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Artificial Intelligence and Digital Maturity in Asia–Pacific Higher Education: A Co-occurrence Analysis and Evidence-Informed Research Agenda

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ABSTRACT

This study synthesizes the supplied analysis of artificial intelligence (AI) and digital maturity in Asia–Pacific (APAC) higher education and reorganizes the findings into a coherent research framework. The analysis combines a conceptual map, keyword co-occurrence networks, a co-occurrence strength matrix, a staged research agenda, an impact feasibility prioritization matrix, a gap to agenda mapping, thematic coverage assessment, and an illustrative latent growth model (LGM) framework for institutional AI-DMI trajectories. Across these outputs, AI and infrastructure emerge as central hubs, while teaching and learning, research, connectivity, high-performance computing (HPC), leadership, strategy, training, utilization, incentives, and curriculum form an interconnected maturity ecosystem. The analysis indicates that the most actionable challenges are not limited to technology availability; rather, utilization, incentives, shared capacity, and the alignment between institutional strategy and implementation represent major leverage points. The proposed research agenda therefore progresses from short-term longitudinal measurement and evaluation of existing pilots to medium-term studies of incentives, shared computing capacity, and curriculum effects, and finally to system-level maturity pathways, governance, ecosystem design, and inclusive AI transformation. The LGM framework extends the analysis from static benchmarking to longitudinal explanation by allowing institutions to differ in baseline maturity and rates of change and by testing predictors of those trajectories.

Keywords: Artificial Intelligence, Digital Maturity, Higher Education, Asia–Pacific, AI-DMI, Co-Occurrence Analysis, Research Agenda, Latent Growth Model, Institutional Transformation, Equity

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1. Introduction

Artificial intelligence is increasingly embedded in the strategic, pedagogical, research, and infrastructural transformation of higher education. In the APAC context, the supplied analysis frames AI readiness as a multidimensional institutional phenomenon rather than a technology adoption problem alone. The AI and Digital Maturity Index (AI-DMI) is used as a conceptual lens through which strategy, people, utilization, technology, teaching and learning, research, infrastructure, connectivity, incentives, and curriculum can be considered as interdependent components of institutional maturity.

The purpose of the present synthesis is to convert the supplied analysis into a journal ready narrative with a clear progression from data context and analytical approach to findings, interpretation, research priorities, and a longitudinal modelling framework. Particular attention is given to the interpretation of all nine figures because the figures provide the principal empirical and conceptual evidence in the supplied material.

An important provenance issue must be made explicit. The supplied file begins with a description of user interaction and tracking logs associated with times higher education.com, including technical identifiers, browsing behavior, inferred profiles, consent choices, third party processing, and data-governance considerations. The subsequent analysis, however, is explicitly centred on AI-DMI and an APAC higher-education whitepaper, with the network figures identifying the Times Higher Education × Huawei AI-DMI whitepaper as their source. The supplied material does not document a direct analytical linkage between the website tracking dataset and the AI-DMI analyses. Accordingly, this rewritten manuscript treats the tracking-log description as contextual data provenance and treats the AI-DMI whitepaper material as the analytical corpus underlying the figures. This distinction should be retained or resolved with the original data documentation before submission to a journal.

2. Background and Early Studies

2.1 AI and Digital Transformation

Artificial Intelligence (AI) is rapidly emerging as a transformative technology in higher education (HE), driving innovation across teaching, learning, research, and academic administration [1]. Its applications span a broad range of educational functions, including personalized learning support systems [2] virtual assistants and cha tbots for instruction [3] automated grading and student competency assessment [4], and learning analytics [5]. These applications show AI's growing capacity to support instructional processes and evidence based educational decision making. In particular, AI-enabled systems can analyze learner behavior and provide individualized support, creating opportunities to improve the efficiency and responsiveness of learning environments.

Despite this rapid expansion, successful AI integration in HE depends not only on technological capability but also on faculty willingness and capacity to adopt and use AI in practice. Faculty adoption therefore critically determines sustainable AI integration. Nevertheless, the intellectual landscape surrounding faculty adoption and AI in HE remains fragmented and inadequately mapped [6]. A systematic understanding of how this research domain has evolved, which themes have emerged, and how research communities are connected is consequently important for identifying the structure of knowledge and future research directions.

Educational technology has become one of the fastest evolving areas of global education research, accompanied by substantial disparities in international collaboration and thematic focus. Erry [7] examined these disparities within the broader educational technology research landscape. Such variation indicates that knowledge production is not geographically or thematically uniform and highlights the value of systematic mapping for understanding the distribution and development of research.

The rapid development of AI has further intensified these transformations in HE, fundamentally influencing teaching, learning, research, and academic management. Although a substantial body of research has examined individual applications of AI in HE, comparatively limited work has systematically mapped the global scientific landscape while connecting it to the Sustainable Development (SD) agenda [8]. This gap is important because the expansion of AI in education increasingly raises questions not only about technological innovation but also about educational quality, accessibility, policy, academic integrity, and sustainable development.

2.2 AI Applications and Research Themes in Higher Education

One of the most prominent areas of AI research in HE concerns teaching and learning. Previous studies have demonstrated that AI can support personalized learning through learning support systems [9, 10], virtual teaching assistants, and automated assessment tools AI has also been applied to analyze learning behavior and develop personalized learning models, thereby helping to improve learning efficiency for students [11]. Collectively, these applications indicate a movement from generalized instructional provision toward more adaptive and data-informed educational environments. At the same time, the diversity of AI applications has expanded the research agenda beyond individual tools to encompass institutional adoption, academic practices, governance, and broader educational transformation.

Hong identified three phases in the development of AI research in HE: 2007–2018, 2019–2022, and 2023–2025 [8]. Across these periods, researchers identified eight major thematic clusters, with recent work placing greater emphasis on Generative AI, academic integrity, and education policy. This temporal development indicates a substantial shift in the research agenda. Earlier work focused more on established AI applications, whereas recent research increasingly addresses rapidly advancing generative technologies and their implications for institutional policy and academic practice.

Hong also identified the United States, the United Kingdom, and Australia as countries maintaining strong and stable positions in the academic landscape [8]. At the same time, the growing academic influence of emerging countries, particularly Singapore and Malaysia, indicates a changing distribution of scholarly influence. Their increasing influence relative to traditional contributors such as China and Saudi Arabia reflects an evolving global knowledge landscape and an increasing emphasis on quality over quantity. This geographic shift is relevant to understanding the internationalization of AI research in HE and the emergence of new centres of expertise.

Within this expanding research landscape, Martis examined the intellectual structure, evolution, and emerging trends of AI in education, with particular attention to student engagement and cognitive disengagement [12]. This focus illustrates an important development in AI-in-education scholarship: research is increasingly concerned not merely with whether AI can be implemented, but with how AI-mediated educational environments influence learner participation, attention, cognition, and educational experience. Such work broadens the field from technology centred investigation toward learner centred evaluation.

2.3 Broader Bibliometric Perspectives on Emerging Technologies and Education

Recent bibliometric studies further demonstrate the value of systematic mapping for understanding the relationship between rapidly developing technologies and education. These studies have examined specific emerging technologies and their implications for education and scientific research, including 4D printing, quantum computing, and bioimplants. Although these technologies represent domains distinct from AI in HE, their bibliometric treatment provides a broader methodological context for examining emerging research fields through trends, thematic structures, collaboration patterns, and visualization.

Lamba et al. [13] conducted a bibliometric study of 4D printing technology in computer engineering to identify research trends and clarify how this emerging technology could be applied in technical education. Similarly, Rawat and Sharma [14] examined how quantum computing could transform approaches to knowledge and visualization in scientific fields, highlighting its potential relevance to HE. Sharma et al. [15] explored the application of control and development within the bioimplants sector in 3D printing from a business perspective, which could help HE institutions understand biomedical technology development and its educational applications.

More recently, Rawat and Yadav [16]investigated the application of quantum computing across key scientific areas using trend analysis and visualization methods to illuminate developments and research gaps in education and scientific research. Taken together, these studies demonstrate the usefulness of bibliometric and science-mapping approaches for emerging technology research. They also provide a broader methodological context for examining AI in HE, where rapid technological development, expanding applications, shifting research priorities, and changing international influence make systematic mapping particularly valuable.

2.4 Research Gap and Rationale for the Present Study

The existing literature demonstrates substantial and rapidly expanding interest in AI applications in HE, particularly in personalized learning, virtual assistants, automated assessment, learning analytics, student engagement, and emerging Generative AI applications. However, the literature remains distributed across diverse application areas, thematic clusters, countries, and research communities. The evidence summarized above also indicates that the field is undergoing a rapid transition, with recent research increasingly incorporating Generative AI, academic integrity, education policy, and learner-centred concerns [17, 18, 19].

At the same time, the literature suggests that important aspects of the global research structure remain insufficiently integrated. Research has identified major developmental phases and thematic clusters [20, 21, 22], investigated faculty adoption as a critical issue [23] , and examined international collaboration disparities [24], but the overall intellectual structure of AI research in HE and its relationship to broader sustainable-development priorities remain insufficiently systematized [25]. The changing influence of countries such as Singapore and Malaysia further indicates the need to examine geographical evolution alongside thematic and intellectual development [26, 27, 28].

Accordingly, a systematic bibliometric and science mapping analysis of AI in HE can identify the field's evolution, dominant and emerging themes, influential research communities, collaboration structures, and research gaps. Such an approach can provide an integrated understanding of how AI research in HE has developed and where the field is moving, while establishing a basis for connecting technological developments with educational, institutional, and sustainable development priorities.

3. Data Context and Analytical Scope

3.1 Digital-tracking data context

The supplied dataset description characterizes a broad digital footprint generated by visitors to the Times Higher Education website. The described data are dynamic rather than a single static file and encompass signals and identifiers collected through cookies, pixels, and related tracking technologies, in coordination with a large third-party advertising and analytics ecosystem. The information includes device and technical identifiers, browsing and interaction records, inferred and profiled attributes, and privacy and consent choices.

Device and technical information includes IP addresses, which can be used for precise or approximate geolocation, along with browser characteristics, language, screen resolution, installed fonts or plugins, and unique device identifiers. Browsing and interaction information includes pages visited, content viewed, visit duration, navigation paths, submitted forms, and interactions with embedded content. The supplied description further notes that activity can be combined with authentication derived or probabilistic identifiers and information from other online or offline sources to construct user profiles. Consent choices are represented through digital signals managed by the consent management platform and communicated to participating vendors.

The stated processing purposes include targeted advertising, content personalization, analytics and measurement, service development, and security functions such as fraud or bot detection and debugging. Data retention varies across vendors, and the supplied description reports periods ranging from hours to several years, with some vendor specific retention extending to 730 days and consent records retained for defined periods. The ecosystem also involves extensive third party sharing, including real time bidding, synchronization, and combination of information from multiple sources. The stated legal bases distinguish processing based on consent from processing based on legitimate business interests.

From a research perspective, this data context is potentially valuable because it combines behavioral observations with inferred profiles and explicit privacy choices. At the same time, the fragmented commercial ecosystem, variable retention periods, dynamic consent, multiple processors, and reproducibility challenges require strong governance, documentation, anonymization, and ethical safeguards. These considerations are relevant to the methodological interpretation of the supplied material even though the AI-DMI figures themselves are not demonstrated to have been computed from these tracking logs.

3.2 AI-DMI analytical corpus

The principal analytical component of the supplied file concerns AI and digital maturity in APAC higher education. The figures operationalize the topic through a set of recurring concepts, including AI, infrastructure, teaching and learning, research, leadership, strategy, training, utilization, incentives, HPC, connectivity, curriculum, maturity stages, shared platforms, adaptive analytics, AI Practice Labs, and virtual tutors. The network figures indicate that the analysis is derived from the Times Higher Education × Huawei AI-DMI APAC whitepaper, while the research agenda translates the identified gaps and uneven maturity patterns into proposed empirical studies.

The analysis is therefore best understood as a structured synthesis rather than a conventional statistical study of individual level observations. Its principal outputs are relational maps, prioritization frameworks, and an illustrative longitudinal modelling strategy. The LGM section is explicitly presented as an illustrative framework, and its trajectories are simulated rather than estimated from observed institutional panel data.

4. Analytical Framework

The analysis proceeds through four complementary stages. First, the conceptual and co-occurrence outputs identify the structure of relationships among AI-DMI concepts. Second, the co-occurrence strength matrix quantifies the relative strength of pairwise conceptual associations on a 0–10 scale. Third, the research agenda converts identified gaps into studies arranged by time horizon and prioritized according to potential impact and feasibility. Fourth, the LGM framework provides a statistical strategy for transforming repeated AI-DMI measurements into trajectories that can distinguish baseline status from rates of institutional change.

The combined framework is important because each analytical output answers a different question. The network analysis asks which concepts are structurally central and which concepts are strongly connected. The matrix asks how strong those relationships are. The roadmap asks when to undertake research. The prioritization matrix asks which studies offer the greatest combination of impact and feasibility. The gap to agenda map asks how observed weaknesses translate into specific research clusters. The thematic coverage plot assesses whether the proposed agenda adequately addresses the major domains. Finally, the LGM framework asks how institutional maturity can be studied dynamically over time.

5. Results

5.1 Conceptual structure of AI-enabled higher-education transformation

Figure 1 presents a conceptual pathway for AI transformation in higher education. The framework begins with national and regional policy contexts, including investment, regulation, and workforce frameworks. These contextual conditions shape two enabling domains: AI-ready infrastructure and leadership and workforce capability. Infrastructure encompasses 5G/Wi-Fi, HPC, shared platforms, and secure data environments, whereas leadership and workforce capability includes mandatory AI training, micro credentials, and incentives incorporated into appraisal and promotion. Together, these enabling conditions support AI-enabled learning and research, which in turn are expressed through teaching and learning and research excellence. Curriculum integration then links institutional AI capability to student and societal outcomes, including personalized learning, employability, inclusion, and discovery.

The figure therefore represents AI transformation as a layered, and partly causal ecosystem rather than as a sequence driven by technology alone. The position of infrastructure and workforce capability between policy context and institutional activity indicates that technology must be combined with human and organizational capacity. The downstream placement of curriculum integration and student and societal outcomes further implies that maturity should ultimately be judged by educational and societal value rather than by infrastructure acquisition alone.

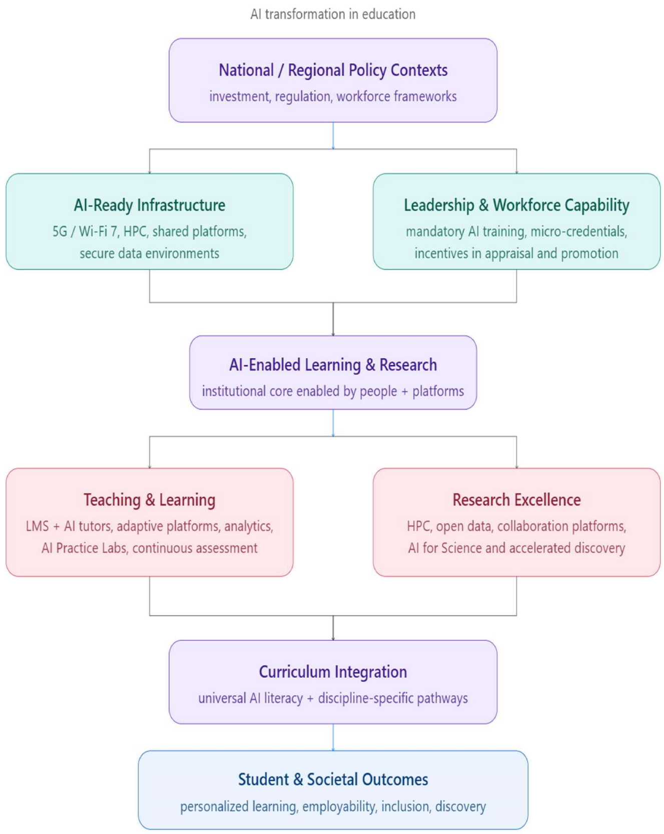

Figure 1. Conceptual framework of AI transformation in higher education. The framework links national and regional policy contexts with AI-ready infrastructure and leadership/workforce capability, which enable AI-supported learning and research and ultimately shape curriculum integration and student and societal outcomes

5.2 Main keyword co-occurrence network

Figure 2 shows the principal keyword co-occurrence structure using a force directed layout. AI and Infrastructure occupy the most prominent hub positions, indicating that they organize much of the conceptual network. The surrounding nodes represent primary dimensions, supporting concepts, and contextual benchmarks. Thicker edges represent stronger co-occurrence, allowing the visual structure to distinguish central relationships from weaker associations.

The network suggests that AI is not an isolated technological topic. It is linked to teaching and learning, research, strategy, utilization, leadership, and supporting educational technologies. Infrastructure forms a second major centre and connects strongly with connectivity and HPC related concepts. This dual hub structure is analytically important because it shows that AI maturity depends on both application domains and the enabling digital substrate. The presence of contextual benchmark nodes, particularly Singapore/Hong Kong, also suggests that some systems serve as reference points within the maturity discourse rather than merely additional observations.

5.3 Structured keyword co-occurrence network

Figure 3 provides a clearer hierarchical representation of the same conceptual field. The network separates core hubs, primary dimensions, supporting concepts, and contextual benchmarks. AI and Infrastructure remain the two dominant hubs. Infrastructure is closely connected to connectivity/Wi-Fi, HPC and big data, shared platforms, and research, whereas AI connects across teaching and learning, research, strategy and utilization, leadership and people, adaptive analytics, curriculum and AI literacy, and AI Practice Labs.

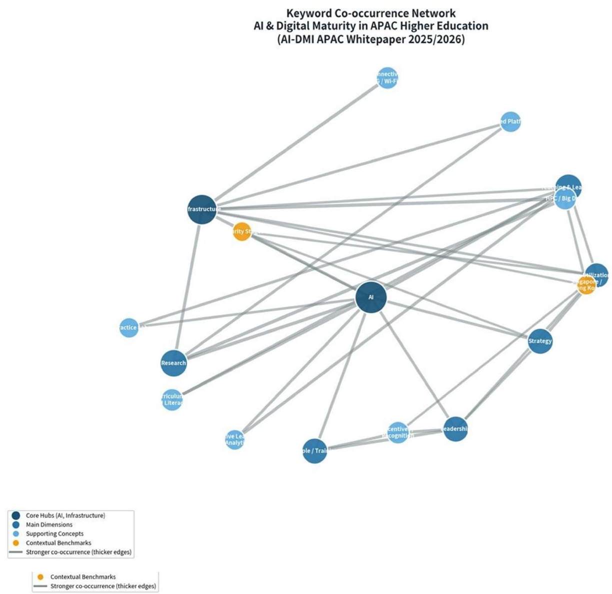

Figure 2. Main keyword co-occurrence network using a force-directed layout. Core hubs are AI and Infrastructure; node categories distinguish major dimensions, supporting concepts, and contextual benchmarks, while thicker edges indicate stronger co-occurrence

The structured layout makes the multidimensional nature of AI-DMI particularly visible. Infrastructure-related concepts cluster around the capacity required to support AI-intensive activities, while the AI hub links this capacity to organizational and educational uses. Leadership and people form an intermediate mechanism between institutional strategy and practical utilization, and incentive recognition appears as a comparatively peripheral node. This peripheral position aligns with the broader view that incentives and recognition may be underdeveloped relative to technology and infrastructure, even though they may be important for translating capability into sustained use.

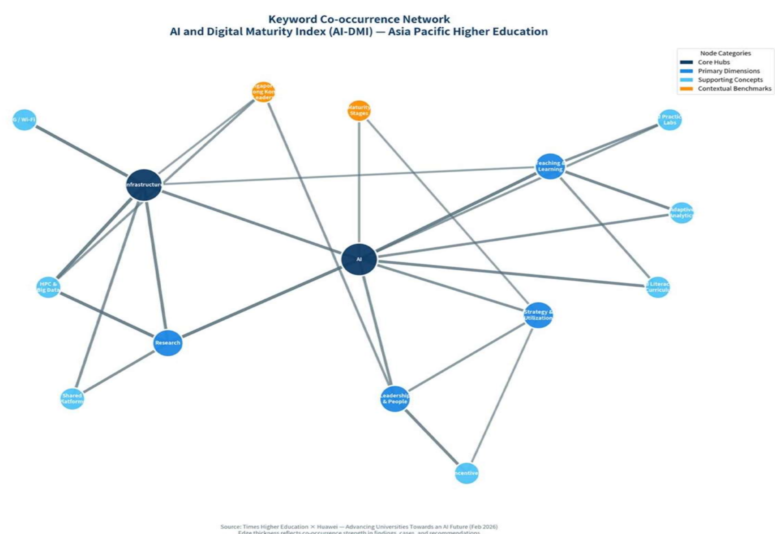

Figure 3. Structured keyword co-occurrence network for AI and digital maturity in APAC higher education. Node categories distinguish core hubs, primary dimensions, supporting concepts, and contextual benchmarks; edge thickness represents co-occurrence strength

5.4 Co-occurrence strength matrix

Figure 4 provides a 0–10 co-occurrence strength matrix for twelve concepts. The diagonal values are 10 by construction, while the off diagonal values identify the relative strength of associations between domains. The strongest off-diagonal relationships include AI–Teaching & Learning (9), AI–Research (9), Infrastructure–HPC (9), Infrastructure–Connectivity (9), Research–HPC (9), and Infrastructure–AI (8). AI also shows relatively strong relationships with Curriculum (8), while Infrastructure is strongly associated with Research (8).

The matrix reinforces the network interpretation while adding quantitative differentiation among relationships. Teaching and learning and research are strongly connected to AI, indicating that AI is embedded in both educational and research functions. Infrastructure, HPC, and connectivity form a distinct technical capacity cluster. By contrast, incentives have weaker associations with several core domains, including Infrastructure (3), Research (3), HPC (2), and Connectivity (2). The relatively modest relationship between Strategy and Utilization is also noteworthy in the context of the supplied interpretation: although the two concepts are conceptually linked, their observed co-occurrence strength is not sufficient to suggest complete alignment. Taken together, the matrix shifts attention from the availability of technology toward the organizational mechanisms required to convert capacity into utilization.

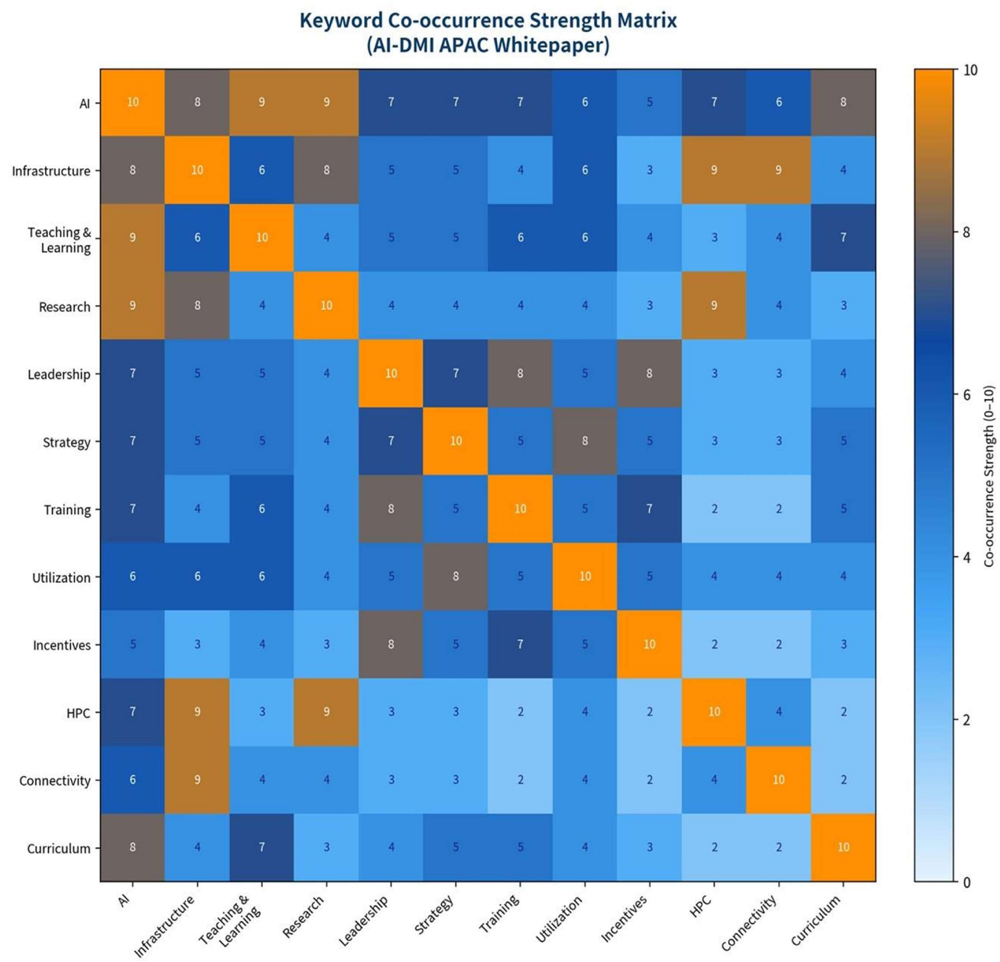

Figure 4. Keyword co-occurrence strength matrix for the AI-DMI APAC whitepaper. Values range from 0 to 10, with larger values indicating stronger co-occurrence. The matrix highlights AI and Infrastructure as central domains and identifies strong links among AI–Teaching & Learning, AI–Research, Infrastructure–HPC, Infrastructure–Connectivity, and Research–HPC

5.5 Synthesis of structural findings

Taken together, Figures 1–4 indicate a consistent architecture. AI and infrastructure constitute the dual structural hubs, while teaching and learning and research are the major application domains. Connectivity and HPC form important infrastructure related supports. Leadership, training, strategy, utilization, incentives, and curriculum represent organizational and educational mechanisms through which infrastructure can be converted into institutional capability. The analysis also identifies a gap cluster around incentives and recognition and around the relationship between strategy and utilization. Singapore/Hong Kong are represented as important contextual benchmark nodes in the network analysis.

The central implication is that the principal research problem is not simply whether APAC universities possess AI-enabling technologies. Instead, the more consequential question is how institutions convert technology and infrastructure into sustained, equitable, and strategically aligned use. This interpretation bridges the structural analysis and the proposed research agenda.

6. Research Agenda

The proposed research agenda is organized into short-term, medium-term, and longer-term/systemic priorities. This sequencing moves from measurement and evidence generation to explanatory studies and, ultimately, system level transformation. The agenda focuses on comparative and longitudinal research across APAC higher education systems, with particular attention to under represented systems and to equity and inclusion.

6.1 Short-term priorities: measurement and early evidence

The first priority is longitudinal tracking of AI-DMI overall scores and the Strategy, People, Utilization, and Technology sub-dimensions across the eight focal systems, with expanded sampling in under-represented settings such as Japan, Indonesia, and the Philippines. Repeated measurement would establish whether apparent maturity differences represent stable structural conditions or changing institutional trajectories.

The second priority is mixed methods investigation of the strategy utilization gap. The central question is why resource rich systems may under utilize available infrastructure while more constrained systems can achieve high intensity of use. The third priority is evaluation of early AI Practice Lab and virtual-tutor deployments, including the KAIST, Wuhan, and Ningxia models, with outcomes covering learning, instructor workload, and equity of access.

6.2 Medium-term priorities: incentives, shared capacity, and curriculum

Medium-term research should examine whether institutional incentive structures affect AI adoption and staff engagement, particularly when AI competence is incorporated into appraisal and promotion. A second line of inquiry should compare the cost, benefit, and equity implications of shared national or regional HPC and data platforms with institution level investments, drawing on the different development models represented in Singapore, China, and emerging ASEAN contexts.

A third medium term priority is curriculum impact research. This should examine whether universal AI-literacy requirements combined with discipline specific pathways improve graduate employ ability and AI readiness across STEM and non-STEM fields. Such research would connect institutional AI maturity with down stream educational outcomes rather than treating maturity as an end in itself.

6.3 Longer-term and systemic priorities

Longer-term research should develop differentiated maturity roadmaps tailored to high income, upper middle income, and lower middle income systems. This matters because a single maturity pathway may not fit systems with different financial, infrastructural, institutional, and workforce conditions.

A second systemic priority concerns governance and ethics, including evaluation of institutional AI principles and guidelines such as the SJTU AI 10 Principles. A third concerns ecosystem design, particularly the role of tripartite investment models and national research and education networks in reducing structural divides in AI-ready research capacity. The fourth concerns inclusive transformation: research should determine whether lighter weight AI applications, including mobile enabled feedback and adaptive platforms, can reduce rather than widen inequities in resource constrained settings.

6.4 Methodological priorities

The supplied agenda calls for multi-level designs spanning systems, institutions, and individuals; integrating quantitative AI-DMI scores with qualitative case studies; including both academic and professional services staff perspectives; and using explicit equity and inclusion metrics. These priorities are methodologically imp ortant because AI maturity is simultaneously a system level policy issue, an institutional capability issue, and an individual adoption issue.

7. Research Agenda Roadmap

Figure 5 translates the agenda into a temporal sequence. Short term work emphasizes measurement and rapid evidence generation through longitudinal AI-DMI tracking, strategy utilization studies, and evaluations of AI Practice Labs and virtual tutors. Medium term work shifts toward institutional mechanisms and resource allocation through incentive studies, shared HPC cost-benefit and equity analyses, and curriculum research. Longer term work addresses systemic design through differentiated maturity roadmaps, governance and ethics, tripartite ecosystem models, and inclusive AI applications in resource constrained settings.

The roadmap provides a coherent progression from descriptive evidence to explanatory and systemic research. Early longitudinal and evaluation studies can generate the empirical evidence required to design more complex causal, economic, and system level investigations. In this sense, the sequencing reduces the risk of attempting highly coordinated systemic interventions before sufficient evidence exists about institutional trajectories and implementation mechanisms.

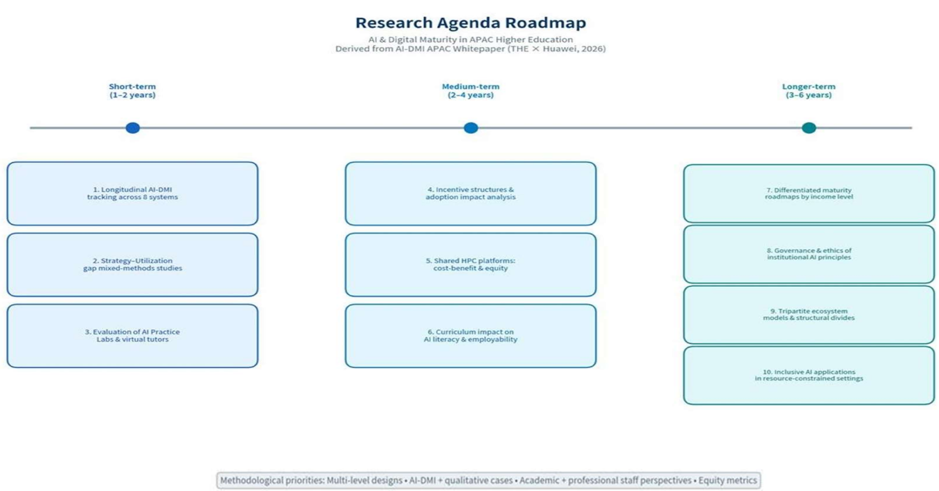

Figure 5. Research agenda roadmap. The agenda progresses from short-term measurement and pilot evaluation to medium-term studies of incentives, shared HPC, and curriculum effects, followed by longer-term work on differentiated maturity pathways, governance, ecosystem models, and inclusive AI

8. Research Agenda Prioritization

Figure 6 positions the ten proposed research areas according to potential impact and feasibility. The upper-right quadrant represents high-impact and high feasibility studies and therefore contains the principal quick wins: longitudinal AI-DMI tracking, strategy utilization gap studies, and AI Practice Lab and virtual tutor evaluations. These studies can build on existing survey infrastructure and documented institutional cases.

The upper left quadrant contains high impact but comparatively lower feasibility strategic investments. Differentiated maturity roadmaps and tripartite ecosystem studies occupy this space because they require broader coordination, more extensive data access, and longer implementation horizons. Inclusive AI in constrained settings lies near the high impact boundary and is similarly important but methodologically demanding. Governance and ethics is also positioned toward the lower feasibility side, reflecting the complexity of evaluating institutional principles and their effects at scale.

The prioritization framework therefore supports a deliberate shift from an infrastructure deficit narrative toward a utilization and coordination narrative. The analysis argues that additional technology is not necessarily the highest leverage intervention when existing assets remain under used or when incentives, strategy, workforce capability, and shared capacity are insufficiently aligned.

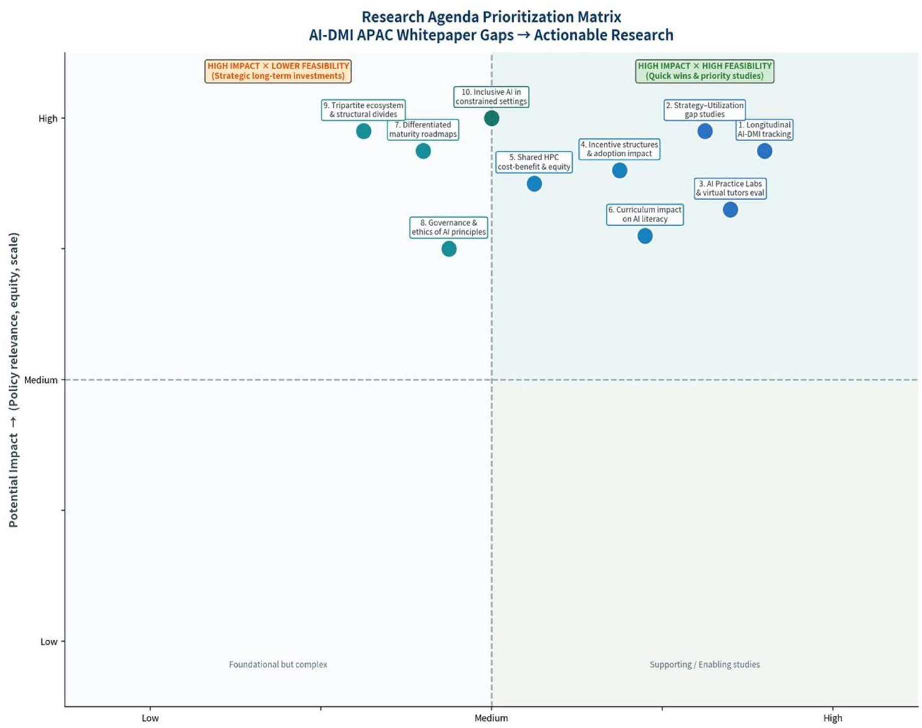

Figure 6. Research agenda prioritization matrix. Research topics are positioned according to potential impact and feasibility. High impact/high feasibility studies represent immediate priorities, whereas high-impact/lower feasibility studies constitute strategic longer term investments

9. From Whitepaper Gaps to an Actionable Research Agenda

Figure 7 explicitly maps five identified gaps to research agenda clusters. The first gap concerns an advanced-connectivity lag, reflected in relatively limited 5G penetration in the supplied findings, and links to longitudinal tracking and Practice Lab evaluation. The second concerns limited access to AI teaching tools, including low reported availability of tutors and analytics, and links to longitudinal and pilot evaluation work, as well as shared platform and equity research.

The third gap is uneven HPC access, with Singapore shown to have markedly higher access than other systems. This maps directly onto shared platform and equity analysis. The fourth gap concerns incentives for AI training, where recognition is reported as below 70%, and maps to incentive and curriculum impact studies. The fifth gap is the strategy utilization mismatch, which connects to incentive/curriculum work and differentiated roadmaps and inclusive models. The central inference in the figure is that gaps in utilization, incentives, and shared capacity represent the highest leverage research targets.

This mapping preserves a visible chain of reasoning from diagnosis to intervention. Rather than listing research topics independently, the framework shows which empirical weaknesses motivate each research cluster, strengthening the justification for the proposed agenda.

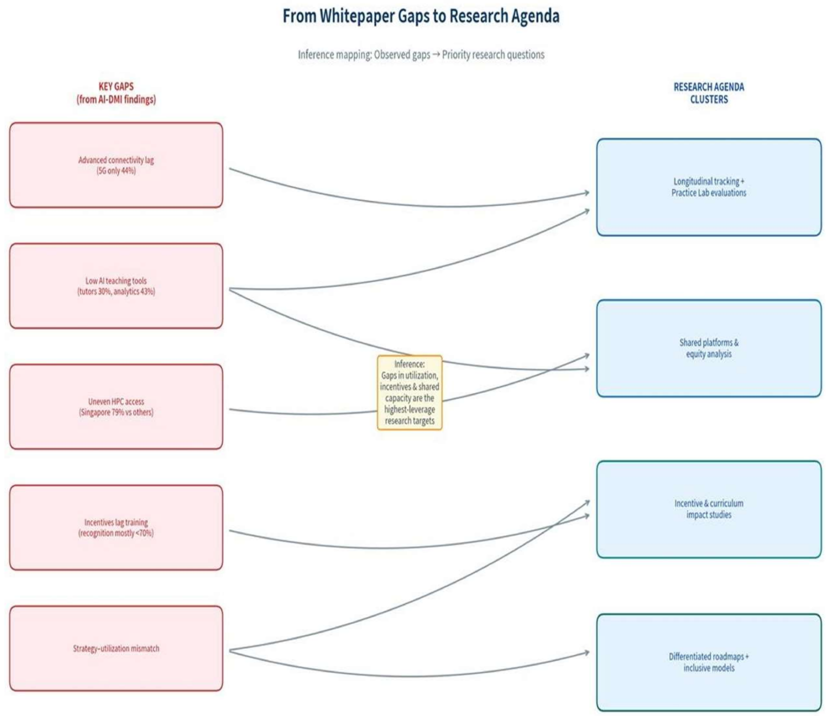

Figure 7. Mapping from whitepaper gaps to the proposed research agenda. Observed gaps in connectivity, AI teaching tools, HPC access, incentives, and strategy utilization alignment are mapped to longitudinal, shared platform, incentive/curriculum, and differentiated roadmap research clusters

10. Thematic Coverage of the Research Agenda

Figure 8 evaluates how well the proposed agenda addresses five core themes. All five themes reach or exceed the stated strong-coverage threshold of 8/10. Strategy and Utilization receives the highest coverage score (9.5), followed by Teaching and Learning AI (9.0). Leadership and Incentives and Infrastructure and Connectivity each receive 8.5, while Research Computing receives 8.0.

The distribution indicates that the agenda is deliberately concentrated on the domains where the supplied analysis identifies the strongest implementation challenges. The highest score for Strategy and Utilization reflects the central concern with converting strategic intent into actual use. Strong coverage of Teaching and Learning AI reflects the emphasis on Practice Labs, virtual tutors, adaptive analytics, and AI literacy. Infrastructure and Research Computing remain strongly represented through shared platform, HPC, and equity studies. The relatively balanced scores suggest that the agenda is broad enough to address the full maturity ecosystem while still concentrating attention on utilization and educational implementation.

11. Overall Research Agenda Inference

The proposed agenda reframes AI-DMI from a diagnostic snapshot into a platform for cumulative knowledge development. Repeated AI-DMI measurement can establish trajectories; deep evaluations of Practice Labs and incentive structures can identify mechanisms; and system level research can translate those findings into differentiated roadmaps, ecosystem models, and inclusion strategies. This progression moves the field from descriptive benchmarking toward explanatory and intervention oriented knowledge.

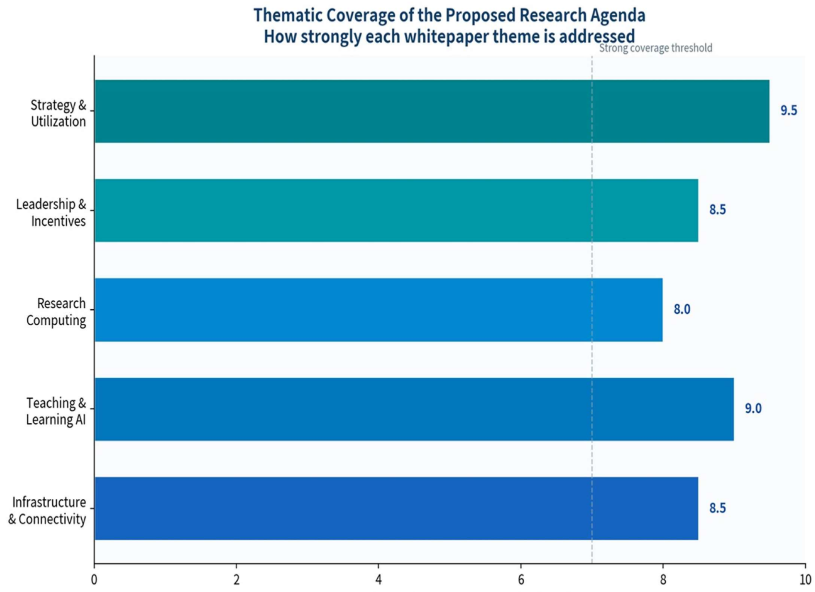

Figure 8. Thematic coverage of the proposed research agenda. All five core themes meet the strong-coverage threshold, with the greatest emphasis on Strategy and Utilization (9.5) and Teaching and Learning AI (9.0)

The broader inference is that APAC universities should not be evaluated solely according to whether they have AI strategies, infrastructure, or isolated AI applications. The more consequential dimensions are whether people are prepared to use AI, whether institutions create incentives for sustained adoption, whether infrastructure is actually utilized, whether strategy is translated into implementation, and whether benefits are distributed equitably. The proposed research agenda is therefore aligned with a maturity perspective in which institutional progress involves coordinated development across technology, people, strategy, utilization, teaching, research, and governance.

12. Latent Growth Models for Institutional AI-DMI Trajectories

The supplied analysis proposes Latent Growth Models (LGMs), also known as latent growth curve or latent trajectory models, as a longitudinal statistical framework for examining how institutions change over time and why institutions differ in their patterns of change. LGMs are particularly appropriate when repeated AI-DMI measurements are available because they distinguish an institution's initial status from its rate of change and allow heterogeneity in trajectories to be modelled explicitly.

12.1 Unconditional linear growth

For institution i observed at wave t, the basic linear model can be represented as $y_{it} = \eta_{0i} + \eta_{1i} t + \varepsilon_{it}$, where y_{it} denotes the AI-DMI overall score or a dimension score, η_{0i} is the institution specific latent intercept, η_{1i} is the institution specific latent slope, t is the time score, and ε_{it} is the time specific residual. The average intercept and average slope describe the typical starting level and average rate of change, while the intercept and slope variances quantify heterogeneity across institutions. Their covariance indicates whether institutions that begin at higher maturity also tend to change faster or slower.

In the AI-DMI context, a positive average slope would indicate improvement in the typical institution over time. Significant slope variance would indicate that institutions do not progress uniformly: some may advance rapidly, while others may stagnate or decline. This distinction matters because cross sectional rankings cannot show whether a system with moderate maturity is improving rapidly or whether a high maturity system has plateaued.

12.2 Quadratic and nonlinear growth

If institutional change is not adequately represented by a straight line, a quadratic term can be introduced: $y\_it = \eta\_{0i} + \eta\_{1i}\, t + \eta\_{2i}\, t^2 + \varepsilon\_it$. The quadratic component allows acceleration or deceleration and can capture patterns such as rapid early improvement followed by plateauing, or delayed acceleration following major investment. The model is therefore useful for testing whether AI maturity evolves through distinct phases rather than at a constant rate.

12.3 Conditional growth models

Conditional LGMs extend the model by introducing predictors of the intercept and/or slope. Candidate predictors in the supplied analysis include baseline incentive recognition, system membership (e.g., Singapore/ Hong Kong versus other systems), research intensity, the presence of a formal AI strategy at baseline, and leadership change. A predictor of the slope is especially informative because it indicates whether the factor is associated with the rate of subsequent improvement rather than merely with the initial maturity level.

12.4 Parallel-process growth

A multivariate or parallel-process LGM can model Strategy, People, Utilization, and Technology simultaneously. This permits researchers to test whether growth in one dimension is associated with subsequent or concurrent growth in another. For example, the framework can examine whether increases in People capability are associated with later increases in Utilization or whether strong Technology growth occurs without corresponding Strategy or People development. Correlations among intercepts and slopes can reveal whether dimensions tend to develop together or diverge.

12.5 Multilevel extension

Because institutions are nested within national or regional systems, a multilevel extension can distinguish institutional-level trajectories from system level variation. This matters for APAC research because policy, funding, infrastructure, workforce conditions, and national digital strategies can shape institutions within the same system. A multilevel growth model can therefore estimate both institution specific change and differences in average trajectories across systems.

13. Interpretation of the Illustrative LGM Figure

Figure 9 contains four simulated panels designed to demonstrate how longitudinal AI-DMI data could be interpreted. These are illustrative simulations, not estimates from observed institutional panel data. Panel A shows multiple institutional trajectories around an average linear growth curve. The dispersion of the trajectories demonstrates that a common positive average trend can coexist with substantial institutional heterogeneity. Some institutions improve faster than average, while others remain relatively flat or decline.

Panel B illustrates alternative trajectory shapes. The steady linear trajectory represents approximately constant improvement. The accelerating trajectory demonstrates increasingly rapid improvement over time and corresponds conceptually to positive quadratic growth. The plateauing pattern shows early improvement followed by slower change, while the declining then recovery pattern illustrates temporary deterioration followed by renewed progress. The flat or stagnant trajectory shows that an institution can remain around a stable maturity level despite broader system level improvement.

Panel C presents parallel trajectories for Strategy, People, Utilization, and Technology. The simulated curves demonstrate that dimensions can develop at different rates. Strategy and Technology show relatively strong upward movement, People also increases, while Utilization remains lower and changes more slowly. This configuration illustrates the substantive problem identified elsewhere in the analysis: technological or strategic capacity may increase without a commensurate increase in practical utilization.

Panel D illustrates conditional growth by comparing institutions with high versus low formal incentive recognition. The high recognition trajectory rises substantially faster than the low recognition trajectory, and the shaded regions illustrate uncertainty around the simulated trajectories. The figure therefore demonstrates the type of moderation or predictive relationship that a conditional LGM could test empirically: whether formal recognition of AI competence is associated with faster institutional maturity growth.

The principal methodological value of Figure 9 is not the simulated numerical pattern itself but the analytical logic it illustrates. Longitudinal AI-DMI research can move beyond asking which institutions currently have higher scores and instead ask how quickly they change, which dimensions change together, which institutions follow distinct developmental pathways, and which organizational conditions predict faster improvement.

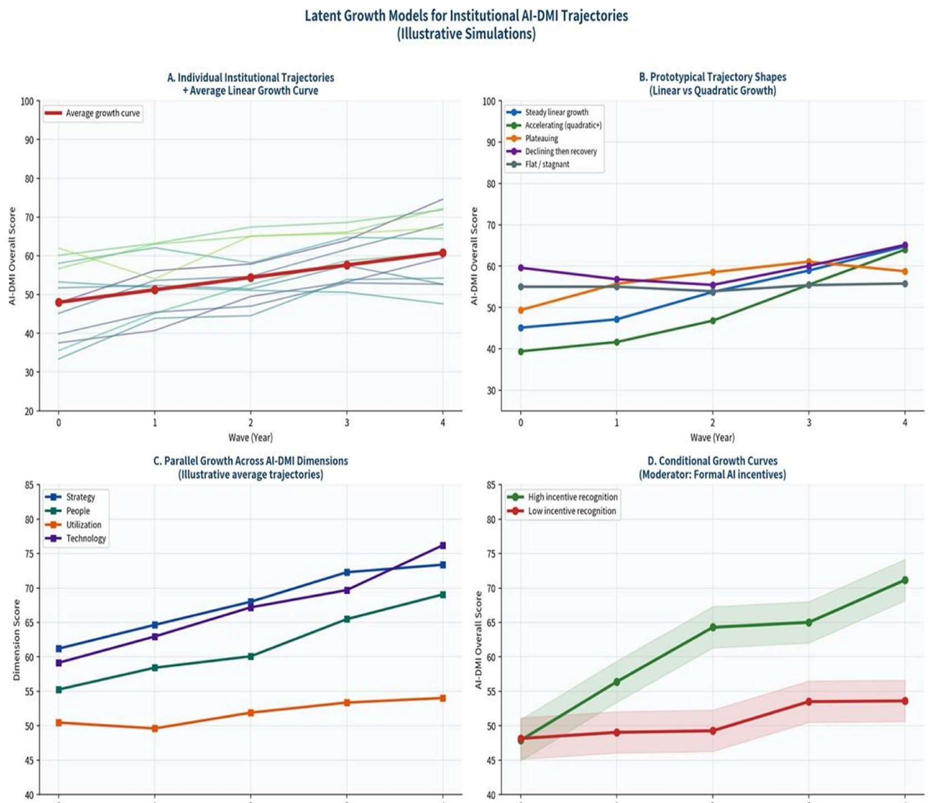

Figure 9. Illustrative latent growth model scenarios for institutional AI-DMI trajectories. Panel A depicts heterogeneous institutional paths around an average linear trend; Panel B shows alternative trajectory shapes; Panel C illustrates parallel growth across Strategy, People, Utilization, and Technology; and Panel D demonstrates simulated conditional growth associated with formal incentive recognition

14. Practical Implementation of the Longitudinal AI-DMI Framework

14.1 Data preparation

Longitudinal data should be organized in long format, with one record per institution wave observation. Code time consistently, for example as 0, 1, 2, 3, and 4 for five annual waves. Handle missing waves using full information maximum likelihood or multiple imputation when the assumptions supporting those approaches are plausible.

14.2 Model-building sequence

The recommended sequence begins with an unconditional linear LGM to establish the average trajectory and the extent of heterogeneity. A quadratic term can then be tested to determine whether the linear assumption is inadequate. Time-invariant predictors can subsequently be introduced in a conditional LGM, followed by time varying covariates when available. The analysis can then be extended to parallel process models across AI-DMI dimensions and finally to multilevel models that account for institutions nested within systems.

14.3 Software and diagnostics

The supplied analysis identifies R packages and modelling environments including lavaan, lcmm, nlme, lme4 and growth, as well as Mplus and Stata. Python options include semopy and statsmodels, although the supplied analysis notes that Python support is more limited for complex LGM applications. Key diagnostics include conventional structural equation model fit indices such as the comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), together with examination of residual variances over time and substantive interpretation of intercept slope covariance.

15. Expected Contributions of the Longitudinal Framework

Applying LGMs to repeated AI-DMI measurements would allow researchers to determine whether APAC universities are moving toward higher maturity stages on average and how much heterogeneity exists across institutions and systems. The models can also test whether baseline leadership, formal incentive recognition, research intensity, or the presence of a formal AI strategy is associated with subsequent growth in utilization and overall maturity.

A further contribution would be identifying dimensions with the steepest average growth and those showing the greatest divergence across institutions. Such evidence would clarify whether APAC systems are experiencing balanced transformation or whether progress is concentrated in infrastructure and strategy while people capability and utilization lag behind. In this respect, longitudinal modelling provides a direct statistical mechanism for testing the central proposition emerging from the network and agenda analyses: that AI maturity depends on coordinated development rather than technology availability alone.

16. Discussion

The integrated findings provide a coherent explanation for why AI transformation in higher education should be conceptualized as an ecosystem problem. The network analyses consistently place AI and infrastructure at the centre, confirming the importance of technical capacity, but the matrix and research agenda reveal that infrastructure is only one component of institutional transformation. Teaching and learning and research represent major application domains, while leadership, strategy, training, utilization, incentives, and curriculum determine how capability is translated into practice.

The strategy utilization relationship is especially important. A formal strategy can establish institutional intent, but its presence does not necessarily imply intensive or equitable use. The research agenda accordingly prioritizes mixed methods investigation of the conditions under which resources are translated into actual practice. This includes leadership, workforce development, incentive recognition, access to shared computing capacity, and educational application design.

The emphasis on shared HPC and platform equity also broadens how we interpret digital maturity. Capacity need not be provided exclusively through institution level investment; national and regional shared platforms may provide alternative routes to advanced research capability. However, the value of shared capacity depends on actual access, utilization, governance, and the ability of institutions and researchers to convert technical availability into productive research activity.

The thematic coverage results show that the proposed agenda is not narrowly focused on infrastructure. Its strongest emphasis is on Strategy and Utilization and Teaching and Learning AI, while leadership and incentives, research computing, and infrastructure and connectivity also receive strong coverage. This balance supports a multidimensional interpretation of AI-DMI in which maturity is expressed through coordinated institutional capabilities.

Finally, the LGM framework provides an important methodological extension. Cross sectional AI-DMI scores are useful for benchmarking, but they cannot establish whether differences reflect different starting points, different rates of change, or different developmental pathways. LGM analysis can address these limitations by estimating average trajectories, institutional heterogeneity, nonlinear change, predictors of growth, and relationships among multiple maturity dimensions. Successful implementation, however, requires repeated institution level measurements comparable across waves.

17. Limitations and Data-Provenance Considerations

Several limitations should be acknowledged. First, the supplied material does not provide the underlying institution level AI-DMI dataset, sample sizes, missingness patterns, statistical estimates, confidence intervals, or inferential tests. Consequently, the network, roadmap, and prioritization outputs should be interpreted as structured analytical and conceptual evidence rather than as a conventional inferential statistical analysis. Second, Figure 9 is explicitly simulated and should not be presented as empirical evidence of institutional growth.

Third, the supplied file distinguishes between a Times Higher Education website tracking dataset description and an AI-DMI whitepaper-based analytical section, but it does not document the transformation or linkage between these components. For journal submission, the authors should either provide the missing linkage and analytical provenance or clearly state that the tracking-log description and AI-DMI analysis constitute separate components. Fourth, the co-occurrence strengths appear to be constructed on a 0–10 scale, but the source file does not provide the exact coding, extraction, thresholding, or normalization procedure. Reproducibility would therefore require a detailed description of keyword extraction, coding, edge weighting, and network construction.

Finally, the proposed LGM framework depends on repeated comparable measurements. Before fitting such models, researchers should establish measurement consistency across waves and systems and document the assumptions governing missing-data treatment. These limitations do not invalidate the proposed framework, but they define the boundary between the supplied conceptual synthesis and a future empirical validation study.

18. Conclusion

The supplied analysis provides a coherent foundation for studying AI and digital maturity in APAC higher education when reorganized around a progression from structural diagnosis to actionable research and longitudinal explanation. AI and infrastructure emerge as dual hubs, while teaching and learning, research, connectivity, HPC, leadership, strategy, training, utilization, incentives, and curriculum form interconnected components of the maturity ecosystem. The strongest substantive inference is that the next stage of research should move beyond asking what technology is available and focus on why available assets are or are not translated into sustained, strategically aligned, and equitable use.

The resulting research agenda provides a staged pathway. Short term priorities emphasize repeated measurement, strategy utilization studies, and evaluation of existing AI pilots. Medium term priorities address incentives, shared HPC capacity, and curriculum effects. Longer term priorities focus on differentiated maturity pathways, governance, ecosystem design, and inclusive transformation. The LGM framework then provides the statistical architecture needed to convert repeated AI-DMI assessments into a dynamic evidence base capable of explaining institutional change.

Overall, the analysis supports a shift from static maturity benchmarking toward cumulative, longitudinal, and intervention oriented research. Such a shift can help distinguish institutions that are merely AI-ready from those that are actually progressing toward integrated and optimized AI-enabled learning, research, and institutional practice.

Source Note
This manuscript is a reorganization and interpretation of the supplied analysis document. We introduced no external sources and added no unsupported empirical estimates. Where the supplied equations were

incomplete or not recoverable as text, the LGM equations above were expressed in standard notation solely to formalize the model descriptions already present in the source material. Figure 9 remains explicitly identified as illustrative simulation rather than observed data.

Appendix: Methodological Details for Co-Occurrence and Network Analysis

This appendix provides the detailed methodology underlying the keyword co-occurrence networks (Figures 2 and 3) and the co-occurrence strength matrix (Figure 4) presented in the main analysis. These procedures align with standard bibliometric and text-mining practices employed in science mapping studies.

A.1 Data Source and Corpus

The analysis was based on the *Times Higher Education × Huawei AI-DMI APAC whitepaper*[citation:29]. This document served as the analytical corpus from which the study extracted key concepts and terms. The focus was on identifying the intellectual structure of the AI-DMI framework, including core hubs (AI, Infrastructure), primary dimensions (Teaching and Learning, Research, Leadership, Strategy, Training, Utilization, Incentives, Curriculum), and supporting concepts (Connectivity, HPC, Shared Platforms)[citation:29].

A.2 Keyword Extraction and Preprocessing

1. Term Identification:

We identified relevant terms from the whitepaper's content, with particular emphasis on recurring concepts across institutional maturity domains. Terms were extracted based on both thematic relevance and frequency of mention.

2. Stop-Word Removal:

Standard stop-words (e.g., "and," "the," "of," "for," "with") were removed using a predefined English stop-word list. Additionally, context specific stop words were excluded to retain only substantive concepts directly related to AI and digital maturity (e.g., generic verbs, prepositions, and conjunctions).

3. Stemming/Lemmatization:

To ensure consistency in concept representation, terms were stemmed or lemmatized where appropriate. This allowed, for instance, "teaching" and "teach" to be represented under a single concept term.

A.3 Co-Occurrence Matrix Construction

A.3.1 Definition of Co-Occurrence

Co-occurrence was defined as the frequency with which two keywords appeared together within the same analytical unit of the whitepaper. Given the document's relatively concise nature compared to a large bibliographic corpus, the co-occurrence window was based on thematic sections rather than fixed word distances, ensuring that conceptually related terms were captured as co-occurring even if physically separated within the text.

A.3.2 Co-Occurrence Counting

For each pair of keywords (*i, j*), the co-occurrence count (c_{ij},) was computed by tallying the number of thematic units in which both terms appeared. The result was a square, symmetric matrix with twelve principal concepts as row and column headings.

A.3.3 Scaling and Normalization

The raw co-occurrence counts were normalized to a 0–10 scale to facilitate interpretation and comparison of relative association strengths. The normalization procedure followed the principles of similarity measurement where observed co-occurrence is compared against expected co-occurrence under independence assumptions. The formula used was:

$$s_{ij}, = (c_{ij}|, \times 10) / \max(c)$$

where *max(c)* represents the maximum observed co-occurrence count among all concept pairs.

This approach, analogous to the association strength similarity measure in bibliometric analysis, ensures that the resulting strength values are proportional to the ratio between observed and expected co-occurrences. Values closer to 10 indicate stronger semantic associations.

A.4 Network Construction and Visualization

A.4.1 Software Environment

Network construction and visualization were performed using bibliometric analysis software, consistent with tools such as **VOSviewer**. This software supports generating co-occurrence networks from text and bibliographic data, using force-directed layout algorithms to position nodes and edges based on association strength.

A.4.2 Node Categories and Edge Weighting

Nodes (concepts) were categorized into four groups based on their functional role in the conceptual framework:

- Core Hubs (e.g., AI, Infrastructure)

- Primary Dimensions (e.g., Teaching and Learning, Research, Strategy)

- Supporting Concepts (e.g., Connectivity, HPC, Shared Platforms)

- Contextual Benchmarks (e.g., Singapore/Hong Kong)

Edge thickness was weighted proportionally to the co-occurrence strength values derived from the matrix. Thicker edges represent stronger conceptual associations between two nodes.

A.4.3 Force-Directed Layout

The network layout was generated using a force directed algorithm that positions nodes such that strongly connected concepts are placed closer together and weakly connected concepts are drawn farther apart. This visualization strategy allows the structural centrality of core hubs (AI and Infrastructure) to emerge clearly, while also revealing the clustering of supporting concepts around them.

A.5 Co-Occurrence Strength Matrix Calculation

The co-occurrence strength matrix (Figure 4) presents the normalized association strengths between all concept pairs. Each cell entry (i, j) represents the strength of the co-occurrence relationship between concept i and concept j, ranging from 0 (no co-occurrence) to 10 (maximum observed strength). Diagonal values are set to 10 by construction to indicate perfect self-association.

Interpretive Guidelines:

- Values 8–10: Strong co-occurrence and conceptual integration (e.g., AI–Teaching & Learning, Infrastructure–HPC)

- Values 5–7: Moderate co-occurrence, indicating a notable but not dominant association

- Values 0–4: Weak co-occurrence, suggesting limited conceptual integration (e.g., Incentives–Infrastructure)

A.6 Validation and Interpretation

The structural interpretation of networks and matrices was validated by examining:

1. Centrality: The frequency and strength of connections for each node.

2. Clustering: The grouping of concepts into thematic clusters (e.g., technical capacity cluster: Infrastructure–HPC–Connectivity; application domain cluster: AI–Teaching & Learning–Research).

3. Consistency with Conceptual Framework: Network findings were cross referenced with the conceptual pathway presented in Figure 1 of the main analysis to ensure logical coherence.

A.7 Limitations

The co-occurrence analysis is based on a single corpus (the AI-DMI whitepaper) and therefore reflects that document's conceptual structure. Future work could extend the analysis to include a broader range of AI-in-education publications to validate the generalizability of the network structure. Additionally, the 0–10 scaling is illustrative and should not be treated as a probabilistic or inferential measure. The complete keyword extraction, counting, and normalization code is not fully recoverable from the source document and should be documented more extensively in future empirical applications.

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