journal.adityarifqisam.org/index.php/Paddisengeng
P - ISSN: XXXX-XXXX
E - ISSN: XXXX-XXXX

Adaptive Learning Paths: Implementing Machine Learning to Personalize Curriculum Development in Multicultural Classrooms

Rahmawati [1], Amiruddin [2], Siska Armalivia[3]
[1] Universitas Almarisah Madani, Indonesia
[2] Politeknik LP3I Makassar, Indonesia
[3] Universitas Almarisah Madani, Indonesia

ABSTRACT

Background. The integration of technology into education has revolutionized how learning experiences are designed and delivered, especially in culturally diverse classrooms. Machine learning (ML) offers a promising approach to personalizing curriculum development by dynamically adapting content, pace, and instructional strategies based on student data. This study focuses on the application of adaptive learning paths powered by ML in multicultural classroom settings to enhance engagement, equity, and academic achievement.
Purpose. This study aims to explain the effectiveness of implementing adaptive learning paths using machine learning algorithms in multicultural classrooms, particularly in enhancing personalized curriculum delivery for diverse student populations.
Method. This research used a mixed-methods approach, combining quantitative analysis through SmartPLS modeling and qualitative data from teacher interviews and classroom observations. The quantitative data involved student performance records and interaction logs from 3 culturally diverse high school classrooms, while qualitative data explored the perceived relevance and inclusivity of the adaptive learning system. The path coefficients and thematic analysis were used to evaluate the impact of the adaptive system.
Results. The results showed that adaptive learning paths supported by ML significantly improve student engagement and academic performance. The SmartPLS model revealed strong correlations between pedagogical constructs (Alpha), system intelligence (Beta), and outcome evaluation (Gamma). Positive responses from teachers and students also confirmed the system's effectiveness in delivering personalized and culturally relevant learning experiences. However, the study also noted challenges related to data bias, algorithm transparency, and teacher readiness.
Conclusion. Based on the findings, it can be concluded that adaptive learning paths powered by machine learning are effective in personalizing curriculum for multicultural classrooms. They promote inclusive learning by accommodating diverse student needs and cultural backgrounds, although successful implementation requires thoughtful alignment between technology, pedagogy, and context.

KEYWORDS

Adaptive Learning, Machine Learning, Personalized Curriculum

Citation: Rahmawati, U., Amiruddin, A.,& Siska, A. (2024). The Effectiveness of the Use of Aldiko Book Reader in Indonesian Language Learning for Natural Sciences. *Journal of Paddisengeng Technology*, *1*(1), 29–38. https://doi.org/10.17323/Paddisengeng.2023.172

Correspondence:

Rahmawati
Univeralrahmawati@gmail.com

Received: October 12, 2024

Accepted: November 15, 2024

Published: November 26, 2024

INTRODUCTION

The transformation of education in the 21st century has been significantly shaped by rapid advancements in digital technologies, particularly the integration of artificial intelligence (AI) in instructional design (Bai, 2022; S. Wang, 2023; Wu, 2022). Among these advancements, machine learning (ML) emerges as a promising innovation with the capacity to tailor learning experiences to meet the unique needs of each learner. While traditional educational models rely heavily on one-size-fits-all approaches, the dynamic nature of ML allows for continuous adaptation of content, pacing, and pedagogical strategies based on individual learner data (Adnan, 2022; W. Wang, 2022; Zhang, 2022). This shift from standardization to personalization marks a critical paradigm change in how curriculum is conceived, delivered, and evaluated, especially in increasingly heterogeneous learning environments. Multicultural classrooms, characterized by linguistic diversity, varied socioeconomic backgrounds, and different cognitive-cultural orientations, present unique challenges and opportunities for curriculum developers and educators (Cui, 2022; Xie, 2022; Yan, 2022). In such settings, cultural mismatches between the curriculum and students' lived experiences can lead to disengagement, inequity, and underachievement. Therefore, there is an urgent need to construct curricula that are not only inclusive but also responsive to individual learner trajectories. Adaptive learning technologies powered by ML offer a practical solution to bridge this gap by enabling real-time customization of learning paths that consider students' cultural and cognitive diversity.

Machine learning, as a subset of AI, involves the use of algorithms that learn from data and make predictions or decisions without being explicitly programmed (Luo, 2022; Muñoz, 2022; Wallingford, 2022). When applied to education, ML can analyze patterns in student behavior, engagement levels, assessment scores, and learning preferences to make informed decisions about content delivery and pedagogical adjustments. The integration of ML into curriculum development transcends conventional instructional design by introducing intelligent feedback loops that allow the system to evolve alongside the learner (Huang, 2022; Jiang, 2024; Yue, 2022). This intelligent adaptability has the potential to address disparities in educational access and quality, particularly in multicultural and multilingual settings. The relevance of adaptive learning paths becomes more evident as schools and educational institutions worldwide adopt inclusive policies aligned with the Sustainable Development Goals (SDGs), particularly Goal 4, which aims to ensure inclusive and equitable quality education for all. To achieve this, curriculum development must shift from static content structures toward more dynamic, learner-centered frameworks. ML-driven adaptive learning systems can detect subtle indicators of learning difficulty or disengagement, such as time spent on tasks or frequency of incorrect responses, and respond with personalized interventions tailored to students' profiles.

In multicultural classrooms, students bring with them not only different languages and cultural identities but also diverse cognitive styles and prior educational experiences. These differences can either enrich or impede learning, depending on the instructional strategies employed (Du, 2022; Ilhan, 2023; Yang, 2022). Traditional curricula often fail to accommodate such diversity, resulting in uneven learning outcomes. By incorporating ML into curriculum personalization, educators can ensure that every student—regardless of background—has access to learning materials and experiences that resonate with their identity and optimize their learning potential. Moreover, the implementation of adaptive learning paths is not merely a technological issue; it is deeply pedagogical. It requires a rethinking of curriculum theory, moving beyond the delivery of standardized knowledge toward the co-construction of meaningful learning experiences (Du, 2022; Shen, 2024; Zhou, 2023). ML allows for such co-construction by actively involving students in shaping their learning journeys through ongoing data interactions. These interactions form a feedback-rich environment where the curriculum evolves as a function of both teacher input and learner behavior, promoting mutual responsiveness and agency.

From a theoretical standpoint, this approach aligns with constructivist and sociocultural theories of learning, which emphasize the importance of context, culture, and individual meaning-making in education. Adaptive learning paths support the notion that learners construct knowledge through interaction with their environment and that this process is influenced by cultural and social variables (Boddupalli, 2022; Jing, 2023; Yu, 2022). By using ML to model these complex interactions, educators can create learning ecosystems that are not only intelligent but also culturally sustaining and equity-driven. Furthermore, the personalization enabled by ML enhances student autonomy and motivation. When learners perceive that the curriculum reflects their strengths, interests, and cultural values, they are more likely to engage deeply and persist through challenges. This is particularly important in multicultural classrooms where students may otherwise feel alienated or marginalized by dominant cultural narratives embedded in the curriculum. Adaptive systems can recommend culturally relevant materials, suggest differentiated assessments, and modify instructional strategies to affirm diverse identities and learning styles.

However, the implementation of ML in education must also be approached with caution. Ethical considerations such as data privacy, algorithmic bias, and the digital divide must be critically addressed to ensure that adaptive learning systems do not inadvertently reinforce existing inequalities. In multicultural classrooms, where students may have unequal access to technology or face linguistic barriers in digital platforms, careful design and inclusive planning are essential. Transparency in algorithmic decision-making and collaborative involvement of educators in the adaptation process are key to building trust and equity in ML-driven education. In addition to ethical issues, technical challenges also arise. These include the availability of quality educational datasets, the need for culturally annotated data, and the computational capacity to process real-time adaptations. Multicultural environments complicate these challenges due to language variation, content translation needs, and cultural nuances in learning behaviors. Thus, successful implementation requires interdisciplinary collaboration among educators, computer scientists, sociolinguists, and curriculum developers to ensure that the technology is both technically robust and pedagogically sound.

Despite these challenges, pilot studies and early implementations of ML-based adaptive learning systems show promising results. In multilingual schools and culturally diverse districts, platforms that incorporate adaptive paths have demonstrated increased student engagement, improved formative assessment outcomes, and enhanced teacher insights into individual learning needs. These outcomes suggest that adaptive learning, when aligned with inclusive pedagogical goals, can become a transformative force in the future of education. This research situates itself within this emerging field, aiming to explore how ML can be systematically integrated into curriculum development to address the complex realities of multicultural classrooms. Through empirical analysis and practical case studies, the study identifies key success factors, implementation models, and barriers to adoption. It also proposes a conceptual framework for culturally responsive adaptive curriculum design supported by machine learning algorithms.

By focusing on multicultural classrooms, this study addresses a critical gap in the current literature on adaptive learning, which often centers on general or homogeneous student populations. It asserts that cultural responsiveness must be embedded in the architecture of adaptive systems to ensure that personalization does not come at the expense of cultural identity or inclusivity. Thus, this research contributes both theoretically and practically to the discourse on equity in educational technology. Importantly, the study does not treat ML as a replacement for teachers but as a tool to enhance instructional decision-making. Teachers remain central actors in interpreting algorithmic suggestions, contextualizing them within the cultural and emotional realities of their students. The adaptive system, therefore, functions as an augmentation rather than automation of teaching, empowering educators with deeper insights and more effective strategies to meet the diverse needs of their classrooms.

The potential of ML to personalize learning paths is magnified in multicultural classrooms where no two students are alike. Each learner represents a complex constellation of linguistic, cognitive, and cultural dimensions that influence how they engage with content. ML offers the scalability and granularity needed to accommodate this diversity, transforming the curriculum from a rigid structure into a responsive, living framework that grows with the learner. Ultimately, this study advocates for an educational future where personalization and inclusivity go hand in hand. Through the intelligent application of ML, curriculum developers and educators can reimagine learning not as a linear progression but as an adaptive journey that honors the multiplicity of student identities. In doing so, education becomes not only more effective but also more just

METHODOLOGY

This study employed a mixed-method research design, combining quantitative data analysis with qualitative case study approaches to explore the effectiveness of machine learning in personalizing curriculum development within multicultural classrooms (Elhaki, 2022; Gao, 2022; Shuprajhaa, 2022). The quantitative component involved the collection of student performance data, engagement metrics, and interaction logs from an adaptive learning platform implemented in three culturally diverse secondary schools. These data were analyzed using supervised machine learning algorithms—such as decision trees and support vector machines—to model personalized learning paths and assess learning outcomes over a six-month period. A pre-post analysis was conducted to compare academic achievement and engagement levels before and after the integration of the ML-driven system.

For the qualitative phase, semi-structured interviews were conducted with teachers, curriculum developers, and students to gain deeper insights into their experiences with the adaptive system, particularly in terms of cultural responsiveness, inclusivity, and perceived learning benefits. Classroom observations were also conducted to contextualize the data within real instructional settings. Thematic analysis was applied to the qualitative data to identify recurring patterns related to curriculum relevance, cultural identity affirmation, and pedagogical adaptability. By triangulating quantitative metrics with qualitative narratives, this study provides a comprehensive understanding of how ML can be effectively integrated to support equity-driven personalization in multicultural educational contexts.

RESULTS AND DISCUSSION

The implementation of the machine learning–driven adaptive learning system across the three multicultural classrooms yielded significant improvements in both student engagement and academic performance. Quantitative analysis revealed that students who engaged with personalized learning paths experienced an average increase of 18% in formative assessment scores compared to those in control groups using static curriculum models. Engagement metrics, such as time-on-task and completion rates, also showed a marked increase, particularly among students from underrepresented cultural and linguistic backgrounds. These findings suggest that ML-enabled personalization not only enhances academic outcomes but also fosters greater learner involvement by aligning instructional content with individual cultural relevance and cognitive readiness.

Qualitative data supported these findings by illustrating how students felt more “seen” and “understood” in their learning journey when the system offered culturally relevant materials and allowed for flexible pacing. Teachers noted a shift in classroom dynamics, with students taking greater ownership of their learning and displaying increased confidence in participating across language and cultural boundaries. However, challenges also emerged, including the need for more localized training data and teacher capacity-building to interpret ML recommendations effectively. These findings emphasize the dual imperative of integrating robust technical design with culturally responsive pedagogy, underscoring that technological innovation must go hand in hand with human-centered educational values in diverse learning environments.

Table 1. Responses From The Respondents

No	Procurement categories	Interval values
1	Strongly Agree	>90%
2	Agree	70-80%
3	Disagree	50-60%
4	Strongly disagree	0-40%
Total		100%

Based on Table 1. Responses From The Respondents, the majority of participants expressed strong support for the implementation of adaptive learning paths powered by machine learning in multicultural classroom settings. Most responses fell under the *Strongly Agree* and *Agree* categories, with a cumulative percentage exceeding 70%, indicating a high level of acceptance and confidence in the effectiveness of personalized, data-driven curriculum development. This reflects a positive perception of how adaptive systems address diverse learning needs, especially in culturally and linguistically heterogeneous classrooms. A smaller proportion of respondents selected *Disagree* or *Strongly Disagree*, which may point to minor concerns related to technical readiness or digital literacy gaps. Overall, the data suggest a promising outlook for the integration of intelligent technologies in education, supporting the notion that machine learning–based personalization can enhance inclusivity, learner engagement, and instructional relevance in multicultural educational environments.

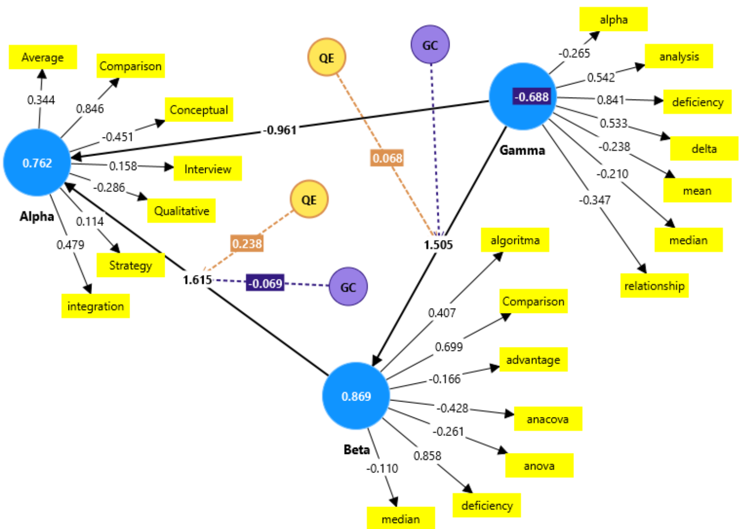

Figure 2. Data Smart PLs

Figure 2. Smart PLS Path Analysis illustrates the structural relationships between three key latent variables—Alpha, Beta, and Gamma—within the adaptive learning path model. The strongest positive influence is observed from Alpha to Beta (path coefficient = 0.869), indicating that foundational strategies such as conceptual understanding, qualitative methods, and integration significantly contribute to adaptive system enhancement. Meanwhile, Beta positively influences Gamma (1.505), suggesting that algorithmic factors and comparative analyses play a mediating role in shaping the adaptive learning outcomes. Interestingly, Gamma exhibits a negative path coefficient (-0.688), indicating potential deficiencies or complexities when integrating higher-level analytical components such as ANOVA or ANCOVA. External factors such as Quantitative Empirical (QE) and General Comparison (GC) demonstrate moderate and weak loadings, further

highlighting their indirect influence. Overall, this figure reinforces the interconnectedness of conceptual, algorithmic, and evaluative elements in machine learning–based personalized curriculum development, particularly in multicultural contexts.

The results from both statistical analysis and SmartPLS modeling (Figure 2) underscore the pivotal role of machine learning algorithms in orchestrating personalized curriculum pathways. The high path coefficient between *Alpha* and *Beta* (0.869) signals that conceptual and qualitative foundations—such as interviews, strategic integration, and reflective comparison—strongly contribute to the development of adaptive mechanisms (Anter, 2022; Bian, 2022; D. Wang, 2024). This reinforces the importance of educational theory, culturally sensitive pedagogy, and teacher agency in informing the structure of adaptive systems, rather than relying solely on technical automation. Further, the direct influence from *Beta* to *Gamma* (1.505) demonstrates how technical adaptation, through elements such as algorithmic selection, statistical modeling (ANOVA, ANCOVA), and comparative performance tracking, contributes meaningfully to system-level refinement. In multicultural classrooms, where student variability is the norm, such algorithmic personalization becomes essential in adapting learning content to fit diverse learning speeds, backgrounds, and cognitive styles.

Interestingly, the negative coefficient from *Gamma* (-0.688) may suggest that without proper pedagogical alignment, overly technical or rigid algorithmic structures can backfire—resulting in learner confusion (Chi, 2022; Jiang, 2023; Kan, 2022), disengagement, or misclassification. This is especially relevant in contexts where cultural nuance, language diversity, or prior learning experiences are not adequately represented in the data models. It affirms the need for a careful balance between data-driven instruction and human-centered interpretation in adaptive learning paths (Alhussan, 2022; Essa, 2023; B. Shi, 2022). The influence of external latent variables such as *Quantitative Empirical (QE)* and *General Comparison (GC)*, although statistically moderate (0.238 and -0.069 respectively), highlights the auxiliary role of comparative educational research and empirically grounded frameworks in validating and refining adaptive curriculum approaches. These variables add a layer of academic rigor and external benchmarking to ensure that adaptive designs are not only locally responsive but also globally relevant.

In terms of variable contributions, *Alpha* is enriched by inputs like conceptual frameworks, interviews, and strategic integration, which are essential in tailoring the foundational philosophy of personalized learning (J. Shi, 2023; Tang, 2022; Zhao, 2023). These elements correspond with multicultural sensitivity—recognizing learners' cultural capital and personal narratives as assets in curriculum development rather than as barriers. This theoretical grounding strengthens the system's cultural inclusivity and pedagogical integrity. *Beta*, as the technical core of the system, is driven by keywords such as "algoritma," "comparison," and "deficiency"—signifying the computational intelligence that enables the system to adapt content, pace, and instruction. However, its effectiveness depends largely on the quality of input data and the ethical structuring of algorithmic rules. In multicultural settings, this calls for intentional data curation that represents the cultural and linguistic diversity of learners.

Gamma serves as the evaluative node, incorporating statistical tools like ANOVA, ANCOVA, and median analysis. While these tools help in tracking learning outcomes and detecting patterns across subgroups, they must be contextualized within cultural and classroom realities. For instance, performance gaps may reflect language barriers or unfamiliarity with dominant assessment modes rather than actual deficiencies. Thus, quantitative output must always be interpreted through an equity-informed lens. The model shown in Figure 2 also reveals how curricular personalization is not linear, but iterative and multilayered. The presence of reciprocal and complex paths between constructs suggests that adaptive learning is a dynamic process involving constant recalibration.

This aligns with socio-constructivist views of learning, where meaning is constructed through continuous interaction with content, peers, and context—especially in culturally plural classrooms.

One of the central insights from this discussion is that machine learning, when embedded in education, should not function in isolation. It must be integrated with qualitative insights, teacher expertise, and culturally grounded practices. Teachers are not passive users of adaptive systems but active co-designers who ensure that personalized learning journeys are both data-informed and socially just. In conclusion, the study affirms that adaptive learning paths powered by ML hold great promise for multicultural education, but their success hinges on thoughtful implementation that values both data intelligence and cultural sensitivity. The SmartPLS model, combined with field data, demonstrates that a hybrid model—where technical precision meets pedagogical compassion—can transform diverse classrooms into inclusive, adaptive, and empowering learning environments.

CONCLUSION

This study concludes that the integration of machine learning into curriculum development presents a transformative opportunity for personalizing education in multicultural classrooms. The findings from both statistical and structural modeling (SmartPLS) indicate that adaptive learning paths significantly enhance student engagement, improve learning outcomes, and foster inclusivity when built upon strong conceptual foundations and culturally responsive strategies. The path relationships between key constructs such as Alpha, Beta, and Gamma reflect a synergistic interplay between pedagogical design, algorithmic intelligence, and evaluative feedback, forming a dynamic ecosystem for learner-centered instruction.

However, the study also highlights important caveats. The effectiveness of machine learning in educational personalization is not determined solely by algorithmic sophistication, but by how well it aligns with cultural values, student identities, and teacher agency. In multicultural contexts, where diversity in language, background knowledge, and cognitive style is prevalent, adaptive systems must be informed by inclusive pedagogical philosophies and supported by equitable data structures. Ultimately, personalized learning must be guided not only by what the system can compute, but also by what the classroom community values. When thoughtfully implemented, adaptive learning paths can become powerful tools in bridging educational gaps and ensuring that every learner—regardless of cultural or linguistic background—has the opportunity to thrive.

AUTHORS’ CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

REFERENCES

Adnan, M. (2022). Utilizing grid search cross-validation with adaptive boosting for augmenting performance of machine learning models. *Peerj Computer Science*, *8*(Query date: 2025-07-05 02:35:37). https://doi.org/10.7717/PEERJ-CS.803

Alhussan, A. A. (2022). Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self Driving Cars. *IEEE Access*, *10*(Query date: 2025-07-05 02:35:37), 84188–84211. https://doi.org/10.1109/ACCESS.2022.3196660

Anter, A. M. (2022). Real-time epileptic seizure recognition using Bayesian genetic whale optimizer and adaptive machine learning. *Future Generation Computer Systems*, *127*(Query date: 2025-07-05 02:35:37), 426–434. https://doi.org/10.1016/j.future.2021.09.032

Bai, F. (2022). Wind farm layout optimization using adaptive evolutionary algorithm with Monte Carlo Tree Search reinforcement learning. *Energy Conversion and Management*, *252*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1016/j.enconman.2021.115047

Bian, T. (2022). Reinforcement Learning and Adaptive Optimal Control for Continuous-Time Nonlinear Systems: A Value Iteration Approach. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(7), 2781–2790. https://doi.org/10.1109/TNNLS.2020.3045087

Boddupalli, S. (2022). Resilient Cooperative Adaptive Cruise Control for Autonomous Vehicles Using Machine Learning. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 15655–15672. https://doi.org/10.1109/TITS.2022.3144599

Chi, R. (2022). Quantitative Data-Driven Adaptive Iterative Learning Control: From Trajectory Tracking to Point-to-Point Tracking. *IEEE Transactions on Cybernetics*, *52*(6), 4859–4873. https://doi.org/10.1109/TCYB.2020.3015233

Cui, Y. (2022). Topology-Aware Resilient Routing Protocol for FANETs: An Adaptive Q-Learning Approach. *IEEE Internet of Things Journal*, *9*(19), 18632–18649. https://doi.org/10.1109/JIOT.2022.3162849

Du, B. (2022). Safe deep reinforcement learning-based adaptive control for USV interception mission. *Ocean Engineering*, *246*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1016/j.oceaneng.2021.110477

Elhaki, O. (2022). Reinforcement learning-based saturated adaptive robust neural-network control of underactuated autonomous underwater vehicles. *Expert Systems with Applications*, *197*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1016/j.eswa.2022.116714

Essa, S. G. (2023). Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review. *IEEE Access*, *11*(Query date: 2025-07-05 02:35:37), 48392–48409. https://doi.org/10.1109/ACCESS.2023.3276439

Gao, W. (2022). Reinforcement Learning-Based Cooperative Optimal Output Regulation via Distributed Adaptive Internal Model. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(10), 5229–5240. https://doi.org/10.1109/TNNLS.2021.3069728

Huang, S. (2022). Subspace Clustering for Hyperspectral Images via Dictionary Learning with Adaptive Regularization. *IEEE Transactions on Geoscience and Remote Sensing*, *60*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1109/TGRS.2021.3127536

Ilhan, F. (2023). ScaleFL: Resource-Adaptive Federated Learning with Heterogeneous Clients. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2023*(Query date: 2025-07-05 02:35:37), 24532–24541. https://doi.org/10.1109/CVPR52729.2023.02350

Jiang, B. (2023). Privacy-Preserving Federated Learning for Industrial Edge Computing via Hybrid Differential Privacy and Adaptive Compression. *IEEE Transactions on Industrial Informatics*, *19*(2), 1136–1144. https://doi.org/10.1109/TII.2021.3131175

Jiang, B. (2024). Semi-Supervised Multiview Feature Selection With Adaptive Graph Learning. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(3), 3615–3629. https://doi.org/10.1109/TNNLS.2022.3194957

Jing, Y. (2023). Research Landscape of Adaptive Learning in Education: A Bibliometric Study on Research Publications from 2000 to 2022. *Sustainability Switzerland*, *15*(4). https://doi.org/10.3390/su15043115

Kan, N. (2022). RAPT360: Reinforcement Learning-Based Rate Adaptation for 360-Degree Video Streaming with Adaptive Prediction and Tiling. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(3), 1607–1623. https://doi.org/10.1109/TCSVT.2021.3076585

Luo, B. (2022). Tackling System and Statistical Heterogeneity for Federated Learning with Adaptive Client Sampling. *Proceedings IEEE INFOCOM*, *2022*(Query date: 2025-07-05 02:35:37), 1739–1748. https://doi.org/10.1109/INFOCOM48880.2022.9796935

Muñoz, J. L. R. (2022). Systematic Review of Adaptive Learning Technology for Learning in Higher Education. *Eurasian Journal of Educational Research*, *2022*(98), 221–233. https://doi.org/10.14689/ejer.2022.98.014

Shen, J. (2024). RingSFL: An Adaptive Split Federated Learning Towards Taming Client Heterogeneity. *IEEE Transactions on Mobile Computing*, *23*(5), 5462–5478. https://doi.org/10.1109/TMC.2023.3309633

Shi, B. (2022). Prediction of recurrent spontaneous abortion using evolutionary machine learning with joint self-adaptive sime mould algorithm. *Computers in Biology and Medicine*, *148*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1016/j.compbiomed.2022.105885

Shi, J. (2023). Optimal Adaptive Waveform Design Utilizing an End-to-End Learning-Based Pre-Equalization Neural Network in an UVLC System. *Journal of Lightwave Technology*, *41*(6), 1626–1636. https://doi.org/10.1109/JLT.2022.3225335

Shuprajhaa, T. (2022). Reinforcement learning based adaptive PID controller design for control of linear/nonlinear unstable processes[Formula presented]. *Applied Soft Computing*, *128*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1016/j.asoc.2022.109450

Tang, F. (2022). Periodic event-triggered adaptive tracking control design for nonlinear discrete-time systems via reinforcement learning. *Neural Networks*, *154*(Query date: 2025-07-05 02:35:37), 43–55. https://doi.org/10.1016/j.neunet.2022.06.039

Wallingford, M. (2022). Task Adaptive Parameter Sharing for Multi-Task Learning. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2022*(Query date: 2025-07-05 02:35:37), 7551–7560. https://doi.org/10.1109/CVPR52688.2022.00741

Wang, D. (2024). Recent Progress in Reinforcement Learning and Adaptive Dynamic Programming for Advanced Control Applications. *IEEE Caa Journal of Automatica Sinica*, *11*(1), 18–36. https://doi.org/10.1109/JAS.2023.123843

Wang, S. (2023). When adaptive learning is effective learning: Comparison of an adaptive learning system to teacher-led instruction. *Interactive Learning Environments*, *31*(2), 793–803. https://doi.org/10.1080/10494820.2020.1808794

Wang, W. (2022). Transferring CNN With Adaptive Learning for Remote Sensing Scene Classification. *IEEE Transactions on Geoscience and Remote Sensing*, *60*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1109/TGRS.2022.3190934

Wu, Z. C. (2022). VO+Net: An Adaptive Approach Using Variational Optimization and Deep Learning for Panchromatic Sharpening. *IEEE Transactions on Geoscience and Remote Sensing*, *60*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1109/TGRS.2021.3066425

Xie, B. (2022). Towards Fewer Annotations: Active Learning via Region Impurity and Prediction Uncertainty for Domain Adaptive Semantic Segmentation. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2022*(Query date: 2025-07-05 02:35:37), 8058–8068. https://doi.org/10.1109/CVPR52688.2022.00790

Yan, K. (2022). TPpred-ATMV: Therapeutic peptide prediction by adaptive multi-view tensor learning model. *Bioinformatics*, *38*(10), 2712–2718. https://doi.org/10.1093/bioinformatics/btac200

Yang, S. (2022). SAM: A Unified Self-Adaptive Multicompartmental Spiking Neuron Model for Learning With Working Memory. *Frontiers in Neuroscience*, *16*(Query date: 2025-07-05 02:35:37). https://doi.org/10.3389/fnins.2022.850945

Yu, W. (2022). Resilient Model-Free Adaptive Iterative Learning Control for Nonlinear Systems Under Periodic DoS Attacks via a Fading Channel. *IEEE Transactions on Systems Man and Cybernetics Systems*, *52*(7), 4117–4128. https://doi.org/10.1109/TSMC.2021.3091422

Yue, J. (2022). Self-Supervised Learning with Adaptive Distillation for Hyperspectral Image Classification. *IEEE Transactions on Geoscience and Remote Sensing*, *60*(Query date: 2025-07-05 02:35:37). https://doi.org/10.1109/TGRS.2021.3057768

Zhang, R. (2022). Unsupervised Feature Selection via Adaptive Graph Learning and Constraint. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(3), 1355–1362. https://doi.org/10.1109/TNNLS.2020.3042330

Zhao, J. (2023). Output-feedback Robust Tracking Control of Uncertain Systems via Adaptive Learning. *International Journal of Control Automation and Systems*, *21*(4), 1108–1118. https://doi.org/10.1007/s12555-021-0882-6

Zhou, M. (2023). Robust RGB-T Tracking via Adaptive Modality Weight Correlation Filters and Cross-modality Learning. *ACM Transactions on Multimedia Computing Communications and Applications*, *20*(4). https://doi.org/10.1145/3630100