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Shaping The Future Of Education With Artificial Intelligence: Scenarios And Strategic Priorities

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ABSTRACT:
The rapid progress of digitalization, particularly the integration of Artificial Intelligence (AI) into education, is transforming learning opportunities. AI enables more personalized learning experiences that transcend traditional time and location constraints. Tools like ChatGPT demonstrate the pace and scale of innovation in this field, underscoring the importance of dialogue among educators, policymakers, technologists, and other stakeholders.
This discussion paper explores three potential future scenarios for AI adoption in institutional education: higher education, continuing education, and school education. Each scenario considers the prerequisites and conditions necessary for successful implementation, emphasizing both opportunities and challenges.
Based on these scenarios, the paper identifies five key fields of action essential for effective AI integration in education:
1. ***Interdisciplinary Cooperation** – fostering collaboration among educators, technologists, and researchers.*
2. ***Qualification and Competence Development** – ensuring teachers and learners have the skills to use AI effectively.*
3. ***Digital Infrastructure and Personnel** – building robust technological systems and skilled support teams.*
4. ***Ethics and Data Sovereignty** – safeguarding privacy, transparency, and responsible AI use.*
5. ***Data Interoperability** – enabling seamless, secure sharing of educational data across platforms.*

By presenting these scenarios and action areas, the paper aims to encourage strategic, cooperative planning for AI's role in education. The ultimate goal is to support a shared vision that balances innovation with ethical, inclusive, and sustainable practices, ensuring AI contributes meaningfully to the future of learning.
Keywords: *Artificial Intelligence in Education, Digitalization, Future Scenarios, Higher Education, Continuing Education, School Education, Interdisciplinary Cooperation, Competence Development, Digital Infrastructure, Ethics, Data Sovereignty, Data Interoperability, Educational Technology, AI Integration.*

INTRODUCTION

1. Brief Overview: Artificial Intelligence in Education

Artificial intelligence in education has been intensively researched for several years and is also used in some areas (Leite, 2025; Rajki, 2025; Wollny et al., 2021; Matos et al., 2025). With the release of ChatGPT at the end of 2022, the topic of AI in education has gained media attention and momentum. The discussions in the educational context include, in particular, effects on (academic) writing and research, examinations as well as on university teaching and school teaching.
An introduction to the role of ChatGPT in university teaching can be found in the curated resources of the Hochschulforum Digitalisierung (HFD) and in the collection assembled by the Technische Universität Berlin. Even before public access to ChatGPT, it was already clear that artificial intelligence would become increasingly relevant in everyday life and at work (e.g. translations, voice control, autonomous driving). However, the level of knowledge and self-assessment of competencies with regard to AI differ considerably within the Indian population (Mhlanga, 2024; Fisher et al., 2025). The influence of AI on their own everyday life is also hardly noticed - in a representative survey, only 14 percent of the citizens surveyed stated that AI had a strong to very

strong influence on their lives (König et al., 2023). Employees are also often unaware that they are working with AI-based systems (Giuntella et al., 2025). The Department of Higher Education (Government of India, GoI) & NITI Aayog (2018) has been increasingly involved in the field of artificial intelligence for several years. With a view to institutional education, AI is increasingly being demanded and integrated as learning content and method within the framework of digitization and future strategies (European Commission, 2020, 2021; Anghe et al., 2025, Xiao, 2025; Standing Scientific Commission of the Conference of Ministers of Education, 2022; Rajki et al., 2025). Digitization in higher education in general and specifically with regard to AI is addressed by means of national funding programs. AI is funded as a digitization component through a wide range of funding programs in educational institutions.
But what about the application of AI in education ("learning with AI")? An overview is presented by Leite (2025), although an update is now necessary due to the dynamics in the field of AI. The international comparison is also worthwhile, because AI is being researched and used in the institutional educational context, particularly in English-speaking countries, but also in China (Matos, et al., 2025).
Institutional education in India is decisively shaped by the following key stakeholders:

- **Micro level:** Students, teachers, and end-users of educational services.
- **Meso level:** Educational institutions such as universities, colleges, schools, and continuing education providers; decision-making bodies within these institutions (e.g., university administrations, school boards); professionals involved in institutional governance; as well as educational companies, trusts, and foundations.
- **Macro level:** Policymaking bodies at the state and national levels, including regulatory authorities such as the University Grants Commission (UGC), All India Council for Technical Education (AICTE), and relevant ministries like the Ministry of Education.

With the growing digitization of education, **educational technology (EdTech) companies** in India are playing an increasingly influential role in supporting and transforming institutional education. This shift is being accelerated by rapid technological advancements, particularly in the use of **Artificial Intelligence (AI)** in teaching, learning, assessment, and institutional management. However, this development also necessitates a critical discourse on the intersection of **commercial interests, ethical considerations**, and **equitable access** in the Indian educational landscape. Technological progress and the use of AI in education reinforce this trend. In return, it is also evident that a discourse on commercial interests and basic ethical principles must be conducted here (Chigbu et al., 2023).
The aim of this discussion paper is to stimulate a discourse on the application of AI in institutional education. It is important to show the conditions for success in concrete application scenarios and to contextualize the topic accordingly.

The discussion paper addresses the following overarching questions:

- **Future scenarios:** What are exemplary future scenarios for the use of AI in institutional education?
- **Prerequisites and conditions for success**: What are the prerequisites and conditions for success of the use of AI in institutional education at the micro, macro and meso levels?
- **Collaboration:** What are the starting points for the joint exchange between key actors in the field of AI and institutional education?

In the following, three future scenarios for the application of AI in institutional education with a focus on further education, universities and schools are presented. For each future scenario, the theoretical background is first outlined, an exemplary scenario is described and recommendations for action for the stakeholders are concluded. Finally, five overarching fields of action are derived and further discussion impulses are formulated.

2. Three future scenarios for the use of artificial intelligence in institutional education

2.1 Scenario 1: Artificial intelligence in the context of universities

2.1.1 BACKGROUND:

There are currently 1,114 universities in India (IndiaStat, 2024). In Uttar Pradesh, there are 84 universities, making it the state with the second-highest number of universities in India. These include 6 central universities, 35 state universities, 35 private universities, and 8 deemed universities. Professors, especially in state institutions or universities, face the challenge that many students have to be trained in large groups at the same time. The composition of such groups can vary depending on the university - in terms of age, origin, gender, thinking styles, numerus clausus, etc. Higher educational institutions in India primarily use the open-source platform Moodle. This is also confirmed by the following Figure 1, which is the result of a study by Edutechnica and LISTedTECH (eLiterate, 2017). eLearn Magazine (2016) also confirms this perception.

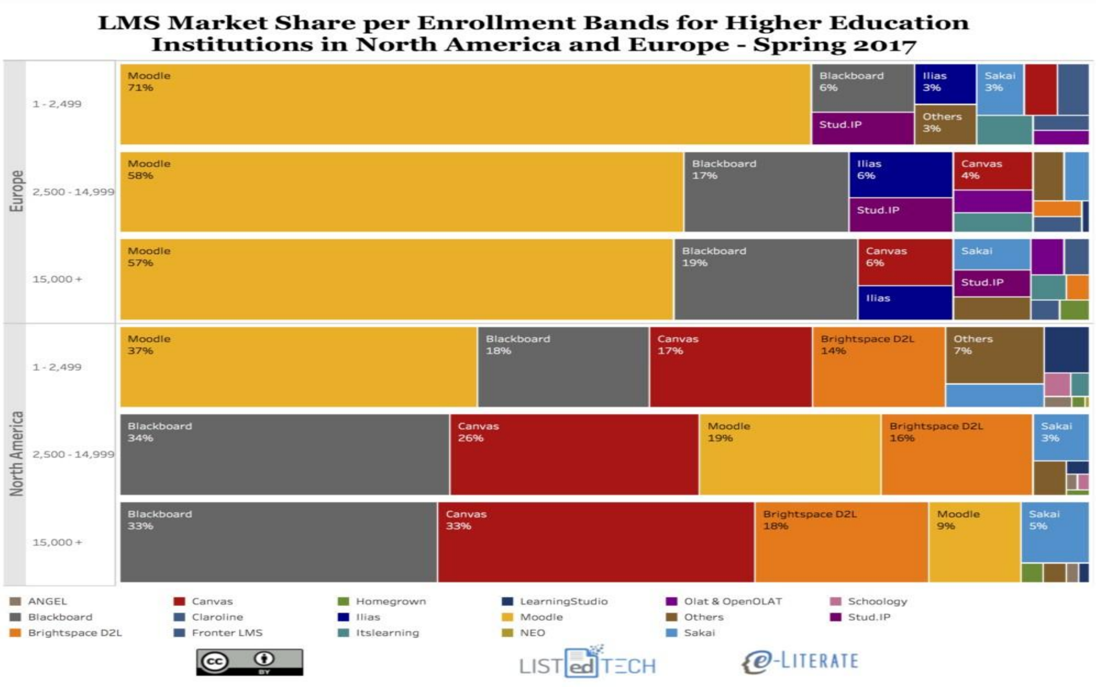

Figure 1: LMS usage in Europe and North America (eLiterate, 2017)

According to lecturers in this country, the use of Moodle in an educational context requires a lot of manual work and has established itself over the years as a collection point for add-ons. Lecturers usually fill out each course individually. They therefore follow an individual structure, which means that students are increasingly confused because they have to adjust to a different structure and different add-ons from course to course. The structure of Moodle also forces students to work their way through a kind of list from top to bottom. AI applications in Moodle are mainly used to monitor attendance, the level of competence or learning progress in the system (e.g. learning analytics), but not to actually identify learning strategies, learning styles, intelligence, competencies, strengths, interests or potential.

AI-supported technologies have been used in an educational context since the 1970s. At that time, the researchers were concerned with the question of whether and to what extent computers could replace personal tutoring by a human (Bloom, 1984). In early attempts, rule-based AI techniques were used to automatically adapt to each individual learner (Carbonell, 1970; Self, 1974). AI-enabled technologies in education have evolved in three directions: (1) learner-centric AI, (2) teacher-centric AI, and (3) managerial/systems-centric AI. In the following, we first focus on teacher-oriented AI and provide an overview of technologies and challenges in relation to questions of pedagogy, ethics and sustainability. UNESCO divides AI applications in education into three categories: (1) education management and delivery, (2) learning and assessment, and (3) teacher empowerment and classroom improvement (Fengchun et al., 2021).

In the following, three visions are developed of how teachers can be supported with the help of AI-supported solutions. The focus is on recognizing potential in students and training future skills (Wang et al., 2024) as part of face-to-face teaching, which is accompanied by digital learning management systems and digital learning assistants.

The considerations are based on the existing AI-based learning management systems, which were found via a keyword search on the Google and Ecosia search engines in September 2022. The search terms used were "ai based lms", "ai powered lms" and "ai edtech". The direct translation of the keywords into the Hindi language did not bring any new findings to light. The list of AI applications in the education sector in the form of an AI map for India supplemented the result (Platform Learning Systems, 2022).

2.1.2 Future Scenario

Education management and implementation scenario

Professors spend a lot of time preparing, uploading and adapting content for students. AI-based learning management systems (LMS) of the future, professors suggest existing tutorials during the semester preparation period based on the course description and the learning objectives contained therein or skills to be acquired, which they integrate into their classroom teaching, which is supported and accompanied by digital instruments. With this method, natural language processing forms the basis for linking different tutorials: By analyzing terms

in the title and description of a course, parallels to existing tutorials and courses can be shown and thus cross-references can be created. The tutorials can be flexibly integrated into the physical teaching or expanded or adapted using adaptive templates. The languages of the tutorials can be freely selected by the students and translated in real time. This enables the teaching content to be focused on information that is not covered in existing tutorials. This makes it easier to contextualize or deepen the specific topics of a course. Tutorial scripts are created automatically. Competences, abilities, skills and strengths are the subject of continuous analysis based on profiles. In this way, the curriculum can be systematically planned and managed across the entire institution. Examinations and teaching content as well as the resulting study feasibility and time load are personalised, estimated and extrapolated. Learning and performance types are also taken into account, which can influence the processing deadlines, learn formats and learn methods suggested by the system to students. The system actively explains to the students which learning style or which learning strategy is to be pursued in order to become more efficient.
To protect the privacy of the students, there is the possibility to decide for yourself which of the data should be made anonymous or personalized for the lecturers. Lecturers can thus create analyzes at any time, even if assignments to specific people are not made without their prior consent. This enables trusting relationships to be deepened, for example in the context of mentoring. The design of the learning situation takes place in a duet between a professor and a teacher. The implementation is carried out by lecturers, tutors and professors. Professors and students are accompanied by a mentor throughout the semester.

Scenario for learning and assessment

based systems provide feedback on the performance status during learning and suggest next learning steps (e.g.: Take a break! Watch the video xy! Talk to peers! Do a coaching session!). The performance status is recorded via emotional affects in the face and eye movements. These suggestions are intended to help students to reflect on their own self-regulation processes over the long term. Tests, exams and quizzes are automatically created and corrected from images and texts using neural networks. In real time, chatbots provide information on errors (spelling), suggestions for wording (ChatGPT), suggestions for illustrations, other methods of calculation or better solutions (legal case discussion). In particular, risky or dangerous learning situations are depicted using virtual realities (e.g. chemical reactors, mediation of wars, de-escalation of captivity, learning treatment techniques, etc.). Careers continue to be determined by the individual; AI-based systems only make suggestions. Purpose, vision, goals and interests are tracked by the system and used as the basis for the learning content and the coaching of bots and teachers. Blind spots about the self are expanded via communication analyzes in groups, which provide information about existing strengths, constructive or destructive dynamics, values or behavior. Evaluations no longer only take place at the level of the teachers, but are expanded to include feedback from mentors, coaches and peers. This creates a 360-degree impression. In addition to learning future skills, the focus is on personality development and alignment with personal goals in life. Learners move in intelligent spaces that adjust to their emotions and body temperature. Flow states are recognized by determining the heart rate (Rissler et al., 2020; Kakhi et al., 2025). Care is taken to ensure that these are not interrupted by phone calls or people coming in. Telephones are automatically muted and digital door signs display the information "Do not disturb" (if necessary, doors are also actively locked). The level of motivation and performance is reported back via language assistants or chatbots and positively strengthened or consciously activated.
Data from students and professors is collected and evaluated sparingly in order to conserve energy reserves. Energy sources are exclusively renewable and the waste heat from the servers. The focus is on acquiring skills and improving performance. In addition, the quality and structure of the data are constantly being optimized by involving the people involved and machine learning processes. For example, teachers check the evaluations and correct incorrect translations, while students give feedback on the composition of the group or on the matching. Diversity and bias officers ensure the quality of the results from the analyzes of the AI systems. Only those situations are shown in VR/AR that harbor a certain danger or risk for people or the planet. In this way, the ethics and sustainability of the procedure are preserved. Coaches and mentors are selected and supported in a lengthy process so that their attitude and intentions fit the program.

Vision to empower teachers and improve teaching

Insights into the potential and intelligence of people are already generated in elementary school and in secondary schools. In addition, a variety of interests and forms of communication of student groups can be identified with the help of social media analyses.
These findings are evaluated automatically and suggestions for meaningful group compositions or supplementary courses to the standard curriculum are derived from them. Personalized learning paths as well as lecturers and

peers are put together based on existing potential. You can draw from a global staff and student pool. Institutions no longer appear alone in the network, but in association with local and international partner institutions. Lecturers and mentors are supplemented by intelligent or domain-specific tutoring systems and matched with suitable students. The matching is based on insights into personality traits, skills and behavior of lecturers and students. eTutors supplement the learning relationship with the knowledge meta-level. For example, they signal discrepancies at the individual or group level, which is recorded by sensors in the room. Tutoring systems suggest communication content and formulations that have a de-escalating and inviting effect or adapt to the other person's way of communicating. eTutors act as coaches for lecturers, encourage and strengthen positive beliefs. They also draw attention to over and under-challenged students and recommend interventions.
People who use eTutoring are continuously involved in their qualification. Teachers give feedback on whether the system has correctly identified situations on an individual and group level and whether the interventions used were helpful or at which points the suggestions of the eTutoring were deviated from. In order to make the process as simple as possible, voice and simple text inputs are used to a large extent. Teachers are also supported by pedagogical experts and can exchange information in regular peer meetings. When putting together networks, attention is paid to diversity criteria.

2.1.3 Implications
In order for the conditions described in scenario 1 to be implemented, certain decisions must be made and preconditions created. These relate mainly to decisions at the level of the university management and the creation of an appropriate teaching and infrastructure environment. For a successful symbiosis of man and machine, it is important to comply with ethical, social and legal conditions at universities and to create a supportive environment at Central level so that feasibility is guaranteed:

Macro level (Central and State)
- IT managers regularly ensure that the infrastructure is up-to-date and secure (external).
- Mentors provide education and training for teachers and learners on AI-based systems.

Meso-level (Universities)
- Together with the deans, the university management is developing a cross-university strategy for the training of future skills.
- Every university has a strategy for data and AI, which defines, among other things, the handling of data and the growth of skills. This strategy should be developed in a participatory manner with all stakeholders.
- There is a cross-university planning of the study programs and electives by the program directors.
- Before the module manuals are published or external video content is made available, a quality committee checks their relation to the university strategy and the didactic concept. It also ensures that diversity and data protection guidelines are observed.
- Mediators accompany the systemic change.

Micro level (Teachers)
- Teachers receive an introduction and regular training from mentors on AI-based applications and their embedding in possible learning situations.
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2.2 Scenario 2: Monitoring of continuing education and lifelong learning
2.2.1 Background
Further education and lifelong learning affect a large part of the Indian population. In 2020, around 60 percent of 18 to 64-year-olds took part in further training (Ministry of Education, Government of India, 2024). The question arises for companies that provide further training as well as for individual learners: What is the right further training offer for your own context? Currently, the search for further training takes place, for example, via the search engines of the Ministry of Labour & Employment and other private agencies further training platforms (e.g. Oncampus). Those interested in learning enter a search text (e.g. “digitization”) and set a filter (e.g. by cost and duration of the offer). However, other important factors are not taken into account, such as the prior knowledge of the learners, the level of competence that is to be achieved and the dependencies between

further training courses. This scenario is about what the search for further education offers might look like in the future. We first describe the desired behavior of the system and then the necessary measures to make such a system possible.

2.2.2 Future Scenario

At the beginning there is a dialogue with a chatbot that helps learners to identify individual training goals (Wollny et al., 2021). Is the further training more for self-development, for preparation for the next career step or for qualification for a specific topic? Which competencies correspond best to your own goal? At the end of the dialogue, learners (and the system) should have clarity as to which level of competence should be achieved in each case.
The captured competency goals themselves must conform to a machine-readable catalog, preferably an ontology, that also captures the relationships between competencies—for example, that the "data science" competency requires programming skills, likely in languages like Python or R (Stancin et al., 2020).
In a next step, the system determines which level of competence the learners already have, for example through certificates already obtained, self-reports or tests. From this, the system then calculates the gap to be closed between the learning objective and the existing level of competence.
Based on the knowledge gained from queries, the system begins the actual search for further training offers. The offer should be as close as possible to the existing level of competence and suitable for getting closer to the further training goal - for example by achieving a partial qualification for a career goal. To this end, all continuing education offerings must provide machine-readable metadata about the required entry level of competency and the expected level of competency upon completion. There is also a whole range of other criteria, such as: Does the offer fit the deadline? Is it fundable? Is the course format appropriate (online or face-to-face, level of support)? The system should allow learners to enter these kinds of additional criteria as needed to filter the search results. In addition, the system should make it possible to understand the automated recommendation (why is this course recommended to me?) and, if necessary, to adjust the individual data in order to correct errors - or to make your own choice, independent of the automated recommendation (Magrani & da Silva, 2024). Natural language processing can help with the collection of all metadata for the offers (especially language models, as they are also used in ChatGPT).
After a course has been selected and completed, the system receives information on how the competency level has progressed, either in the form of a final test result, a certificate or a report by the learner. Based on this information, the system can adjust the skill level assessment and recommend the next course. Overall, the system should continuously accompany lifelong learning and always recommend the offers that match the current level of competence and the current goals.
It is important that the system we designed not only helps learners, but also the institutions of further education: By evaluating the search queries, it is possible to find out which skills are particularly in demand and where there are still gaps that can be closed with new offers.

2.2.3 Importance of Artificial Intelligence in Continuing Education

Every step of our scenario contains parts of artificial intelligence. Chatbots, for example, are considered artificial intelligence and are already being used in part for mentoring and advisory purposes in education (Wollny et al., 2021). For our scenario, a chatbot must be able to extract competence goals from the dialogue with the learners: Which competence should be learned at which level? This requires natural language processing techniques.
So that the system can automatically search for suitable further training offers, the offers must also be assigned to the competencies from the machine-readable catalogue. While this can be done through human labor, it is arguably helpful to use automatic language processing to extract the competency assignment from the natural language descriptions of the training content.
The recommendation itself can then be made via AI-supported recommendation systems (Magrani & da Silva, 2024). However, it is not enough to find offers that cover the desired competences; the offers must be suitable for closing the gap between the actual level of competence and the target level of competence. To do this, the system must have information about the current level of competence of the learners and the effect of the respective offer on the level of competence.
The actual level of competence can be determined using certificates, self-reports or assessments. However, all of these indicators must in turn be assigned to the competencies that are also available in the machine-readable catalogue. This assignment can either be done by human work at the educational institutions or is supported by automatic language processing.

After all, every offer needs information about what entry level is expected for each relevant competence and what level of competence can be expected after completing the course. Ideally, this information is provided directly by the educational institutions themselves in machine-readable form, otherwise this information must be estimated using natural language processing or testing.
In several places we note that relevant data can be collected either via human handwork or via automated processes (particularly natural language processing). A hybrid strategy is probably the most promising, where the production of the machine-readable information is proposed by AI tools, but follows human-developed schemes and can be corrected by humans (Meyer-Vitali, 2019).

2.2.4 Implications

Macro level

- The standardization of the metadata of further education offers should be promoted (Noguera et al., 2024). In particular, a common standard for awarding competencies (e.g. an evolution of ESCO) should be applied as soon as possible.
- The national education platform or national further education platform should be expanded into a database that collects metadata for all Indian further education offers and makes them available in a uniform format.
- Advice and support should be provided to enable further training providers to label their offers with machine-readable metadata.
- Funding programs should support projects that develop recommendation and advice systems using the new metadata (e.g. based on current INVITE projects).

Meso level

- Education providers and industry representatives should agree on machine-readable and standardized competency models and catalogs within individual industries and promote linking across industries - for example moderated by the national further education platform, the national education platform, (INVITE) research projects or ESCO.
- Training providers should mark their own offers as soon as possible with metadata about their own offers (skills, duration, costs, entry conditions, achievable certificates, etc.)
- Education providers and research institutes should develop tests for all competencies relevant to the offers and validate them scientifically as far as possible. This also serves to ensure quality.
- Research projects and EdTech companies should develop supporting tools for educational providers to support and partially automate the machine-readable description of courses.
- Education providers and platforms should collect anonymous data on the use of the offers (which offers were visited in which order?) and the learning success during use.
- Research projects, educational platforms and EdTech companies should develop recommendation tools and make them available to learners and coaches.

Micro Level

- Learners should familiarize themselves with how the recommendation and counseling tools work and make an informed decision about how much information they are willing to hand over in order to receive a customized recommendation - and which criteria are particularly important to them in their own further education.
- Learners should report back to platforms and providers if they are dissatisfied with the tools and offers provided.

2.3 Scenario 3: Artificial intelligence as a support tool in the school context

2.3.1 Background

Although homework has long been the subject of controversy, teachers, students and parents mostly consider homework to be useful and necessary (Ciraso-Calí et al., 2022). However, the question of whether homework actually has a positive effect on school competence development has not been clearly clarified empirically. The homework frequency and continuity, but not the homework time, seem to have positive effects here. The handling of homework in class and the type of homework control are also relevant. According to Wang et al. (2025) a completion and solution check can be distinguished from a process-oriented homework check. A process-oriented homework check, in which the teacher addresses mistakes in the homework, attaches particular importance to solution processes and new solution paths, and individually appreciates the efforts and efforts of

the students, is particularly advantageous. However, such a type of homework control requires a great deal of time and resources and can therefore often not be guaranteed in the classroom. At this point, technological support systems are a conceivable way.
On the one hand, these could relieve the teachers' time and, on the other hand, offer the possibility of direct and individual feedback for the students. Feedback is one of the most important factors influencing learning success (Hattie & Timperley, 2007; Kluger & DeNisi, 1996) and learner motivation (Shute, 2008). Automatic adaptive feedback as learning support during homework has many advantages, as it enables immediate feedback. Feedback that promotes learning offers students the opportunity to uncover their mistakes and misconceptions, to correct them and to develop helpful problem-solving strategies (Van der Kleij et al., 2015), thereby reducing the distance between the current and the desired learning level (Hattie & Timperley, 2007).
In the following we outline a possible application of a fictitious AI-based homework support in a school context. We embed this in the NaWi lessons. In some states, NaWi is a preparatory collective subject for the future subjects of physics, chemistry and biology in the 5th and 6th grade. Implications for the feasibility of such a scenario description in everyday school life can be found in the following section 2.3.3.

2.3.2 Scenario
Nesrin and Mila attend the 5th grade together at a secondary school with an open all-day concept. The two meets in the afternoon to do their homework together. They should prepare a protocol for NaWi for an experiment that they carried out in tandem with the entire class the day before. Nesrin and Mila carried out the experiment together, made some notes on it and also made assumptions about their observation results in advance.
However, the two of them do not write their test protocol by hand, but do their homework on a special digital platform that is used at their school for all subjects for homework assignment and completion, the HA-Box. This platform makes it possible to do and hand in homework alone or together in tandems or small groups. The students do not have to enter their homework in their homework books - which is sometimes forgotten - but they are informed by the platform via message directly to their smartphones about the homework to be done and reminded of upcoming submissions. The teachers can submit and collect the homework directly via the platform. There you can answer questions about the homework and adjust the deadlines individually if necessary. The teachers can also see which students have submitted their homework on time and which homework is still missing. The teachers can then either discuss the homework together in class or give individual feedback via the HA-Box. This feedback is suggested by the HA-Box and can be supplemented or changed by the teacher as required. With closed tasks, the students can see which solutions are right and which are wrong immediately after completing the tasks. The HA-Box has prevailed in Nesrin's and Mila's school mainly because the company that developed the platform offers very good support, which answers questions quickly and easily and helps with problems via video consultation hours. There is also a popular online tutorial for the teachers and an explanatory video for the students who register independently with the HA-Box from grade 5 onwards.
Nesrin and Mila sit at Nesrin's home in front of their school tablets, which they are allowed to take home with them in the afternoons and at weekends. You take another close look at the NaWi homework. They should first create a material list in bullet points, then add a cloze to the experiment and briefly describe their observations. Finally, in a short text, the two should compare their observation results with their assumptions and justify which mixtures of substances filtration is a suitable separation process for.

2.3.3 Implications
When testing and using such a fictitious application in a school context, different questions and the resulting implications arise. Of course, these arise not only for the homework context, but for the AI-related design of school learning opportunities as a whole.
Macro level (Central and State)
- **Financing, provision and maintenance of a digital infrastructure in schools:**
  In order to be able to implement AI-based systems in schools, the Central and State governments must provide sufficient financial resources in a cross-state strategy so that all schools are equipped with a well-functioning WLAN connection and school laptops or tablets in a timely manner. This is necessary so that all students can benefit from AI-based applications, even those who do not have access to appropriate devices privately.
- **Concretization of the GDPR for the use of AI-based tools in schools:**
  The General Data Protection Regulation (GDPR) is an EU law that regulates the processing and sharing of personal data. It is currently often unclear in schools which digital tools may be used under which conditions in order to ensure compliance with the GDPR. Clear recommendations for action are required for schools here, which clarify what scope for action there is in the school context and how AI-based tools can be

integrated into school learning in compliance with the GDPR. Appropriate specifications and recommendations for action must be formulated at Central or State level and made available to all those involved in a transparent and understandable way.

- **Creation of nationwide qualification offers:**
  School management, teachers, parents and students have different information needs regarding the use of AI-based systems in the school context, which must be addressed specifically to the target group:
  - For school management, the framework conditions for the use of AI-based systems must be clarified in a comprehensible manner.
  - Teachers must receive information about what AI-based systems can do, what potential and limits exist and what changes the use of AI-based systems can bring about, for example in performance recording and evaluation. Sometimes teachers also report reservations and concerns about the use of AI in schools (Wang et al., 2024). Such topics must be addressed and discussed openly. Appropriate qualification and exchange offers can be made by the respective state institutes.
  - Parents must agree to data processing by AI-based systems up to the age of 16 for their children. To do this, they must be informed about the advantages and possible risks of use. They need information about what data is being collected from their children and also how the systems work so that they can support their children at home if necessary.
  - Pupils must be given the opportunity to familiarize themselves with how AI-based systems work. It is also necessary to inform them about which of their data is processed and stored and how.

Meso level (Schools and Companies)

- **AI infrastructure:**
  Calculation-intensive AI models for free text evaluation in applications such as the HABox require a strong IT infrastructure. Servers capable of running AI inference are expensive to purchase. In addition, there is the management of the infrastructure, network costs and electricity costs, which should not be underestimated. Large AI models cannot be operated on school computers or on the end hardware of the students. Therefore, on the one hand, there is the possibility of purchasing such equipment, on the other hand, cloud services can be used. It must be considered here that servers in cloud solutions are often located outside the EU. There may be less restrictive data protection regulations there. It is therefore important, in consultation with experts, to evaluate how long-term an infrastructure can be created that addresses these implications.
- **Internal school data protection concept (DSK):**
  The DSK must be expanded with regard to the use of the AI system. According to Art. 37 of the GDPR, a data protection officer must be appointed in every school if data processing according to Art. 37 takes place there. This person can be a trained teacher or an external person. It is important that she has specialist knowledge in the area of data protection law and data protection practice (Article 37 (5) GDPR). The person must be familiar with the implications of dealing with AI.
- **Involvement of the companies in the application context:**
  Companies must provide multipliers who accompany the use in the school context. When introducing a new system (possibly digital), company employees should offer target group-specific information events for parents and teachers. Teachers must be introduced to the system in detail in order to keep the training period as short as possible given the diverse requirements of their everyday school life. Explanatory videos available online and a chatbot should also offer teachers the opportunity to receive support if they have questions or are unclear. Explanatory videos must also be made available for the students, which make the introduction to the system as simple as possible and thus relieve the teacher.
- **Ethical dilemma of denied consent:**
  Schools have to decide how to deal with it if parents or students over the age of 16 do not consent to data processing by the AI-based system. Then only anonymous use of the system would be possible. It would therefore no longer be possible for the teacher to gain insight into the individual learning outcomes of the students concerned and provide them with personalized feedback or additional materials. It would then only be possible to evaluate the learning development cumulatively for the entire learning group. However, this would render many advantages of the AI-based system obsolete. Alternatively, if their parents or they themselves do not agree, students would have to switch to analog offers and might not experience the same educational opportunities as their peers. Schools need to address this dilemma and make a decision that is ethical for them.

Micro level (level of action of individuals)

- **Freedom of choice and room for manoeuvre in the use for teachers:**
  On the basis of the qualification offers (see macro level), teachers must be able to decide autonomously when and how they didactically integrate such an AI-based system into their (subject) lessons. In our view, this freedom of choice is a prerequisite for the social acceptance of AI systems.
- **Use-related freedom of choice as well as information about possible disadvantages:**
  The parents of the students or themselves from the age of 16 must agree to the data processing by the AI-based system. If they don't do this, they should be aware of possible disadvantages (no individual feedback, no opportunity to ask questions in the system, etc.) based on the information provided to them.
- **Training data of the AI and development of the algorithms:**
  The discipline of Natural Language Processing (NLP) deals with the analysis of natural language such as the evaluation of the free texts generated in the fictitious HA box. Modern systems increasingly rely on machine learning (ML), - especially deep learning (DL) methods (Johri et al., 2021). New implications arise from the use of these technologies. For example, training such an artificial intelligence requires data that is either self-generated, purchased, or taken from freely available sources. Since the writing style and vocabulary in freely available datasets are mainly composed of specialist literature and web content (Gao et al., 2020), this could have an impact on the quality of integration into the software system in the school context. Pre-trained language models are trained on precisely this data. Therefore, the developers must be aware of possible biases and biases and try to minimize them with regard to the school context. From a technical point of view, data must be collected in compliance with data protection regulations. To do this, the question must be answered as to which parts of the data can already be anonymized during the collection and which data are stored and how cleaned. Developed algorithms must also be checked for any weaknesses and maintained.

3. Fields of action, discussion and outlook

ChatGPT impressively illustrates how dynamic developments in the field of AI are. Against this background, the three future scenarios presented for AI in institutional education must be partially recontextualized. The current media attention may accelerate the need to deal with AI in institutional education. At least AI in education is currently moving into the center of many educational debates. It is essential that stakeholders at the micro, meso and macro level enter into a dialogue and constructively discuss the potential and challenges.
The aim of this discussion paper is to strengthen the discourse on the conditions for success in the use of AI in the educational context and to identify common fields of action for key stakeholders. With this focus, five overarching fields of action are derived from the outlined scenarios of further education, university and school as common interface areas of the central stakeholders:

1. Interdisciplinary collaboration

The integration of Artificial Intelligence (AI) in education impacts a wide range of stakeholders, each bringing unique perspectives and expertise. To address this complexity, interdisciplinary collaboration is essential—bringing together experts from pedagogy, psychology, instructional design, educational technology, and management studies. Indian universities should foster research frameworks that enable data sharing and critical evaluation of AI's implications in diverse educational settings.
Additionally, it is important to involve students and teachers throughout research and implementation processes. Research initiatives and EdTech startups should establish stakeholder advisory boards to ensure that the voices of all relevant parties are heard and reflected in outcomes.
Universities can create or join national-level networks and platforms that support such collaboration—for example, initiatives like the National Digital Education Architecture (NDEAR), the AICTE's NEAT (National Educational Alliance for Technology), or consortia hosted by bodies like UGC and NAAC. These platforms can serve as hubs for policy dialogue, research partnerships, and the responsible adoption of AI in Indian higher education.

2. Qualification offers and competence development

Basic data and AI skills are required for a considered and mature use of AI in institutional education and in general in everyday life and at work. Qualification offers should be systematically implemented and offered in educational institutions, especially for learners, teachers, coaches and decision-makers. It is essential to address data literacy and AI basics both as learning content and as a method (Leite, 2025). In this context, integration should also be discussed, for example how data can be collected and used meaningfully in learning scenarios. With a focus on universities, for example, increased cooperation with university didactic centers and technical facilities is an option. A concrete application example for the systematic integration of pedagogically prepared AI learning content in university teaching is the fellowship program of the KI-Campus, which has now resulted in three years. How the open digital learning offers (Open Educational Resources) on the subject of AI (didactically) were used in various departments is presented in two anthologies (Anghe et al., 2025, Xiao, 2025).

3. Digital infrastructure and human resources

Digital infrastructure in the form of computing power and secure data hubs is required as framework conditions for the use of AI in education. In addition, educational institutions must hire qualified IT staff to administer educational technologies at the institutions, accompany the introduction of new technologies and be constantly available to answer questions from students and teachers. Here it is important to take into account the needs and framework conditions of all actors. With regard to the status of the IT infrastructure in Indian schools, the study by Witthöft et al. (2024) far-reaching insights into the status quo. Challenges in expanding the digital infrastructure exist in particular in the form of a lack of human, financial and time resources. Eight recommendations for action are presented at the level of the Central and states, municipalities and the Conference of Ministers of Education (KMK), for example the creation of cross-state technical standards, IT specialist and qualification offensives as well as the professionalisation of school IT operations and support through inter-municipal cooperation are proposed the involvement of IT service providers is recommended (Witthöft et al., 2024). Where educational technologies from the private sector are used, a closer connection with the respective provider company should also be examined, for example the integration of company-side support structures.

4. Ethics and data sovereignty

The use of learner data must be supported by data protection regulations, and it is essential that individuals retain sovereignty over their data. Data protection should be considered directly in the development in order to promote innovation and not prevent it. In order to assess ethical, legal and social implications in development and in use, advisory boards (e.g. Ethical-Legal-Social-Implications (ELSI) advisory boards) or oversight boards of stakeholders should be established and professionalized. This requires simplified and standardized handling that supports companies, developers and educational institutions in operationalizing ethics and data protection.

5. Interoperability of data in educational contexts

All scenarios of AI in education shown are based on the assumption of availability and interoperability of data in educational contexts. It is advisable to build on existing efforts and to establish and operationalize the standards for collecting and exchanging (meta)data. It is essential that the standards are developed, supported and implemented jointly by all relevant actors. Examples are the standardization of competence descriptions based on ESCO or the extension of the description of metadata for learning objects (Santos-Hermosa, 2023). On this basis, available offers can be enriched and networked more easily.

The derived fields of action clearly show that networking and joint efforts of all stakeholders are necessary in order to successfully bring AI to an application in education. This discussion paper is intended to provide impetus for more exchange, cooperation and cooperation between relevant stakeholders in institutional education. The aim should be that the identified fields of action of networks and cross-stakeholder working groups are implemented in concrete measures in order to establish the strategic embedding of AI in educational scenarios in the long term.

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