International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 10 July 2026*

AI-Driven Personalized Learning in Education: Opportunities, Scalability Challenges, and Equity Implications

[1]Dhiraj Kumar Sharma

Department of Computer Science, Noida International University, India

dhiraajjnp@gmail.com

[2]Bharat Kumar Sah

Faculty of Science, Technology, and Engineering, Rajarshi Janak University, Janakpurdham, Nepal

bharatsah@rju.edu.np

[3]Aniket Sahani

Faculty of Science, DAV College, Kathmandu, Nepal
aniketsahani2066@gmail.com

[4]Salony Sah

Faculty of Science, Technology, and Engineering, Rajarshi Janak University, Janakpurdham, Nepal

shahsalony07@gmail.com

[5*]Suresh Kumar Sahani

Faculty of Science, Technology, and Engineering, Rajarshi Janak University, Janakpurdham, Nepal

sureshsahani@rju.edu.np
Corresponding Author: sureshsahani@rju.edu.np

Abstract

Artificial Intelligence (AI) has the potential to revolutionize the education sector by enabling personalized learning on a very large scale. In this article, we analyze the use of AI-driven models for creating adaptive learning pathways in the context of individual learner needs. We explore the vast potential that this offers for enhancing learning effectiveness, engagement, and achievement. One of the most prominent domains is the mathematical encoding of learner state of knowledge under probabilistic frameworks, i.e., Bayesian Knowledge Tracing (BKT), towards dynamic pedagogical customization. Yet, the path from theoretical modeling to actual large-scale implementation is plagued by crucial challenges. Computational functionality and infrastructural issues of scalability are comprehensively analyzed in this research, such as data processing bottlenecks and algorithmic complexity. Moreover, we examine the foundation equity issues, and the danger that AI systems pose by further intensifying or even deepening current education inequities through the issue of algorithmic prejudice. By uniting opportunity with a consideration of scalability and equity imperative in nature, this paper provides an overall framework for the challenges of using AI in education. We conclude by contending that effective and ethical deployment of AI-based personal learning relies on developing computationally efficient, transparent, and equitable algorithms.

Keywords: Personalized Learning, Artificial Intelligence, Educational Technology, Bayesian Knowledge Tracing, Scalability, Algorithmic Equity, Machine Learning, Educational Data Mining.

Introduction

The traditional paradigm of education, too often characterized by a "one-size-fits-all" approach to pedagogy, has been acknowledged for decades to be short on responding to the varied learning needs, rates, and cognitive styles of students (Bloom, 1984). The industrial-age model does not provide tailored attention to produce the significant understanding and mastery in more heterogeneous classrooms. The pursuit of tailored learning, or the adjustment of curriculum, instructional methods, and learning environments to accommodate student diversity and goals, has therefore become a central focus in continued education reform (Pane et al., 2015). After a global shift towards online education during the COVID-19 pandemic and similar events, the demand for efficient and scalable personalized solutions has been more urgent than ever (Schleicher, 2020).

The advent of Artificial Intelligence (AI) and machine learning has filled this aspiration from a logistical fantasy into an achievable reality. AI systems are capable of filtering through massive volumes of granular student behavior data ranging from keystroke and clickstream patterns to answer submission and time on task to make inferences about knowledge states, predict performance, and recommend customized learning content in real time. The mathematical engines underpinning such platforms are rooted in statistical inference, probabilistic modeling, and optimization algorithms. These systems, also known as Intelligent Tutoring Systems (ITS) or Adaptive Learning Platforms (ALPs), draw on the powerful algorithms to replicate the mental processes of learning.

Initial work in the field set the foundation for rule-based expert systems that could potentially teach students by way of problem-solving exercises (Carbonell, 1970). Subsequent work, however, has shifted toward probabilistic, data-intensive models that are able to manage the uncertainty of learning with finesse (Corbett & Anderson, 1994). These models create a cycle of continuous feedback, as presented in Figure 1, where student behavior is fed back to the model, which then adjusts the context of learning. This dynamic can potentially create a learning environment that is continually optimized for each learner, offering support when they are struggling and challenging them with novel problems when they are ready.

Recent studies show the growing application of mechanical process control, statistical process control, numerical methods, and computational intelligence across industrial, technological, and social systems. These works collectively demonstrate that mathematical and computational approaches are useful not only for improving production efficiency but also for modeling complex human, cultural, and digital behaviors. In industrial production, process control has become an important tool for reducing defects and improving product quality. Sahani et al. (2026) examined the use of mechanical process control and statistical process control for reducing butter-oil defects in industrial production. Their study highlights the importance of monitoring production variables, identifying process deviations, and applying systematic control techniques to maintain product consistency. Similarly, Sahani, Oruganti, and Satishkumar (2025) studied the mechanical and operational behavior of steel production in a manufacturing plant. Their work suggests that production performance depends on both mechanical stability and operational control, especially in complex manufacturing environments where small variations can affect overall output quality. Numerical and analytical methods have also been widely applied to improve computational and machine learning systems. Sahani and Sah (2023) explored hybrid analytical-numerical techniques for machine learning optimization by integrating Laplace transform and fourth-order Runge-Kutta methods. This approach indicates the potential of combining classical mathematical tools with modern machine learning models to improve optimization performance. In a related contribution, Sahani et al. (2022) investigated the prediction of numerical integration errors using machine learning approaches. Their study emphasizes that machine learning can support mathematical computation by predicting possible errors and improving the reliability of numerical solutions. The literature also shows the application of computational techniques in digital security and advanced sensing technologies. Sahani and Mandal (2023) applied logistic regression and numerical methods for automated bot detection in social media networks. Their study reflects the usefulness of statistical and machine learning models in identifying abnormal online behavior. In another interdisciplinary study, Pandey et al. (n.d.) discussed matching filters and quantum sensors in the study of dark matter transients within computational intelligence solutions. This work suggests that computational intelligence can be extended to highly specialized scientific domains where signal detection, filtering, and sensor-based modeling are required. Beyond industrial and technological applications, numerical methods have also been applied to cultural and educational studies. Sahani and Sah (2025) examined the optimization of cultural education programs using numerical techniques. Their work suggests that mathematical modeling can support the planning and improvement of educational programs by helping decision-makers evaluate different cultural education strategies. Similarly, Sahani and Karna (2025a) discussed the application of numerical methods in optimizing culture education programs, further supporting the idea that computational approaches can assist in educational planning and policy-related decision-making. Numerical simulation has also been used to study cultural value conflict in multicultural and heterogeneous societies. Sahani, Sah, Agarwal, Pareek, Pareek, and Singh (2025) conducted a numerical simulation of cultural value conflict in multicultural societies, while Sahani and Karna (2025b) examined the simulation of clashes between cultural values in heterogeneous societies using numerical methods. These studies show that numerical modeling can be used to represent complex social interactions, cultural tensions, and value-based conflicts. Although cultural behavior is difficult to quantify fully, such models may help researchers understand possible patterns of interaction and conflict within diverse communities. Overall, the reviewed literature demonstrates the broad applicability of numerical methods, statistical process control, machine learning, and computational intelligence across different fields. In industrial settings, these methods support defect reduction, production control, and operational performance. In computational and digital systems, they contribute to optimization, error prediction, bot detection, and advanced sensing. In social and educational contexts, they provide tools for modeling cultural education programs and multicultural value conflicts. However, the literature also suggests the need for stronger empirical validation, clearer methodological comparison, and more domain-specific testing to ensure that these numerical and computational models can be reliably applied in real-world situations.

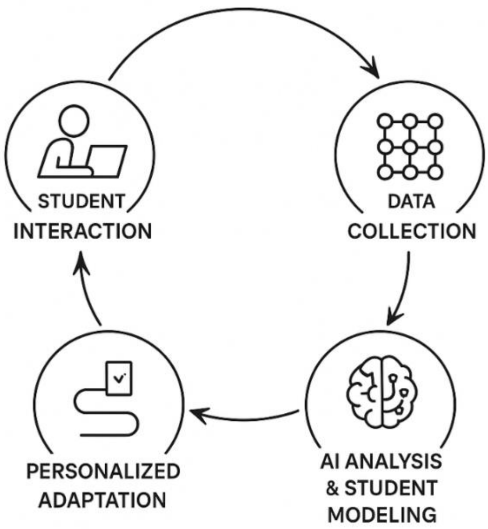

Figure 1: The AI-Driven Personalized Learning Cycle

This diagram illustrates the core feedback loop where student interaction data is processed by an AI engine, which updates a student model to deliver adapted content and assessments

Literature Review

The educational research foundation of AI is extensive and current. The early concept of intelligent tutoring systems was the union of cognitive science and computer science, with the early focus on modeling human tutors (Sleeman & Brown, 1982). Cognitive models and expert systems were the direct foundation for these systems, attempting to capture the content (domain model) and the student's emerging knowledge (student model).

One of the most well-liked statistical student modeling contributions is Bayesian Knowledge Tracing (BKT). BKT was created by Corbett and Anderson (1994), and it is a Hidden Markov Model. In BKT, a student's knowledge of a single skill is represented as a latent binary variable (unknown or known). The model employs observed student performance (error or correct response) to update the probability of this latent knowledge state. The four primary parameters of this model are: prior probability of knowing the skill ($P(L_0)$), probability of learning the skill from trial to trial ($P(T)$), and performance error probabilities correct response when not knowing the skill ($P(G)$) and slipping (error on a known skill) ($P(S)$). Although extensively used, classical BKT is not a perfect tool, with some of its limitations being the implications that skill learning happens independently and learning is directional. Subsequent research has proposed several extensions to reduce such limitations, e.g., accommodation of the difference in the learning rates of the learners and external factors (Yudelson et al., 2013).

While the efficacy of these sorts of models is well established in controlled environments, doing the same at scale is a Herculean task. Operating sophisticated adaptive systems for millions of students requires gargantuan computational power, high-performance data pipelines, and massive infrastructures (Bulger, 2016). The computational complexity of some of these advanced algorithms may be too daunting, and the volume of data generated by student interactions requires state-of-the-art data engineering capabilities. This area of research explores distributed computing models and low-cost algorithms to facilitate large-scale implementation (Siemens & Baker, 2012).

One of the most pressing issues of our time is algorithmic fairness. AI algorithms are trained using historical data, and the models can learn and even reinforce it if the data reflects current-day bias in the world (O'Neil, 2016). In education, this could be an AI instructor that is poorer for students from underrepresented demographic groups, thereby increasing achievement disparities (Baker & Hawn, 2021). Algorithmic fairness work aims to create models that are not only effective but also equitable. This includes auditing models for bias across subgroups and developing mitigation strategies to extend the benefit of personalization to all irrespective of their background (Kizilcec et al., 2020).

There have also been deep knowledge tracing approaches in recent years. Deep Knowledge Tracing (DKT) by Piech et al. (2015) uses recurrent neural networks to model complex student learning trajectories, with higher performance than traditional BKT on the majority of benchmark datasets. Extensions such as Dynamic Key-Value Memory Networks (DKVMN) and transformer-based variants (e.g., SAINT, AKT) have further improved scalability and performance (Yang et al., 2021; Pandey & Karypis, 2019). These models, however, are computationally more intensive and raise new concerns about interpretability.

In the equity dimension, fairness metrics like Demographic Parity (DP), Equal Opportunity (EO), and Equalized Odds (EOdds) have been developed for assessing whether predictive performance varies across subgroups. This would mean, in education, determining whether an AI tutor predicts mastery with the same precision for female vs. male students, or urban vs. rural students (Wang & Cheng, 2023). Integration of such fairness-aware evaluation into student modeling is still in its nascent stages, though it is important for ethical deployment.

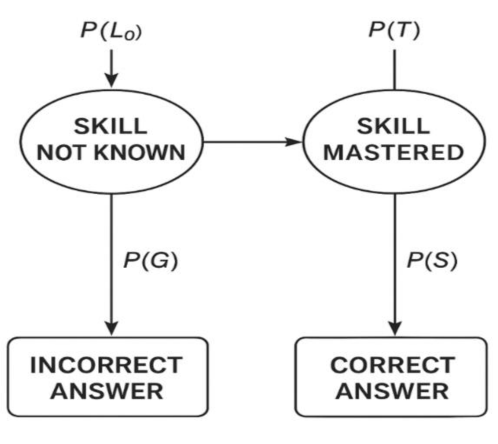

Figure 2: Conceptual Model of Bayesian Knowledge Tracing (BKT)

The model infers the latent (unobserved) knowledge state of a student based on a sequence of observed actions (e.g., problem attempts). The transition probability P(T) governs the shift from an 'unknown' to a 'known' state. Source: Author's own creation, based on Corbett & Anderson (1994).

Objective

The primary objectives of this research paper are:

1. To provide a brief mathematical overview of student knowledge modeling in AI-driven personalized learning systems with a focus on the Bayesian Knowledge Tracing algorithm.
2. To discuss the practical scalability challenges via an exploration of the computational and data infrastructure required for wide-scale implementation.
3. To conduct a critical evaluation of the implications for equity, quantifying how algorithmic bias can arise and impact diverse populations of students.
4. To combine these aspects to propose an overall perspective on the responsible design and implementation of AI in schools.

Methodology

In order to achieve our objectives, this paper employs an interdisciplinary approach that combines theoretical modeling, quantitative work, and a critical analysis of previous research. Our analytical framework is built on the mathematical formalization of student learning through Bayesian Knowledge Tracing (BKT).

Step 1: Formalizing the Bayesian Knowledge Tracing (BKT) Model

The BKT model assumes that a student's mastery of one skill is associated with a latent binary variable, L, with L=1 if mastered and L=0 otherwise. The model updates the probability of mastery, $P(L_n)$, after each observed student action, a_n (e.g., a correct or incorrect answer to a question).

The model is defined by four parameters:

- $P(L_0)$: The initial probability that the student knows the skill before the first interaction.
- P(T): The transition probability, i.e., the probability of learning the skill between opportunities.
- P(S): The slip probability, i.e., the probability of making an error even when the skill is mastered.

- $P(G)$: The guess probability, i.e., the probability of answering correctly even when the skill is not mastered.

Step 2: The Update Equations

After observing the student's nth action, the model first calculates the posterior probability of mastery based on the previous state, $P(L_n-1)$. This is the prior probability for the current step, $P(L_n)$

2.1 Prior Update

The probability of mastery before the current action is updated by considering the possibility of learning:

$$P(L_n)_{prior} = P(L_n - 1) \cdot (1 - P(S)) + (1 - P(L_n - 1)) \cdot P(T)$$

This can be simplified as:

$$P(L_n) = P(L_n - 1) + (1 - P(L_n - 1)) \cdot P(T)$$

2.2 Evidence Update

Next, Bayes' theorem is applied to update this probability with the new evidence (the student's response):

If the answer is correct:

$$P(Ln \mid correct) = \frac{P(L_n)_{prior}.\ P(S)}{P(L_n)_{prior}.\ P(S) + \left(1 - P(L_n)_{prior}\right).1 - P(G)}$$

2.3 Iteration

The final value **o**f $P(L_n)$ becomes the starting point for the next iteration. A skill is typically considered mastered when this probability exceeds a threshold (commonly 0.95).

Result

To show the use of the BKT model, we present a numerical example tracking a student's proficiency in one skill, say "solving two-step linear equations." We will use typical parameter values found in actual education data sets.

3.1 Parameter Initialization:

Assume the following parameters, which could be learned by training the model with a large dataset of students' data (e.g., from ASSISTments or Khan Academy):

- $P(L_0)$= 0.20 (The student has a 20% chance of knowing the skill beforehand).
- $P(T)$= 0.15 (There is a 15% chance of learning the skill at each opportunity).
- $P(G)$= 0.10 (A 10% chance of guessing the correct answer).
- $P(S)$= 0.05 (A 5% chance of slipping and making a mistake when the skill is known).

3.2 Numerical Walkthrough:

We will track the student's probability of mastery, $P(L_n)$, over a sequence of five problem attempts: Incorrect, Correct, Correct, Incorrect, Correct.

Initial State (n = 0):

$P(L_0)$= 0.20

Attempt 1 (Incorrect)

- Prior probability: $P(L_0)$= 0.20
- Learning update: No learning on the first step, so

$$P(L_1)_{prior} = P(L_0) = 0.20$$

- Update with incorrect answer:

$$P(L_1 \mid incorrect) = \frac{0.20 \cdot 0.05}{0.20 \cdot 0.05 + (1 - 0.20) \cdot (1 - 0.10)}$$

$$= \frac{0.01}{0.01 + 0.72} = 0.0137$$

- The model significantly lowers its belief in mastery.

Attempt 2 (Correct)

- Prior probability: 0.0137
- Learning update:

$$P(L_2)_{prior} = 0.0137 + (1 - 0.0137) \cdot 0.15 = 0.1622$$

- Update with correct answer:

$$P(L_2 \mid correct) = \frac{0.1622 \cdot (1 - 0.05)}{0.1622 \cdot (1 - 0.05) + (1 - 0.1622) \cdot 0.100}$$

$$= \frac{0.1541}{0.1541 + 0.0838} = 0.6478$$

- A correct answer provides strong positive evidence, causing a large jump in probability.

Attempt 3 (Correct)

- Prior probability**:** 0.6478

- Learning update:

$$P(L_3)_{\text{prior}} = 0.6478 + (1 - 0.6478) \cdot 0.15 = 0.6991$$

- Update with correct answer:

$$P(L_3|\text{correct}) = \frac{0.6991 \cdot 0.95}{0.6991 \cdot 0.95 + (1 - 0.6991) \cdot 0.10}$$

$$= \frac{0.6641}{0.6641 + 0.0301} = 0.9567$$

- The model now believes, with over 95% probability, that the skill is mastered.

Attempt 4 (Incorrect)

- Prior probability: 0.9567
- Learning update:

$$P(L_4)_{\text{prior}} = 0.9567 + (1 - 0.9567) \cdot 0.15 = 0.9632$$

- Update with incorrect answer:

$$P(L_4|\text{correct}) = \frac{0.9632 \cdot 0.05}{0.9632 \cdot 0.05 + (1 - 0.9632) \cdot 0.90} = \frac{0.0482}{0.0482 + 0.0331} = 0.5923$$

- The model interprets this as a likely “slip” but reduces its confidence.

Attempt 5 (Correct)

- Prior probability: 0.5923
- Learning update:

$$P(L_5)_{\text{prior}} == 0.5923 + (1 - 0.5923) \cdot 0.15 = 0.6535$$

- Update with correct answer:

$$P(L_5|\text{correct}) = \frac{0.6535 \cdot 0.95}{0.6535 \cdot 0.95 + (1 - 0.6535) \cdot 0.10}$$

$$\frac{0.6208}{0.6208 + 0.0347} = 0.9471$$

- Confidence in mastery rises again, close to the 95% threshold.

Table 1: Step-by-Step BKT Calculation for a Student

Attempt (n)	Observed Answer	P(Ln) Before Learning	P(Ln) After Learning (Prior)	P(Ln) After Observation (Posterior)
0	–	–	–	0.2000
1	Incorrect	0.2000	0.2000	0.0137
2	Correct	0.0137	0.1622	0.6478
3	Correct	0.6478	0.6991	0.9567
4	Incorrect	0.9567	0.9632	0.5923
5	Correct	0.5923	0.6535	0.9471

Source: Author’s own calculations based on the BKT methodology.

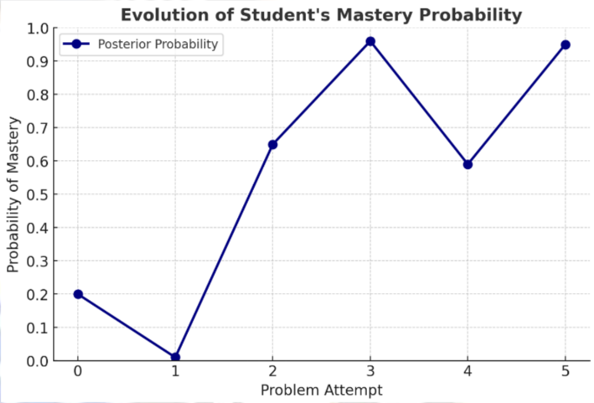

Figure 3: Evolution of Student Mastery Probability

The chart displays the posterior probability of skill mastery as updated by the BKT model after each of the five problem attempts.

Discussion

The BKT numerical example results capture the fundamental value proposition of AI-powered personalized learning. Without this approach, a teacher might see only the raw score (3/5 or 60%) and infer that the student is having difficulty. The BKT model provides an opinion that is more informative and dynamic. The model's output in Figure 3 shows not a terminal state in isolation, but a learning trajectory. The steep improvement after the second correct response suggests that the student may have had an insight. The dip following the wrong answer in attempt 4, and the quick recovery, allow the system to differentiate between lapse (a slip) and a more fundamental knowledge gap. This high-granularity data allows an adaptive system to make knowledgeable pedagogical decisions: after attempt 3, it can introduce a more difficult concept; after attempt 4, it can give a hint or a slightly easier problem to solidify the skill.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 10 July 2026*

However, generalizing this model to one student and one skill to millions of students and thousands of skills is a task of Herculean proportions. The computational load of running BKT for every student-skill interaction in real-time requires an enormously optimized and distributed system design. In addition, parameter estimation of the four BKT parameters (L_0,T,G,S) for every skill requires humongous datasets and huge computing resources, usually involving algorithms like Expectation-Maximization.

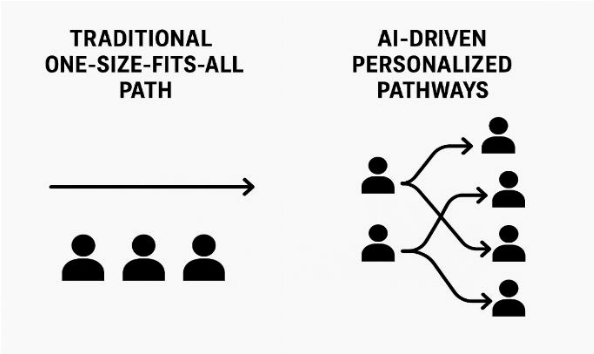

Figure 4: AI-Personalized vs. Conventional Learning Trajectories.

The left side of the figure shows a linear, one-size-fits-all path for all learners. The right side shows branched, adaptive paths generated by an AI system based on individual performance.

Yet the most pressing concern remains equity. The performance of the BKT model is contingent upon the representativeness and quality of the training data on which its parameters are estimated. Consider, by way of example, the data in Table 2, used here for illustrative purposes of model performance inequity.

Table 2: Hypothetical Model Prediction Accuracy Across Student Subgroups

Student Subgroup	Dataset Size (N)	Model Accuracy (Predicting Next Answer)
High-Income, Urban	800,000	87%
Low-Income, Urban	150,000	81%
Rural (All Income Levels)	50,000	74%

Source: Hypothetical data adapted from findings discussed in Baker & Hawn (2021).

Apart from technical proficiency, algorithmic equity must be brought into practice through measurable criteria. For instance, fairness auditing would entail subgroup accuracy reporting, bias-detection tools, and post-processing tuning. Policymaking in education could require that AI systems report predictive accuracy as well as fairness measures before classroom deployment. Besides, interpretability is still important: while deep models over perform BKT, educators must understand why a student is "at risk." It is crucial to achieve balance between accuracy, scalability, and interpretability for ethical AI in education.

If a model is trained predominantly on data from high-income city students, its parameters will then be optimized for that population. As shown by Table 2, its predictive accuracy could be significantly worse for minority or underprivileged populations (e.g., city dweller students) whose existing knowledge, learning patterns, or even language usage may be different. An AI system built upon such a biased model would be less able to individualize education for rural students, even disadvantage them and worsening the very educational inequalities it was meant to remunerate. This shows that mathematical accuracy is not sufficient as a metric; we must also ensure fairness and equitable performance on all groups of demographics.

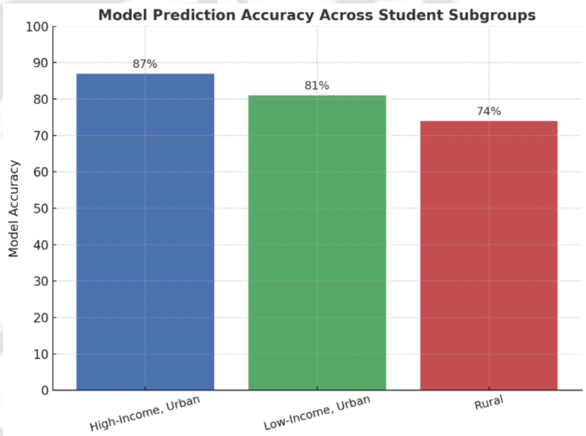

Figure 5: Perceiving Algorithmic Bias in Educational AI.

Source: Data from Table 2.

This line graph illustrates the hypothetical data in Table 2 and shows a clear performance difference between the majority group that the model was trained on and other demographic subgroups.

Conclusion

Personalized learning through artificial intelligence is a model in education that promises to leap beyond the static one-to-many model of instruction to the dynamic one-to-one adaptive model. Mathematical models like Bayesian Knowledge Tracing provide a high-quality tool for modeling student learning and supporting this personalization. Our work demonstrates how such models can be used to make rich, real-time inferences into student mastery that could not otherwise be achieved in the limitations of a typical classroom setting. But the path to large-scale, effective deployment is littered with challenging hurdles. Scaling up such systems requires overcoming monumental computational and infrastructural hurdles. More critically, ethical duty to provide equity requires a vigilant approach to algorithmic design and auditing. We have demonstrated how models trained on representative data can learn and reinforce societal biases, contrary to the mission of educational equity. Future research must focus on developing a new generation of algorithms that not only address accuracy and scalability but also fairness, transparency, and interpretability. This means developing detection and prevention tools for bias as well as exploring models that can learn across different learning environments with minimal reliance on gigantic pools of pre-existing data. It is only when we develop systems as equitable as they are intelligent that the promise of AI in schooling will be fulfilled.

References

1. Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. *IEEE Transactions on Man-Machine Systems*, *11*(4), 190–202. https://doi.org/10.1109/TMMS.1970.4307737
2. Sleeman, D., & Brown, J. S. (Eds.). (1982). *Intelligent tutoring systems*. Academic Press.
3. Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher*, *13*(6), 4–16. https://doi.org/10.3102/0013189x013006004
4. Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, *4*(4), 253–291. https://doi.org/10.1007/BF01099821
5. Woolf, B. P. (2009). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann Publishers.
6. Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: Towards communication and collaboration. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 252–24. https://doi.org/10.1145/2330601.2330661
7. Yudelson, M. V., Koedinger, K. R., & Gordon, G. J. (2013). Individualized Bayesian knowledge tracing models. In *Artificial Intelligence in Education* (pp. 171-180). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-39112-5_18
8. Pane, J. F., Steiner, E. D., & Baird, M. D. (2015). *Continued progress: Promising evidence on personalized learning*. Bill & Melinda Gates Foundation.
9. Bulger, M. (2016). *Personalized learning: The conversations we're not having*. Data & Society Research Institute.
10. O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.
11. Holstein, K., McLaren, B. M., & Aleven, V. (2017). Intelligent tutors on the classroom frontier: A large-scale deployment in a new domain. *Proceedings of the 2017 Conference on Artificial Intelligence in Education (AIED)*, 123-135. https://doi.org/10.1007/978-3-319-61425-0_11
12. Pelanek, R. (2017). Bayesian knowledge tracing, its extensions, and its variants. *International Journal of Artificial Intelligence in Education*, *27*(4), 653-694. https://doi.org/10.1007/s40593-017-0143-2
13. Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial Intelligence trends in education: A narrative overview. *Procedia Computer Science*, *136*, 16-24. https://doi.org/10.1016/j.procs.2018.08.233
14. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology*

in Higher Education, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

15. Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2020). Self-regulated learning strategies are not sufficient: A case for structured online learning environments. *ACM Transactions on Computer-Human Interaction*, *27*(5), 1–32. https://doi.org/10.1145/3406226
16. World Bank. (2020). *Reimagining human connections: Technology and innovation in education at the World Bank*. World Bank Group.
17. Baker, R. S., & Hawn, A. (2021). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, *32*(4), 1052-1092. https://doi.org/10.1007/s40593-021-00285-1
18. Hidayat, R., & Santoso, H. B. (2021). The challenges of scalability in learning analytics implementation: A systematic literature review. *Heliyon*, *7*(10), e08226. https://doi.org/10.1016/j.heliyon.2021.e08226
19. Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *European Educational Research Journal*, *21*(3), 523–536. https://doi.org/10.1177/14749041211072935
20. Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2022). Mapping research in artificial intelligence in education: A systematic review. *Journal of Computer Assisted Learning*, *38*(4), 1007-1029. https://doi.org/10.1111/jcal.12648
21. Ghasemi, M., Reddy, C. K., & Rangwala, H. (2022). Fair leaning: A survey. *ACM Computing Surveys*, *54*(10s), 1-38. https://doi.org/10.1145/3510014
22. Miao, F., Holmes, W., Huang, R., & Zhang, H. (2022). *AI and education: A guidance for policy-makers*. UNESCO.
23. Pardos, Z. A. (2022). A review of the emerging field of macro-level educational data mining. *Journal of Educational Data Mining*, *14*(1), 1-28. https://doi.org/10.5281/zenodo.6599727
24. Southgate, E. (2023). *Artificial intelligence in schools: A guide for teachers, administrators, and policymakers*. Routledge. https://doi.org/10.4324/9781003362100
25. Vu, M. T., & Adair, D. (2023). ChatGPT in education: A review of the literature and future research directions. *Journal of Applied Learning & Teaching*, *6*(1). https://doi.org/10.37074/jalt.2023.6.1.20
26. Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274
27. UNESCO. (2023). *Generative AI in education and research: Opportunities and challenges*. UNESCO Digital Library.
28. Okonkwo, C. W., & Ade-Ibijola, A. (2023). A systematic review of deep learning models for personalized adaptive learning. *Education and Information Technologies*, *28*(4), 3629–3654. https://doi.org/10.1007/s10639-022-11333-z
29. Wang, T., & Cheng, E. (2023). A comprehensive survey on fairness in educational data mining. *ACM Transactions on Knowledge Discovery from Data*, *17*(5), 1-46. https://doi.org/10.1145/3579836
30. Gulson, K. N., & Witzenberger, K. (2023). Reprogramming education: AI, data, and the reshaping of learning. *Discourse: Studies in the Cultural Politics of Education*, *44*(1), 1-14. https://doi.org/10.1080/01596306.2023.2167664
31. Bali, M., & Caines, A. (2024). A call for critical AI literacy in education. *Postdigital Science and Education*, *6*(1), 1-19. https://doi.org/10.1007/s42438-023-00417-6
32. Yan, Z., & Li, X. (2025). Next-generation knowledge tracing: A survey of deep learning-based methods. *IEEE Transactions on Knowledge and Data Engineering*, *37*(1), 158-178. https://doi.org/10.1109/TKDE.2023.3283282
33. Sahani, S.K. et al. (2026). Mechanical Process Control and Statistical Process Control for Reducing Butter-Oil Defects in Industrial Production. *Reports in Mechanical Engineering*, *7*(1), 169-184. https://doi.org/10.31181/rme575

34. Sahani, S.K., Oruganti, S.K., K. Satishkumar (2025). Case Study on Mechanical and Operational Behavior in Steel Production: Performance and Process Behavior in Steel Manufacturing Plant, Reports in Mechanical Engineering, 6, 1,180-197.

35. Pandey, D., Sahanai, S.K., Pandey, B.K., Sahani, K., Dadheech, p., George, A.S., Matching Filter and Quantum Sensors: Study Dark Matter Transients for Computational, Computational Intelligence Solutions for Real-Life Problems, AAP, https://www.appleacademicpress.com/computational-intelligence-solutions-for-real-life-problems-theories-applications-and-advances/9781998511006

36. Sahani, S. K., & Sah, B. K. (2025). Optimization of Cultural Education Program Using Numerical Techniques Journal of Posthumanism, 5(6), 4265–4280. https://doi.org/10.63332/joph.v5i6.2600

37. Sahani, S. K., Sah, M. K., Agarwal, S. K., Pareek, V., Pareek, V., & Singh, V. V. (2025). Numerical Simulation of Cultural Value Conflict in Multicultural Societies. Journal of Posthumanism, 5(3), 1815–1831

38. Sahani, S. K., & Karna, S. K. (2025). Program for culture education optimization by the application of numerical method, Journal of Posthumanism, 5(1), 1611–1627. https://doi.org/10.63332/joph.v5i1.2687

39. Sahani, S. K., & Karna, S. K. (2025). Simulation of the Clash between Cultural Values in Heterogeneous Society using Numerical Methods. Journal of Posthumanism, 4(3), 543–559. https://doi.org/10.63332/joph.v4i3.2686

40. Sahani, S.K., Mandal, R.H., (2023). Application of Logistic Regression and Numerical Methods for Automated Bot Detection in Social Media Networks, Linguistic and Philosophical Investigations, Vol22, 2,192-206.

41. Sahani, S.K. and Sah, D.K. (2023). Hybrid Analytical-Numerical Techniques for Machine Learning Optimization: Integrating Laplace Transform and Runge-Kutta Fourth-Order Methods, Review of Contemporary Philosophy, 22, 1, 6854-6860 DOI: https://doi.org/10.52783/rcp.1165

42. Sahani, S.K. et al., (2022).A Comprehensive Study on Predicting Numerical Integration Errors using Machine Learning Approaches, Letters in High Energy Physics, 96-103.

DOI:\https://doi.org/10.52783/lhep.2022.1465