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Artificial Intelligence, Teaching Quality and Management Efficiency
A Governance Perspective on Higher Education in Shenyang, China

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Abstract

Artificial intelligence may influence teaching and university administration, but the two areas do not create value in the same way. Treating deployment or processing speed as evidence of educational improvement risks overlooking weak learning outcomes, additional review work, bias, privacy concerns and blurred responsibility. Drawing on policy documents and a narrative reading of higher-education research, this article develops a governance framework for local institutions. The framework begins with a shared foundation of data, platforms, staff capability and institutional rules, then separates a teaching pathway from a management pathway. Teaching is considered in terms of learning goals, feedback, differentiated support, student engagement and teachers' professional judgement. Administration is considered in terms of turnaround time, error and rework, access to services, transparency and the cost of appeal. The analysis proposes an evidence cycle that moves from problem definition and risk classification to a limited pilot, human review, multidimensional evaluation and a decision to scale, revise or stop. For institutions in Shenyang, the practical priorities are shared technical standards with controlled data access, role-specific AI literacy, explicit evidence thresholds and an auditable division of responsibility between people and systems.

Keywords: *AI empowerment; teaching quality; management efficiency; higher education governance; local universities; Shenyang*

1. INTRODUCTION

AI use in higher education now extends well beyond isolated classroom tools. Universities are experimenting with course-material preparation, question answering, learning analytics, assessment support, admissions enquiries, scheduling, student services and quality monitoring. Reviews show that the literature is concentrated in assessment, prediction, intelligent assistance, tutoring and learning management [1-3]. These applications can make feedback faster and reduce some repetitive work, yet evidence of genuine learning improvement remains uneven, and administrative use has received less careful study [3]. A local university therefore needs to ask not simply what a system can do, but which problem it addresses, how improvement will be recognised and who is responsible when the result is wrong. Teaching and administration also call for different standards of success. In teaching, the central questions concern learning goals, the substance of feedback, higher-order thinking and professional judgement. In administration, service quality, timeliness, error, transparency and fairness are more immediate. Both rely on data, platforms, procurement and staff capability, but a single efficiency score would hide important trade-offs. Faster content production may create more checking for teachers, and quicker decisions may leave students with less explanation or weaker routes of appeal. The relevant judgement is whether quality, access and accountability improve together. Shenyang's universities are working within a policy environment shaped by national educational digitalisation and Liaoning's AI strategy. The Outline for Building a Leading Country in Education (2024-2035) supports AI-enabled reform and the use of data and AI in evaluation and decision-making [16]. National guidance issued in 2025 highlights values, higher-order thinking and educational governance [17], and the 2026 Action Plan for AI Plus Education establishes a dedicated programme [18]. Liaoning's 2025 plan names Shenyang and Dalian as leading centres and includes teaching, examinations, evaluation and administration among the proposed applications [19]. A further plan for provincial universities followed in July 2026 [20]. These policies create room for action, but they do not replace evidence from actual courses and services. Accordingly, this article treats improvement as a proposition to be demonstrated under specified conditions. It does not assume that the potential capabilities of AI have already produced better outcomes in Shenyang. Task suitability, human review, data governance and outcome evidence remain necessary parts of any claim about benefit.

2. Method and Analytical Framework

The analysis combines policy documents with a narrative review of academic work. Policy sources were selected for their direct relevance to higher-education AI, educational digitalisation, teacher capability and Liaoning's implementation context. The academic literature covers technology adoption, systematic reviews of higher-education AI, generative-AI applications, AI literacy and university governance. This is not an exhaustive systematic review. Sources were read across four recurring questions: the setting in which AI is used, the mechanism through which it might create value, the evidence used to judge outcomes and the governance conditions attached to use. AI empowerment is used here in a deliberately narrow sense. It refers to an improvement that can be observed when an AI capability is incorporated into people's work, institutional rules and an existing process; installing software is not enough. Teaching quality concerns the extent to which courses and learning processes realise educational goals. Management efficiency concerns the provision of accurate, lawful, fair and timely services with reasonable use of resources. Coordination between the two domains therefore means sharing a secure foundation and a common governance language while retaining separate outcome measures.

3. Teaching and Management as Distinct but Connected Pathways

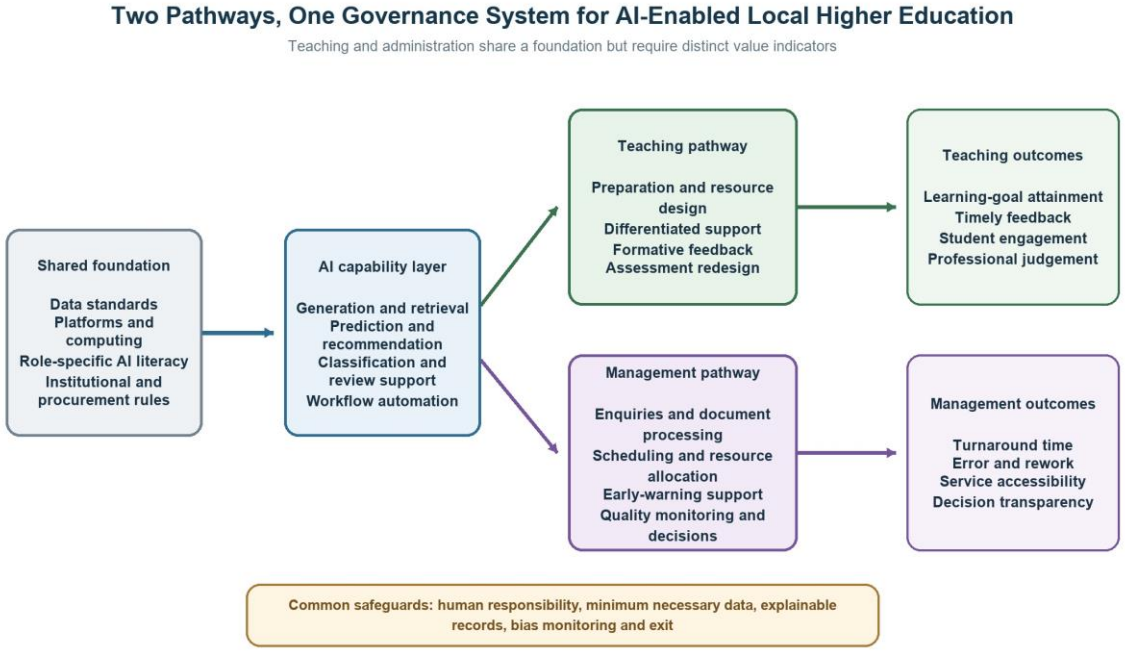


Figure 1Two Pathways, One Governance System for AI-Enabled Local Higher Education

Source: Developed by the author from research on higher-education AI applications, digital education ecosystems and accountable governance.

3.1 Shared Foundation: Data, Platforms, Literacy and Rules

The starting point is governable data rather than the largest possible pool of data. Teaching materials, student work, grades, enquiries, personnel records and financial information do not carry the same level of sensitivity. Institutions need practical classifications, minimum-access rules and role-based authorisation. They also need platforms that can be maintained and connected over time. OECD has noted that weak interoperability forces education systems to enter the same information repeatedly and limits the use of data for improvement [4]. For a local university with limited resources, shared identity, permissions, logs and interfaces are often more valuable than a collection of disconnected departmental tools. People and rules are part of that foundation. Teachers need to judge whether a system serves a course objective and how its output should be checked. Administrators need a working knowledge of permissions, automation boundaries and incident handling, while technical teams need to understand the educational and service consequences of design choices. China's Digital Literacy for Teachers standard covers awareness, knowledge and skills, application, social responsibility and professional development [21], providing a useful basis for role-specific development. Institutional rules must also anticipate procurement review, service changes, logging, student notice, human review and exit.

3.2 Teaching Pathway: From Content Generation to Learning Design

AI is particularly effective at generating, reorganising and explaining information, but those capabilities acquire educational value only when they are tied to a learning purpose. A teacher might use AI to draft cases at different levels, prepare formative questions, suggest feedback or identify common difficulties in learning records. Each use still demands judgement. Generated content can be inaccurate, biased or oversimplified, and students may do less intellectual work when a fluent answer is treated as the end of inquiry. Research on teacher-AI-student collaboration therefore remains persuasive only when the teacher retains responsibility for educational purpose and evaluation [6-9,13-15].

Evidence for the teaching pathway should extend beyond login counts, the volume of generated material or general satisfaction. Relevant indicators include learning-goal attainment, the quality and timeliness of feedback, differentiated support, student engagement, higher-order thinking and changes in teachers' workload. High-impact assessment requires a stronger boundary. AI may help organise evidence for grading, academic-integrity review or graduation decisions, but an authorised teacher or committee must examine that evidence and remain responsible for the final decision.

3.3 Management Pathway: From Process Acceleration to Better Public Services

Administrative gains are often easier to express as time saved, which makes them especially easy to overstate. Chatbots may route routine enquiries, classification tools may help organise records, predictive models may flag students who could need support, and optimisation tools may assist scheduling. The evaluation should still include first-contact resolution, error and rework, accessibility, the quality of transfer to a person and the burden of appeal. Admissions, financial aid, discipline, academic warnings and employment decisions carry greater consequences and need explainable evidence, documented human review and an effective appeal route. Efficiency also depends on the design of the underlying process. Adding a prediction or text-generation step to a workflow that still requires duplicate entry, manual reconciliation and paper approval may increase rather than reduce work. A process map can reveal where delay, repeated entry, information gaps and recurring errors actually occur. Only then is it possible to decide whether the appropriate response is AI, rule-based automation or a conventional information system. For many stable tasks, deterministic rules remain easier to explain, audit and maintain.

Table 1Scenario-Value-Risk-Indicator Matrix for AI in Local Higher Education

Scenario	Expected value mechanism	Human task that must remain	Recommended outcome indicators	Principal risks
Preparation and resource redesign	Accelerate drafts of cases, questions and multilevel materials	Verify facts, align goals, judge difficulty and educational values	Preparation time, material error rate, alignment with course goals	Hallucination, bias, copyright and homogenisation
Formative feedback	Provide timely, personalised draft feedback and practice suggestions	Explain key errors, consider affect and difference, decide final feedback	Waiting time, feedback uptake, learning improvement, review workload	Incorrect feedback, overreliance and privacy
Learning support and Q&A	Extend service hours and route common questions	Handle complexity, crises and special needs	Resolution rate, transfer quality, satisfaction and accessibility	Incorrect advice, digital divide and unclear accountability
Assessment support	Draft questions, scoring prompts and evidence leads	Design assessment, review evidence, decide grades and integrity cases	Consistency, appeal rate, review time and higher-order coverage	Misclassification, narrowed assessment and integrity risks

Scenario	Expected value mechanism	Human task that must remain	Recommended outcome indicators	Principal risks
Document classification and drafting	Reduce repetitive organisation and improve retrieval	Confirm content, approve release and retain external accountability	Turnaround time, error, rework and retrieval success	Sensitive-data leakage and factual error
Scheduling and resource allocation	Generate options under multiple constraints	Set rule weights and resolve conflicts and exceptions	Conflicts, revisions, utilisation and perceived fairness	Opaque weights and structural bias
Academic early-warning support	Identify students who may need support from multiple sources	Verify context, contact students and choose support rather than punishment	Lead time, effective support, false alerts and group fairness	Labelling, privacy, discrimination and feedback loops

Note: Baselines should be defined before each pilot. A final high-impact decision must not rely solely on model output.

4. How Risk Can Erode Both Quality and Efficiency

4.1 Unreliable Outputs Create Hidden Rework

Fluent language can conceal an incorrect answer. When no one is assigned to check sources or own the final decision, errors can move quickly into teaching materials, institutional documents and student advice, only to reappear later as corrections, complaints or reputational damage. Bender et al. discuss risks arising from training data, bias and scale in large language models [11]. Kasneci et al. similarly place opportunities for feedback and personalisation alongside error, bias and overreliance in education [7]. A credible efficiency measure must therefore include review, rework and incident handling rather than counting only the time saved at the first step.

4.2 Data and Algorithmic Bias Can Harm Educational Fairness

Historical university data reflect earlier institutional choices and inequalities. A model can reproduce those patterns even when its overall accuracy appears acceptable. In early-warning, aid, admissions or staff evaluation, false positives and false negatives may be distributed unevenly across groups. Fairness therefore requires continuing examination of error rates, access to service and appeal outcomes, not a single pre-deployment check. Personal information also needs lawful, proper and necessary processing, while people affected by automated decisions retain rights to notice, explanation and protection from unreasonable effects [22-23].

4.3 Outsourced Accountability Weakens Professional Judgement

Human review becomes weak when a model's output is treated as an objective answer and the reviewer adds only a signature. UNESCO's human-centred approach to generative AI emphasises privacy, institutional validation and human agency [5]. In a university, responsibility for course goals, grades, discipline, admissions, aid and personnel decisions remains with the people who hold the relevant professional or legal duty. AI can assist by producing a draft, highlighting a pattern or presenting options; it cannot carry that duty itself.

5. Governing AI Use through an Evidence Cycle

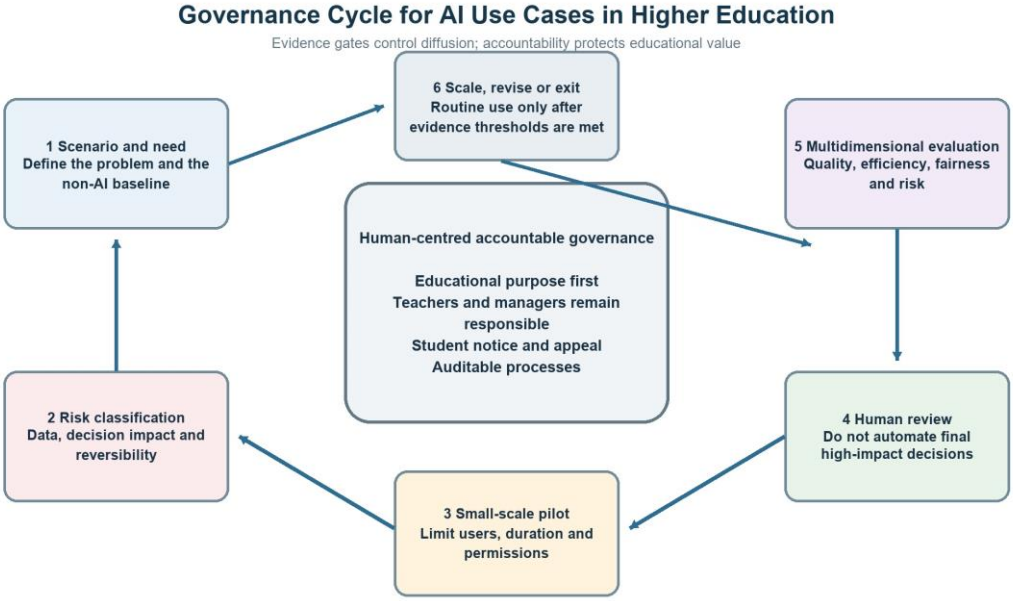


Figure 2Governance Cycle for AI Use Cases in Higher Education

Source: Developed by the author from UNESCO, OECD and higher-education AI policy frameworks.

5.1 Define the Problem before Selecting the Technology

A proposal should begin with the present process: who is affected, where delay or error occurs, and what the non-AI baseline looks like. Conventional digitalisation and rule-based automation deserve consideration alongside AI. No model can resolve duplicated responsibilities or an unclear approval structure on its own. At minimum, a proposed use case needs a statement of expected value, the data it will use, an accountable owner, prohibited applications and the conditions under which it will be stopped.

5.2 Classify Risk by Data Sensitivity and Decision Impact

Risk varies with both the sensitivity of the data and the consequence of the decision. A low-risk use relies on public or non-sensitive information, produces a reversible output and remains a draft. A medium-risk use may involve internal data or affect access to a service, making logs and mandatory human review necessary. A high-risk use touches sensitive personal information, important rights or decisions that are difficult to reverse. Such cases require specialised review and should not, as a general rule, make final decisions automatically. The classification then determines the pilot's scope, approval route, monitoring frequency and vendor obligations.

5.3 Conduct Small-Scale Pilots and Multidimensional Evaluation

A useful pilot has a limited duration, a defined group of participants, restricted data access and a recorded model or service version. Its results are compared with the existing process. Evaluation covers time, quality, error, distributional fairness, staff workload, student experience and incidents. A faster process that creates more errors or appeals is not an improvement. For generative systems, recording the extent of human revision and the errors that recur can show whether work has actually been reduced or merely moved.

5.4 Scale, Revise or Exit according to Evidence

Evidence, not the existence of a pilot, should determine what happens next. Routine use is justified only when agreed indicators are met, the main risks are controlled, responsibility is clear and resources can be sustained. Partial success calls for revision and another evaluation. A project that remains below threshold, depends on an opaque service or creates risks greater than its benefit should be stopped. Treating exit as a normal governance decision helps to limit sunk-cost bias and keeps attention on educational and service outcomes.

Table 2Governance Stages, Responsibilities and Evidence Thresholds for Higher-Education AI

Stage	Lead and participating actors	Required evidence	Threshold for the next stage
Need definition	Operational unit leads; teachers, students or service users participate	Process baseline, problem boundary, affected groups and comparison with non-AI alternatives	The problem is genuine and AI offers explainable incremental value
Risk classification	Data governance, legal or ethics, IT and operational units	Data inventory, permissions, impact assessment, prohibited uses and vendor information	Risk level is explicit; high-risk uses receive specialised review
Pilot design	Operational owner, technical team and evaluation staff	Duration, users, model version, human-review points and exit conditions	The pilot is reversible and monitorable, with named owners and incident response
Operation and review	Front-line teacher or manager remains accountable; technical team supports	Input sources, model outputs, human changes, incidents and complaint logs	Humans review all critical decisions; serious incidents trigger prompt suspension
Multidimensional evaluation	Relatively independent teaching-quality or management-evaluation team	Quality, efficiency, fairness, cost, experience and risk indicators	Net improvement over baseline with no unacceptable group harm
Scale or exit	Institutional governance body decides; affected groups are informed	Reassessment, resources, continuing monitoring and exit plan	Scale only when evidence passes; otherwise revise, reduce or exit

Note: Responsible parties may vary with institutional size, but the following principles should remain: the operational unit retains final responsibility; the technical team provides support; evaluation remains relatively independent; and students have access to appeals.

6. Implications for Higher-Education Institutions in Shenyang

6.1 Share Technical Standards while Keeping Data Access Local

Shenyang's institutions differ considerably in size and mission, yet repeated procurement can produce unnecessary cost and uneven security. Universities can share standards, evaluation tools, contract clauses, training materials and examples without pooling sensitive raw data. Within each institution, common arrangements for identity, data classification, logging and interfaces can support departments that retain only the permissions required for their work. What is shared is basic capability and a common rule set, not unrestricted access to institutional data.

6.2 Build AI Literacy around Professional Roles

The content of AI literacy should follow professional responsibility. Teachers need to work through course goals, feedback and assessment design; administrators need to understand processes, permissions, explanation and appeal; leaders need to judge investment, evidence and risk; technical staff need to connect system performance with educational purpose and fairness. A scenario plan, risk register and human-review procedure provide more meaningful evidence of learning than a record that someone completed a set of tool demonstrations.

6.3 Evaluate Teaching and Management Separately

Teaching projects can be judged through learning-goal attainment, feedback quality, student engagement, teacher workload and assessment validity. Administrative projects require measures of turnaround time, error and rework, accessibility, transparency and appeal cost. The two sets of measures can sit beside common governance indicators such as data incidents, recurring model errors, group disparities, rates of human review and time taken to suspend a failing use case. Reporting both benefits and problems would give annual reviews more value than a catalogue of successful examples.

6.4 Start with Low-Risk Uses that Offer Clear Value

For institutions with limited resources, sensible early uses rely on public information, create reversible outputs, allow straightforward checking and address a visible need. Examples include public-policy question answering, draft course materials, organisation of meeting documents and routing of routine enquiries. Grades, admissions, financial aid, discipline, mental-health crises and personnel decisions require more mature arrangements for data, ethics and appeal. Experience gained in low-risk work offers a firmer foundation than an immediate attempt at university-wide automation.

7. Conclusion

AI contributes to local higher education only when technological capability is joined to organisational capacity and the resulting improvement can be shown. Teaching and administration can share technical foundations and governance principles, but their mechanisms and outcome measures remain different. The framework developed in this article connects those foundations to a practical sequence of problem definition, risk assessment, limited testing, human review and a reversible decision about wider use. For universities in Shenyang, the important capacity is not the number of systems purchased. It is the ability to maintain auditable human-AI work, develop staff capability for particular roles, compare outcomes with a credible baseline and discontinue a weak project. The article has not analysed primary data from local institutions, and its proposed indicators need to be tested across different types of university, discipline and workflow. Comparative case studies and stratified surveys would be useful next steps, especially if they include evidence from actual courses and administrative processes.

References

ZAWACKI-RICHTER O, MARIN V I, BOND M, et al. Systematic review of research on artificial intelligence applications in higher education: Where are the educators?[J]. International Journal of Educational Technology in Higher Education, 2019, 16: 39. DOI: 10.1186/s41239-019-0171-0.

CROMPTON H, BURKE D. Artificial intelligence in higher education: The state of the field[J]. International Journal of Educational Technology in Higher Education, 2023, 20: 22. DOI: 10.1186/s41239-023-00392-8.

BOND M, KHOSRAVI H, DE LAAT M, et al. A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour[J]. International Journal of Educational Technology in Higher Education, 2024, 21: 4. DOI: 10.1186/s41239-023-00436-z.

OECD. OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem[R]. Paris: OECD Publishing, 2023. DOI: 10.1787/c74f03de-en.

UNESCO. Guidance for generative AI in education and research[R]. Paris: UNESCO, 2023. https://unesdoc.unesco.org/ark:/48223/pf0000386693.

POPENICI S A D, KERR S. Exploring the impact of artificial intelligence on teaching and learning in higher education[J]. Research and Practice in Technology Enhanced Learning, 2017, 12: 22. DOI: 10.1186/s41039-017-0062-8.

KASNECI E, SESSLER K, KUCHEMANN S, et al. ChatGPT for good? On opportunities and challenges of large language models for education[J]. Learning and Individual Differences, 2023, 103: 102274. DOI: 10.1016/j.lindif.2023.102274.

TLILI A, SHEHATA B, ADARKWAH M A, et al. What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education[J]. Smart Learning Environments, 2023, 10: 15. DOI: 10.1186/s40561-023-00237-x.

CHAN C K Y. A comprehensive AI policy education framework for university teaching and learning[J]. International Journal of Educational Technology in Higher Education, 2023, 20: 38. DOI: 10.1186/s41239-023-00408-3.

NG D T K, LEUNG J K L, CHU S K W, et al. Conceptualizing AI literacy: An exploratory review[J]. Computers and Education: Artificial Intelligence, 2021, 2: 100041. DOI: 10.1016/j.caeai.2021.100041.

BENDER E M, GEBRU T, McMILLAN-MAJOR A, et al. On the dangers of stochastic parrots: Can language models be too big?[C]//Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency. New York: ACM, 2021: 610-623. DOI: 10.1145/3442188.3445922.

FLORIDI L, CHIRIATTI M. GPT-3: Its nature, scope, limits, and consequences[J]. Minds and Machines, 2020, 30: 681-694. DOI: 10.1007/s11023-020-09548-1.

YANG Z K, WANG J, WU D, et al. The impact of ChatGPT and generative artificial intelligence on education and corresponding strategies[J]. Journal of East China Normal University (Educational Sciences), 2023, 41(7): 26-35. DOI: 10.16382/j.cnki.1000-5560.2023.07.003.

ZHU Y X, YANG F. ChatGPT, generative artificial intelligence and educational innovation: Opportunities, challenges and the future[J]. Journal of East China Normal University (Educational Sciences), 2023, 41(7): 1-14. DOI: 10.16382/j.cnki.1000-5560.2023.07.001.

ZHOU H Y, LI Y Y. ChatGPT and the modernisation of educational governance: Transformation of educational governance in the digital age[J]. Journal of East China Normal University (Educational Sciences), 2023, 41(7): 36-46. DOI: 10.16382/j.cnki.1000-5560.2023.07.004.

CENTRAL COMMITTEE OF THE COMMUNIST PARTY OF CHINA; STATE COUNCIL. Outline for Building a Leading Country in Education (2024-2035)[EB/OL]. 2025-01-19.

https://www.moe.gov.cn/jyb_xxgk/moe_1777/moe_1778/202501/t20250119_1176193.html.
MINISTRY OF EDUCATION OF THE PEOPLE'S REPUBLIC OF CHINA, et al. Opinions on Accelerating Educational Digitalisation[EB/OL]. 2025-04-16. https://www.moe.gov.cn/srcsite/A01/s7048/202504/t20250416_1187476.html.
MINISTRY OF EDUCATION OF THE PEOPLE'S REPUBLIC OF CHINA, et al. Action Plan for AI Plus Education[EB/OL]. 2026-04-10. https://www.moe.gov.cn/srcsite/A16/s3342/202604/t20260410_1433240.html.
GENERAL OFFICE OF THE LIAONING PROVINCIAL PEOPLE'S GOVERNMENT. Implementation Plan for Promoting Artificial Intelligence Innovation and Development in Liaoning Province[EB/OL]. 2025-06-05. https://www.ln.gov.cn/web/zwgkx/zfwj/szfbgtwj/2025n/2025061116302953701/index.shtml.
EDUCATION LEADING GROUP OF THE CPC LIAONING PROVINCIAL COMMITTEE. Action Plan for High-Quality Development of AI Plus Education in Liaoning Province[EB/OL]. 2026-07-02. https://jyt.ln.gov.cn/jyt/gk/zxtz/2026070911305693309/index.shtml.
MINISTRY OF EDUCATION OF THE PEOPLE'S REPUBLIC OF CHINA. Digital Literacy for Teachers: JY/T 0646-2022[S/OL]. 2022-11-30. https://www.moe.gov.cn/srcsite/A16/s3342/202302/W020230214594527529113.pdf.
CYBERSPACE ADMINISTRATION OF CHINA, et al. Interim Measures for the Management of Generative Artificial Intelligence Services[EB/OL]. 2023-07-13. https://www.gov.cn/zhengce/zhengceku/202307/content_6891752.htm.
STANDING COMMITTEE OF THE NATIONAL PEOPLE'S CONGRESS. Personal Information Protection Law of the People's Republic of China[Z/OL]. 2021-08-20. https://www.cac.gov.cn/2021-08/20/c_1631050028355286.htm.