AI in Higher Education

SSC considerations and recommendations

SSC Secretariat Working Paper

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The Swiss Science Council

The Swiss Science Council SSC is the advisory body to the Federal Council for issues related to science, higher education, research and innovation policy. The goal of the SSC, in conformity with its role as an independent consultative body, is to promote the framework for the successful development of the Swiss higher education, research and innovation system. As an independent advisory body to the Federal Council, the SSC pursues the Swiss higher education, research and innovation landscape from a long-term perspective.

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AI in Higher Education: challenges and recommendations

Generative AI is being rapidly integrated into core academic functions, including teaching, assessment, student support, research workflows and institutional management. This has a direct impact on educational processes and outcomes, given that AI use in education is inherently data-intensive and relies on profiling, learning analytics, prediction and automated or semi-automated decision support. The challenge is that AI is entering all relevant educational domains faster than governance frameworks, evidence bases and institutional capacities can adapt.

This applies in particular to higher education institutions (HEI), which occupy a dual role within the education, research and innovation (ERI) system. They act as operational users of AI by deploying it in teaching, assessment, administration and quality assurance, while also serving as sites of research and innovation. In this capacity, they develop, test and evaluate AI-based educational systems and produce knowledge that can feed back into policy, educational practice and EdTech markets. The increasing combination of experimentation and routine operation of AI by HEI may blur the boundary between responsible educational service provision and innovation-driven risk-taking.

This tension can be illustrated by two analytically distinct but practically overlapping research strands. The first, "Education for AI", treats AI as the subject of learning, focusing on AI literacy, critical understanding and professional competence. This strand does not directly affect educational decisions or learner trajectories, but it requires research in real educational settings to study authentic AI use, learning processes and human-AI interaction patterns. The second strand, "AI for Education", involves researching AI as an active agent in educational processes, including tutoring, feedback, assessment support, analytics and decision-making. This strand directly shapes learning processes, outcomes and institutional practices. It depends on training, fine-tuning and contextual data from real educational settings, which makes the boundary of responsibility between development, testing and use difficult to define. Implementation research is therefore needed to study how AI systems are enacted in real institutional contexts, including organisational routines, professional practices and governance arrangements. This applies across all educational sectors, including K–12 education, where the risks of premature scaling and weak governance are particularly pronounced.

Existing framework and identified gaps

To address the challenges facing HEI in using and researching AI, the SSC has adopted a pragmatic approach, building on existing resources. The Educa Report "Datennutzungspolitik im Bildungsraum Schweiz"[1] provides a coherent framework for responsible data use and AI-related practices in the Swiss education system, based on shared principles, legal consistency and inter-cantonal coordination. It proposes a common orientation for data governance across all educational levels and offers a clear reference point for addressing emerging challenges related to AI in education. Although primarily developed for compulsory and upper secondary education, the framework contains transferable conceptual elements that can be extended to higher education, taking into account its institutional autonomy, the close integration of research and teaching, and cross-institutional collaboration. The Educa Report therefore serves as a basis for the SSC's considerations on AI in higher education.

While the Educa development lines provide a solid foundation, challenges remain in translating these principles into the specific institutional realities of HEI, particularly in the context of AI-enabled practices. This is especially the case with regard to research on and with AI in HEI, which is not the focus of the Educa Report. Applying the Educa development lines to higher education reveals for example an AI governance gap with three underlying, interrelated causes. First, there is a context gap: HEI lack a clear differentiation between "Education for AI", "AI for Education" and operational AI use, despite their distinct purposes, risk profiles and governance requirements. Second, there is a lifecycle governance gap: no governance approaches explicitly address the transitions between research, experimentation,

[1] Educa (2025): Datennutzungspolitik im Bildungsraum Schweiz. Entwicklungsansätze für eine kohärente Umsetzung. Educa, Bern. https://www.educa.ch/sites/default/files/2025-07/DNP_Abschlussbericht_de_V1.1.pdf (last checked on 16.03.2026).

piloting and routine deployment of AI systems in higher education, leading to uncertainty about when and how responsibilities shift. Third, there is a coordination gap: responsibilities within HEI are fragmented across domains such as research ethics, data protection, IT governance, teaching and institutional management. This fragmentation is further compounded when multiple HEI collaborate and apply divergent interpretations to similar AI use cases. Thus, these challenges are especially evident in inter-institutional and cross-cantonal settings, where AI-related research, shared infrastructures and collaborative projects require coordinated interpretations of responsibilities, data use and risk.

These challenges highlight the need for a coordinated, system-level approach to AI governance in higher education, as case-by-case decisions alone cannot resolve this structural governance gap.

Recommendations

The SSC therefore recommends developing and establishing a national reference framework for AI governance in higher education to provide shared orientation across institutions and cantons. In addition, the Council recommends enabling differentiated sandbox models and providing support structures such as expert groups for AI in higher education, as well as education-specific data access and data spaces.

National reference framework: The national reference framework should differentiate AI in higher education according to three key dimensions: use context and purpose, lifecycle stage, and risk level. With regard to use context and purpose, a clear distinction should be made between “Education for AI”, “AI for Education”, and operational AI use. The lifecycle stage should cover transitions from research and experimentation through piloting to routine deployment, while the risk level should reflect the potential impact of AI systems on learners, academic processes and institutional decision-making. Such a framework supports the development of a case-based knowledge base for AI governance in higher education, reduces variability across institutions, increases consistency and transparency, and strengthens trust in the responsible use of AI for research, teaching and innovation.

Sandbox models: Differentiated but complementary sandbox models should be enabled and aligned with the national reference framework. In particular, technical sandboxes should be established for “AI for Education” and pedagogical sandboxes for “Education for AI”. Technical sandboxes support the development, training, testing and evaluation of AI systems intended for later educational use, such as tutoring systems, feedback tools and analytics applications. Pedagogical sandboxes enable authentic human-AI interaction for teaching and research purposes, for example to study AI literacy, learning strategies, misconceptions and appropriation practices when learners interact with generative AI systems. Pedagogical sandboxes are particularly relevant at the national level because they enable the empirical assessment of AI literacy, human-AI interaction and learning processes at scale, under consistent governance conditions across institutions, sectors and cantons.

Expert groups: Local or regional expert groups are needed to make the sandbox models operational in practice, by guiding access, supporting use and managing transitions across the AI lifecycle. They can help translate legal requirements, ethical principles and the national framework into practice, in support of research and innovation in AI-enabled education.

Education-specific data spaces: Access to scalable and proportionate education-specific data through interoperable data spaces is a basic requirement for AI use and AI-related research in higher education, and promotes inter-institutional, inter-cantonal and international collaboration.

Broader infrastructure context

These SSC recommendations for AI in higher education build on the Council's broader recommendations for AI and computing infrastructure in the ERI domain.[2] AI in higher education serves as a flagship use case for the recommended national AI infrastructure strategy, which includes establishing a tiered computing infrastructure based on guiding principles such as flexibility, scalability, efficiency, interoperability, digital sovereignty, knowledge security and data lifecycle management. As the SSC envisions a tiered computing infrastructure system which provides computing resources[3] that include all the necessary components, services and resources required to make computing power usable by end users, it also functions as pools of regional and national experts to provide user and scientific support, including AI developments. The national AI infrastructure strategy complements computing infrastructure with a data lifecycle management strategy. Consequently, data services, including access to interoperable data spaces built on FAIR data principles, form an integral part of the tiered infrastructure system. Therefore, the SSC's recommendations for AI and computing infrastructure in the ERI domain extend far beyond the establishment of computing hardware. The reason being that sufficient computing capacity alone is not enough to enable the use of and research on AI across the ERI system.

The flagship use case of AI in higher education and the corresponding recommendations further illustrate what is outlined in the national AI infrastructure strategy as well as what is required at an operational level. AI-enabled practices in higher education depend not only on computing capacity but also on access to educational and application interaction data, clear rules for data reuse and the governance of transitions from research and experimentation to routine use. This is particularly critical where AI supports or influences high-stakes academic processes such as assessment. This flagship use case therefore makes the case for addressing structural governance gaps through a national reference framework, reinforces the need for data spaces as research and innovation infrastructures within a data lifecycle management strategy, illustrates the need for differentiated sandboxes embedded within the tiered computing infrastructure, and highlights the need for local or regional expert groups as support structures bridging computing infrastructure and research and innovation in AI-enabled education.

For this to happen, the SSC recommends that the relevant stakeholders (e.g. higher education institutions, federation, cantons) engage in dialogue to develop, coordinate, establish and finance the necessary mechanisms at national level with a long-term commitment.

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[2] Swiss Science Council. Synergise. Strategise. Realise. SSC recommendations for AI computing infrastructure in the ERI domain. 2026. Doi: 10.5281/zenodo.18850058.

[3] Computing resources include all the necessary components, services and resources required to make computing power usable for end users. For example: hardware, software to run and use the hardware for its purpose (e.g. academic research), personnel to set up and maintain the computing resources hardware, to code the necessary software and to run it on the hardware, to support end users (e.g. researchers) in the use of the computing infrastructure as well as scientifically (e.g. scientific programming, analysis), other associated resources like energy and water for cooling.

KI in der Hochschulbildung: Herausforderungen und Empfehlungen

Generative KI wird rasch in zentrale akademische Funktionen integriert, darunter Lehre, Leistungsbewertung, Studierendenbetreuung, Forschungsabläufe und Hochschulmanagement. Dies hat direkte Auswirkungen auf Bildungsprozesse und -ergebnisse, da der Einsatz von KI im Bildungsbereich naturgemäss datenintensiv ist und auf Profilerstellung, Lernanalytik, Vorhersagen sowie automatisierten oder halbautomatisierten Entscheidungshilfen beruht. Die Herausforderung besteht darin, dass KI schneller in alle relevanten Bildungsbereiche vordringt, als sich Governance-Rahmen, Evidenzgrundlagen und institutionelle Kapazitäten anpassen können.

Dies gilt insbesondere für Hochschulen, die innerhalb des Bildungs-, Forschungs- und Innovationssystems (BFI) eine doppelte Rolle einnehmen. Sie fungieren als operative Nutzende von KI, indem sie diese in Lehre, Leistungsbewertung, Verwaltung und Qualitätssicherung einsetzen, dienen aber gleichzeitig auch als Orte der Forschung und Innovation. In dieser Funktion entwickeln, testen und bewerten sie KI-basierte Bildungssysteme und generieren Wissen, das in die Politik, die Bildungspraxis und die EdTech-Märkte zurückfliessen kann. Die zunehmende Verknüpfung von Experimentieren und dem routinemässigen Einsatz von KI durch Hochschulen kann die Grenze zwischen verantwortungsvoller Bildungsdienstleistung und innovationsgetriebenem Eingehen von Risiken verwischen.

Diese Spannung lässt sich anhand von zwei analytisch unterschiedlichen, sich jedoch in der Praxis überschneidenden Forschungssträngen veranschaulichen. Der erste, «Bildung für KI», behandelt KI als Gegenstand des Lernens und konzentriert sich auf KI-Kompetenz, kritisches Verständnis und fachliche Kompetenz. Dieser Strang hat keinen direkten Einfluss auf bildungspolitische Entscheidungen oder Lernverläufe, erfordert jedoch Forschung in realen Bildungskontexten, um den authentischen Einsatz von KI, Lernprozesse und Interaktionsmuster zwischen Mensch und KI zu untersuchen. Der zweite Strang, «KI für die Bildung», umfasst die Erforschung von KI als aktivem Akteur in Bildungsprozessen, einschliesslich Lernbegleitung, Feedback, Unterstützung bei der Leistungsbewertung, Analytik und Entscheidungsfindung. Dieser Strang prägt Lernprozesse, Lernergebnisse und institutionelle Praktiken unmittelbar. Er ist auf Training, Feinabstimmung und Kontextdaten aus realen Bildungsumgebungen angewiesen, was die Abgrenzung der Verantwortlichkeiten zwischen Entwicklung, Erprobung und Nutzung erschwert. Daher ist Implementierungsforschung erforderlich, um zu untersuchen, wie KI-Systeme in realen institutionellen Kontexten umgesetzt werden, einschliesslich organisatorischer Routinen, beruflicher Praktiken und Governance-Regelungen. Dies gilt für alle Bildungsbereiche, so auch für die K–12-Bildung, wo die Risiken einer verfrühten Skalierung und einer schwachen Governance besonders ausgeprägt sind.

Bestehender Rahmen und festgestellte Lücken

Um die Herausforderungen anzugehen, denen sich Hochschulen bei der Nutzung und Erforschung von KI gegenübersehen, hat der Schweizerische Wissenschaftsrat SWR einen pragmatischen Ansatz gewählt, der auf bestehenden Ressourcen aufbaut. Der Educa-Bericht «Datennutzungspolitik im Bildungsraum Schweiz»[4] bietet einen kohärenten Rahmen für den verantwortungsvollen Umgang mit Daten und KI-bezogene Praktiken im Schweizer Bildungssystem, der auf gemeinsamen Grundsätzen, rechtlicher Kohärenz und interkantonaler Koordination basiert. Er schlägt eine gemeinsame Ausrichtung für die Datenverwaltung auf allen Bildungsstufen vor und bietet einen klaren Bezugspunkt für die Bewältigung neuer Herausforderungen im Zusammenhang mit KI im Bildungswesen. Obwohl der Rahmen in erster Linie für die obligatorische Bildung und die Sekundarstufe II entwickelt wurde, enthält er übertragbare konzeptionelle Elemente, die auf die Hochschulbildung ausgeweitet werden können, wobei deren institutionelle Autonomie, die enge Verflechtung von Forschung und Lehre sowie die hochschulübergreifende Zusammenarbeit berücksichtigt werden müssen. Dieser Educa-Bericht dient daher als Grundlage für die Überlegungen des SWR zur KI im Hochschulbereich.

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[4] Educa (2025): Datennutzungspolitik im Bildungsraum Schweiz. Entwicklungsansätze für eine kohärente Umsetzung. Educa, Bern. https://www.educa.ch/sites/default/files/2025-07/DNP_Abschlussbericht_de_V1.1.pdf (zuletzt abgerufen am 28.04.2026).

Zwar bieten die Educa-Entwicklungslinien eine solide Grundlage, doch bestehen weiterhin Herausforderungen bei der Umsetzung dieser Grundsätze in die spezifischen institutionellen Gegebenheiten von Hochschulen, insbesondere im Zusammenhang mit KI-gestützten Praktiken. Dies gilt insbesondere für die Forschung über und mit KI an Hochschulen, die nicht im Mittelpunkt des Educa-Berichts steht. Die Anwendung der Educa-Entwicklungslinien auf den Hochschulbereich offenbart beispielsweise eine Lücke in der KI-Governance, die auf drei zugrunde liegende, miteinander verknüpfte Ursachen zurückzuführen ist. Erstens besteht eine Kontextlücke: Den Hochschulen fehlt eine klare Unterscheidung zwischen «Bildung für KI», «KI für die Bildung» und dem operativen Einsatz von KI, obwohl diese unterschiedliche Zwecke, Risikoprofile und Governance-Anforderungen haben. Zweitens besteht eine Lücke in der Lebenszyklus-Governance: Kein Governance-Ansatz befasst sich explizit mit den Übergängen zwischen Forschung, Experimentieren, Pilotierung und routinemässigem Einsatz von KI-Systemen im Hochschulbereich, was zu Unsicherheit darüber führt, wann und wie sich Verantwortlichkeiten verschieben. Drittens besteht eine Koordinationslücke: Die Zuständigkeiten innerhalb der Hochschulen sind auf verschiedene Bereiche wie Forschungsethik, Datenschutz, IT-Governance, Lehre und institutionelles Management verteilt. Diese Fragmentierung wird noch verstärkt, wenn mehrere Hochschulen zusammenarbeiten und ähnliche KI-Anwendungsfälle unterschiedlich interpretieren. Daher treten diese Herausforderungen besonders deutlich in interinstitutionellen und kantonsübergreifenden Kontexten zutage, wo KI-bezogene Forschung, gemeinsam genutzte Infrastrukturen und Kooperationsprojekte eine koordinierte Auslegung von Zuständigkeiten, Datennutzung und Risiken erfordern.

Diese Herausforderungen unterstreichen die Notwendigkeit eines koordinierten, systemischen Ansatzes für die KI-Governance im Hochschulbereich, da Einzelfallentscheidungen allein diese strukturelle Governance-Lücke nicht schliessen können.

Empfehlungen

Der SWR empfiehlt daher, einen nationalen Referenzrahmen für die KI-Governance im Hochschulbereich zu entwickeln und zu etablieren, um eine gemeinsame Orientierung für Hochschulen und Kantone zu schaffen. Darüber hinaus empfiehlt der Rat, differenzierte Sandbox-Modelle einzurichten und Unterstützungsstrukturen wie Expertengruppen für KI im Hochschulbereich sowie bildungsspezifische Datenzugänge und Datenräume bereitzustellen.

Nationaler Referenzrahmen: Der nationale Referenzrahmen sollte den Einsatz von KI im Hochschulbereich anhand von drei Schlüsseldimensionen unterscheiden: Anwendungskontext und -zweck, Lebenszyklusphase sowie Risikostufe. In Bezug auf Anwendungskontext und -zweck sollte klar zwischen «Bildung für KI», «KI für die Bildung» und operativem Einsatz von KI unterschieden werden. Die Lebenszyklusphase sollte den Übergang von Forschung und Experimentieren über Pilotprojekte bis hin zum routinemässigen Einsatz abdecken, während das Risikoniveau die potenziellen Auswirkungen von KI-Systemen auf Lernende, akademische Prozesse und institutionelle Entscheidungsprozesse widerspiegeln sollte. Ein solcher Rahmen unterstützt die Entwicklung einer fallbasierten Wissensbasis für die KI-Governance im Hochschulbereich, verringert Unterschiede zwischen den Einrichtungen, erhöht die Konsistenz und Transparenz und stärkt das Vertrauen in den verantwortungsvollen Einsatz von KI für Forschung, Lehre und Innovation.

Sandbox-Modelle: Es sollten differenzierte, aber sich ergänzende Sandbox-Modelle eingerichtet und auf den nationalen Referenzrahmen abgestimmt werden. Insbesondere sollten technische Sandboxes für «KI für die Bildung» und pädagogische Sandboxes für «Bildung für KI» eingerichtet werden. Technische Sandboxes unterstützen die Entwicklung, das Training, das Testen und die Bewertung von KI-Systemen, die für den späteren Einsatz im Bildungsbereich vorgesehen sind, wie beispielsweise Tutorsysteme, Feedback-Tools und Analyseanwendungen. Pädagogische Sandboxes ermöglichen authentische Mensch-KI-Interaktion zu Lehr- und Forschungszwecken, beispielsweise um KI-Kompetenz, Lernstrategien, Fehleinschätzungen und Aneignungspraktiken zu untersuchen, wenn Lernende mit generativen KI-Systemen interagieren. Pädagogische Sandboxes sind auf nationaler Ebene besonders relevant, da sie die empirische Bewertung von KI-Kompetenz, Mensch-KI-Interaktion und Lernprozessen in grossem Massstab unter einheitlichen Rahmenbedingungen über Institutionen, Sektoren und Kantone hinweg ermöglichen.

Expertengruppen: Es bedarf lokaler oder regionaler Expertengruppen, die diese Sandbox-Modelle in der Praxis umsetzbar machen, indem sie den Zugang begleiten, die Nutzung unterstützen und Übergänge über den gesamten KI-Lebenszyklus hinweg betreuen. Sie können dazu beitragen, gesetzliche Anforderungen, ethische Grundsätze und den nationalen Referenzrahmen in die Praxis umzusetzen und so Forschung und Innovation im Bereich der KI-gestützten Bildung zu fördern.

Bildungsspezifische Datenräume: Der Zugang zu skalierbaren und zweckmässigen bildungsspezifischen Daten über interoperable Datenräume ist eine Grundvoraussetzung für den Einsatz von KI und für die KI-bezogene Forschung in der Hochschulbildung und fördert die interinstitutionelle, interkantonale und internationale Zusammenarbeit.

Erweiterter Infrastrukturkontext

Diese Empfehlungen des SWR zu KI in der Hochschulbildung bauen auf den umfassenderen Empfehlungen des Rates zur KI-Recheninfrastruktur im BFI-Bereich auf.[5] KI in der Hochschulbildung dient als beispielhafter Anwendungsfall für die empfohlene nationale KI-Infrastrukturstrategie, die den Aufbau einer mehrstufigen Recheninfrastruktur vorsieht, die auf Leitprinzipien wie Flexibilität, Skalierbarkeit, Effizienz, Interoperabilität, digitale Souveränität, Wissenssicherheit und Datenlebenszyklusmanagement basiert. Da der SWR ein mehrstufiges Recheninfrastruktursystem empfiehlt, das Rechenressourcen[6] bereitstellt, welche alle notwendigen Komponenten, Dienste und Ressourcen umfassen, die erforderlich sind, um Rechenleistung für Endnutzer nutzbar zu machen, fungiert es auch als Pool regionaler und nationaler Experten, um Nutzer- und wissenschaftliche Unterstützung zu leisten, auch in Bezug auf die Weiterentwicklung von KI. Die nationale KI-Infrastrukturstrategie ergänzt die Recheninfrastruktur durch eine Strategie zum Data-Lifecycle-Management. Folglich bilden Datendienste, einschliesslich des Zugangs zu interoperablen Datenräumen, die auf den FAIR-Datenprinzipien basieren, einen integralen Bestandteil des mehrstufigen Infrastruktursystems. Daher gehen die Empfehlungen des SWR für KI- und Recheninfrastruktur im BFI-Bereich weit über die Einrichtung von Rechenhardware hinaus. Der Grund dafür ist, dass ausreichende Rechenkapazität allein nicht ausreicht, um den Einsatz von KI und die Forschung im Bereich KI im gesamten BFI-System zu ermöglichen.

Der beispielhafte Anwendungsfall für den Einsatz von KI in der Hochschulbildung und die entsprechenden Empfehlungen verdeutlichen zusätzlich, was in der nationalen KI-Infrastrukturstrategie dargelegt ist und was auf operativer Ebene erforderlich ist. KI-gestützte Praktiken in der Hochschulbildung hängen nicht nur von der Rechenkapazität ab, sondern auch vom Zugang zu Daten über Bildungs- und Anwendungsinteraktionen, von klaren Regeln für die Wiederverwendung von Daten sowie von der Steuerung des Übergangs von Forschung und Experimentieren hin zur routinemässigen Nutzung. Dies ist besonders entscheidend, wenn KI akademische Prozesse mit hoher Tragweite, wie beispielsweise die Leistungsbewertung, unterstützt oder beeinflusst. Dieser beispielhafte Anwendungsfall spricht daher dafür, strukturelle Governance-Lücken durch einen nationalen Referenzrahmen zu schliessen, unterstreicht die Notwendigkeit von Datenräumen als Forschungs- und Innovationsinfrastrukturen im Rahmen einer Strategie zum Datenlebenszyklusmanagement, verdeutlicht den Bedarf an differenzier-

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[5] Schweizerischer Wissenschaftsrat. Synergien nutzen. Strategien entwickeln. Realitäten schaffen. Empfehlungen des SWR für eine KI-Infrastruktur m BFI-Bereich. 2026. Doi: 10.5281/zenodo.18850058 (Bericht auf Englisch mit Zusammenfassungen auf Deutsch, Französisch und Italienisch).

[6] Rechenressourcen umfassen alle notwendigen Komponenten, Dienste und Ressourcen, die erforderlich sind, um Rechenleistung für Endnutzer nutzbar zu machen. Beispiele hierfür sind: Hardware, Software zum Betrieb und zur Nutzung der Hardware für ihren Zweck (z. B. akademische Forschung), Personal für die Einrichtung und Wartung der Rechenressourcen-Hardware, für die Programmierung der erforderlichen Software und deren Ausführung auf der Hardware, für die Unterstützung der Endnutzenden (z. B. Forschende) bei der Nutzung der Recheninfrastruktur sowie in wissenschaftlicher Hinsicht (z. B. wissenschaftliche Programmierung, Analyse) sowie weitere damit verbundene Ressourcen wie Energie und Wasser für die Kühlung.

ten Sandboxes, die in die mehrstufige Recheninfrastruktur eingebettet sind, und hebt die Notwendigkeit lokaler oder regionaler Expertengruppen als Unterstützungsstrukturen hervor, die eine Brücke zwischen Recheninfrastruktur und Forschung und Innovation im KI-gestützten Bildungswesen schlagen.

Damit dies geschehen kann, empfiehlt der SWR, dass die relevanten Akteure (z. B. Hochschulen, Bund, Kantone) in einen Dialog treten, um die notwendigen Mechanismen auf nationaler Ebene mit langfristigem Engagement zu entwickeln, zu koordinieren, zu etablieren und zu finanzieren.

L'IA dans l'enseignement supérieur: défis et recommandations

L'IA générative s'intègre rapidement aux fonctions académiques fondamentales, notamment l'enseignement, l'évaluation, l'accompagnement des étudiants, les processus de recherche et la gestion des établissements. Cela exerce un impact direct sur les processus et les résultats éducatifs, étant donné que l'utilisation de l'IA dans l'éducation est intrinsèquement gourmande en données, et repose sur le profilage, l'analyse des données d'apprentissage, la prévision et l'aide à la décision automatisée ou semi-automatisée. Le défi réside dans le fait que l'IA s'introduit dans tous les domaines éducatifs pertinents à un rythme très rapide, auquel les cadres de gouvernance, les bases probantes et les capacités institutionnelles peuvent difficilement s'adapter.

Cela concerne en particulier les hautes écoles, qui jouent un double rôle au sein du système de formation, de recherche et d'innovation (FRI). Elles agissent en tant qu'utilisatrices opérationnelles de l'IA en la déployant dans l'enseignement, l'évaluation, l'administration et l'assurance qualité, tout en jouant le rôle de pôles de recherche et d'innovation. À ce titre, elles développent, testent et évaluent des systèmes éducatifs basés sur l'IA et produisent des connaissances susceptibles d'alimenter les politiques, les pratiques éducatives et les marchés des technologies de l'éducation. La combinaison croissante d'expérimentation et d'utilisation courante de l'IA par les hautes écoles risque d'estomper la frontière entre la prestation de services éducatifs responsables et la prise de risques motivée par l'innovation.

Cette tension peut être illustrée par deux volets de recherche distincts sur le plan analytique, mais qui se chevauchent dans la pratique. Le premier, intitulé «l'éducation à l'IA», considère l'IA comme un objet d'apprentissage, en mettant l'accent sur la culture numérique en matière d'IA, la compréhension critique et les compétences professionnelles. Ce volet n'influence pas directement les décisions éducatives, ni les parcours des apprenants, mais il requiert des recherches menées dans des contextes éducatifs réels afin d'étudier l'utilisation concrète de l'IA, les processus d'apprentissage et les modèles d'interaction entre l'humain et l'IA. Le second volet, «l'IA au service de l'éducation», consiste à étudier l'IA en tant qu'agent actif dans les processus éducatifs, notamment le tutorat, le retour d'information, l'aide à l'évaluation, l'analyse et la prise de décision. Ce volet façonne directement les processus d'apprentissage, les résultats et les pratiques institutionnelles. Il repose sur l'entraînement, le réglage fin et les données issues de contextes éducatifs réels, ce qui rend difficile la délimitation des responsabilités entre le développement, les tests et l'utilisation. La recherche sur la mise en œuvre est donc nécessaire pour étudier comment les systèmes d'IA sont appliqués dans des contextes institutionnels réels, y compris les routines organisationnelles, les pratiques professionnelles et les dispositifs de gouvernance. Cela s'applique à tous les secteurs de l'éducation, y compris l'enseignement primaire, secondaire et gymnasial, où les risques d'une mise à l'échelle prématurée et d'une gouvernance défaillante sont particulièrement prononcés.

Cadre existant et lacunes identifiées

Pour relever les défis auxquels sont confrontées les hautes écoles en matière d'utilisation et de recherche sur l'IA, le Conseil suisse de la science CSS a adopté une approche pragmatique, s'appuyant sur les ressources existantes. Le rapport Educa intitulé «Politique d'utilisation des données dans l'espace suisse de formation»[7] fournit un cadre cohérent pour une utilisation responsable des données et des pratiques liées à l'IA dans le système éducatif suisse, fondé sur des principes communs, la cohérence juridique et la coordination intercantonale. Il propose une orientation commune pour la gouvernance des données à tous les niveaux d'enseignement et offre un point de référence clair pour relever les nouveaux défis liés à l'IA dans l'éducation. Bien qu'élaboré principalement pour l'enseignement obligatoire et le secondaire supérieur, ce cadre contient des éléments conceptuels transférables pouvant être étendus à l'enseignement supérieur, en tenant compte de son autonomie institutionnelle, de

[7] Educa (2025): Politique d'utilisation des données dans l'espace suisse de formation. Approches de développement pour une mise en œuvre cohérente. Educa, Berne. https://www.educa.ch/sites/default/files/2025-07/DNP_Abschlussbericht_fr_V1.1.pdf (consulté le 28.04.2026).

l'étroite intégration de la recherche et de l'enseignement, ainsi que de la collaboration interinstitutionnelle. C'est pourquoi ce rapport Educa sert de base aux réflexions du CSS sur l'IA dans l'enseignement supérieur.

Bien que les axes de développement d'Educa constituent une base solide, des défis subsistent quant à la transposition de ces principes dans les réalités institutionnelles spécifiques des hautes écoles, en particulier dans le contexte des pratiques fondées sur l'IA. C'est notamment le cas de la recherche sur et avec l'IA dans les hautes écoles, laquelle ne figure pas au centre du rapport Educa. L'application des axes de développement d'Educa à l'enseignement supérieur révèle, par exemple, un déficit de gouvernance en matière d'IA s'expliquant par trois causes sous-jacentes et interdépendantes. Premièrement, il existe un fossé contextuel: les établissements d'enseignement supérieur ne font pas de distinction claire entre «l'éducation à l'IA», «l'IA au service de l'éducation» et l'utilisation opérationnelle de l'IA, bien qu'ils présentent des objectifs, des profils de risque et des exigences en matière de gouvernance distincts. Deuxièmement, il existe un déficit dans la gouvernance du cycle de vie: aucune approche de gouvernance n'aborde explicitement les transitions entre la recherche, l'expérimentation, le pilotage et le déploiement courant des systèmes d'IA dans l'enseignement supérieur, ce qui entraîne une incertitude quant au moment et à la manière dont les responsabilités sont transférées. Troisièmement, il existe une divergence de coordination: les responsabilités au sein des établissements d'enseignement supérieur sont fragmentées entre différents domaines tels que l'éthique de la recherche, la protection des données, la gouvernance informatique, l'enseignement et la gestion institutionnelle. Cette fragmentation est encore accentuée lorsque plusieurs établissements d'enseignement supérieur collaborent et appliquent des interprétations divergentes aux cas d'utilisation similaires de l'IA. Ainsi, ces défis sont particulièrement évidents dans les contextes interinstitutionnels et intercantonaux, où la recherche liée à l'IA, les infrastructures partagées et les projets collaboratifs nécessitent des interprétations coordonnées des responsabilités, de l'utilisation des données et des risques.

Ces défis soulignent la nécessité d'une approche coordonnée et systémique de la gouvernance de l'IA dans l'enseignement supérieur, car les décisions au cas par cas ne peuvent à elles seules combler ce déficit structurel de gouvernance.

Recommandations

Le CSS recommande donc d'élaborer et de mettre en place un cadre de référence national pour la gouvernance de l'IA dans l'enseignement supérieur, afin de fournir une orientation commune aux établissements et aux cantons. En outre, le Conseil recommande la mise en place de modèles de «bac à sable» différenciés et la mise à disposition de structures de soutien telles que des groupes d'experts pour l'IA dans l'enseignement supérieur, ainsi que des espaces de données et un accès aux données spécifiques à l'enseignement.

Cadre de référence national: Le cadre de référence national devrait classer l'IA dans l'enseignement supérieur selon trois dimensions clés qui résident dans le contexte et l'objectif d'utilisation, les étapes du cycle de vie ainsi que le niveau de risque. En ce qui concerne le contexte et l'objectif d'utilisation, il convient d'établir une distinction claire entre «l'éducation à l'IA», «l'IA au service de l'éducation» et l'utilisation opérationnelle de l'IA. Les étapes du cycle de vie devraient couvrir les transitions allant de la recherche et de l'expérimentation pilote au déploiement d'une routine, tandis que le niveau de risque devrait refléter l'impact potentiel des systèmes d'IA sur les apprenants, les processus académiques et la prise de décision institutionnelle. Un tel cadre favorise le développement d'une base de connaissances fondée sur des cas concrets pour la gouvernance de l'IA dans l'enseignement supérieur, réduit les disparités entre les établissements, renforce la cohérence et la transparence, et consolide la confiance dans l'utilisation responsable de l'IA pour la recherche, l'enseignement et l'innovation.

Modèles de bac à sable: Il convient de mettre en place des modèles de bac à sable différenciés mais complémentaires, et de les aligner sur le cadre de référence national. Des bacs à sable techniques devraient être créés pour l'«IA au service de l'éducation» et des bacs à sable pédagogiques pour l'«éducation à l'IA». Les bacs à sable techniques facilitent le développement, la formation, les tests et l'évaluation de systèmes d'IA destinés à un usage éducatif ultérieur, tels que les systèmes de tutorat, les outils de retour d'information et les applications d'analyse. Les bacs à sable pédagogiques permettent une interaction authentique entre l'humain et l'IA à des fins d'enseignement et de recherche, par exemple pour étudier la littératie en IA, les stratégies d'apprentissage ainsi que les idées fausses et les pratiques d'appropriation lorsque les apprenants interagissent avec des systèmes d'IA générative. Les bacs à sable pédagogiques sont particulièrement pertinents au niveau national, car ils permettent l'évaluation empirique de l'ensemble des compétences, connaissances et compréhensions en IA, de l'interaction entre l'humain et l'IA ainsi que des processus d'apprentissage à grande échelle, et ce dans un cadre de gouvernance cohérent entre les institutions, les secteurs et les cantons.

Groupes d'experts : Des groupes d'experts locaux ou régionaux sont nécessaires pour rendre les modèles de «bac à sable» opérationnels dans la pratique, en guidant l'accès, en facilitant l'utilisation et en gérant les transitions tout au long du cycle de vie de l'IA. Ils peuvent contribuer à traduire en pratique les exigences légales, les principes éthiques et le cadre national afin de soutenir la recherche et l'innovation dans le domaine de l'éducation assistée par l'IA.

Espaces de données spécifiques à l'éducation: L'accès à des données spécifiques à l'éducation, évolutives et adaptées à l'objectif, par le biais d'espaces de données interopérables, représente une condition fondamentale pour l'utilisation de l'IA et la recherche liée à l'IA dans l'enseignement supérieur, et favorise la collaboration interinstitutionnelle, intercantonale et internationale.

Cadre infrastructurel élargi

Ces recommandations du CSS concernant l'IA dans l'enseignement supérieur s'appuient sur les recommandations plus générales du Conseil relatives à l'IA et à l'infrastructure de calcul dans le domaine FRI[8]. L'IA dans les hautes écoles constitue un cas d'usage emblématique de la stratégie nationale recommandée en matière d'infrastructure d'IA, qui prévoit la mise en place d'une infrastructure informatique à plusieurs niveaux, fondée sur des principes directeurs tels que la flexibilité, l'évolutivité, l'efficacité, l'interopérabilité, la souveraineté numérique, la sécurité des connaissances et la gestion du cycle de vie des données. Dans la mesure où le CSS envisage un système d'infrastructure informatique à plusieurs niveaux, lequel fournit des ressources informatiques[9] comprenant tous les composants, services et ressources nécessaires pour rendre la puissance de calcul utilisable par les utilisateurs finaux, il fait également office de pool d'experts régionaux et nationaux chargés d'apporter un soutien aux utilisateurs et aux scientifiques, y compris en matière de développements en IA. La stratégie nationale en matière d'infrastructure d'IA complète l'infrastructure informatique par une stratégie de gestion du cycle de vie des données. Par conséquent, les services de données, y compris l'accès à des espaces de données interopérables fondés sur les principes FAIR, font partie intégrante du système d'infrastructure à plusieurs niveaux. Ainsi, les recommandations du CSS concernant l'IA et l'infrastructure informatique dans le domaine FRI vont bien au-delà de la mise en place de matériel informatique. En effet, la capacité de calcul suffisante ne permet pas, à elle seule, l'utilisation et la recherche en IA à l'échelle du système FRI.

Le cas d'usage emblématique de l'IA dans l'enseignement supérieur et les recommandations qui s'y rapportent illustrent davantage les grandes lignes de la stratégie nationale en matière d'infrastructures d'IA ainsi que les exigences au niveau opérationnel. Les pratiques fondées sur l'IA dans l'enseignement supérieur dépendent non seulement de la capacité de calcul, mais aussi de l'accès aux données

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[8] Conseil suisse de la science. Exploiter les synergies. Développer des stratégies. Créer de nouvelles réalités. Recommandations du CSS pour une infrastructure de calcul dans le domaine FRI. 2026. Doi: 10.5281/zenodo.18850058.

[9] Les ressources de calcul comprennent tous les composants, services et ressources nécessaires pour rendre la puissance de calcul utilisable par les utilisateurs finaux. Par exemple : le matériel informatique, les logiciels permettant de faire fonctionner et d'utiliser le matériel à des fins spécifiques (par exemple, la recherche universitaire), le personnel chargé de mettre en place et d'entretenir le matériel informatique, de coder les logiciels nécessaires et de les faire fonctionner sur le matériel, d'assister les utilisateurs finaux (par exemple, les chercheurs) dans l'utilisation de l'infrastructure informatique ainsi que sur le plan scientifique (par exemple, programmation scientifique, analyse), et d'autres ressources associées telles que l'énergie et l'eau pour le refroidissement.

relatives aux interactions éducatives et applicatives, de règles claires concernant la réutilisation des données et de la gouvernance des transitions entre la recherche et l'expérimentation vers l'utilisation courante. Cela revêt une importance particulière lorsque l'IA soutient ou influence des processus académiques à forts enjeux, tels que l'évaluation. Ce cas d'usage emblématique plaide donc en faveur de la résolution des lacunes structurelles en matière de gouvernance par le biais d'un cadre de référence national, renforce la nécessité de disposer d'espaces de données en tant qu'infrastructures de recherche et d'innovation dans le cadre d'une stratégie de gestion du cycle de vie des données, illustre la nécessité de disposer de bacs à sable différenciés intégrés dans l'infrastructure informatique à plusieurs niveaux, et souligne la nécessité de groupes d'experts locaux ou régionaux en tant que structures de soutien faisant le lien entre l'infrastructure informatique et la recherche et l'innovation dans l'enseignement assisté par l'IA.

Pour ce faire, le CSS recommande que les parties prenantes concernées (par exemple, les établissements d'enseignement supérieur, la confédération, les cantons) engagent un dialogue afin de développer, coordonner, mettre en place et financer les mécanismes nécessaires au niveau national dans le cadre d'un engagement à long terme.

L'intelligenza artificiale nelle scuole universitarie: sfide e raccomandazioni

L'IA generativa viene rapidamente integrata nei principali ambiti di attività delle scuole universitarie, tra cui l'insegnamento, la valutazione, il sostegno agli studenti, le attività di ricerca e la gestione istituzionale. Questa integrazione ha un impatto diretto sui processi e sugli esiti formativi, dato che l'uso dell'IA in ambito formativo richiede per sua natura un grande volume di dati e si basa sulla profilazione, sull'analisi dei dati sull'apprendimento, su sistemi predittivi e su sistemi di supporto alle decisioni automatizzati o semiautomatizzati. Il problema risiede nel fatto che l'IA sta entrando in tutti i settori formativi a un ritmo più rapido di quanto i quadri di governance, le evidenze disponibili e le capacità istituzionali riescano ad adattarsi.

Tutto ciò vale in particolare per le scuole universitarie, che ricoprono un duplice ruolo all'interno del sistema ERI (educazione, ricerca e innovazione). Queste istituzioni fungono da utenti dell'IA, in quanto impiegano questa tecnologia nell'insegnamento, nella valutazione, nell'amministrazione e nell'assicurazione della qualità, ma costituiscono al contempo anche centri di ricerca e innovazione. In questa veste sviluppano, testano e valutano sistemi formativi basati sull'IA e producono conoscenze che possono confluire nell'elaborazione delle politiche, nella pratica formativa e nello sviluppo dei mercati della formazione digitale (EdTech). La crescente combinazione di sperimentazione e uso dell'IA nelle attività quotidiane da parte delle scuole universitarie potrebbe rendere meno netto il confine tra l'erogazione responsabile di servizi formativi e l'assunzione di rischi in nome dell'innovazione.

Questa tensione può essere illustrata tramite due filoni di ricerca distinti sul piano analitico ma che, nella pratica, si sovrappongono. Il primo, denominato «formazione all'IA», considera l'IA come oggetto di apprendimento, concentrandosi sull'alfabetizzazione all'IA, sulla comprensione critica e sulle competenze professionali. Questo filone non influisce direttamente sulle decisioni formative o sui percorsi formativi degli studenti, ma rende necessaria una ricerca in contesti educativi reali per studiare l'uso autentico dell'IA, i processi di apprendimento e le modalità di interazione tra uomo e IA. Il secondo filone, denominato «IA per la formazione», indaga il ruolo dell'IA come componente attiva nei processi formativi, ad esempio nel supporto didattico, nel feedback, nel supporto alla valutazione, nell'analisi dei dati di apprendimento e nei processi decisionali. Questo filone incide direttamente sui processi di apprendimento, sui risultati e sulle attività istituzionali. Dipende dall'addestramento, dall'adattamento specifico (*fine-tuning*) e dai dati contestuali ricavati da ambienti formativi reali, il che rende difficile definire i confini di responsabilità tra sviluppo, test e utilizzo. È quindi necessaria una ricerca sull'implementazione per studiare come i sistemi di IA vengono concretamente impiegati in contesti istituzionali reali, ad esempio nelle procedure organizzative quotidiane, nelle attività professionali e negli assetti di governance. Questa esigenza di ricerca vale per tutti i settori formativi, compresa la scuola dell'obbligo e il livello secondario II, dove i rischi di una diffusione prematura su larga scala e di una governance insufficiente sono particolarmente accentuati.

Quadro di riferimento esistente e lacune individuate

Per rispondere alle problematiche che le scuole universitarie incontrano nell'uso dell'IA e nella ricerca in materia, il CSS ha adottato un approccio pragmatico, basandosi sulle risorse esistenti. Il rapporto Educa «Datennutzungspolitik im Bildungsraum Schweiz»[10] fornisce un quadro di riferimento coerente per un uso responsabile dei dati e per attività responsabili relative all'IA nel sistema formativo svizzero, fondato su principi condivisi, coerenza giuridica e coordinamento intercantonale. Il rapporto propone un orientamento comune per la governance dei dati a tutti i livelli formativi e costituisce un chiaro punto di riferimento per affrontare le problematiche emergenti legate all'IA in ambito formativo. Sebbene sviluppato principalmente per la scuola dell'obbligo e il livello secondario II, il quadro di riferimento contiene elementi concettuali trasferibili che possono essere estesi alle scuole universitarie, tenendo conto dell'autonomia istituzionale, della stretta integrazione tra ricerca e insegnamento e della collaborazione

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[10] Educa (2025): Datennutzungspolitik im Bildungsraum Schweiz. Educa, Bern. https://www.educa.ch/sites/default/files/2025-07/DNP_Abschlussbericht_de_V1.1.pdf (il documento è disponibile in francese e tedesco; consultato il 28.04.2026).

interistituzionale. Il rapporto Educa funge quindi da base per le considerazioni del CSS sull'IA nelle scuole universitarie.

Sebbene le linee di sviluppo di Educa forniscano una solida base, permangono difficoltà nel tradurre questi principi nelle specifiche realtà istituzionali delle scuole universitarie, in particolare nel contesto delle attività e delle procedure supportate dall'IA. Ciò vale soprattutto per quanto riguarda la ricerca sull'IA e mediante l'IA nelle scuole universitarie, dato che il tema non viene approfondito nel rapporto Educa. L'applicazione delle linee di sviluppo di Educa al settore delle scuole universitarie rivela, ad esempio, una lacuna nella governance dell'IA con tre cause interconnesse alla base. In primo luogo, vi è una lacuna contestuale: le scuole universitarie non operano una chiara differenziazione tra «formazione all'IA», «IA per la formazione» e l'uso operativo dell'IA, nonostante la diversità di scopi, profili di rischio e requisiti di governance. In secondo luogo, vi è una lacuna a livello di governance del ciclo di vita: non viene infatti esplicitamente stabilito come gestire i passaggi tra le fasi di ricerca, sperimentazione, progetto pilota e uso corrente nelle scuole universitarie, il che genera incertezza su quando e come cambino le responsabilità. In terzo luogo, vi è una lacuna di coordinamento: le responsabilità all'interno delle scuole universitarie sono frammentate tra diversi ambiti, quali l'etica della ricerca, la protezione dei dati, la governance IT, l'insegnamento e la gestione istituzionale. Questa frammentazione è ulteriormente aggravata quando più scuole universitarie collaborano e applicano interpretazioni divergenti a casi d'uso dell'IA simili. Pertanto, queste problematiche sono particolarmente evidenti in contesti interistituzionali e intercantonali, dove la ricerca relativa all'IA, le infrastrutture condivise e i progetti collaborativi richiedono interpretazioni coordinate di responsabilità, uso dei dati e rischio.

Queste sfide evidenziano la necessità di affrontare la governance dell'IA nelle scuole universitarie con un approccio coordinato a livello sistemico, dato che le decisioni caso per caso non possono colmare da sole questa lacuna strutturale.

Raccomandazioni

Il CSS raccomanda pertanto di elaborare e istituire un quadro di riferimento nazionale per la governance dell'IA nelle scuole universitarie, al fine di fornire un orientamento comune tra le istituzioni e i Cantoni. Raccomanda inoltre di creare modelli di sandbox differenziati e di mettere a disposizione strutture di supporto, quali gruppi di esperti in materia di IA nel settore delle scuole universitarie, nonché modalità di accesso ai dati e spazi di dati specifici per il settore della formazione.

Quadro di riferimento nazionale: il quadro di riferimento nazionale deve essere inteso per differenziare l'IA nelle scuole universitarie in base a tre dimensioni chiave: contesto e finalità d'uso, fase del ciclo di vita e livello di rischio. Per quanto riguarda il contesto e la finalità d'uso, occorre operare una chiara distinzione tra «formazione all'IA», «IA per la formazione» e uso operativo dell'IA; per quanto riguarda il ciclo di vita, nel quadro di riferimento vanno considerati i vari passaggi tra le fasi di ricerca, sperimentazione, progetto pilota e uso corrente; infine, il livello di rischio deve riflettere il potenziale impatto dei sistemi di IA sugli studenti, sull'attività accademica e sui processi decisionali degli istituti. Un quadro di questo tipo sostiene lo sviluppo di una base di conoscenze fondata su casi concreti per la governance dell'IA nelle scuole universitarie, riduce la variabilità tra gli istituti, aumenta la coerenza e la trasparenza e rafforza la fiducia nell'uso responsabile dell'IA per la ricerca, l'insegnamento e l'innovazione.

Modelli di sandbox: occorre creare modelli di sandbox differenziati ma complementari, in linea con il quadro di riferimento nazionale. In particolare, è necessario istituire sandbox tecniche per l'«IA per la formazione» e sandbox pedagogiche per la «formazione all'IA». Le sandbox tecniche favoriscono lo sviluppo, l'addestramento, il collaudo e la valutazione di sistemi di IA destinati a un successivo impiego nell'ambito della formazione, quali sistemi di tutoraggio automatico, strumenti di feedback e applicazioni di analisi dei dati. Le sandbox pedagogiche consentono un'autentica interazione uomo-IA a fini didattici e di ricerca, ad esempio per studiare l'alfabetizzazione all'IA, le strategie di apprendimento, le concezioni erronee e i modi in cui gli studenti integrano l'IA generativa nell'apprendimento quando interagiscono con questi sistemi. Le sandbox pedagogiche sono particolarmente rilevanti a livello nazionale perché consentono, su larga scala, la valutazione empirica dell'alfabetizzazione all'IA, dell'interazione uomo-IA e dei processi di apprendimento, in condizioni quadro uniformi tra istituti, settori e Cantoni.

Gruppi di esperti: sono necessari gruppi di esperti a livello locale o regionale per rendere concretamente operativi i modelli di sandbox. Il compito di questi gruppi è di definire le condizioni di accesso alle sandbox, sostenerne l'uso e gestire i passaggi tra le varie fasi lungo il ciclo di vita dell'IA. Possono contribuire a tradurre nella pratica i requisiti giuridici, i principi etici e il quadro di riferimento nazionale, promuovendo la ricerca e l'innovazione nella formazione supportata dall'IA.

Spazi di dati specifici per la formazione: l'accesso a dati specifici per la formazione, scalabili e proporzionati, tramite spazi di dati interoperabili costituisce un requisito fondamentale per l'uso dell'IA e la ricerca in materia di IA nel settore delle scuole universitarie e promuove la collaborazione interistituzionale, intercantonale e internazionale.

Contesto infrastrutturale più ampio

Queste raccomandazioni del CSS relative all'IA nelle scuole universitarie si inseriscono nel quadro delle raccomandazioni più generali del CSS in materia di IA e infrastrutture di calcolo nel settore ERI.[11] L'IA nelle scuole universitarie costituisce un caso d'uso esemplare per la strategia nazionale raccomandata per le infrastrutture di IA, che propone la creazione di un sistema di infrastrutture di calcolo a più livelli basato su principi guida quali flessibilità, scalabilità, efficienza, interoperabilità, sovranità digitale, sicurezza delle conoscenze e gestione del ciclo di vita dei dati. Il CSS propone un sistema di infrastrutture di calcolo a più livelli che fornisce risorse di calcolo[12] comprendenti tutti i componenti, i servizi e le risorse necessari per far sì che gli utenti finali possano accedere alla potenza computazionale. Il sistema funge inoltre da pool di esperti a livello regionale e nazionale per fornire assistenza agli utenti e supporto sotto il profilo scientifico, anche in relazione allo sviluppo dell'IA. La strategia nazionale per le infrastrutture di IA integra l'infrastruttura di calcolo con una strategia di gestione del ciclo di vita dei dati. Di conseguenza, i servizi di dati, compreso l'accesso a spazi di dati interoperabili basati sui principi FAIR, costituiscono parte integrante del sistema a più livelli. Pertanto, le raccomandazioni del CSS per l'IA e l'infrastruttura di calcolo nel settore ERI vanno ben oltre la semplice creazione di hardware di calcolo. Una capacità di calcolo sufficiente, infatti, da sola non basta per consentire l'uso dell'IA e la ricerca in materia in tutto il sistema ERI.

Il caso d'uso esemplare dell'IA nelle scuole universitarie e le relative raccomandazioni illustrano ulteriormente quanto delineato nella strategia nazionale per le infrastrutture di IA, nonché ciò che è necessario a livello operativo. Le attività supportate dall'IA nelle scuole universitarie dipendono non solo dalla capacità di calcolo, ma anche dall'accesso ai dati didattici e ai dati relativi all'interazione con le applicazioni, da regole chiare per il riutilizzo dei dati e dalla gestione dei vari passaggi tra le fasi di ricerca, sperimentazione e uso corrente. Questo insieme di condizioni è particolarmente importante quando l'IA supporta o influenza processi accademici di ampia portata, come la valutazione. Questo caso d'uso esemplare dimostra quindi la necessità di un quadro di riferimento nazionale per colmare le lacune strutturali di governance e di spazi di dati come infrastrutture di ricerca e innovazione nell'ambito di una strategia di gestione del ciclo di vita dei dati. Illustra inoltre il bisogno di sandbox differenziate integrate nel sistema di infrastrutture di calcolo a più livelli e di gruppi di esperti a livello locale o regionale che

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[11] Consiglio svizzero della scienza. Synergise. Strategise. Realise. SSC recommendations for AI computing infrastructure in the ERI domain. 2026. Doi: 10.5281/zenodo.18850058.
[12] Le risorse di calcolo includono tutti i componenti, i servizi e le risorse necessari per far sì che gli utenti finali possano accedere alla potenza computazionale, ad esempio: hardware, software per far funzionare e utilizzare l'hardware secondo il suo scopo (ad es. ricerca accademica), personale per configurare l'hardware del sistema di calcolo e occuparsi della manutenzione, per programmare il software necessario ed eseguirlo sull'hardware, per fornire assistenza agli utenti finali (ad es. ricercatori) nell'uso dell'infrastruttura di calcolo e sotto il profilo scientifico (ad es. programmazione scientifica, analisi), nonché altre risorse correlate come energia e acqua per il raffreddamento.

fungano da supporto e da tramite per l’utilizzo dell’infrastruttura di calcolo per la ricerca e l’innovazione nella formazione supportata dall’IA.

Affinché ciò avvenga, il CSS raccomanda che le parti interessate (ad es. scuole universitarie, Confederazione, Cantoni) avviino un dialogo per sviluppare, coordinare, istituire e finanziare i meccanismi necessari a livello nazionale in una prospettiva di lungo periodo.

SSC Secretariat Working Paper

AI in Higher Education:
Challenges and their Implications for Higher Education, Research and Innovation

Analysis conducted on behalf of the SSC Secretariat by Sabine Seufert

Content

Disclaimer: This expert analysis is intended to provide food for thought and is not intended to be exhaustive.

1 Framing and context

1.1 Why this topic – AI in Higher Education?

Rapid diffusion and systemic relevance

- Generative AI is rapidly diffusing into core academic functions, including teaching, assessment, student support, research workflows and institutional management.
- AI use is intrinsically data-intensive, relying on profiling, learning analytics, prediction and automated or semi-automated decision support, thereby directly affecting educational processes and outcomes.

Core problem: AI is entering all relevant educational domains faster than governance frameworks, evidence bases and institutional capacities can adapt.[13, 14, 15]

Dual role of higher education institutions within the ERI system - Higher education institutions (HEI) simultaneously act as:

1. Operational users of AI
    - Deployment of AI in teaching, assessment, administration and quality assurance
    - Direct implications for legal compliance, ethics, accountability and institutional responsibility
2. Sites of research and innovation
    - Development, testing, and evaluation of AI-based educational systems
    - Knowledge production with the potential of feeding back into policy, educational practice and EdTech markets

Core problem: HEI increasingly combine experimentation and routine operation, blurring the boundary between responsible educational service provision and innovation-driven risk-taking.[16, 17, 18, 19, 20]

In research: analytically distinct but practically entangled strands are emerging and existing.

1. Education for AI

- AI as the object of learning
- Focus on AI literacy, critical understanding and professional competence, no direct impact on educational decisions or learner trajectories
- requires research in real educational settings to study authentic AI use, learning processes and human–AI interaction patterns (e.g. interaction and process data)

2. AI for Education

- AI as an active agent in educational processes (e.g. tutoring, feedback, assessment support, analytics, decision-making)
- Directly shapes learning processes, outcomes and institutional practices
- Depends on training, fine-tuning and contextual data from real educational settings, blurring the responsibility line between development, testing and use.

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[13] Azevedo, L., Robles, P., Best, E., Mallinson, D. J. "Institutional Policies on Artificial Intelligence in Higher Education: Frameworks and Best Practices for Faculty." New Directions for Adult and Continuing Education. 2025. no. 188: 70–78. https://doi.org/10.1002/ace.70013.

[14] Liu, D.Y.T., Bates, S. Generative AI in higher education: Current practices and ways forward. APRU. January 2025. https://www.apru.org/resources_report/whitepaper-generative-ai-in-higher-education-current-practices-and-ways-forward/.

[15] Miao, F., Holmes, W. Guidance for generative AI in education and research. UNESCO. 2023. https://doi.org/10.54675/EWZM9535.

[16] Dekker, I., Bredeweg, B., te Winkel, W. et al. Ethical procedures for responsible experimental evaluation of AI-based education interventions. AI Ethics 5, 2977–2986. 2025. https://doi.org/10.1007/s43681-024-00621-4.

[17] 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. Int J Educ Technol High Educ 21, 4. 2024. https://doi.org/10.1186/s41239-023-00436-z.

[18] Fitzpatrick, N., Hayes, P., Schmidt, J.C. et al. Policy Recommendations for Higher Education Institutions to Begin Advancing from Digital Transformation to Bifurcation. Nanoethics 19, 10. 2025. https://doi.org/10.1007/s11569-025-00476-x.

[19] Giannini, S. Reflections on generative AI and the future of education. © UNESCO 2023.

[20] Sector Insights Volume 2: Highlighting Innovation in our Sector. Strive Higher. May 2025. https://www.strivehigher.co.uk/sector-insights.

Implementation Research as a missing but critical lens:

- AI in education is increasingly deployed before robust evidence on effectiveness, equity and unintended effects is available (e.g. EdTech providers integrating LLM-based feedback and assessment tools).
- Implementation Research is required to study how AI systems are enacted in real institutional contexts, including organisational routines, professional practices and governance arrangements.
- This applies across all educational sectors, including AI implementation in K–12 education, where risks of premature scaling and weak governance are particularly pronounced.

As a result, HEI face many unresolved tensions between innovation with AI and the responsibilities attached to core educational functions. Given the high costs and constraints of conducting rigorous AI-in-education research in real settings, the balance between innovation and responsibility becomes a central unresolved issue for HEI.[21, 22, 23]

1.2 Legal points of reference in connection with AI

1.2.1 Policy and legal foundations in Switzerland (not exhaustive)

- Federal Act on Data Protection (FADP/DSG, revised 2023), providing the overarching legal framework for the processing of personal data, including data-intensive AI applications.
- Cantonal data protection laws governing public HEI, with variations in scope, interpretation and enforcement.
- Federal Act on Copyright and Related Rights (CopA) in relation to the questions of whether AI results are protected by copyright and whether the training of AI is relevant to copyright or not.[24]
- Federal Act on Funding and Coordination of the Swiss Higher Education Sector (HedA) with one objective of avoiding competitive distortions between higher education institutions and professional education institutions with regard to the provision of services and continuing education and training courses, which might apply to AI.
- Cantonal acts on higher education as well as the Regulation of the ETH domain, which might be used to regulate AI implementation and scientific integrity.
- Sector-independent ethical principles relevant to AI use in education, including proportionality, purpose limitation, transparency and accountability.[25, 26, 27, 28, 29]
- Status quo: A solid legal baseline exists but leaves substantial room for interpretation at institutional level and is not AI-specific

1.2.2 Sector-specific frameworks and HEI position paper, recommendations (not exhaustive):

- Educa Data Use Policy (Educa Report "Datennutzungspolitik im Bildungsraum Schweiz"): Provides a system-wide reference framework for responsible data use in the Swiss education sector, with focus on K–12. It defines common principles and development lines for data governance across educational levels (primary, secondary I and II).

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[21] Azevedo, L., Robles, P., Best, E., Mallinson, D. J. "Institutional Policies on Artificial Intelligence in Higher Education: Frameworks and Best Practices for Faculty." New Directions for Adult and Continuing Education. 2025. no. 188: 70–78. https://doi.org/10.1002/ace.70013.
[22] Giannini, S. Reflections on generative AI and the future of education. © UNESCO 2023.
[23] Dekker, I., Bredeweg, B., te Winkel, W. et al. Ethical procedures for responsible experimental evaluation of AI-based education interventions. AI Ethics 5, 2977–2986. 2025. https://doi.org/10.1007/s43681-024-00621-4.
[24] BAKOM. Auslegeordnung zur Regulierung von künstlicher Intelligenz. Bericht an den Bundesrat. 12. Februar 2025. https://www.bakom.admin.ch/de/kuenstliche-intelligenz.
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[26] Floridi, L. The Ethics of Artificial Intelligence Principles, Challenges, and Opportunities. Oxford University Press. 2023. DOI: 10.1093/oso/9780198883098.001.0001.
[27] OECD AI Principles. https://www.oecd.org/en/topics/ai-principles.html.
[28] UNESCO. Recommendations on the Ethics of Artificial Intelligence. 2022. https://unesdoc.unesco.org/ark:/48223/pf0000381137.
[29] European Commission. High-Level Expert Group on Artificial Intelligence. Ethics Guidelines for Trustworthy AI. 2019. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai.

- Swissuniversities Position paper “Die Schweizer Hochschulen und künstliche Intelligenz” advocates a pragmatic and open integration of AI into teaching and assessment, with a strong focus on competence development, academic integrity and responsible use. It addresses HEI as operational users of AI.
- SSC recommendations for AI computing infrastructure in the ERI domain.

1.2.3 Existing institutional practices in higher education (not exhaustive):

- Designation of institutional data protection officers or equivalent roles responsible for compliance with federal and cantonal data protection law.
- Existence of ethics committees or review boards, primarily focused on research ethics, with limited and uneven relevance for AI use in teaching, assessment and administration.
- Established IT governance structures, including central IT services responsible for infrastructure, access management, data security and system integration.
- Procurement processes for digital tools and services with increasing attention to data protection clauses, contractual safeguards and vendor compliance.
- Limited but growing experience with learning analytics and data-driven educational tools, essential for e.g. development and optimisation, typically implemented at faculty, project, or pilot level rather than institution-wide.
- Fragmented responsibility for AI-related decisions across academic units, administrative leadership, IT services, legal offices and quality assurance.

Status quo: Most HEI possess relevant partial structures, but these are not integrated into a coherent national reference framework for AI governance in higher education. In particular, there is no shared framework that categorises the use of AI according to its purpose and context (e.g. AI for education, education for AI, and operational AI use), its risk level (from low to high) and its lifecycle stage (from experimentation and piloting to routine deployment), which would enable responsible innovation across these stages.

Existing policies and institutional arrangements tend to address data protection, research ethics and IT governance as separate domains. However, AI-related educational practices cut across all three of these areas, creating uncertainty, fragmented responsibilities and coordination gaps. These gaps are particularly problematic in inter-institutional and cross-cantonal settings, where divergent regulatory interpretations can hinder collaboration and the scalability of AI-related research and innovation.

1.3 Approach to address AI in Higher Education

The Educa Report “Datennutzungspolitik im Bildungsraum Schweiz” serves as a basis for the considerations for AI in higher education outlined here, because:

Educa data use recommendations:
This Educa Report provides a coherent framework for responsible data use and AI-related practices in the Swiss education system, based on shared principles, legal consistency and inter-cantonal coordination.

Relevance for further system development:
It proposes a common orientation for data governance across all educational levels, the framework offers a clear reference point for addressing emerging challenges related to AI in education.

Extension to higher education:
Although primarily developed for compulsory and upper secondary education, the framework contains transferable conceptual elements that can be extended to higher education, taking into account its institutional autonomy, the close integration of research and teaching and cross-institutional collaboration.

Therefore, the considerations for AI in higher education are outlined in three subsequent chapters:

Analytical focus (Chapter 2):
Building on this foundation, this expert analysis examines current AI-related educational practices in higher education and their interaction with existing institutional structures and Educa principles.

Clarifying the delta (Chapter 3):
The subsequent chapter identifies areas requiring further clarification or differentiation to adequately address the specific conditions of higher education.

Guiding recommendations (Chapter 4):

On this basis, this working paper formulates guiding recommendations to complement the existing framework and support coherent, responsible and innovation-oriented AI use in higher education.

2 Analysis along the Educa Development Lines 1–7 (HEI perspective)

2.1 Ensuring digital self-determination and digital identity in education

Educa development approaches 1.1.–1.8. (page 18–21 of the Educa Report)**:**

1 Strengthening digital self-determination through protection against manipulation

2 Promote educational data spaces that enable digital self-determination

3 Conduct a needs assessment for digital credentials in the education system

4 Clarify the legal use of digital credentials

5 Implement a technical prototype for using the e-ID infrastructure for digital credentials

6 Introduce digital credentials

7 Issue a federated identity across all levels of education

8 Ensure connectivity to new digital identities

HEI Perspective:

- The development line provides essential infrastructural and normative foundations for digital self-determination and identity in education.
- Its underlying logic is primarily protection oriented, reflecting K–12 contexts characterised by vulnerability, prevention and uniform safeguards.
- In higher education, the main challenges shift from protection to transparency, contestability and responsibility in AI-supported academic judgements.
- Digital identities, credentials and data spaces function in HEI not only as safeguards but as operational inputs for AI-enabled teaching, assessment, research and inter-institutional collaboration.
- Extending this development line to higher education therefore requires context- and use-specific differentiation rather than a direct transfer of K–12 protection logics.

2.2 Strengthening data competence as a prerequisite for responsible data use

Educa development approaches 2.1.–2.8. (page 24–29 of the Educa Report)**:**

1 Support internal competence building through data literacy officers

2 Expand the school management profile

3 Integrate lead data stewards into education departments

4 Provide tools to support data management

5 Promote data-driven school development

6 Conduct systematic monitoring of pupils' data skills

7 Carry out regular awareness-raising measures

8 Promote federal learning through a community of practice

HEI perspective:

- This development line rightly positions data competence as a key enabler for responsible AI use in education.
- In higher education, data skills extend to include evaluative judgement, authorship and responsibility in AI-mediated academic practices.
- In HEI, insufficiently coordinated data competence contributes directly to the blurring of responsibilities between research, teaching, administration, one of the core problems identified earlier, which is why strengthening data competence as a prerequisite for responsible data use is also essential for higher education.

2.3 Lean application tests

Educa development approaches 3.1.–3.4. (page 31–33 of the Educa Report):

1 Convey data protection expertise for each area of responsibility

2 Develop uniform and iterative processes for application testing

3 Collaborate across cantons on application testing processes

4 Make the results of application testing visible

HEI perspective:

- This development line addresses an important need for efficiency, clarity and risk reduction in the approval of digital and AI-based applications.
- Its underlying logic reflects school- and administration-centred use cases, whereas HEI face a much broader spectrum of applications spanning teaching, assessment, research and experimentation.
- In higher education, AI tools often move rapidly between research use, pilot deployment and routine teaching, directly reinforcing the previously identified problem of blurred boundaries between experimentation and operation (see core problem).
- Uniform and inter-cantonal testing processes are highly relevant for HEI but must accommodate academic autonomy, disciplinary diversity and research-specific requirements.
- Extending this development line to higher education therefore requires a national reference framework for AI governance in HE that distinguishes use contexts and lifecycle stages, rather than treating all AI tools as homogeneous operational systems (“one-size-fits-all logic”)

2.4 Providers, procurement and market regulation

Educa development approaches 4.1.–4.5. (page 36–37 of the Educa Report):

1 Provide low-threshold tools for procurement

2 Define and enforce data protection measures as mandatory requirements

3 Consider data usage requirements as a procurement criterion

4 Establish a “community of practice” for procurement

5 Increase coordination of procurement

HEI perspective:

AI use in HEI (operational use)

- Procurement is a key governance lever shaping which AI systems enter routine teaching, assessment and administration.

- In higher education, decentralised procurement practices and faculty-level adoption amplify challenges of coordination, transparency and accountability.

Research and innovation

- Research-based AI development does not follow provider or market logics, yet often falls outside existing procurement and governance frameworks.
- Experimental systems, prototypes and pilot projects may resemble operational AI tools but are not subject to the same rules and decision-making processes. In particular, it is often unclear how research-based AI systems that rely on real-world data and are tested in authentic educational settings should be evaluated, authorised or transitioned into regular use within higher education institutions.
- This constitutes a governance gap at the boundary between research, experimentation and operational AI use. This cannot be addressed by institutional policies alone but requires a coherent national framework for AI governance in higher education that provides shared guidance on use contexts, lifecycle stages and risk levels.

2.5 Secondary and multiple use of educational data

Educa development approaches 5.1.–5.14. (page 41–47 of the Educa Report)**:**

1. Use public registries of data processing activities to gain an overview of data flows
2. Ensure the discoverability of datasets
3. Systematically publish non-personal data as “open government data”
4. Develop organisational, semantic and technical standards
5. Establish the foundations for legal interoperability
6. Develop cantonal legislation aligned with the Federal Act on the Use of Electronic Means for the Fulfilment of Official Tasks
7. Assess the potential of multiple and secondary data use within the education system
8. Provide technical methods for anonymised data use
9. Ensure uniform data access for research
10. Establish a right of data access for research
11. Ensure access to application data
12. Leverage opportunities to influence the development of future sector-specific data spaces
13. Participate in cross-sectoral federal initiatives for data space prototypes
14. Enable the emergence of interoperable educational data spaces

HEI perspective:

- Secondary and multiple use of educational data is a core enabling condition for AI use and AI-related research in higher education.
- In HEI, data reuse spans research, teaching, assessment, quality development and innovation, making governance inherently cross-domain.
- A key HEI-specific requirement is the clear distinction between learning/teaching data and research data, which follow different purposes, expectations and legal logics.
- Different cantonal acts with fragmented legal interpretation (e.g. data protection) lead to high coordination costs, slow evidence generation and limited scalability of AI-related research.

- Uniform access to data for research and access to application data are particularly critical, as AI development and evaluation depend on authentic interaction and process data from real educational settings.
- At the same time, HEI face heightened sensitivity around profiling, inference and downstream reuse of educational data, especially when learning data are reused beyond their original educational purpose.
- Research-based AI development often requires training, adaptation and testing in real educational contexts. However, existing legal frameworks, organisational responsibilities and approval processes are usually developed for either research ethics or operational data use and do not systematically address this hybrid use of educational data.

Why data spaces are highly relevant for HEI (research perspective)

- For higher education, data spaces are not primarily administrative infrastructures but strategic research and innovation infrastructures.
- They enable secure, interoperable and purpose-bound access to heterogeneous data sources across institutions and cantons.
- Data spaces support the controlled separation and selective linkage of learning/teaching data and research data, helping to uphold purpose limitation while still enabling meaningful analysis.
- They provide a framework for AI development, training and evaluation in real-world educational settings, without requiring full data centralisation.
- Data spaces are particularly relevant for inter-institutional, cross-cantonal and international collaboration, possibly reducing legal fragmentation and coordination overhead.
- Finally, data spaces support AI lifecycle governance, helping HEI manage transitions between research, piloting and routine operational use, which is why secondary and multiple use of educational data is an essential prerequisite for research on AI and education in higher education.

2.6 Using the potential of AI in a legally compliant and controlled manner

Educa development approaches 6.1.–6.8. (page 51–54 of the Educa Report):

1. Clarify the permissibility of data processing in algorithmic systems within the educational mandate
2. Review the use of algorithmic systems and, where appropriate, extend the educational mandate
3. Represent the needs of the education system in AI regulatory initiatives at the federal level
4. Disclose the use of algorithmic systems in education through public registries
5. Label interactions with and content generated by algorithmic systems in education
6. Regulate automated individual decisions in a practicable manner
7. Regularly review data accuracy and data quality in algorithmic systems
8. Ensure access to generative AI systems

HEI Perspective:

AI use in HEI (operational use)

- Measures such as registries, transparency requirements or quality checks provide useful orientation but require context-sensitive adaptation to HEI contexts

Research and innovation

- Research on and with AI often requires training, adaptation and testing of algorithmic systems in real educational settings, using authentic interaction and process data. Such research activities do not fit neatly into operational compliance frameworks, yet intersect with the same legal, ethical and quality considerations.

- Experimental systems may temporarily resemble operational tools while serving primarily exploratory or evaluative purposes, creating ambiguity at the boundary between research and use.
- The existing framework provides important legal safeguards but does not fully clarify how research-based AI systems should be accompanied, evaluated or transitioned into operational contexts.
- Extending this development line to higher education therefore requires differentiated and coordinated governance approaches that enable research in real settings without compromising legal compliance or institutional trust.

2.7 Promoting data-driven development and innovation

Educa development approaches 7.1.–7.4. (page 59–60 of the Educa Report):

1. Introduce pilot clauses
2. Support dialogue between public and private actors through an "innovation hub"
3. Learn through regulatory sandboxes
4. Establish systematic trend reports on data and digitalisation topics

HEI perspective:

- This development line addresses the need for adaptive and learning-oriented governance, which is particularly relevant for higher education given the rapid evolution of AI technologies.
- Instruments such as pilot clauses, innovation hubs and sandboxes align well with the research and innovation mission of HEI, where experimentation under uncertainty is structurally necessary.

Research and innovation

A regulatory sandbox is a real-world laboratory that enables new technologies and regulatory approaches to be tested in a controlled environment. This allows experimentation to take place within defined legal boundaries and helps to identify regulatory needs while limiting risks.[30]

Why differentiate sandbox logics in higher education?

AI for Education (technical sandboxes):

- Sandboxes focus on the development, training, testing and evaluation of AI systems intended for later use in teaching, assessment or administration. These sandboxes require access to realistic data and workflows, combined with controlled risk exposure, clear evaluation criteria and explicit transition points from experimentation to operational use.
- This type of sandbox aligns with the Educa framework's approach to innovation under controlled and legally compliant conditions.

Education for AI (pedagogical sandboxes):

- Sandboxes aim to study and foster authentic human–AI interaction, for example how learners use generative AI tools such as LLMs for writing, problem-solving or revision.
- This represents an emerging research field that seeks to understand learning processes, misconceptions, appropriation strategies and AI literacy under real-world conditions.
  Such settings require minimally constrained, realistic interaction with AI systems (i.e., functioning like real-world LLMs) in order to generate valid insights.
- Pedagogical sandboxes thus serve as research gateways to interaction and process data but require targeted governance and institutional support, particularly in K–12 contexts where existing

[30] BAKOM. Auslegeordnung zur Regulierung von künstlicher Intelligenz. Bericht an den Bundesrat. 12. Februar 2025. https://www.bakom.admin.ch/de/kuenstliche-intelligenz.

protection logics prioritise prevention and risk minimisation and may otherwise limit pedagogical authenticity and research validity.

At present, governance frameworks do not systematically distinguish these pedagogical sandbox needs from operational or regulatory sandboxes, creating a gap between research requirements and existing protection-oriented approaches.

3 Remaining governance challenges for Higher Education

- The Educa Data Use Policy provides a strong system-level foundation.
- The remaining challenges arise where these principles need to be translated into the specific institutional realities of higher education institutions, particularly in the context of AI-enabled practices.
- Outside its scope: Research.

3.1 Recurring governance challenges in Higher Education (not exhaustive)

- Blurred boundaries between research, piloting and routine AI use, as AI systems move incrementally across contexts without explicit institutional decisions.
- Fragmented responsibilities across domains and roles, with data protection, ethics, IT governance, research, teaching and assessment addressed separately rather than in an integrated manner.
- Tensions between operational AI use and research logics, particularly where AI development and evaluation require real educational settings and authentic interaction data.
- Data governance tensions between learning/teaching data and research data, as AI-enabled practices increasingly connect data types governed by different purposes and legal logics.
- Coordination challenges across institutions and cantons, especially for AI-related research, data access and collaborative initiatives.

3.2 AI use contexts and their governance implications

Aspect	Education for AI	AI for Education	Operational AI use
Purpose	AI Literacy, research on human-AI interaction	Development, testing, improvement of AI systems	Service provision in teaching, assessment, administration
Environment	Pedagogical sandbox based on LLMs (used in real / supervised settings)	Technical sandbox, pilot environments, including iterative use and training in real educational settings	Institutional systems embedded in formal teaching, etc.
Primary Risk location	Learner exposure, interpretation, potential influence	Design choices, data use, model behaviour	Academic consequences (e.g. grading, assessment = high risk)
Quality assurance	Research validation	System validation & testing	Continuous monitoring & review
Governance Focus	Proportional safeguards (e.g. stronger in K–12-contexts), transparency of AI role, supervision	Validation, documentation, responsible design, explainability, controlled data use	Accountability, transparency, human oversight, contestability

Table 1: Contexts of AI use in Higher Education

AI governance gap in Higher Education

The AI governance gap in higher education refers to a systematic mismatch between
(a) existing legal, ethical and organisational frameworks, and
(b) the actual contexts in which AI is developed, tested and used in higher education, including research, teaching, pilot projects and routine operations, particularly where these contexts overlap, transition into one another or extend across institutional boundaries.

This gap becomes especially evident in inter-institutional and cross-cantonal settings, where AI-related research, shared infrastructures and collaborative projects require coordinated interpretations of responsibilities, data use and risk.

The governance gap has three interrelated underlying causes:

- Context gap
  The lack of clear differentiation between *Education for AI*, *AI for Education* and *operational AI use*, despite their distinct purposes, risk profiles and governance requirements.

- Lifecycle gap
  The absence of governance approaches that explicitly address transitions between research, experimentation, piloting and routine deployment of AI systems, leading to uncertainty about when and how responsibilities shift.

- Coordination gap
  Fragmented responsibilities across domains such as research ethics, data protection, IT governance, teaching and institutional management, an issue that is further complicated when multiple higher education institutions collaborate and apply divergent interpretations to similar AI use cases.

These recurring friction points highlight a structural governance gap that cannot be resolved through case-by-case decisions alone; rather, it requires a coordinated, system-level approach. Therefore the following recommendations are proposed:

4 Guiding recommendations

The recommendations are framed within the tiered system logic established by the SSC for AI computing infrastructure in the ERI domain, which follows a national strategy based on guiding principles such as flexibility, scalability, efficiency, interoperability, digital sovereignty, knowledge security, data lifecycle management. It ensures that AI use/research in higher education serves ERI stakeholders throughout Switzerland, including institutions and actors beyond the technical disciplines, within which the ERI system is embedded. This logic distinguishes between different levels of capacity and support that are interoperable:

Tier 1 addresses national and international supercomputing resources for highly compute-intensive AI research;

Tier 2 offers shared national high-performance computing services for a broad range of AI applications that do not require supercomputing; and

Tier 3 comprises regional compute with local/regional expert groups that support users locally.

The SSC envisions a tiered system in which all tiers provide computing resources (see definition[31]) that include all the necessary components, services and resources required to make computing power usable by end users, thereby also functioning as pools of national experts for user and scientific support including AI developments. As the national strategy encompasses data lifecycle management, data[32] services are an integral component of the tiered system and, consequently, of all tiers.

R1 − Establish a shared national reference framework for AI governance in higher education

Develop a **coherent national reference framework for AI governance in higher education** that provides shared orientation across institutions and cantons. The framework should differentiate AI use according to three key dimensions:

- **Use context and purpose**, distinguishing in particular between *Education for AI*, *AI for Education* and *operational AI use*;
- **Lifecycle stage**, covering transitions from research and experimentation through piloting to routine deployment; and
- **Risk level**, reflecting the potential impact of AI systems on learners, academic processes and institutional decision-making.

These dimensions should be explicitly mapped onto the **tiered infrastructure logic**, ensuring that governance expectations, support structures and resource allocation are proportionate to the specific AI use context.

Examples

- Experimental and research-oriented AI applications in education, such as pedagogical sandboxes and research gateways, can usually be supported by a combination of Tier 2 capacity and Tier 3 expertise. Such use cases are generally associated with low to moderate risk and require flexible, research-oriented governance arrangements;
- Highly compute-intensive AI research in education, including large-scale model training or advanced AI development with cross-institutional or international relevance, should be linked to Tier 0/1 infrastructures. These use cases are not the standard for AI in education and are usually associated with greater coordination and governance requirements.

[31] Computing resources include all the necessary components, services and resources required to make computing power usable for end users. For example: hardware, software to run and use the hardware for its purpose (e.g. academic research), personnel to set up and maintain the computing resources hardware, to code the necessary software and to run it on the hardware, to support end users (e.g. researchers) in the use of the computing infrastructure as well as scientifically (e.g. scientific programming, analysis), other associated resources like energy and water for cooling.
[32] Data here refers to information in digital form that can be transmitted or processed. Thus, data also includes software.

Why?

- A shared national reference framework for AI governance in higher education establishes a common governance language across institutions and cantons. This national reference framework is meant as a national guideline developed possibly by Swissuniversities, the EDK[33] and the relevant committees within HedA that supports proportionality by ensuring that low-risk educational research and pedagogical experimentation are not assessed using standards designed for high-risk operational AI systems.
- For ethics committees and data protection bodies, this reference offers ex ante orientation, helping to:
  - distinguish pedagogical research from operational deployment,
  - identify genuinely low-risk studies, and
  - enable simplified or expedited review processes where appropriate.
- Over time, the framework supports the development of a case-based knowledge base for AI governance in higher education, reducing variability across institutions, increasing consistency and transparency, and strengthening trust in the responsible use of AI for research, teaching and innovation.

R2 – Enable differentiated sandbox models embedded in the tiered system

Explicitly recognise and support **two complementary sandbox models**, embedded within the tiered system and aligned with the **coherent national reference framework for AI governance in higher education**.

Sandbox models:

- **Technical sandboxes (*AI for Education*)**

  Technical sandboxes support the development, training, testing and evaluation of AI systems intended for later educational use (e.g. tutoring systems, feedback tools analytics applications).

  They should be enabled through a combination of:

  - **Tier 2**: shared national compute and data services, including secure environments for model development, access to relevant educational and application data under controlled conditions, documentation standards and interfaces to educational data spaces; and
  - **Tier 3**: local or regional expert support providing contextualised guidance on data use, validation, ethical and legal requirements, and the transition from experimentation to piloting or deployment.

  Where required, highly compute-intensive components may be escalated to **Tier 1**.

- **Pedagogical sandboxes (*Education for AI*)**

  Pedagogical sandboxes enable authentic human–AI interaction for teaching and research purposes, for example to study AI literacy, learning strategies, misconceptions and appropriation practices when learners interact with generative AI systems (e.g. LLMs).

  They should be provided as **federated regional or national services**, combining:

  - **a Tier 2 technical core**, offering stable, scalable access to AI systems, logging and storage of interaction and process data under defined conditions, and interfaces for research access; and
  - **Tier 3 pedagogical and research support**, including guidance on study design, consent and transparency practices, supervision models and alignment with institutional teaching and research contexts.

[33] Swiss Conference of Cantonal Ministers of Education (EDK).

Why?

- Such differentiated sandbox models also with regard to the applicable legal framework (e.g. cantonal, national, international) embedded in the tiered system enable proportional governance and responsible experimentation. In combination with Tier 3 interface structures (R3), they ensure that sandbox activities remain transparent, appropriately governed, and do not silently transition into operational deployment.
- Pedagogical sandboxes are particularly relevant at a national level because they enable the empirical assessment of AI literacy, human–AI interaction and learning processes at scale under consistent governance conditions across institutions, sectors and cantons. This approach strengthens the evidence base for AI in education while respecting institutional autonomy and federal structures.

R3 – Provide support structures as interface between infrastructure and educational practice

In line with the SSC's recommendations regarding AI and computing infrastructure, Tier 3 should comprise local or regional AI expert groups to support users and direct them to the relevant resources within the tiered system. Although technical expertise in AI development and computing is distributed across all tiers, the use of AI in education requires a dedicated interface function to connect shared infrastructure with concrete educational practice.

Within the proposed tiered system, this interface function should be explicitly anchored at Tier 3, operating as the governance–usability layer between national and regional infrastructure (Tier 1/2) and institutional implementation in higher education. Tier 3 is particularly important for making the two sandbox models described in R2 usable in practice by guiding access, supporting responsible use and managing transitions across the AI lifecycle.

Core functions of Tier 3 AI-and-Education expert groups:

- Access, routing and onboarding for sandboxes and shared services (R2)
- Tier 3 acts as a low-threshold entry point for educators and researchers. It supports onboarding into technical (AI for Education) and pedagogical (Education for AI) sandboxes, and routes users to the appropriate Tier 2 services (and Tier 1 resources where necessary). This includes providing practical guidance on the necessary prerequisites (e.g. data access, secure environments, documentation) and helping users select suitable sandbox set-ups.
- They should also translate system-level frameworks into educational contexts and interpret legal requirements, ethical principles and the coherent national reference framework for AI governance in higher education in a context-sensitive manner across disciplines and educational settings. This translation function helps ensure proportional safeguards for low-risk pedagogical research and clear requirements for higher-risk use cases, without prescribing pedagogy.
- Cross-domain coordination and case-based support: Supporting the coordination of research ethics, data protection, IT services, teaching units and institutional management, particularly for AI projects and sandbox activities that cut across domains. Tier 3 helps to resolve recurring uncertainties (e.g. the separation and linkage of learning/teaching and research data; access to application and interaction data; transparency and consent practices) on a case-by-case basis.
- Lifecycle support and controlled transitions (R2): ensuring that sandbox activities do not silently drift into operational deployment. Tier 3 supports the definition of transition points and decision criteria (e.g. from sandbox to pilot, or from pilot to routine use) and helps to align governance expectations with changing risk and impact. Where necessary, Tier 3 escalates to a more formal review or higher-tier support.

Why?

- Tier 3 support structures make the tiered AI computing infrastructure actionable and trusted in educational practice. They reduce coordination burdens for educators and researchers, strengthen responsible experimentation and evidence generation, and ensure that the sandbox models in R2 can be used at scale without undermining legal compliance, institutional autonomy or public trust.

- Support responsible research and innovation in AI-enabled education.

R4 – Education-specific data access and data spaces within the tiered system

Ensure that the tiered AI infrastructure system as a whole supports education-specific data access and interoperable data spaces as a core enabling condition for AI use and AI-related research in higher education. Within this system, Tier 2 should be positioned as the shared national compute–data–coordination layer for education, while Tier 3 provides the interface that makes data access usable, proportionate and context-sensitive in practice.
In clearly defined exceptional cases, Tier 0/1 infrastructures may complement this set-up for highly compute-intensive or internationally coordinated AI research. In such cases, data governance, access control and purpose limitation remain anchored in Tier 2 and are mediated through Tier 3.

Roles of the tiers in education-specific data access:

Tier 2 – Shared national compute–data–coordination layer
Tier 2 should provide reusable and interoperable foundations for education-specific data access by supporting:

- access to relevant educational data types, including learning and teaching data, research data and application and interaction data generated through AI use *(e.g. prompts, revisions, feedback traces, usage logs)*;
- clear differentiation between data types according to purpose and governance logic, with controlled and auditable linkages where justified; and
- interoperability through interfaces to educational and cross-sectoral data spaces, aligned with FAIR principles and data lifecycle management.

Through these functions, Tier 2 acts as the national backbone for scalable, interoperable and governable education data access across institutions and cantons, while remaining compatible with international research infrastructures.

Tier 3 – Interface for access, mediation and responsible use
Tier 3 expert groups translate Tier-2 data capacities into concrete educational and research practice. In particular, Tier 3:

- mediates access to data and data spaces and routes users to appropriate Tier-2 services;
- supports proportional data governance by interpreting data protection, research ethics and institutional requirements in relation to specific AI use contexts; and
- assists institutions in operationalising the separation and justified linkage of learning/teaching data and research data, including in sandbox and research-gateway settings (see R2), for example, when interaction or process data from educational use are reused for research purposes.

Through this interface role, Tier 3 ensures that education-specific data access is not only technically available but usable, interpretable and trusted in practice.

Tier 0/1 – Exceptional escalation for compute-intensive research
Tier 0/1 infrastructures may be involved in exceptional cases requiring high-end computing resources (e.g. large-scale model training or advanced simulations). Research data generated in educational contexts may be processed and analysed across tiers, while data classification, access conditions and governance decisions remain anchored in Tier 2, with Tier 3 supporting coordination and oversight.

Why this matters?

- The tiered system enables scalable, interoperable and proportionate education-specific data access by combining Tier 2 data infrastructures, Tier 3 mediation and coordination, and Tier 0/1 escalation where justified.
- Responsible reuse of research data generated in educational contexts is possible across tiers, while data classification, access conditions and governance decisions remain anchored in Tier 2 and are supported through Tier 3 coordination. This facilitates inter-institutional and international collaboration without undermining data protection, institutional autonomy or public trust.

Overall, these recommendations focus on *enabling system conditions*, not on regulating pedagogical practice or institutional implementation.

Education as a flagship use case for the recommended SSC AI computing infrastructure in the ERI domain

The SSC recommendations on AI computing infrastructure in the ERI domain emphasise that computing capacity alone is insufficient to enable the use of and research on or with AI in this domain. To make AI computing infrastructure usable across the ERI system, it must be complemented by a data lifecycle management, including data access to interoperable data spaces that harbour FAIR data, and to expert support, which is why the national strategy for AI computing infrastructure includes these guiding principles among others.

Higher education represents a high-impact domain in which these foundations become immediately operational. AI-enabled practices in higher education depend not only on compute but also on access to educational and application interaction data, clear rules for data reuse, and the governance of transitions from research and experimentation to routine use. This is particularly critical where AI supports or influences high-stakes academic processes such as assessment.

In addition, cross-institutional and cross-cantonal research in education highlights how divergent interpretations and fragmented responsibilities can increase transaction costs and slow evidence generation.

Positioning research and innovation in education as a flagship use case within the ERI system helps translate the SSC AI computing infrastructure strategy into practice. It connects tiered compute capacity with **practical guidance and coordination**, strengthens the role of data spaces as research and innovation infrastructures, and makes the need for differentiated sandbox models for technical AI development (*AI for Education*) and pedagogical experimentation and interaction research (*Education for AI*) visible.

5 Annex

5.1 Abbreviations

AI	Artificial Intelligence
CopA	Federal Act on Copyright and Related Rights
Educa	Swiss Agency for the Digital Education Area
EDK	Swiss Conference of Cantonal Ministers of Education
EdTech	Educational Technology
e-ID	Electronic Identity
ERI	Education, Research, Innovation
FADP	Federal Act on Data Protection
FAIR	Findable, Accessible, Interoperable, Reusable
HE	Higher Education
HedA	Federal Act on Funding and Coordination of the Swiss Higher Education Sector
HEI	Higher Education Institution(s)
IT	Information Technology
LLM	Large Language Model
SERI	State Secretariat for Education, Research and Innovation
SSC	Swiss Science Council

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