student engagement, improve access to educational resources, and optimize institutional operations [3]-[8]. Smart campus models support real-time monitoring, integrated communication, and more efficient use of physical and digital resources, while also contributing to sustainability, safety, and service quality [5]-[8]. At the same time, the increasing use of AI in higher education creates new opportunities for adaptive learning, academic support, automated administration, and predictive analysis of student performance [10], [11].

Another important dimension of smart education infrastructure is the use of learning analytics and cloud technologies. Learning analytics enables institutions to identify patterns in student behavior, monitor academic progress, detect risks of underperformance, and design more personalized interventions [12], [13]. Cloud computing, in turn, provides scalable and flexible solutions for content delivery, data storage, collaborative learning, and institutional information systems, making it a fundamental component of contemporary educational infrastructure [14]. However, the growing dependence on digital systems also raises significant concerns related to cybersecurity, privacy protection, and ethical data governance, especially in universities with uneven technological readiness [15], [16].

Despite the growing body of literature on educational technologies, many existing studies focus on isolated tools or specific innovations, such as AI applications, cloud platforms, or smart classrooms, rather than examining smart education infrastructure as a unified and multidimensional system [4], [7], [9]. This creates a research gap in understanding how technological, pedagogical, and organizational components interact within a comprehensive smart education environment. In addition, there remains a need to synthesize international practices and conceptual approaches that can guide universities in designing sustainable and effective smart education ecosystems [2], [3], [8].

Therefore, the purpose of this study is to develop a decision-support model for assessing smart education infrastructure in higher education institutions. The proposed approach transforms smart education infrastructure into a measurable framework based on six institutional dimensions: interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance [4]-[9], [14]-[16]. The main contributions of this study are threefold. First, it formalizes smart education infrastructure as a multidimensional institutional assessment framework rather than treating it only as a conceptual or review-based construct [3], [4], [7]-[9]. Second, it introduces the Smart Education Infrastructure Readiness Index (SEIRI), which combines weighted readiness calculation, readiness-level classification, and deficit-priority ranking. Third, it proposes a deployable decision-support workflow that links institutional scoring results to targeted managerial recommendations for digital development planning. Unlike prior review-oriented studies, the proposed model operationalizes smart education infrastructure through measurable indicators and algorithmic prioritization of improvement actions [3], [4], [7], [9]-[13].

2 METHODS

This study proposes a decision-support model for assessing smart education infrastructure in higher education institutions. The method is designed to transform smart education infrastructure into a measurable institutional framework that supports digital assessment and priority-based decision-making [3], [4], [7]-[9].

The proposed approach includes four main stages: definition of assessment dimensions and indicators, expert-based institutional scoring, calculation of the Smart Education Infrastructure Readiness Index (SEIRI), and generation of prioritized recommendations through a rule-based mechanism. The structure of the model is grounded in prior studies on smart campuses, digital transformation, artificial intelligence in higher education, learning analytics, cloud-based educational platforms, and cybersecurity in universities [2]-[16].

Based on the literature, six core dimensions of smart education infrastructure were defined: interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance [4]-[9], [14]-[16]. Each dimension was represented by a set of measurable indicators reflecting the technological and organizational readiness of a higher education institution. The indicators were evaluated using a structured scoring scale from 0 to 5, where higher values indicate stronger implementation maturity.

For each assessment dimension, the corresponding indicator scores were averaged to obtain a criterion-level score C_j. The criterion-level values were then normalized to a 0-1 scale using the relation $S_j=C_j/5$, where 5 represents the maximum maturity score. The final readiness value for each institutional unit was calculated as a weighted sum of the six normalized criterion scores. The same scoring scale, aggregation procedure, and normalization logic were applied consistently across all assessed units. This aggregation logic is consistent with the multidimensional interpretation of digital transformation and smart campus assessment reported in prior studies [3], [4], [9]-[14].

To obtain an integrated institutional assessment, the indicator scores were aggregated into criterion-level values and normalized for index calculation.

The readiness score for each institution or structural unit was computed using a weighted aggregation model, where the contribution of each criterion was determined by its relative importance in the overall smart education infrastructure framework. This approach is consistent with the multidimensional nature of digital transformation in higher education reported in recent studies [3], [4], [9]-[14]. As a simple robustness check, the pilot ranking was also examined under equal weights, and the ordering of the assessed units remained unchanged.

The final Smart Education Infrastructure Readiness Index (SEIRI) was used to classify readiness into three levels: low, moderate, and high. In addition to the overall score, deficit values were calculated for each dimension in order to identify the weakest infrastructure areas. These deficits were ranked and processed by a rule-based recommendation module that generated priority actions for institutional improvement.

To demonstrate the applicability of the model, a pilot assessment scenario was used to illustrate the calculation workflow, readiness classification, and recommendation generation. The proposed method therefore contributes not only a conceptual interpretation of smart education infrastructure, but also a formalized applied IT instrument for institutional evaluation and decision support. The six-dimensional assessment structure used in the proposed model is presented in Table 1.

Table 1: Smart education infrastructure assessment dimensions.

Criterion	Indicators	Weight
Interconnectivity	network coverage, LMS integration, device interoperability	0.18
Automation	scheduling automation, workflow automation, digital support services	0.16
Adaptivity	adaptive learning tools, personalized feedback, recommendation systems	0.17
Data-driven management	dashboards, reporting, performance monitoring	0.17
Flexibility	hybrid delivery, mobile access, remote participation	0.15
Security and governance	authentication, backup, access control, audit logging	0.17

The criterion weights were assigned through expert-informed analytical judgment while preserving a balanced multidimensional structure of the index. Slightly higher weights were assigned to interconnectivity, adaptivity, data-driven management, and security and governance because these dimensions more directly affect institutional integration, decision quality, and the resilience of digital operations. At the same time, the weighting scheme was intentionally kept relatively balanced in order to avoid overdominance of any single criterion in the final composite index. Within this balanced scheme, Interconnectivity received the single highest weight (0.18) because it functions as an enabling precondition for the other five dimensions - automation, adaptivity, data-driven management, and security mechanisms all depend on a working network/LMS/device foundation - whereas Flexibility received the lowest weight (0.15) because hybrid/remote delivery, while valuable, was judged comparatively less foundational to institutional readiness than the other five dimensions. The specific expert elicitation process underlying these judgments - including the number of experts consulted, their fields of expertise, and the method used to aggregate their individual judgments into single weight values (e.g., simple averaging, Delphi consensus, or pairwise comparison) - is not documented in the present description and should be reported explicitly in a future revision to support the reproducibility and external validation of the weighting scheme.

$$SEIRI_i = \sum_{j=1}^{6} \omega_j \cdot s_{ij}, \quad \sum_{j=1}^{6} \omega_j = 1 \quad (1)$$

where $SEIRI_i$ is the Smart Education Infrastructure Readiness Index for institution i, ω_j is the weight of criterion j, and s_{ij} is the normalized score of criterion j. Each criterion score C_j (from which s_ij is normalized) is intended to be derived from a small set of measurable or assessor-rated sub-indicators specific to that dimension - for example, Interconnectivity from network/Wi-Fi coverage (% of campus area), LMS integration status (number of integrated systems or a binary/ordinal integration scale), and device interoperability (number of supported device/OS categories); Automation from the number of digitized administrative workflows and the proportion of scheduling processes automated; Adaptivity from the availability and usage rate of adaptive learning tools and personalized feedback mechanisms; Data-driven Management from the existence and update frequency of institutional dashboards and reporting pipelines; Flexibility from the proportion of courses offered in hybrid/remote format and mobile-access availability; and Security and Governance from the presence of multi-factor authentication, backup frequency, and audit-logging coverage. Each sub-indicator is then rated on the underlying 1–5 scale (x_ij) by institutional assessors and aggregated into C_j prior to normalization via Equation (2). These illustrative mappings are provided here to concretize the constructs described in Table 1; a fully standardized indicator protocol with fixed measurement definitions was not implemented in the present pilot and is recommended for future development of the framework.

$$s_{ij} = \frac{x_{ij}}{5} \tag{2}$$

The readiness level is classified as follows: low readiness if *SEIRI* < 0.40, moderate readiness if 0.40≤ *SEIRI* <0.70, and high readiness if *SEIRI* ≥ 0.70.

The readiness thresholds were defined as interpretation-oriented decision bands rather than strict statistical cut-off points. Values below 0.40 indicate fragmented or weak implementation of smart education infrastructure components, values from 0.40 to 0.69 indicate partial but operational readiness, and values of 0.70 or higher indicate comparatively mature and institutionally integrated implementation. These thresholds were selected to support managerial interpretation and prioritization in pilot decision-support settings.

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Input: institutional indicator scores X, criterion weights W
Output: readiness index, readiness class, prioritized recommendations
 1. Aggregate indicators into six criterion scores C₁…C₆
 2. Normalize each score: Sⱼ=Cⱼ/5
 3. Compute readiness index: SEIRI=∑(Wⱼ×Sⱼ)
 4. If SEIRI<0.40, assign Low readiness
 5. Else if SEIRI<0.70, assign Moderate readiness
 6. Else assign High readiness
 7. Compute deficit priority: Pⱼ=Wⱼ×(1-Sⱼ)
 8. Rank criteria by descending Pⱼ
 9. Generate recommendations for the top-ranked deficits
10. Return SEIRI, class, and recommendation set
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Algorithm 1: Smart education infrastructure readiness assessment.

The formulation of SEIRI reflects the multidimensional character of smart education infrastructure reported in prior studies on smart campuses, learning analytics, cloud-based systems, and cybersecurity in higher education [4]-[9], [12]-[16].

Figure 1 summarizes the dashboard-oriented workflow of the proposed system, from institutional score input and normalization to SEIRI computation, readiness classification, deficit ranking, and recommendation output.

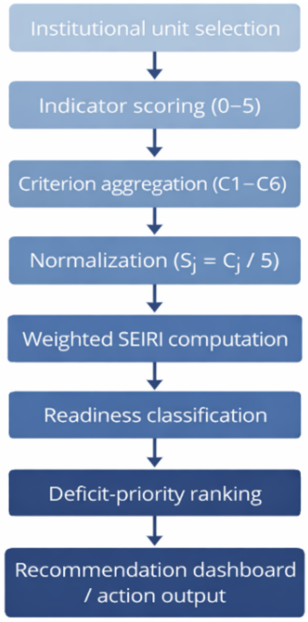

Figure 1: Dashboard-oriented workflow of the proposed SEIRI-based decision-support system: indicator input, criterion aggregation, score normalization, weighted SEIRI computation, readiness classification, deficit-priority ranking, and recommendation generation.

The proposed workflow combines structured scoring, index-based classification, and rule-based ranking of infrastructure deficits, which makes the model suitable for institutional digital assessment and decision support [3], [4], [9]-[16].

In practical terms, the deficit-priority mechanism operates in three sequential steps. First, each criterion score is normalized to the 0-1 range. Second, the weighted deficit is computed as the gap between the observed criterion score and the target maturity level, adjusted by the corresponding criterion weight. Third, the criteria are ranked in descending order of deficit priority, after which the recommendation module assigns predefined intervention rules to the top-ranked weaknesses. For example, a high deficit in security and governance triggers recommendations related to authentication, backup procedures, access control, and audit logging, whereas a high deficit in automation leads to recommendations focused on workflow digitization and service process automation. Such a workflow is aligned with the broader logic of digital assessment and institutional decision-support discussed in prior smart campus and digital transformation studies [3], [4], [9]-[16].

Table 2: Pilot assessment results.

Unit	C_1	C_2	C_3	C_4	C_5	C_6	SEIRI	Class
Faculty A	4.2	3.1	3.4	3.8	4.0	2.9	0.71	High
Faculty B	3.5	2.8	3.0	3.2	3.7	2.6	0.63	Moderate
Faculty C	4.4	3.6	3.8	4.1	4.2	3.1	0.77	High

For demonstration purposes, the model was applied to an expert-informed illustrative scenario involving three anonymized institutional units in a higher education context. The scenario was constructed to reflect institutionally plausible conditions and evaluated using a shared scoring guide with anchor descriptions for the 0-5 maturity scale. The resulting scores were aggregated into criterion-level values and used for SEIRI computation. This pilot scenario is intended to demonstrate the operational logic of the proposed model rather than to claim broad empirical generalizability.

3 RESULTS

The proposed model was applied in a pilot assessment scenario to demonstrate the calculation of the Smart Education Infrastructure Readiness Index (SEIRI), readiness classification, and priority-based recommendation generation. In contrast to the previous review-oriented interpretation of smart education infrastructure as a conceptual ecosystem, the present approach operationalizes the assessment process through measurable institutional criteria, weighted aggregation, and ranked deficit analysis [3], [4], [7], [9]-[16].

3.1 Assessment Structure and Indicator Configuration

The pilot implementation was based on six assessment dimensions: interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance. These dimensions were derived from the literature on smart campuses, artificial intelligence in higher education, learning analytics, cloud-based platforms, and cybersecurity in university environments [4]-[9], [10]-[16]. Each dimension was represented by a set of operational indicators and evaluated on a 0-5 maturity scale. The resulting scores were aggregated into criterion-level values and processed by the SEIRI calculation model.

3.2 Pilot Readiness Assessment Results

To demonstrate the applicability of the proposed model, three anonymized institutional units were represented in an illustrative pilot scenario designed to show the assessment workflow, readiness classification, and deficit-priority logic. The computed criterion scores and final readiness levels are presented in Table 2.

The pilot results show that Faculty Cachieved the highest readiness level, with a SEIRI value of 0.77, indicating comparatively stronger digital maturity across the assessed dimensions. Faculty A also reached a high readiness level (0.71), although with visible weaknesses in security and governance and automation. Faculty B demonstrated moderate readiness (0.63), reflecting comparatively weaker implementation across several dimensions, especially automation and security-related components. Across all three units, interconnectivity and flexibility produced comparatively stronger scores, whereas security and governance remained the most constrained dimension. This pattern is consistent with previous studies reporting that digital infrastructure often develops faster than institutional cybersecurity readiness and governance mechanisms [13]-[16].

Although the pilot dataset is limited in scale, it confirms the operational applicability of the model for institutional comparison and priority-based digital planning.

3.3 Priority Deficit Ranking and Recommendation Output

To support decision-making, the model calculated deficit priorities for each criterion using the weighted gap between the observed score and the target maturity level. The ranking procedure identified the most critical improvement areas for each assessed unit. In the pilot scenario, the highest deficit priorities were associated with security and governance, automation, and adaptivity. Based on this ranking, the recommendation module generated targeted actions such as strengthening authentication and access control, expanding workflow automation, and improving adaptive learning support.

For Faculty B, the model assigned the highest priority to security and governance, followed by automation. For Faculty A, the main recommendation concerned reinforcement of governance controls and optimization of automated support services. For Faculty C, although the overall readiness level was higher, the model still identified security-related enhancement as the most important improvement direction. These findings show that the proposed method is able to move beyond descriptive assessment and provide prioritized digital development guidance. Summarized explicitly, the unit-level linkage between identified weaknesses and recommended actions is: Faculty A - weakest in security/governance and automation → reinforce governance controls (multi-factor authentication, access-control policy) and optimize automated support services; Faculty B - weakest in security/governance, then automation → prioritize authentication and access-control strengthening, followed by workflow-automation expansion; Faculty C - despite higher overall readiness, weakest in security/governance → targeted security-related enhancement (e.g., audit logging, backup policy review) as the top-priority action. A fully tabulated version of this mapping, extended to all six criteria per unit, is recommended for a future revision to further increase the framework's practical usability.

3.4 Practical Implications of the Model

The proposed decision-support model can be implemented as a dashboard-oriented institutional assessment tool. In a practical deployment scenario, university administrators or designated experts enter indicator scores for each faculty, department, or institutional unit. The system then automatically aggregates the scores into criterion-level values, normalizes them, computes SEIRI, assigns a readiness class, and ranks the most critical deficits. Based on this ranking, the recommendation module generates targeted actions for digital development planning. Such a workflow enables university management to compare institutional units, identify weak infrastructure dimensions, prioritize investment areas, and monitor digital transformation progress over time. In this sense, the model functions not only as an assessment framework, but also as an applied IT instrument for evidence-based governance of smart education infrastructure [3], [4], [9]-[16].

4 DISCUSSION

The proposed decision-support model demonstrates that smart education infrastructure can be assessed not only as a conceptual institutional ecosystem, but also as a measurable digital framework suitable for applied IT evaluation. This interpretation is consistent with broader applied IT research, where computational modeling is used to formalize assessment logic and support structured evaluation workflows [17]. At the same time, the domain-specific foundation of the proposed model is grounded in studies on digital transformation, smart campuses, learning analytics, and higher education infrastructure assessment [3], [4], [7]-[9].

One of the main advantages of the proposed approach is its multidimensional structure. The six selected dimensions-interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance-capture both technical and organizational aspects of institutional digital readiness [4]-[9], [14]-[16]. This allows the model to move beyond descriptive review and offer a structured basis for comparing institutional units and prioritizing digital transformation actions.

The pilot assessment results indicate that the proposed SEIRI model is able to differentiate readiness levels across institutional units and identify the most critical infrastructure weaknesses. In the illustrative scenario, interconnectivity and flexibility achieved comparatively higher scores, while security and governance consistently remained the weakest dimension. This pattern is consistent with prior studies showing that digital service expansion in higher education often outpaces the development of cybersecurity and governance mechanisms [13]-[16].

Another important contribution of the proposed model is the integration of rule-based recommendation generation. Instead of limiting the analysis to score reporting, the method ranks infrastructure deficits and links them to priority intervention areas. This strengthens its practical value for university administrators, since the model can support evidence-based allocation of resources, phased implementation planning, and continuous monitoring of digital transformation progress [3], [4], [9]-[16].

At the same time, the proposed approach has several limitations. First, the current study demonstrates the model through a pilot scenario rather than a large-scale institutional dataset. Second, the weighting scheme may vary depending on national, organizational, or policy priorities. Adapting the weights to a different context could be approached procedurally by re-running the same expert-elicitation process described above with a context-appropriate expert panel, or by applying a structured method such as the Analytic Hierarchy

Process (AHP) or Delphi consensus to derive a new weight vector, followed by re-normalization to ensure the weights continue to sum to 1; this recalibration procedure is proposed here conceptually and was not itself implemented or tested in the present study. Third, the effectiveness of the recommendation module depends on the quality of institutional scoring and indicator design. Ensuring this quality could, in future implementations, draw on mechanisms such as periodic expert calibration sessions to align assessors' scoring interpretations, pilot testing of new or revised indicators before full deployment, and formal inter-rater reliability assessment (e.g., using Cohen's or Fleiss' kappa) when multiple assessors independently score the same institutional unit; none of these quality-assurance mechanisms were implemented in the present pilot, and their introduction is recommended as a priority for future validation of the framework. Nevertheless, these limitations do not reduce the methodological value of the study; rather, they indicate directions for further refinement and empirical validation.

Overall, the discussion indicates that the proposed model is suitable for pilot institutional assessment and decision support. By combining indicator-based assessment, algorithmic readiness calculation, and recommendation-oriented prioritization, the model extends the smart education infrastructure literature toward operational institutional evaluation, while remaining methodologically aligned with broader applied IT approaches based on computational formalization and structured assessment workflows [3], [4], [7]-[9], [17].

5 LIMITATIONS

The main limitations of this study are summarized here explicitly. First, model validation is based on a pilot involving only three institutional units (Faculties A, B, and C), which constrains the statistical generalizability of the reported readiness scores and priority rankings to the broader population of higher education institutions. Second, the criterion weights were derived through expert-informed analytical judgment without a fully documented expert-elicitation protocol (number of experts, their expertise, and the aggregation method), and a formal procedure for recalibrating these weights to different institutional, national, or policy contexts has not yet been implemented or tested. Third, the six assessment dimensions are operationalized through composite, assessor-rated scores on a 1–5 scale rather than a fully standardized set of directly measurable indicator definitions, and no mechanisms for ensuring assessment quality - such as expert calibration sessions, pilot validation of individual indicators, or inter-rater reliability testing - were implemented in the present pilot. Broader empirical validation across a larger and more diverse set of institutions, together with the methodological refinements noted above, are identified as priorities for future work.

6 CONCLUSIONS

This paper proposed a decision-support model for assessing smart education infrastructure in higher education institutions through six measurable dimensions: interconnectivity, automation, adaptivity, data-driven management, flexibility, and security and governance. In contrast to review-based and predominantly conceptual approaches, the study translates smart education infrastructure into a formalized institutional assessment framework supported by a weighted Smart Education Infrastructure Readiness Index (SEIRI), readiness-level classification, and a rule-based recommendation mechanism [3], [4], [7]-[9], [14]-[16].

The methodological contribution of the study lies in the integration of indicator-based scoring, weighted aggregation, normalization, deficit-priority ranking, and recommendation generation within a unified applied IT workflow. In this sense, the proposed model does not merely describe digital transformation trends in higher education, but operationalizes them through an algorithm-supported assessment procedure that can be used for structured institutional evaluation and digital planning [3], [4], [7]-[9], [12]-[16].

The pilot assessment demonstrated that the model can classify institutional readiness, identify the most constrained infrastructure dimensions, and generate priority-oriented recommendations for improvement. The results also indicated that security and governance may remain weaker than other readiness dimensions even when other aspects of digital development are relatively advanced, which is consistent with prior studies emphasizing persistent cybersecurity, privacy, and governance challenges in higher education environments [13]-[16]. From a practical perspective, the proposed approach may support university administrators, IT managers, and policymakers in comparing institutional units, prioritizing interventions, planning phased implementation, and strengthening evidence-based management of smart education infrastructure [3], [4], [9]-[16].

At the same time, the study has several limitations. The current validation is based on a pilot scenario involving three institutional units rather than a large-scale empirical dataset. In addition, the weighting structure may require calibration depending on institutional context, policy priorities, and national education systems, while the effectiveness of the recommendation module depends on the consistency and quality of institutional scoring. Future research should therefore focus on broader empirical validation, expert calibration of weights and thresholds, dashboard-based implementation, and cross-university testing of the proposed model. Overall, the study contributes an applied IT artifact that strengthens the transition from conceptual discussion of smart education infrastructure toward measurable, decision-oriented, and operational institutional assessment.

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