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Adaptive Learning Technologies and Educational Innovation for Future Skill Development

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Abstract

Technology and the economy are evolving at a rapid rate, and this is challenging conventional curricula and the way subjects are taught. AI-powered adaptive learning technologies offering personalized content, pacing, and feedback, based on an artificial model of the learner, are increasingly recommended as a solution. This conceptual paper reviews the latest literature on adaptive learning and proposes a comprehensive framework for the future development of skills. It brings cognitive theories into technologies for learner modeling, content sequencing, a four-level adaptive architecture with governance and interoperability protections, and future-ready competencies into algorithmic intervention pathways. It then delves into questions related to institutionality, inefficiency in teaching and measurement of skills, algorithmic bias, and the dehumanization of teaching and the ethics of education surveillance. The paper ends with suggestions for practitioners and policymakers and an agenda for further research.

Keywords: Adaptive Learning, Artificial Intelligence in Education, Personalized Learning, Future Skills, Educational Innovation, Learning Analytics.

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The Pedagogy of Personalization: Rethinking Educational Paradigms

Breaking the Industrial Mold

Much of the organization of contemporary education systems has been passed on to them from the industrial societies. Instructional programs were standardized, and students learned at the same rate with the same sequence of content, and mastery was assessed by the ability to duplicate the learning. It was a good model to use in mass education, but it demanded that the students be interchangeable and that the content of knowledge be learnable in a different sequence and time. Both these suppositions are no longer readily accepted. Employers' and society's desired skills do not follow a linear progression over time, but are evolving at a much faster pace than traditional curricular cycles, leaving some learners with inadequate offerings and others with a lack of learning.

All of these pressures have attracted attention to technologies which can be used to deliver personalized teaching at a massive scale. Another recent study indicates that AI-based adaptive learning is key to sustainable education transformation, and that systems that learn from and adapt to individual learners can make education more inclusive and sustainable (Strielkowski et al., 2025). The research landscape is reflected in the research record itself; a bibliometric study of adaptive learning in education, in which more than 20 years (2000-2022) of research in this field have been mapped (Jing et al., 2023). Adaptive learning is thus no longer an experiment but now a part of the mainstream of concerns. It is an accepted field, and claims must be explored and critically analyzed.

The Algorithmic Classroom

The algorithmic classroom is an untidy class where things are not scripted in advance. The system observes the learner's behavior in response to the material presented, infers what the learner knows, what he does not yet know, and sets up the next activity, explanation, or hint accordingly. This approach has three mechanisms: first, AI that gets to know the learner's state; second, dynamic content delivery that selects or develops the next learning step; and third, real-time feedback loops that close the action-response gap.

Applications are proving to be effective. There are reports of improvements to the adaptive learning process when using AI in education and to the learning-teaching process in general in the classroom context of adaptive learning strategies (Demartini et al., 2024; Rincon-Flores et al., 2024). A systematic review of AI and adaptive education has identified the tools that are employed in personalized learning, and how varied (Hariyanto et al., 2025). It is no different with these studies, which are of differing contexts, modalities, and scales, and which yield results that cannot be compared.

Scholarly Objectives and Roadmap

The aim of this paper is to discuss three research questions. What is the way to bring together these theories of cognition and learning with intelligent systems so that adaptive learning can be designed? Secondly, what is needed in terms of an architecture and governing structure to make adaptive technologies work for developing future-ready skills? Thirdly, what are the implementation issues and ethical concerns that have to be considered if such systems are to be put into use responsibly? The study is a conceptual and integrative study. It does not provide new primary data, but it tries to foresee from the studies in the reference list, and formulate an analytical framework out of that.

The paper is organized the same as above. Section II presents the theoretical background, linking cognitive science with intelligent systems. Section III presents the adaptive skill framework and architecture. Section IV discusses implementations in institutions and measures of competence gains. In Section V, algorithmic bias, equity, the human element, and privacy are discussed. Section VI closes the argument and offers suggestions for teachers and policymakers, along with research directions for the future.

Epistemic Foundations: Merging Cognitive Science with Intelligent Systems

The Architecture of Human Cognition

This is because all adaptive systems, whether explicit or implicit, are based on a model of human learning. Constructivist approaches emphasize what learners can build on their prior knowledge (or lack thereof), so teaching conceptualization should come from the learner's perspective, not the curriculum's. Also, according to cognitive load theory, working memory is limited – the material presented too quickly, too complex or not sufficiently supported will leave the learner overwhelmed; too easy will leave the learner's efforts wasted. The zone of proximal development is a range of tasks which the learner cannot do independently, but can with guidance. Together these ideas offer a good design principle for adaptivity: 'Keep each learner in ZPD at a manageable load level and reasonable level of productive challenge.

Learning does not happen through 'setting up learning' institutions. Literature on technology and innovation in education highlights the importance of pedagogical goals and institutional readiness to connect education and technology (Çelik & Baturay, 2024). Theoretical learning in organizations occurs at the organizational level; adaptive leadership and change self-efficacy are linked to organizational innovativeness (Chughtai et al., 2024). Cognitive theory in this paper is the methods used to support an individual learner, and organizational theory is whether the learner's home institution will support the individual learner.

The Tech-Pedagogy Nexus

Technology is how things work and reflects the principles of cognition. Learner-modeling engines log the changing knowledge estimate of the learner, machine learning models predict the performance of the learner on future tasks, and knowledge-tracing approaches describe the dependency relations among skills and concepts, which allows for the selection of the next task that will fill the "hole" that is most important for the learner. A literature review of AI-based adaptive learning in e-learning identified the use of adaptive techniques to tailor learning content, delivery speed, and evaluation in an e-learning environment (Gligorea et al., 2023). The review also reveals a huge variation in the repertoire, and no single method was predominant.

This also involves a shift in the role of the instruction provider in terms of technology. The role of pedagogical agents in supporting learners by guiding, explaining, and encouraging them to provide personalized adaptive learning has been discussed (Apoki et al., 2022). As education gradually shifts from the technological focus of Industry 4.0 to the human-centered focus of Industry 5.0, smart education focuses not only on software but also on the convergence of intelligent education, robots, and IoT (Adel, 2024). The commonality is growing sensory richness, responsiveness, and autonomy in the learning environment—which extends the opportunities and responsibilities of those shaping it.

Theoretical Blind Spots

There are 3 blind spots in the discussion of adaptive learning. First of all, algorithmic reductionism. There is an unavoidable simplicity to a learner model, and what it can't model, for example, curiosity, motivation, identity or the importance of productive struggle, is left in a way that it doesn't matter. If the ultimate goal of education is that which is measurable, then education is in danger of becoming what is measurable. The second is that of social learning. The individualized optimized pathway can replace the approach in constructivist traditions that focuses on dialogue, cooperation, and joint meaning-making. The emphasis on humans in Industry 5.0, however, indicates the need to put humans at the center of design. The third is the "digital equity gap. However, in adaptive systems, devices, connectivity, and digital self-confidence are de facto taken for granted, and the broader body of technological or innovation literature in education cautions that benefits of technological use will not be equally distributed.

Architectural Blueprint: Engineering the Adaptive Skill Framework

Structural Anatomy of the Adaptive Ecosystem

The adaptive ecosystem proposed in this paper has four levels, as illustrated in fig. 2, preceded by a governance level that cuts across all levels. The first level uses learner telemetry: Interaction logs, assessment answers, and interaction signals while the learner works. The second level is a diagnostic cognitive engine that converts this raw evidence into an interpretable model of the learner, used to estimate mastery and detect recurring misconceptions. The third is a dynamic content-sequencer (which determines what skill path to play next, changes the difficulty level, and provides feedback and hints). The final tier is outcome analytics, which delivers a summary of mastery, retention, and skill gain to consumers and teachers and passes the evidence back up to the other tiers and the model’s 'revise'.

The design of this layered system is inspired by the literature that discusses adaptive systems in terms of learner modeling, content adaptation, and feedback (Demartini et al., 2024; Hariyanto et al., 2025; Gligorea et al., 2023). The tiers can be separated if this is helpful. These may be developed individually, tested and replaced individually; the diagnostic logic may be checked independently of the content logic; and teachers have the ability to intervene at the point at which a problem occurs. Most importantly, adaptation is an ongoing process and not a calibration, as can be seen in the feedback loop on the left side of the diagram.

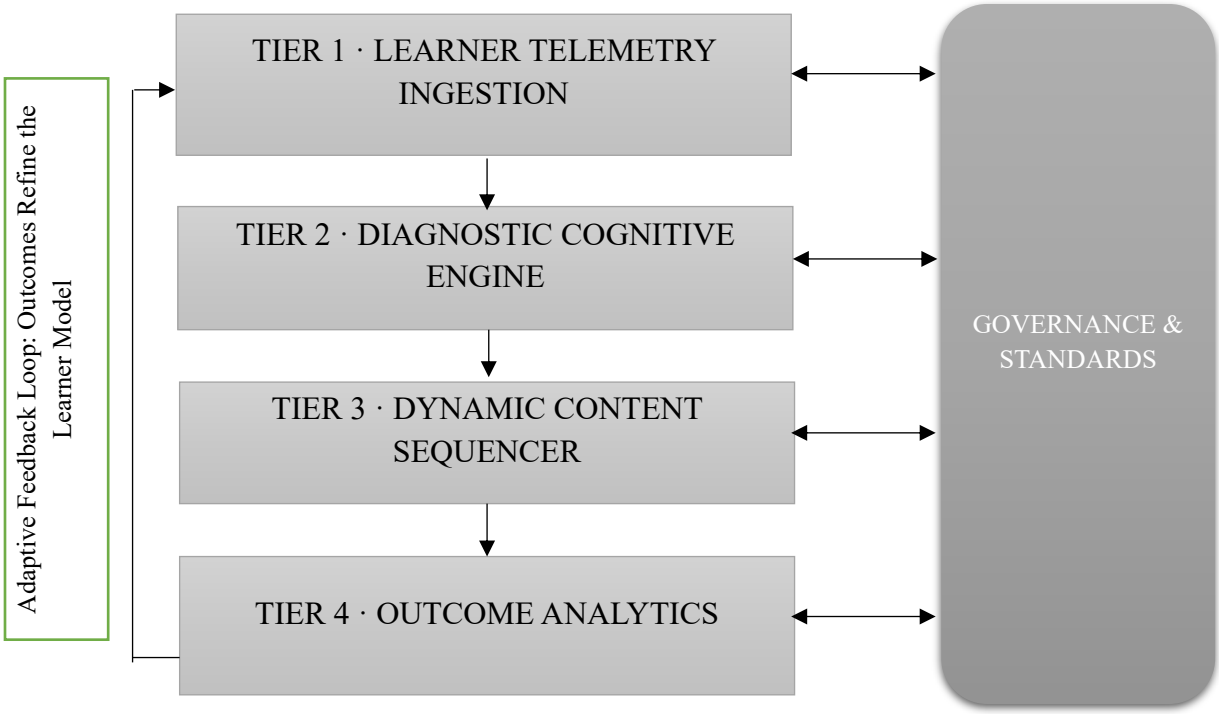


Fig. 1: Four-Tier Adaptive Learning Framework Integrating Cognitive Diagnosis, Content Sequencing, and Outcome Analytics

Four layers of adaptive learning are shown in fig. 1. Learner telemetry ingestion: Ingests interaction logs, assessment responses, and engagement signals. The knowledge tracing and learner modeling, as well as misconception detection techniques, induce learning needs from the diagnostic cognitive engine. The dynamic content sequencer selects the skill paths, adjusts the difficulty, and provides hints and feedback. Outcome analytics is based on educator reports and dashboards to determine mastery, retention, and skill gain. A learning cycle that updates the learning model and learning decisions based on learning outcomes. Governance includes all aspects of privacy and consent audits, data standards and access control, security, bias audits and more, to facilitate responsible personalization and continuous learning and development.

Skill-Mapping Vectors

Any plan for the future development of skills needs to link theoretical skills to practical action. Each competency is a collection of observable skills, and each skill is linked to a family of learning activities and evidence of growth. For example, complex problem-solving skills can be divided into problem framing, choosing a problem-solving strategy, checking work, and reviewing results. The adaptive engine can then be used to provide a scaffolded task with prompts that can be gradually dropped out, and the learner can be prompted to describe a chosen strategy. Progress is shown through evidence of independent strategy selection and correct final answers.

Digital Literacy is another case. It is also a skill of technical fluency and an ability to evaluate information, so adaptive intervention requires assistance with the use of tools and practice in evaluating the reliability and usefulness of information. Cognitive agility is the ability to switch between concepts, representations, and approaches, and it involves interleaved practice and multiple contexts for problems and prompts to transfer to the new ones. In each, the task of the engine is to deduce the position of the learner in the vector and choose the following activity in the sequence that is going to extend the vector. The vectors are clear, and hence can be reviewed by the teachers and edited, avoiding any hidden reductionism as mentioned in Section II.

This sort of knowledge of capabilities also provides some understanding of what adaptive technology cannot do by itself. Educators and peers provide the human interaction needed for skills such as collaboration, ethical thinking, and communication, and the system is relegated to a supporting role in that; therefore, the system must prepare the learner for, and provide evidence of, the skills.

In the final phase, the focus should be on reviewing the skill vectors in the context of evolving needs in society, the world of work, and the lives of the learners. The framework is explicit about its competencies, which means that it is

not about retraining a black-box model, but rather an issue of editorial and pedagogical decision, in which teachers, employers, and learners can all participate. One of the advantages of the framework is the flexibility in the content of the learning outcomes for future-ready skills, which is one of the reasons why it is appropriate for a time when the content for future-ready skills is not known.

Interoperability and Data Governance

Adaptive systems need to know information about learners; the more information that can be passed across platforms and over time, the more valuable it will be. Interoperability is therefore a practical need since evidence of the learner, competency definitions, and activity data must be based upon common, documented standards to ensure that institutions are not dependent on one vendor and that learners can transfer evidence from one course to another and to different providers. This is more evident in the "smart" education environment where the tutoring systems are enhanced by the use of robotics and connected devices that increase the number and flow of data (Adel, 2024).

There needs to be a governance process in place to support interoperability. It proposes 5 principles: Data collection for a stated purpose of education; Informed consent, the consent should be updated when the use of data is changed; Rules of access and security; Rules of retention periods and learner's right to access and modify data; Rules of review for models for bias. These are the safeguards in the governance layer of fig. 2.

The diagnostic cognitive engine is concreted by adding a simple learner modeling relation. Suppose that the success probability of a learner mastering a skill is P_0 and the success probability of acquiring the skill in each opportunity he or she completes is $P = T$. Assuming the slips and lucky guesses are absent, the probability of mastery, $P(n)$, is $P(n) = 1 - (1 - P_0)(1 - T)^n$ and a threshold of mastery is reached after $n = \frac{\ln\left(\frac{1-\theta}{1-P_0}\right)}{\ln(1-T)}$ opportunities. Here the relation is purposefully kept simple because knowledge-tracing models in use include further parameters for slips and guesses. It is nevertheless useful as it demonstrates that the learning rate T and not the number of exercises per se, determine how quickly a learner will be ready to move on. The sequencer should then make an estimate for each learner and for each skill and not provide a set number of exercises.

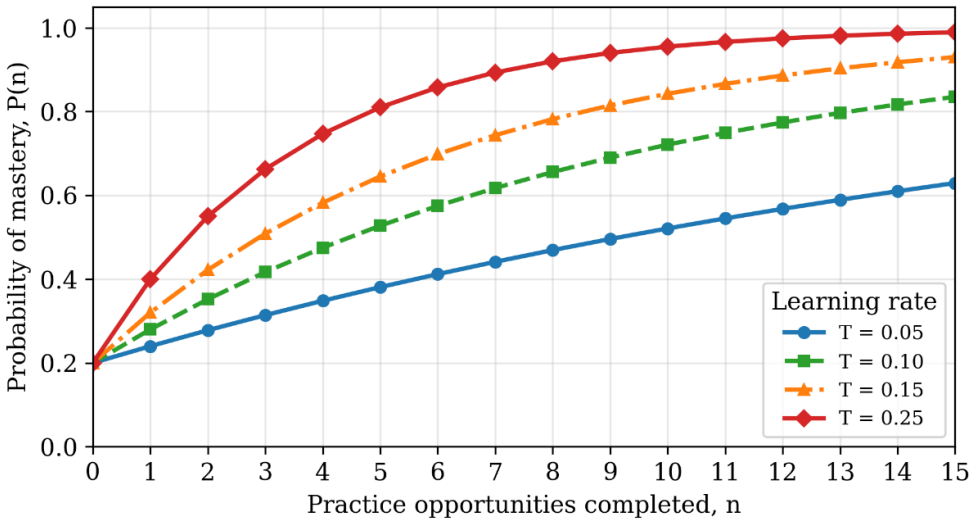


Fig. 2: Probability of Skill Mastery as a Function of Practice Opportunities for Different Learning Rates

Fig. 2: The number of practice opportunities on the horizontal axis and the probability of mastery on the vertical axis with P_0 (initial probability of mastery) $= 0.2$. The learning rates are 0.05, 0.10, 0.15 and 0.25 and all curves start at 0.2 without any practice. The curve corresponding to 0.25 is steep, and intersects 0.95 at the 10-th spot, while the curve corresponding to 0.05 only reaches approximately 0.52 at the same time. If the mastery level is 0.95, the four learners above would require approximately 10, 18, 27 and 55 opportunities to master the skill. The figure demonstrates that a fixed practice quota is inefficient: It wastes time for fast learners and results in slow learners being under mastery. The adaptive sequencer can terminate practice at an appropriate time, and prompt the learner to practice another skill or other explanation. The curves are stylised model output and not empirical results and the parameters should not be used for making decisions regarding individual learners or for institutional reporting, but rather they

should be determined from real interaction logs. Such curves can be used by teachers to inform learners of their adaptive decisions.

The second design problem is how to select the next task. An item response model, like item response theory, can be used to represent the probability that a learner of ability θwill answer a task of difficulty $b$correctly as $p(\theta, b) = \frac{1}{1+e^{-(\theta-b)}}$. The theory of cognitive load and the zone of proximal development implies that tasks should not be too easy nor too hard; thus the sequencer can aim for a probability of success around 70%. The solution to the equation is $b = \theta - \ln(0.7/0.3) \approx \theta - 0.85$, which means that the next task will be just below the learner's current ability level. The rule is clear, easy to understand and can be checked by the teacher.

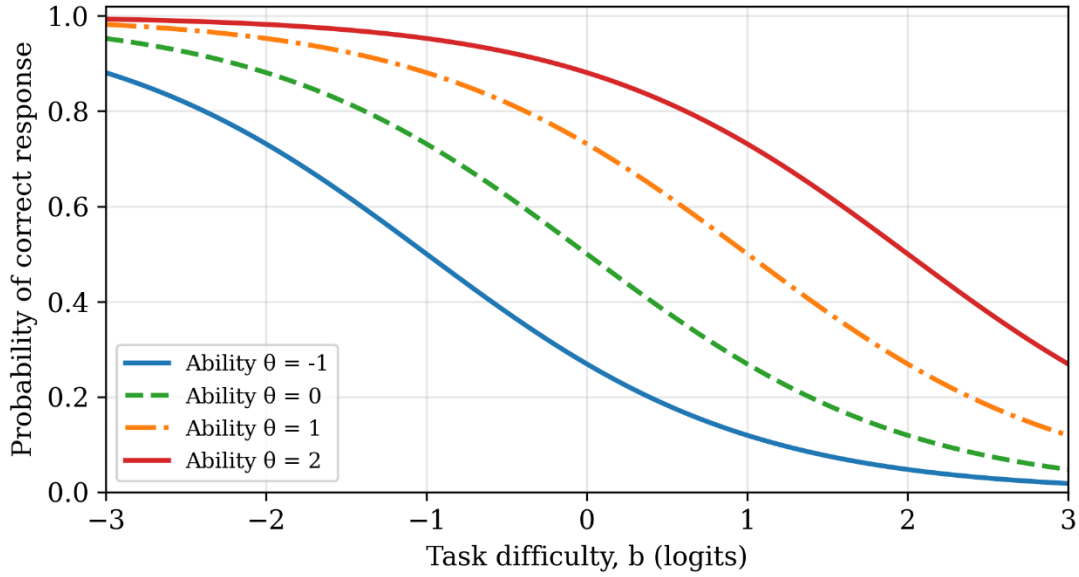


Fig. 3: Probability of a Correct Response as a Function of Task Difficulty for Learners of Different Ability

The difficulty of a task is measured on the horizontal axis in "logits" and the probability of a correct response on the vertical axis ($\frac{1}{1+e^{-(\theta-b)}}$). There are four S-shaped curves, corresponding to students with ability levels of -1, 0, 1 and 2. Each curve drops and a harder learner's curve is to the right of a harder learner's curve, so a learner with a stronger curve is able to do a task with ease and a weaker learner is able to do a task with difficulty. The success probabilities at a difficulty level of zero are approximately 0.27, 0.50, 0.73 and 0.88 for the four abilities. The average difficulty of the next tasks recommended by the target probability of success are approximately: -1.85, -0.85, 0.15, and 1.15, indicating the difficulty of the tasks will vary accordingly with the learner's level of performance. The design principle shown is that all learners should be within the ZPD at a manageable load, maintaining the ZPD at an appropriate level. It also shows a risk: under or over estimating ability means that the sequencer will be playing tasks that are constantly too easy or too difficult, which is a similar bias feedback loop that was described earlier. The curves are not empirical curves but are for illustrative purposes only. These can be used by teachers to give a rationale for the different tasks given to different learners.

Empirical Realities: Institutional Implementation and Competency Metrics

Stress-Testing the Algorithmic Curriculum

This section looks at the Characteristics of Adaptive curricula as implemented and does not rely on new data, but on the literature reviewed. There are 3 interesting settings: The emphasis in school education is on the possibility of classes with a mixed readiness level, while in the class, research on adaptive strategies indicates an improved learning-teaching process (Rincon-Flores et al., 2024). In higher education, the use of adaptive systems is found in large introductory courses and e-learning, and there are many applications of adaptive systems in e-learning in the literature (Gligorea et al., 2023). In corporate upskilling, the emphasis is on speed and relevance, and organizational literature shows that organizational ability to learn and change is not dependent on the training approach that is implemented (Chughtai et al., 2024).

A case study for an adaptive approach with AI as a tool is provided that helps with the improvements (Demartini et al., 2024). The systematic review of AI techniques in personalized learning provides a more general overview and exhibits the percentage of use of the different techniques in both settings (Hariyanto et al., 2025). Combined, these sources suggest that adaptive curricula are able to operate in a variety of settings.

An application note is that deployment should be done in the form of staged pilots. A pilot programme should involve a small group of classes or cohorts, have a clear definition of success, obtain feedback from learners and teachers, data from the system and have a clearly defined decision point with regard to expanding, redesigning or terminating the programme. This helps defuse the negative consequences of early mistakes and helps ensure that learning in the institutions identified in the organisational literature is in place prior to any successful change (Chughtai et al., 2024).

Operational Friction Points

There is always a point in the occurrence of friction in each system. The number one challenge that was listed is faculty resistance. The primary worry teachers have about adaptive systems is that will de-skill or substitute for the teacher, fail to accurately diagnose and fail to alleviate teacher workload. The teacher's biggest concerns about adaptive systems are that will take over the skills of the teacher, that the systems will make inaccurate diagnoses, and that will take time from the teacher but won't provide any benefit to the teacher. Research on adaptive leadership and change self-efficacy suggests that change self-efficacy is one of the important variables that influence organizations to be successful in their innovation (Chughtai et al., 2024). Professional development and leadership support needs to therefore be continuous, visible and for teachers to be involved at the start of design.

Another source of friction is legacy constraints of the institutions. What adaptive learning is looking for is to escape from the uniform model that is imposed by fixed schedules of lessons, the term-based credit system, standardized exams, and incompatible information systems. The student is not credited for time so a student moving through at his own pace does not fit into an institution which requires a student to move through in a certain way. The third group of barriers are ones related to technological literacy. There are more general topics, such as education technology, technology and innovation in education, which highlight that technology, as new or novel, is useful only when it is used properly by teachers and learners (Çelik & Baturay, 2024). The use of adaptive technology can help to either narrow or widen the gap between current infrastructure or competencies. To implement change, there need to be practical solutions, including phase-by-phase implementation, interoperability with existing tools, and the provision of appropriate teacher and learner support to implement the changes, particularly funding.

The friction points discussed above can be connected to the tiers of the proposed architecture and to measurable responses. Table 1 summarises this connection so that institutions can decide where to intervene first.

Table 1: Principal Implementation Frictions, Affected Architectural Tiers, Mitigation Measures and Monitoring Indicators

Friction point	Affected tier	Mitigation measure	Indicator to monitor
Faculty resistance	Tier 4, governance	Teacher co-design, continuous professional development, transparent dashboards	Teacher adoption rate
Legacy institutional constraints	Tier 3, Tier 4	Competency-based credit, phased integration with existing systems	Share of courses with flexible pacing
Technological literacy and access gaps	Tier 1	Onboarding, device and connectivity support	Share of learners with reliable access
Algorithmic bias	Tier 2, governance	Subgroup audits, human review of placement decisions	Subgroup performance gap
Privacy and surveillance risk	Tier 1, governance	Data minimisation, revocable consent, independent reporting	Share of data fields with documented purpose

The operational friction discussion was converted to a handy planning tool in table 1. Every row refers to a friction point, the architectural level where it is most likely to impact, what action to take to mitigate, and one indicator that can be used to gauge progress. The faculty resistance is addressed in the outcome analytics tier and governance layer, and is influenced by the outcome analytics tier, with the teacher adoption rate as the indicator. The legacy constraints are for the sequencer and analytics tiers, where the fixed schedules do not allow for any flexibility on progress and are therefore recommended to be phased and/or competency-based credit. Telemetry ingestion is impacted by access and literacy gaps: a learner whose device is not reliable to collect evidence is not doing much. Algorithmic bias occurs in the diagnostic engine, and is controlled by performing subgroup audits and manually reviewing placement decisions. Privacy risk relates to data collection and minimisation, revocable consent and independent reporting reduce privacy

risk. The table demonstrates that there is not a single level of frictions, but rather specific levels of frictions; and that each of those frictions can be measured with a simple measure. Institutions may add responsible persons, timelines and budgets for each pilot program and each review cycle in the institution, and extend it.

Quantifying Skill Acquisition Velocity

Ultimately all claims of adaptive learning are based on measurements. This paper proposes to use 4 complementary velocity indicators for skill acquisition of complementary skills. The first is a "normalized" measure of learning gain and the ratio is the ratio of pre- and post-intervention performance to the improvement that could have occurred. The second is time to mastery; the number of practice opportunities needed to attain a given level of proficiency. The third is the retention of knowledge as measured by delayed tests that are administered weeks or months after training. Future readiness is the ability to use skills in new tasks or environments - assessed by performance tasks in the future, not in what was taught - is the measure of the 4th.

If that are to be credible, the design of the measures must be carefully considered. Comparisons should be made with a pre- and post-intervention comparison, but comparisons with a control group, taught the same using the traditional method should also be included as improvement over the time period may be due to maturation, familiarity with the test or attention that is given to any new programme. Outcomes need to be determined prior to the intervention and results reported for different subgroups of learners to make sure that no strategy is applied that would obscure larger gaps. The studies summarized here, using various designs and measures of improvement, report improvements with adaptive approaches Demartini et al., (2024); Rincon-Flores et al., (2024) but the magnitudes of the improvement cannot be pooled or compared directly. A map of techniques, rather than an effect size, is suggested by the reviews of the literature in the field (Hariyanto et al., 2025; Gligorea et al., 2023). The paper thus does not give any quantified results for itself, but rather continues the agenda of indicators presented above as a measurement agenda.

To support the measurement agenda proposed above, table 2 defines the velocity indicators together with a subgroup measure, giving a typical formulation for each.

Table 2: Skill Acquisition Velocity Indicators, Typical Formulation, Related Architectural Tier and Desired Direction of Change

Indicator	Typical formulation	Related tier	Desired change
Normalised learning gain	(Post − Pre) ÷ (Maximum − Pre)	Tier 4	Increase
Time to mastery	Practice opportunities needed to reach threshold θ	Tier 2, Tier 3	Decrease
Knowledge retention	Delayed test score ÷ immediate post-test score	Tier 3, Tier 4	Increase
Future readiness (transfer)	Score on novel tasks ÷ score on taught tasks	Tier 3	Increase
Subgroup performance gap	Mean outcome of reference group − mean outcome of comparison group	Governance	Decrease

Table 2 presents five indicators, each of which describes one aspect of the speed and equity of skill acquisition. The first column identifies the indicator and the second provides an example of a formulation for each indicator, which enables institutions to compute each indicator in a similar fashion. Learning gain can be normalised to make a comparison between learners with different starting points possible by dividing by the possible improvement. Time to mastery is the number of practice opportunities that are required to achieve the threshold, which was related to the amount of quantity n. Knowledge retention is the comparison of scores achieved in a delayed test and immediate test, while future readiness is the comparison between performance of the novel tasks and performance of the taught tasks; this is what constitutes transfer, not memorisation. The average improvement is included in the subgroup performance gap as it could mask increasing gaps between groups of learners. The third column connects each indicator with the architectural tier which has the biggest impact on it, while the fourth column indicates the direction of change. The indicators are reported together, which helps to mitigate the danger that one positive number could mask the negative characteristics of the system in the other ones. Study design should be done in advance to establish thresholds, timing of studies and comparison groups for comparison and interpretation of the results across institution, programme and cohort of learners in the institution.

Retention can be demonstrated also. Suppose the memory for a skill fades exponentially, so that after t days it is retained by a fraction $R(t) = e^{-t/s}$, where s is the stability of the memory. Suppose that the memory for a skill fades exponentially so that after t days it is retained by a fraction $R(t) = e^{-t/s}$, where s is the stability of the memory. Why this is so is that each review at the right time should raise s, which is expected to level off the curve for an adaptive scheduler that schedules reviews just before forgetting. The model itself is a simplified version of an empirical forgetting curve that helps to explain why delayed tests proposed above are a necessary component in any test.

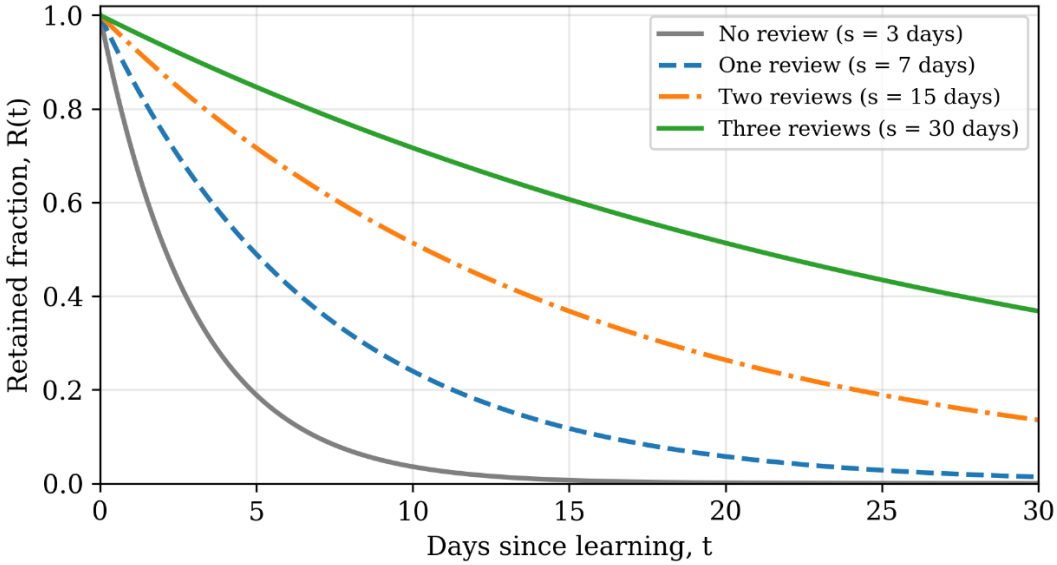


Fig. 4: Knowledge Retention over Thirty Days with Zero to Three Adaptively Scheduled Reviews

The days since learning are plotted along the horizontal axis and the fraction retained are plotted along the vertical axis as illustrated in fig. 4, where R(t) = e^(−t/s). Four curves – memory stability values of 3, 7, 15 and 30 days – are shown, representing no review and one, two and three adaptively scheduled reviews. No review results in retention of less than 0.10 in a week and near to 0 at the end of the month. The three numbers that come to mind are 0.37, 0.63, and 0.79, as these are the approximate rates of retention after one, two, and three reviews, respectively. Following 30 days, the three curves are still in a rather similar shape with values of approximately 0.01, 0.14 and 0.37. The curves do not intersect each other so the advantage of each extra review can be seen over the whole time, but as the interval is increased the gain with each review decreases if it is longer than the practical teaching time. The figure supports delayed assessment when measuring, as well as planning revisits of previous skills in the sequencer, not just forward. These values are hypothetical and should be adjusted based on the context of the real learners when the forgetting was observed in similar tasks and under similar retention conditions; forgetting is different across subjects, ages and task types.

Systemic Vulnerabilities: Algorithmic Bias, Equity, and the Human Element

The Bias Feedback Loop

Historical data is based on the conditions under which it is collected, and adaptive systems learn from historical data. Learning models developed from a particular group of learners, with specific backgrounds, language or/and learning styles can not necessarily be representative of other learners. There is a feedback loop between the consequences. The examples that a learner is mis-modelled (from a content perspective) are not quite as suitable, the learner's performance is not as well, and the data appear to confirm the initial misclassification. Over time learners with different, or atypical, profiles can be 'funnelled' into the lower tiers; the programme is objective and so hard to challenge.

The diversity of data sources and modelling techniques in the reviews of AI techniques and adaptive learning in e-learning Hariyanto et al., (2025; Gligorea et al., (2023) suggests that bias can be introduced during the following: data collection, features selected, modelling and reporting of recommendations. Therefore, mitigation needs to be a structured approach. Training data should be evaluated for representativeness, the model performance should be reported at a sub-group level, inferences drawn by model should be made available to learners and teachers for review

and contestation, and a process of human review should be in place for consequential decisions, such as placement and progression.

The Empathy Deficit

Learning is a relating experience. A teacher observes the discouragement in a learner, realises that a learner has some ability that hasn't been shown to them or that a learner is showing them, but that is not yet understood from what said, and provides an explanation that takes this into account, encouraging the learner. While the computational tutor can give immediate, patient and consistent feedback, it is not as though the computational tutor knows what life is like a mentor. The motivation, belonging and role modelling that mentoring can offer to learners might diminish if seen as being freed from human contact through the use of adaptive systems.

This tension is also mentioned in the pedagogical agents literature, both in terms of the roles an agent can assume, and in terms of the significance of the learner-agent relationship (Apoki et al., 2022). Technology, instead, should not replace human-centric goals and objectives, hence the push towards Industry 5.0 also reflects this in the scope of smart education. The framework presented in this paper reacts by giving over the task of the diagnosis, of the practice and of the feedback to technology and keeping the task of the discussion, of the cultivation of values for people. Any institutions must take account of the time freed up due to automation as time back to humans – time to connect with people as well as measure achievement, and keep track of wellbeing and sense of belonging of learners.

Data Privacy and Surveillance in Education

When you're going to adapt, you're going to have to observe. The information from the eyes, eye-gaze, physiological/biometric data, response time and keystrokes are captured to measure subjectively what is being attended to, what emotions are being felt, in relation to the environment. This monitoring can enhance personalization, but also can make detailed records of children and young people that are difficult to withdraw from the institutions that require them to use the tools. The risks are that data will be misused, data can be hacked, data can be sold commercially and because of the fear of being constantly monitored, no inquiries or experiments are performed.

The greater the surface area, as in a smart education environment, in which tutoring systems are interconnected with sensors and devices (Adel, 2024) and its potential in education transformation by adaptive learning (Strielkowski et al., 2025) is linked to public trust in dealing with data. The moral limit suggested here is proportionality, that is, the extent to which data collection is intrusive should be proportionate to the clearly specified educational benefit that cannot be achieved in less intrusive ways. Biometric/emotional monitoring must be in line with explicit, specific and revocable consent; avoided without very good reason when used in use with young learners; and not used for disciplinary purposes or sold to third parties. These pledges have to be made effective and kept accountable with independent and transparent reporting of data practices.

Horizons Ahead: Strategic Synthesis and Future Trajectories

Adaptive learning technologies can change the face of institutional education and lifelong learning by being able to represent learning needs and adapt support as it goes. But it's not all about having the technical skills to get the job done. For effective adoption, it is necessary to have a match between the principles of the cognition, the institutions' capacity, and the educator practice and social expectations. The plan to implement adaptive technology into this broader system of education. Institutions need to start with learning goals and measurable competencies, invest in teacher training and use open learning standards that allow for data portability and institutional choice. Governance must provide independent oversight and bias audits, security, data minimization and informed consent. Time should be freed; collaboration should be possible and opportunity for meaningful human interaction should be provided through automation. Evaluation should be done using comparison groups, delayed assessments and subgroup reporting should be done, and the positive and negative should be openly published. Policymakers must ensure equitable access to connectivity and devices and skills in digital competence; and establish boundaries over the collection of data by learners and automated decision about learners. Generative Ai mentorship should be explored in research (accuracy, dependence, authorship, effortful thinking) But, special attention should be given to the privacy of physiological data when using Neuro-adaptive virtual reality in complex skills training. A longitudinal, cross-cultural and cross-linguistic study is recommended to explore the nature of learner models and the understanding of what constitutes an understandable explanation as well as teacher interactions and the decisions made to adapt. Comparative research: within schools, across universities and workplaces. Adaptive learning is a result of intelligence in the end: an intelligence that has an educational and moral base. Its added value is to increase access to knowledge, to tailor it and support it through human relationships, to consider the learner's autonomy and to ensure that technology can be a tool that has a life-long impact on sustainable and equitable skill development.

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