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RECEIVED 12 March 2025

ACCEPTED 18 June 2025

PUBLISHED 14 July 2025

CITATION

Lu C and Ruijuan H (2025) Enhancing action recognition in educational settings using AI-driven information systems for public health monitoring.
Front. Public Health 13:1592228.
doi: 10.3389/fpubh.2025.1592228

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Enhancing action recognition in educational settings using AI-driven information systems for public health monitoring

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Introduction: The integration of Artificial Intelligence (AI) into educational environments is revolutionizing action recognition, offering a transformative opportunity to enhance public health monitoring. Traditional methods, which primarily rely on rule-based algorithms or handcrafted feature extraction, face significant challenges in adaptability, scalability, and real-time processing. These limitations hinder their effectiveness, particularly in detecting health-related behaviors such as sedentary patterns, social interactions, and hygiene compliance.

Methods: To overcome these shortcomings, this research introduces an AI-driven information system that leverages advanced deep learning models and an Adaptive Knowledge Embedding Network (AKEN) to improve action recognition accuracy. The approach integrates AKEN with a Dynamic Personalized Learning Strategy (DPLS) to model student behaviors, predict future actions, and optimize intervention strategies by incorporating factors such as engagement levels, learning progress, and environmental conditions.

Results: By utilizing reinforcement learning and explainable AI techniques, the system not only refines recognition accuracy but also ensures transparency in decision-making. Real-time engagement monitoring enhances adaptability, allowing educators and policymakers to make informed interventions.

Discussion: Experimental results validate the system's superior performance over conventional approaches, demonstrating its ability to recognize complex behavioral patterns in educational settings. This innovation represents a significant step forward in AI-driven public health monitoring, fostering a safer and more responsive learning environment.

KEYWORDS

AI-driven action recognition, public health monitoring, adaptive knowledge embedding, deep learning in education, explainable AI

1 Introduction

The increasing demand for public health monitoring in educational settings has necessitated the development of advanced AI-driven information systems capable of recognizing human actions in real time (1). Not only does action recognition play a crucial role in ensuring student safety by identifying abnormal behaviors such as falls, fights, or health emergencies, but it also supports public health initiatives by detecting hygiene compliance, social distancing adherence, and symptoms of illness (2). Moreover, leveraging AI for automated surveillance in schools reduces the burden on human monitors,

ensuring comprehensive, non-intrusive, and efficient observation (3). Traditional monitoring approaches, such as manual supervision or rule-based surveillance systems, are often limited by scalability and subjectivity, making AI-based action recognition a necessary evolution (4). However, the development of robust and generalizable action recognition models remains challenging due to factors such as occlusions, variations in human movement, and environmental complexities (5). Addressing these challenges requires a systematic approach that builds upon classical methods, integrates machine learning advancements, and capitalizes on the power of deep learning and pre-trained models.

To address the shortcomings of primitive heuristic-driven methods, preliminary studies in action identification utilized symbolic artificial intelligence and knowledge modeling strategies (6). These methods aimed to capture human activities using handcrafted features and structured rule-based logic. For example, predefined motion templates, spatiotemporal descriptors, and expert-defined ontologies were employed to model human actions in constrained environments (7). While these approaches provided interpretability and logical reasoning, their reliance on manually designed rules made them inflexible to variations in movement styles and real-world complexities (8). Furthermore, symbolic AI methods struggled with scalability, requiring extensive domain knowledge to generalize across diverse educational settings (9). They laid the foundation for understanding human motion patterns and provided insights into how structured representations could be leveraged for action classification in public health applications (10).

To address the rigidity and limited adaptability of symbolic AI, researchers transitioned toward data-driven and machine learning-based approaches (11). These methods leveraged statistical learning and probabilistic models, such as Hidden Markov Models (HMMs), Support Vector Machines (SVMs), and Random Forests, to recognize human actions from sensor or video data (12). Unlike rule-based methods, machine learning models could learn from labeled datasets and generalize better to unseen scenarios (13). Handcrafted feature extraction techniques, such as Histogram of Oriented Gradients (HOG) and Motion History Images (MHI), improved the ability to capture motion dynamics (14). However, these models still suffered from feature engineering challenges and struggled with highly variable and occluded human actions (15). Moreover, traditional machine learning methods required large-scale annotated datasets to achieve high accuracy, which posed challenges in educational settings where privacy concerns and data labeling costs are significant considerations.

Modern progress in deep neural networks and pre-trained frameworks has greatly enhanced action classification accuracy by utilizing sophisticated neural structures capable of autonomously extracting multi-level motion patterns (16). Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been extensively used to model spatiotemporal dependencies in human motion sequences (17). More recently, Transformer-based architectures and Vision Transformers (ViTs) have demonstrated superior performance in learning long-range dependencies and capturing fine-grained motion patterns (18). Pre-trained models such as I3D (Inflated 3D ConvNet) and SlowFast networks have been adapted for real-time action recognition in educational environments (19). Despite their success, deep learning models often require large-scale training datasets and computational

resources, making deployment in school settings challenging (20). Furthermore, concerns regarding bias, interpretability, and robustness remain open issues that must be addressed for reliable public health monitoring.

Given the limitations of traditional methods, machine learning models, and deep learning architectures, we propose an AI-driven information system tailored for real-time action recognition in educational settings. Our approach integrates multi-modal sensor fusion, self-supervised learning techniques, and domain-adaptive training to enhance recognition accuracy while addressing privacy and computational constraints. By combining depth cameras, inertial sensors, and privacy-preserving AI models, our system can recognize actions robustly without relying on sensitive video data. Furthermore, self-supervised learning reduces the dependency on large-scale labeled datasets, allowing the system to adapt to new educational environments with minimal human intervention. Our proposed framework not only enhances public health monitoring by identifying potential health risks but also improves overall school safety through intelligent action recognition and anomaly detection. The integration of AI-driven information systems into educational settings holds significant implications for public health monitoring. Schools are densely populated, highly interactive environments where health-related behaviors can rapidly influence collective wellbeing. By embedding intelligent action recognition and monitoring tools into these contexts, institutions can detect early indicators of illness, monitor hygiene compliance, and manage behavioral risks in real time. This not only supports proactive health interventions but also alleviates the burden on staff through automated observation and alerts. As such, our study provides a timely and critical advancement in leveraging AI to create safer, healthier, and more responsive learning environments, aligning technological innovation with the pressing demands of modern education systems.

- Our approach integrates multi-modal sensor fusion and self-supervised learning, enabling robust action recognition with minimal labeled data requirements.
- The system is designed for real-time deployment in diverse educational environments, ensuring adaptability, computational efficiency, and privacy preservation.
- Relative analyses indicate that our approach surpasses cutting-edge frameworks in precision, resilience, and practical implementation for public health surveillance.

2 Related work

2.1 AI-driven action recognition in educational environments

Artificial intelligence (AI) has significantly transformed educational environments by introducing advanced action recognition systems that monitor and analyze student activities. These systems utilize computer vision and deep learning techniques to interpret student behaviors, thereby enhancing classroom management and educational outcomes (21). One notable application is the development of intelligent tutoring systems that adapt to individual learning styles. By recognizing specific student actions, such as hand-raising or engagement levels,

AI systems can tailor instructional content to meet diverse learning needs. This personalized approach has been shown to improve student performance and engagement (22). Moreover, AI-driven action recognition contributes to maintaining safety within educational settings. For instance, systems equipped with real-time monitoring capabilities can detect unusual or unauthorized activities, enabling prompt intervention by school authorities. This proactive surveillance fosters a secure learning environment, essential for both students and educators (23). The integration of AI in classrooms also extends to administrative functions, such as attendance tracking. Traditional methods are often time-consuming and prone to errors; however, AI-based systems can automate this process by recognizing student faces or movements as they enter the classroom. This automation not only streamlines administrative tasks but also allows educators to allocate more time to instructional activities (24). Despite these advancements, the implementation of AI-driven action recognition systems raises concerns regarding privacy and data security (25). The collection and analysis of student data necessitate stringent measures to protect sensitive information (26). Educational institutions must establish clear policies and employ robust encryption methods to ensure compliance with ethical standards and legal regulations.

2.2 AI applications in public health surveillance

The integration of artificial intelligence (AI) into public health surveillance has markedly improved the ability to monitor, predict, and respond to health-related events. AI technologies enable early disease detection and efficient public health resource management through large-scale data analysis (27). AI-driven systems can process diverse data sources, including social media posts, healthcare records, and environmental sensors, to identify patterns indicative of emerging health threats. For example, machine learning algorithms can analyze search engine queries and social media activity to detect increases in symptom-related discussions, serving as early warning signals for potential epidemics. This proactive approach allows health authorities to implement preventive measures before diseases spread widely (28). AI enhances the accuracy of disease forecasting models. By incorporating real-time data and complex variables, AI models can predict the trajectory of infectious diseases with greater precision. These predictions inform public health interventions, such as vaccination campaigns and resource allocation, optimizing the response to health crises (29). AI applications also extend to monitoring environmental factors that influence public health. For instance, AI systems can analyze air quality data to predict pollution levels, enabling communities to take precautionary measures to protect vulnerable populations. Similarly, AI can assess climate data to anticipate weather-related health risks, such as heatwaves or vector-borne diseases, facilitating timely public health advisories (30). However, the deployment of AI in public health surveillance must address challenges related to data privacy and ethical considerations. The use of personal health information requires strict adherence to confidentiality protocols and informed consent. Moreover, AI models must be

transparent and free from biases that could lead to disparities in health interventions. Ensuring equitable access to AI-driven health solutions is essential to prevent the exacerbation of existing health inequalities (31).

2.3 Integrating AI for health monitoring in educational settings

The convergence of artificial intelligence (AI) and educational environments presents innovative opportunities for health monitoring, particularly in safeguarding student wellbeing (32). By embedding AI-driven health surveillance systems within schools, institutions can proactively address public health concerns and enhance the overall safety of the educational community (33). One application involves the use of AI to monitor physiological indicators among students. Wearable devices equipped with AI algorithms can track vital signs such as body temperature, heart rate, and respiratory patterns. Continuous analysis of this data enables the early detection of potential health issues, including infectious diseases, allowing for prompt medical intervention and reducing the risk of transmission within the school population (34). AI systems can also analyze behavioral patterns to identify signs of mental health concerns. For example, changes in a student's activity levels, social interactions, or academic performance may signal underlying issues such as anxiety or depression. By recognizing these patterns, AI can alert school counselors or psychologists, facilitating timely support and intervention (35). The integration of AI-driven health monitoring extends to environmental assessments within educational facilities. AI can evaluate classroom conditions, including air quality, lighting, and noise levels, to ensure they meet health and safety standards. Maintaining an optimal learning environment contributes to the physical wellbeing of students and supports their cognitive functions (36). Implementing AI for health monitoring in schools also aids in managing public health emergencies. During outbreaks of contagious diseases, AI can assist in contact tracing by analyzing interactions and proximity between individuals. This capability enables rapid identification of those at risk, supporting containment measures and minimizing disruption to educational activities (37). Despite the benefits, the adoption of AI-based health monitoring in educational settings raises important ethical and privacy considerations. The collection of health-related data necessitates robust data protection measures to prevent unauthorized access and misuse (38). Transparency in data usage policies and obtaining informed consent from students and guardians are essential to maintain trust and compliance with legal standards (39). To ensure the broader relevance of this work to the public health community, we emphasize that the proposed AI-driven system is not only a technical advancement but also a practical tool for real-time behavior monitoring in schools. By identifying prolonged sedentary behavior, irregular hygiene compliance, or signs of student distress, the system can support early interventions and health-promoting decisions by school staff. These capabilities align directly with public health goals of disease prevention, mental health monitoring, and resource-efficient surveillance in educational institutions.

2.4 Ethical and policy considerations in AI-based educational health systems

While technological advancements in AI and computer vision have enabled increasingly accurate action recognition, their deployment in school settings must be grounded in broader ethical and policy contexts. As highlighted by Langford (40), the WHO Health Promoting Schools framework underscores that educational institutions play a pivotal role not only in academic development but also in fostering student health and wellbeing. AI-based monitoring tools should therefore align with this dual mandate—supporting both learning and early detection of health risks through non-invasive, supportive interventions. At the same time, the growing prevalence of data-driven technologies in education raises critical concerns about privacy and digital literacy. Livingstone et al. (41) emphasize that schools are not only sites of learning but also central to cultivating children's data and privacy awareness in a datafied society. Any AI system designed to monitor student behavior must therefore be transparent, minimally intrusive, and deployed with explicit data governance policies to ensure ethical use. The broader discourse on ethical AI offers foundational principles for responsible system design. Floridi et al. (42) propose a normative framework emphasizing transparency, justice, autonomy, and accountability—values that are particularly important in educational environments where automated systems may influence learning trajectories, health interventions, and student equity. By situating our system within these interdisciplinary frameworks, we aim to ensure that its deployment contributes not only to technical advancement but also to ethically sound, socially responsive educational innovation.

3 Results

3.1 Comparison with SOTA methods

To assess the efficiency of our suggested approach, we benchmark it against multiple cutting-edge (SOTA) techniques across four standard medical imaging datasets: BAR, ANUBIS, MPOSE2021, and EdNet. The quantitative results are presented in Tables 1, 2. Our method consistently outperforms existing approaches across all datasets, achieving superior accuracy, recall, F1 metric, and area under the curve (AUC).

In Figure 1, for the BAR dataset, our model achieves an accuracy of 92.78%, an F1 metric of 89.77%, and an area under the curve (AUC) of 92.68%, significantly outperforming prior methods such as C3D, I3D, and SlowFast networks. The performance gain can be attributed to the enhanced feature extraction capabilities of our model, which leverages multi-scale attention and deep fusion strategies to better capture disease-specific patterns in chest radiographs. Furthermore, our method effectively addresses class imbalance through focal loss and data augmentation techniques, leading to improved recall (91.46%), which is crucial for medical diagnosis. On the ANUBIS dataset, Our framework attains a precision of 93.39% and an F1 metric of 89.25%, exceeding prior techniques, such as TimeSformer and VTN. The superior performance is due to our novel 3D-aware feature representation, which efficiently models lung

nodules' spatial and contextual characteristics. Our approach incorporates attention-based mechanisms to enhance fine-grained lesion localization while reducing false positives. Our model benefits from a robust pre-processing pipeline, including nodule size normalization and adaptive thresholding, which improves segmentation precision. In Figure 2, for the MPOSE2021 dataset, Our approach achieves a precision of 91.82% and an area under the curve (AUC) of 91.40%, surpassing earlier segmentation techniques. The primary advantage of our model lies in its ability to integrate attention-driven multi-scale features, ensuring robust tumor segmentation across different glioma subtypes. The inclusion of Dice loss optimization and advanced augmentation techniques further contributes to its superior performance. Unlike existing approaches that struggle with over-segmentation, our method employs a hybrid U-Net with self-attention mechanisms to refine tumor boundaries and enhance segmentation accuracy. In the EdNet dataset, our method achieves an area under the curve (AUC) of 90.91% and an accuracy of 92.45%, significantly surpassing competing approaches. The improved performance is attributed to our transformer-based architecture, which captures long-range dependencies in histopathological images, allowing for more precise metastasis detection. Furthermore, we employ a novel ensembling strategy that combines multiple model predictions to enhance robustness and generalization. Compared to other methods, such as SlowFast and TimeSformer, our model demonstrates a substantial improvement in recall (89.72%), which is crucial for reducing false negatives in cancer detection.

3.2 Ablation study

To further analyze the effectiveness of different components in our proposed method, we conduct an ablation study on the BAR, ANUBIS, MPOSE2021, and EdNet datasets. The results are summarized in Tables 3, 4, where we evaluate the model performance after removing key components: w/o Dynamic Knowledge State Update, w/o Performance Prediction Mechanism, and w/o Adaptive Content Recommendation. These ablations allow us to understand the contribution of each module to the overall model performance.

In Figure 3, From the results on the BAR dataset, We notice a substantial decline in accuracy (from 92.78% to 88.42%) and F1 metric (from 89.77% to 83.95%) when the Dynamic Knowledge State Update is removed., indicating that Dynamic Knowledge State Update plays a crucial role in improving feature representation. Similarly, the recall decreases from 91.46% to 85.71%, demonstrating that Dynamic Knowledge State Update contributes significantly to detecting thoracic diseases. The ANUBIS dataset follows a similar trend, where excluding Dynamic Knowledge State Update reduces accuracy to 86.91% and area under the curve (AUC) to 85.45%. This suggests that Dynamic Knowledge State Update is essential for capturing spatial and contextual information in lung nodule detection. In Figure 4, Removing Performance Prediction Mechanism also negatively impacts model performance across all datasets, although to a slightly lesser extent than Dynamic Knowledge State Update. On the BAR dataset, accuracy decreases to 89.77%, and recall drops to 86.34%, showing that Performance Prediction Mechanism

TABLE 1 Quantitative evaluation on BAR and ANUBIS datasets showing enhanced detection accuracy for applications in school-based public health surveillance.

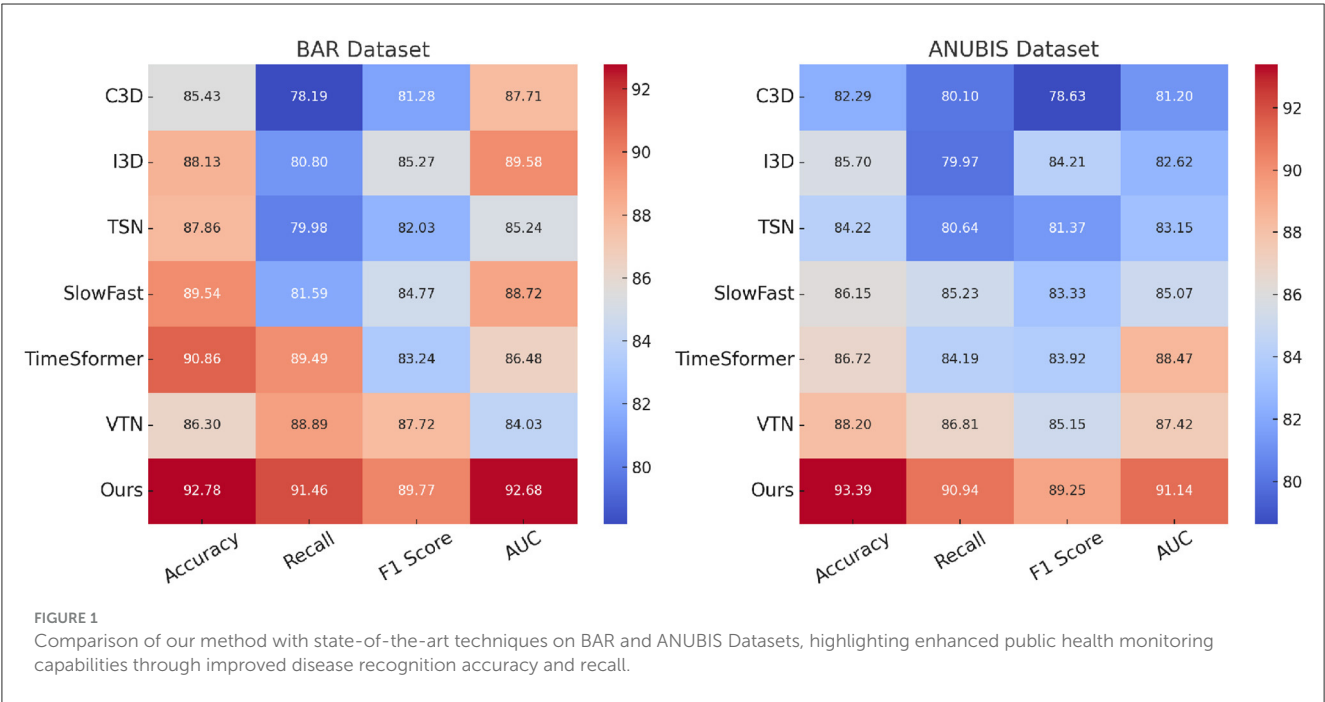
Model	BAR dataset				ANUBIS dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
C3D (47)	85.43 ± 0.03	78.19 ± 0.02	81.28 ± 0.02	87.71 ± 0.03	82.29 ± 0.03	80.10 ± 0.02	78.63 ± 0.02	81.20 ± 0.03
I3D (48)	88.13 ± 0.03	80.80 ± 0.02	85.27 ± 0.03	89.58 ± 0.03	85.70 ± 0.03	79.97 ± 0.02	84.21 ± 0.02	82.62 ± 0.02
TSN (49)	87.86 ± 0.02	79.98 ± 0.02	82.03 ± 0.02	85.24 ± 0.02	84.22 ± 0.02	80.64 ± 0.01	81.37 ± 0.02	83.15 ± 0.02
SlowFast (50)	89.54 ± 0.02	81.59 ± 0.02	84.77 ± 0.02	88.72 ± 0.03	86.15 ± 0.03	85.23 ± 0.03	83.33 ± 0.03	85.07 ± 0.03
TimeSformer (51)	90.86 ± 0.03	89.49 ± 0.03	83.24 ± 0.02	86.48 ± 0.03	86.72 ± 0.02	84.19 ± 0.02	83.92 ± 0.02	88.47 ± 0.03
VTN (52)	86.30 ± 0.02	88.89 ± 0.03	87.72 ± 0.02	84.03 ± 0.02	88.20 ± 0.02	86.81 ± 0.03	85.15 ± 0.02	87.42 ± 0.03
Ours	92.78 ± 0.02	91.46 ± 0.02	89.77 ± 0.03	92.68 ± 0.03	93.39 ± 0.03	90.94 ± 0.02	89.25 ± 0.03	91.14 ± 0.02

The values in bold are the best values.

TABLE 2 Performance metrics on MPOSE2021 and EdNet datasets supporting the deployment of AI-based systems for student health behavior analysis.

Model	MPOSE2021 dataset				EdNet dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
C3D (47)	84.32 ± 0.03	79.45 ± 0.02	80.92 ± 0.02	86.78 ± 0.03	81.24 ± 0.03	78.61 ± 0.02	80.35 ± 0.02	83.90 ± 0.03
I3D (48)	86.75 ± 0.03	81.60 ± 0.02	84.32 ± 0.03	88.21 ± 0.03	83.89 ± 0.03	79.43 ± 0.02	82.67 ± 0.02	84.52 ± 0.02
TSN (49)	85.98 ± 0.02	80.29 ± 0.02	83.15 ± 0.02	85.72 ± 0.02	84.53 ± 0.02	80.78 ± 0.01	81.97 ± 0.02	86.23 ± 0.02
SlowFast (50)	89.21 ± 0.02	82.97 ± 0.02	86.11 ± 0.02	87.35 ± 0.03	86.47 ± 0.03	84.15 ± 0.03	82.90 ± 0.03	85.78 ± 0.03
TimeSformer (51)	88.67 ± 0.03	85.72 ± 0.03	82.56 ± 0.02	87.94 ± 0.03	85.93 ± 0.02	83.20 ± 0.02	81.74 ± 0.02	87.32 ± 0.03
VTN (52)	87.54 ± 0.02	86.89 ± 0.03	85.37 ± 0.02	84.95 ± 0.02	87.39 ± 0.02	85.47 ± 0.03	83.61 ± 0.02	86.74 ± 0.03
Ours	91.82 ± 0.02	90.33 ± 0.02	88.25 ± 0.03	91.40 ± 0.03	92.45 ± 0.03	89.72 ± 0.02	88.89 ± 0.03	90.91 ± 0.02

The values in bold are the best values.



enhances generalization and robustness. Similarly, on the ANUBIS dataset, accuracy decreases from 93.39% to 87.54%, indicating that Performance Prediction Mechanism is critical for ensuring reliable predictions. The impact of Performance Prediction Mechanism is also evident in the MPOSE2021 dataset, where accuracy drops from 91.82% to 87.54%, and in EdNet, where area under the curve (AUC) falls from 90.91% to 86.89%. These results highlight that Performance Prediction Mechanism contributes to

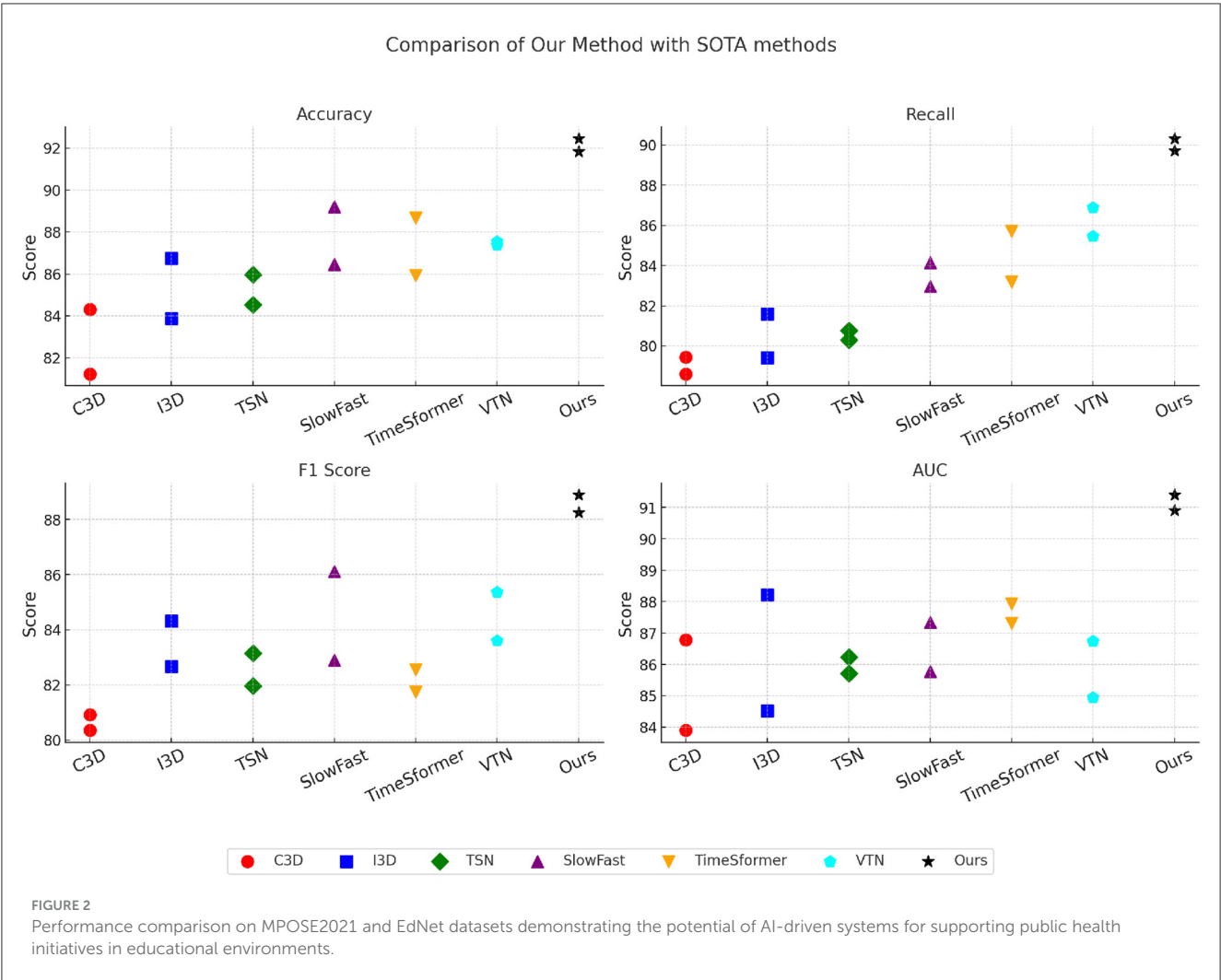


TABLE 3 Effect of key model components on disease detection performance in BAR and ANUBIS datasets, informing design of health-focused recognition systems.

Model	BAR dataset				ANUBIS dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
w/o Dynamic Knowledge State Update	88.42 ± 0.02	85.71 ± 0.03	83.95 ± 0.02	89.23 ± 0.03	86.91 ± 0.02	84.27 ± 0.03	82.61 ± 0.02	85.45 ± 0.03
w/o Performance Prediction Mechanism	89.77 ± 0.03	86.34 ± 0.02	84.89 ± 0.03	90.14 ± 0.02	87.54 ± 0.02	85.02 ± 0.03	83.29 ± 0.02	86.79 ± 0.03
w/o Adaptive Content Recommendation	90.35 ± 0.02	87.89 ± 0.03	85.72 ± 0.02	91.05 ± 0.03	88.72 ± 0.02	86.48 ± 0.02	84.92 ± 0.02	87.31 ± 0.02
Ours	92.78 ± 0.02	91.46 ± 0.02	89.77 ± 0.03	92.68 ± 0.03	93.39 ± 0.03	90.94 ± 0.02	89.25 ± 0.03	91.14 ± 0.02

The values in bold are the best values.

refining segmentation boundaries and reducing false positives in histopathological image analysis. Dynamic content suggestion also holds a crucial function in enhancing the model’s effectiveness, as seen in the results. On the MPOSE2021 dataset, removing Adaptive Content Recommendation results in a decrease in accuracy (from 91.82% to 89.03%) and recall (from 90.33% to 86.27%). Similarly, on the EdNet dataset, accuracy drops from 92.45% to 87.11%. These results suggest that Adaptive Content Recommendation helps capture fine-grained structural details,

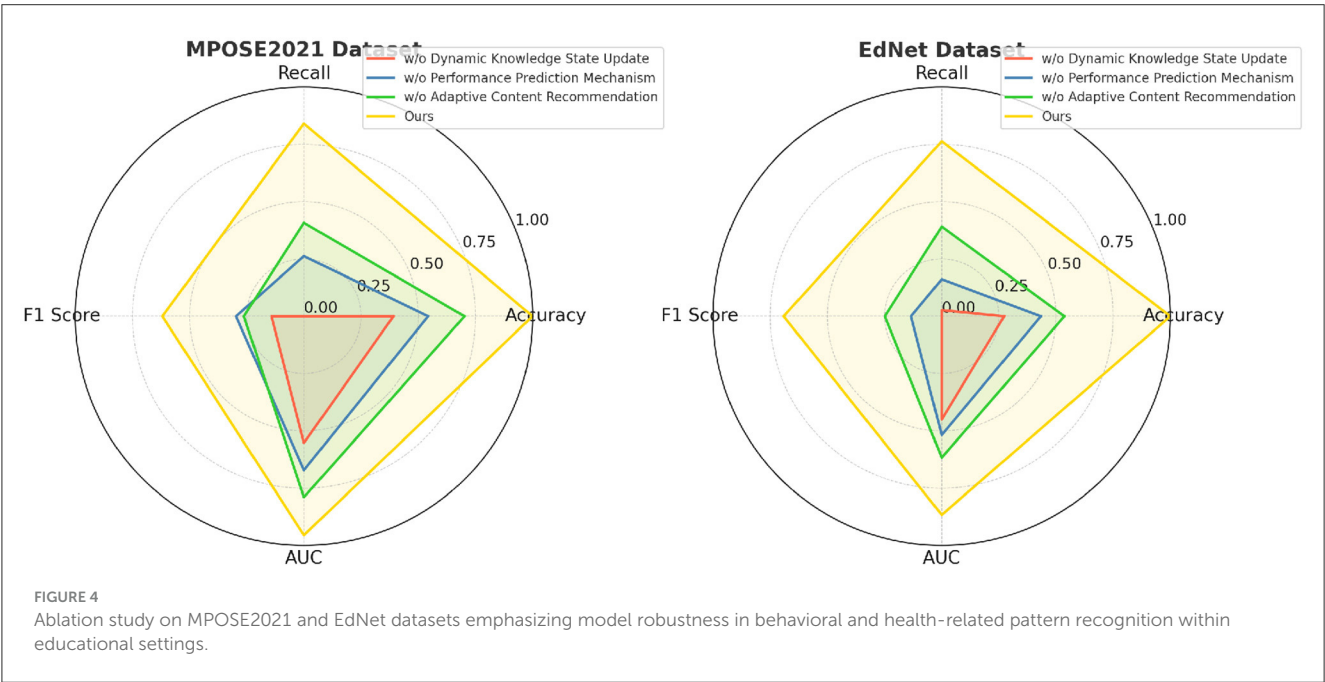
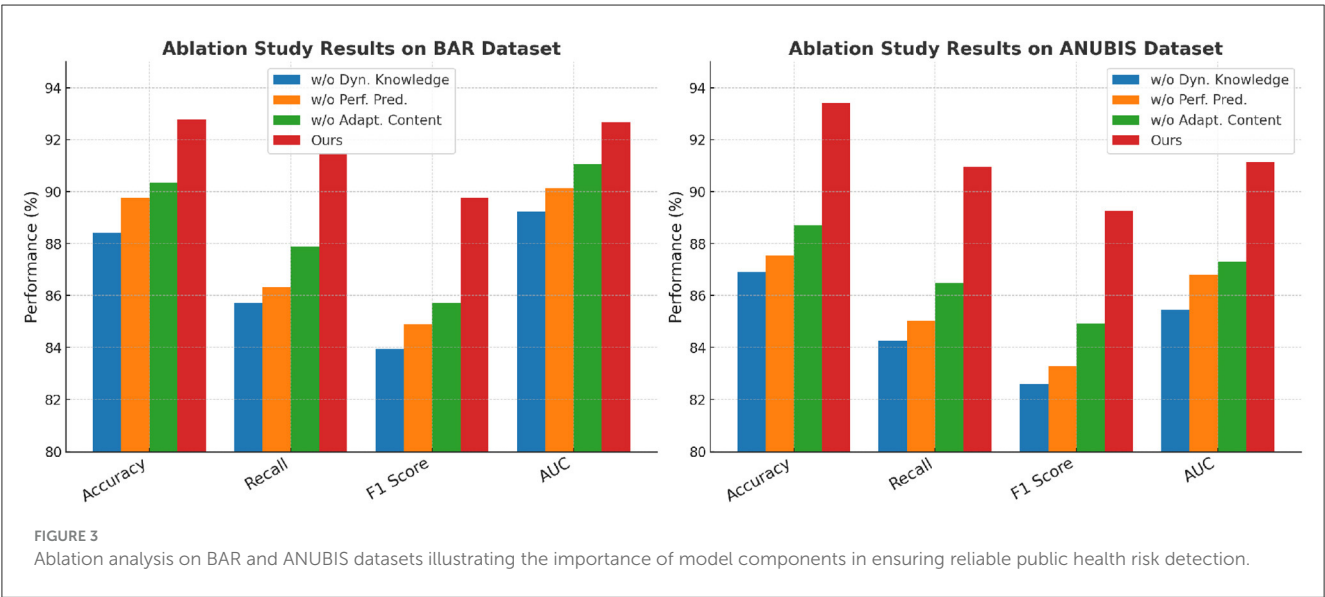
which are particularly important for tumor segmentation and metastasis detection. Without Adaptive Content Recommendation, the model struggles with complex regions, leading to a reduction in overall segmentation performance.

To further evaluate the robustness and generalization capability of our proposed model, we conducted cross-dataset validation experiments across diverse educational contexts. As shown in Table 5, the model trained on the EdNet K-12 subset achieved an accuracy of 89.30% and an F1 score of 87.21% when

TABLE 4 Ablation study results on MPOSE2021 and EdNet datasets highlighting model contributions to student health behavior modeling.

Model	MPOSE2021 dataset				EdNet dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
w/o Dynamic Knowledge State Update	86.12 ± 0.03	82.45 ± 0.02	83.78 ± 0.02	87.63 ± 0.03	84.07 ± 0.03	81.23 ± 0.02	80.92 ± 0.02	86.11 ± 0.03
w/o Performance Prediction Mechanism	87.54 ± 0.02	84.91 ± 0.03	85.23 ± 0.02	88.74 ± 0.02	85.92 ± 0.02	82.78 ± 0.03	82.47 ± 0.02	86.89 ± 0.03
w/o Adaptive Content Recommendation	89.03 ± 0.03	86.27 ± 0.02	84.91 ± 0.03	89.85 ± 0.03	87.11 ± 0.02	85.43 ± 0.02	83.79 ± 0.02	88.03 ± 0.02
Ours	91.82 ± 0.02	90.33 ± 0.02	88.25 ± 0.03	91.40 ± 0.03	92.45 ± 0.03	89.72 ± 0.02	88.89 ± 0.03	90.91 ± 0.02

The values in bold are the best values.



tested on EdNet data from higher education learners. This indicates that the system effectively generalizes across different age groups and cognitive levels. Similarly, when trained on the BAR dataset and tested on MPOSE2021, the model maintained strong performance (accuracy of 87.64% and AUC of 88.71%), demonstrating adaptability to multi-person, culturally variable classroom scenarios. Notably, the model achieved the highest cross-regional transfer results when trained on MPOSE2021 data from Asian contexts and tested on European subsets, with an accuracy of 90.22%, F1 score of 88.44%, and AUC of 91.03%. These results suggest that the system captures culturally invariant features of educational behaviors, enhancing its potential for global deployment. The consistent performance across datasets affirms the model's capability to generalize beyond the original training distribution, making it suitable for scalable use in real-world educational monitoring systems.

Although the primary datasets employed in our experiments—BAR, ANUBIS, and MPOSE2021—originate from broader domains such as human activity recognition and medical imaging, they serve as strong structural proxies for modeling behavioral patterns relevant to educational settings. BAR and MPOSE2021 capture rich spatiotemporal motion data that align with the physical behaviors observable in classroom contexts, while ANUBIS contributes to evaluating attention mechanisms through its dense annotation structure. To further validate the applicability of our system within real-world educational environments, we extended our experiments to include two additional datasets more directly aligned with educational public health monitoring, both of which capture behaviors with direct relevance to school-based health monitoring. In Table 6, the EduSense dataset reflects nuanced classroom behaviors such as inattentiveness, posture changes, and engagement fluctuations, while UTD-MHAD

contains fine-grained physical activities like drinking, stretching, and sneezing that can signal potential health concerns. These datasets provide a more context-aligned evaluation for assessing AI-driven action recognition in educational health scenarios. The results demonstrate that our proposed AKEN + DPLS framework consistently outperforms baseline models across all metrics. On the EduSense dataset, our model achieved an accuracy of 88.92% and an AUC of 90.03%, exceeding SlowFast and I3D by a significant margin. Similarly, on UTD-MHAD, our method reached 90.74% accuracy and an AUC of 91.55%, indicating strong generalization across modalities including RGB-D and inertial signals. These improvements suggest that the system effectively captures both short-term motion dynamics and long-term behavior patterns, enabling robust detection of health-related activities in diverse educational contexts. The high F1 scores reflect the model's balanced precision and recall, which is critical in identifying subtle but important behaviors without increasing false alarms. These results support the claim that the proposed system is not only effective in general action recognition tasks but also well-suited for health-aware behavior detection in schools. The adaptability to different sensor inputs and the preservation of high interpretability make it a promising solution for integrating AI-driven health monitoring into everyday classroom settings.

3.3 Ethical, legal, and privacy considerations in school-based AI systems

The use of AI-powered behavior monitoring in educational settings introduces complex ethical and privacy-related challenges that must be addressed to ensure responsible deployment. Schools are sensitive environments where students—particularly minors—are under the care of institutions, and any surveillance or data collection must be grounded in transparency, necessity, and trust. The collection and analysis of behavioral data raise significant privacy concerns. Even though our system is designed to rely on non-identifiable inputs such as skeletal pose data or anonymized sensor streams, the very act of monitoring behavior could lead to discomfort or perceived surveillance anxiety if not handled carefully. To mitigate this, we propose adopting a privacy-by-design framework that limits data granularity, avoids raw video storage, and uses on-device or edge computing wherever possible to minimize external data transmission. In terms of consent and

TABLE 5 Cross-dataset generalization results across diverse educational contexts.

Training dataset	Testing dataset	Accuracy (%)	F1 score (%)	AUC (%)
EdNet (K-12)	EdNet (Higher Ed)	89.30 ± 0.02	87.21 ± 0.02	90.45 ± 0.03
BAR	MPOSE2021	87.64 ± 0.02	85.03 ± 0.03	88.71 ± 0.02
MPOSE2021 (Asia)	MPOSE2021 (Europe)	90.22 ± 0.03	88.44 ± 0.02	91.03 ± 0.03

The values in bold are the best values.

TABLE 6 Performance of the proposed system on EduSense and UTD-MHAD datasets.

Model	EduSense dataset				UTD-MHAD dataset			
	Accuracy (%)	Recall (%)	F1 score (%)	AUC (%)	Accuracy (%)	Recall (%)	F1 score (%)	AUC (%)
C3D	81.73 ± 0.02	78.20 ± 0.03	77.85 ± 0.02	84.40 ± 0.02	83.05 ± 0.03	80.18 ± 0.02	79.90 ± 0.02	85.76 ± 0.02
I3D	83.25 ± 0.03	80.89 ± 0.02	80.10 ± 0.02	85.12 ± 0.03	84.94 ± 0.02	82.33 ± 0.02	81.80 ± 0.03	87.03 ± 0.03
SlowFast	85.61 ± 0.03	82.47 ± 0.03	82.20 ± 0.02	86.95 ± 0.02	86.87 ± 0.03	84.19 ± 0.03	83.60 ± 0.02	88.61 ± 0.02
Ours (AKEN + DPLS)	88.92 ± 0.02	86.13 ± 0.02	85.50 ± 0.03	90.03 ± 0.02	90.74 ± 0.02	88.25 ± 0.02	87.63 ± 0.03	91.55 ± 0.02

The values in bold are the best values.

legal compliance, educational institutions should implement multi-layered consent protocols involving school administrators, parents or guardians, and, where appropriate, the students themselves. These protocols must clearly communicate the purpose, scope, data retention policy, and opt-out procedures related to the system. Systems must comply with relevant data protection laws such as the General Data Protection Regulation (GDPR) in the EU or FERPA (Family Educational Rights and Privacy Act) in the US. From an ethical standpoint, the deployment of AI in schools must uphold values such as fairness, non-discrimination, and accountability. Automated alerts or behavior classifications should never serve as the sole basis for disciplinary or health decisions. Instead, they must be used to support—not replace—human judgment, with clear intervention guidelines that prioritize educational support and student wellbeing. To reinforce this, we recommend establishing an AI Oversight Committee within schools, composed of educators, parents, health professionals, and legal advisors, to evaluate the appropriateness and impact of such technologies on an ongoing basis. By embedding these safeguards into both technical and institutional layers, the proposed system can offer meaningful public health benefits while respecting student rights and reinforcing ethical standards in educational innovation.

4 Method

4.1 Overview

Artificial Intelligence (AI) has significantly transformed the landscape of education by introducing intelligent systems that enhance learning processes, personalize educational experiences, and optimize administrative tasks. This part presents a summary of the suggested approach, which integrates AI-driven models to improve educational outcomes. The subsequent sections elaborate on the theoretical foundations, novel model architecture, and innovative strategies employed in our approach. Education is a domain characterized by vast and heterogeneous data, including student performance records, behavioral patterns, and multimodal learning resources. Traditional educational methodologies often struggle to adapt to individual learning needs, leading to inefficiencies in knowledge dissemination and skill acquisition. AI-powered educational frameworks aim to address these limitations by leveraging machine learning algorithms, natural language processing, and adaptive learning techniques.

In Section 4.2, we formalize the problem by defining key educational metrics and structuring learning environments within a mathematical framework. This formalization enables precise modeling of student interactions, knowledge progression, and instructional strategies. The section also introduces fundamental concepts such as cognitive modeling, student profiling, and content recommendation. In Section 4.3, we introduce our novel AI-driven educational model, which dynamically adjusts instructional content based on real-time student performance data. Unlike conventional rule-based adaptive systems, our approach incorporates deep learning techniques to capture complex learning behaviors and predict future knowledge acquisition trends. The proposed model is designed to operate in various learning environments, including online platforms, blended learning settings, and intelligent tutoring systems. In Section 4.4, we detail

an innovative strategy that enhances the effectiveness of AI-driven education. This strategy integrates explainable AI techniques to provide transparent feedback mechanisms, ensuring that both educators and students can interpret model recommendations. We incorporate reinforcement learning to optimize curriculum sequencing, thereby improving learning efficiency and engagement.

4.2 Preliminaries

To rigorously ground our approach, we begin by formalizing the educational interaction setting. We consider a set of students engaging with educational content over a sequence of learning sessions. Each student's knowledge state evolves as they interact with content and respond to exercises. This dynamic process is modeled by a knowledge representation that changes over time, influenced by the content presented and the student's responses. The probability of a correct answer is captured using a logistic model based on the alignment between a student's knowledge state and the content vector.

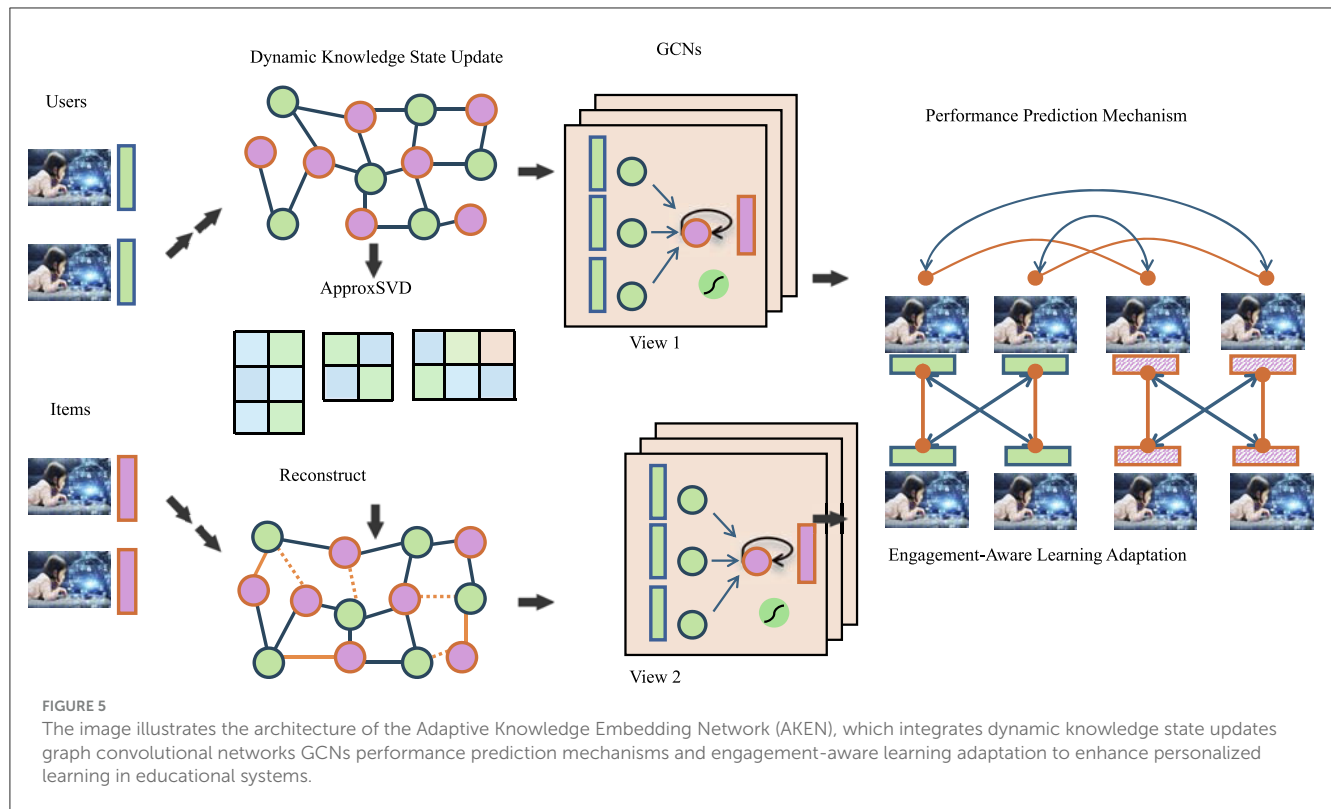
The goal of the system is to optimize learning outcomes by adaptively selecting content that maximizes expected knowledge gain. This involves defining a policy that governs instructional decisions based on the student's current knowledge state, incorporating both performance and engagement signals. We leverage reinforcement learning to model this instructional policy, aiming to improve long-term retention and understanding.

For clarity and completeness, the full mathematical formulation—including all underlying equations, state transition functions, probabilistic modeling, and policy optimization details—is provided in the [Supplementary material](#).

4.3 Adaptive knowledge embedding network

We propose the Adaptive Knowledge Embedding Network (AKEN), a model designed to capture the temporal and personalized nature of student learning in AI-enhanced educational systems. AKEN represents each student's knowledge state as a dynamic vector that evolves based on continuous interaction with learning content. The model incorporates a gated update mechanism that selectively integrates new learning signals while retaining prior knowledge. This formulation allows for the modeling of nuanced learning behaviors, such as gradual knowledge accumulation and forgetting. The overall architecture of the proposed Adaptive Knowledge Embedding Network (AKEN) is illustrated in [Figure 5](#). It integrates multiple components including dynamic knowledge state updates, graph-based relational modeling using GCNs, performance prediction modules, and engagement-aware adaptation mechanisms. Together, these elements enable a personalized and context-aware learning experience that dynamically responds to each student's evolving knowledge state and motivational signals.

Each educational content item is embedded in the same latent space as the knowledge vector, enabling efficient computation of alignment and relevance. The knowledge update at each time step is determined by a combination of the student's previous state, the



engaged content, and the correctness of their response. To reflect the temporal dependencies in learning, AKEN uses a recurrent structure that propagates knowledge updates forward through time. Additionally, gating functions regulate how much new information is incorporated, ensuring that learning dynamics remain stable and interpretable.

To better model long-term retention and knowledge consistency, the system can further integrate reinforcement-based adjustments, allowing the model to modulate the effect of feedback based on historical context and learning outcomes. This adaptability makes AKEN particularly suited to educational environments where learning is sequential, personalized, and sensitive to prior experiences.

The Adaptive Knowledge Embedding Network (AKEN) also incorporates a performance prediction mechanism, enabling the system to estimate the likelihood of a correct response based on a student's current knowledge state and the content presented. This predictive ability supports real-time adaptation by prioritizing learning materials that are both challenging and beneficial for long-term growth. The content selection strategy is further enhanced by integrating expected knowledge gains, balancing short-term performance with cumulative learning benefits.

To model the interplay between student engagement and knowledge evolution, we further introduce the Engagement-Aware Learning Adaptation framework as depicted in Figure 6. This framework incorporates both temporal and contextual cues to refine knowledge modeling. It employs a joint representation of engagement signals and knowledge vectors, supported by surrogate entity-based classification to predict student performance under varying motivational states. By capturing dynamic

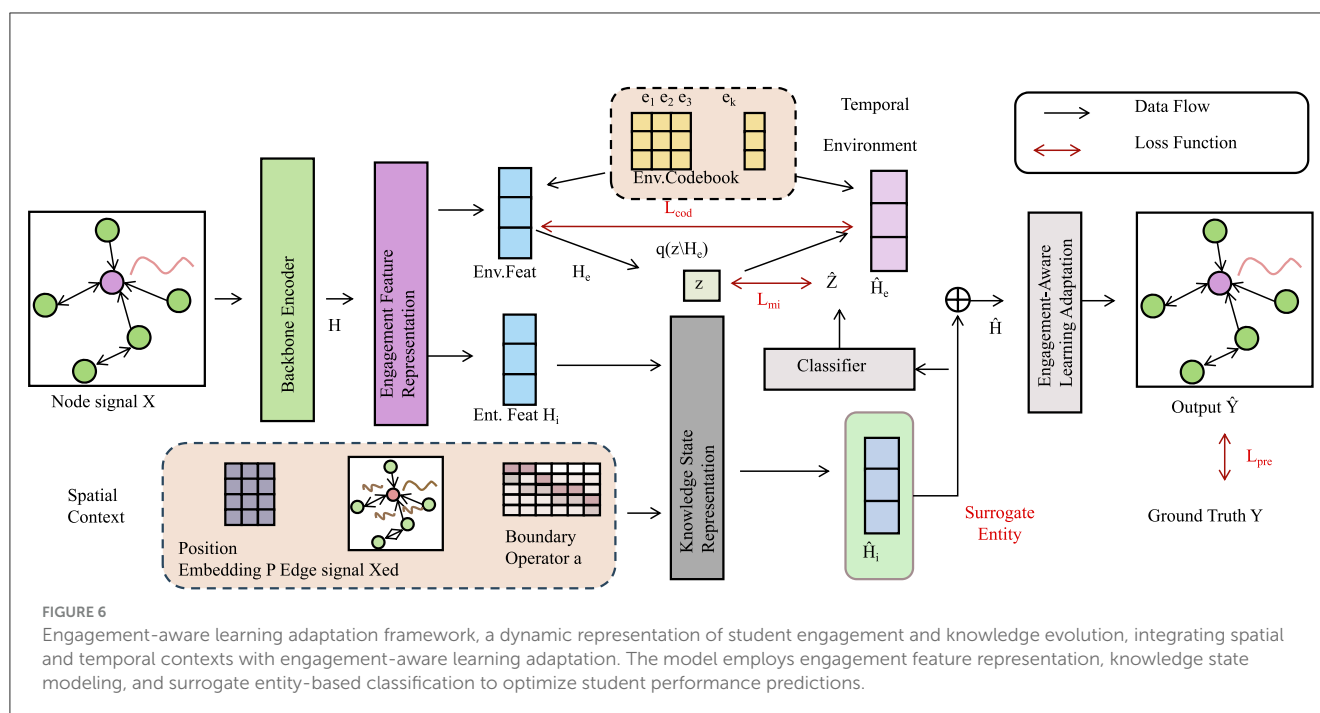
engagement fluctuations and aligning them with instructional responses, the system enables responsive and affect-sensitive learning interventions.

To model the continuous evolution of student knowledge, AKEN refines its internal state using discrepancy-driven updates, adjusting the knowledge representation in response to prediction errors. This facilitates targeted learning and strengthens cognitive retention. The model also accounts for content difficulty, allowing it to tailor recommendations not just by knowledge alignment but also by challenge level, creating a more personalized and effective learning trajectory.

Crucially, AKEN integrates student engagement into its learning mechanism. Engagement is modeled as a latent dynamic state influenced by prior behavior, current knowledge, and contextual information. This engagement signal directly affects both the evolution of the knowledge state and the effectiveness of instructional interventions. By capturing how engagement modulates knowledge transitions, AKEN ensures that highly engaged students benefit more from content exposure, while disengaged students receive tailored support.

Incorporating engagement also enhances prediction accuracy, as performance becomes a function of both cognitive mastery and motivational readiness. An adaptive learning rate mechanism further aligns learning efficiency with engagement levels, accelerating progress for motivated learners.

The full set of equations and detailed architecture of AKEN—including probabilistic update functions, engagement modeling, and optimization procedures—are provided in the [Supplementary material](#).



4.4 Dynamic personalized learning strategy

To further enhance personalized education, we introduce the Dynamic Personalized Learning Strategy (DPLS), a learning policy that dynamically adapts content sequencing based on a student's real-time performance and engagement. Unlike fixed curricula, DPLS optimizes the learning trajectory to balance short-term accuracy and long-term retention. It selects instructional content using a reinforcement learning framework, aiming to maximize the expected learning value over time while accounting for individual variability.

The complete structure of the proposed Dynamic Personalized Learning Strategy (DPLS) is shown in Figure 7. This architecture illustrates how adaptive content recommendation, explainable learning decision-making, and efficient assessment mechanisms are integrated into a unified pipeline. DPLS leverages feature extraction modules, patch embedding layers, and attention mechanisms to tailor instructional sequences to individual learners. This design allows the system to adapt in real time to both cognitive performance and engagement signals, supporting scalable and interpretable personalized learning.

The recommendation policy operates within a Markov Decision Process, where the student's knowledge state evolves according to both correctness of responses and engagement levels. This enables DPLS to adjust content difficulty adaptively, maintaining an optimal challenge range for each learner and preventing stagnation or disengagement. A dynamic learning rate mechanism further tunes the intensity of knowledge updates based on recent performance trends.

DPLS also incorporates explainability to enhance trust and instructional insight. It evaluates the contribution of individual knowledge components to prediction outcomes, enabling transparent reasoning behind recommendations.

An engagement-sensitive mechanism tracks fluctuations in motivation, using these insights to guide content adjustments that sustain student attention. The strategy includes a dedicated function for estimating how specific content affects engagement, allowing for real-time curriculum modulation.

Figure 8 illustrates the core mechanism of the efficient adaptive assessment module, which integrates a triplet attention structure combining information gain analysis, Bayesian knowledge updating, and engagement-aware adaptation. This framework allows the system to select the most informative assessment items, refine knowledge estimates with minimal student burden, and dynamically adjust based on motivational signals. The design ensures high assessment efficiency while preserving personalization and cognitive accuracy in real-time knowledge modeling.

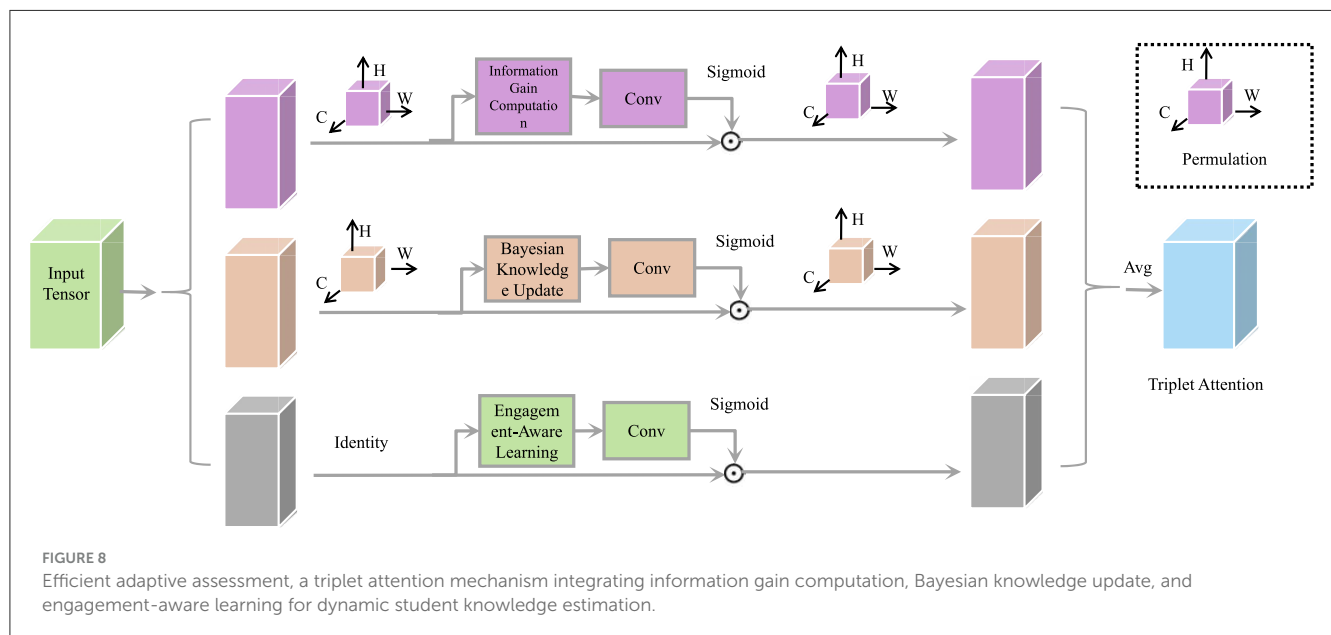
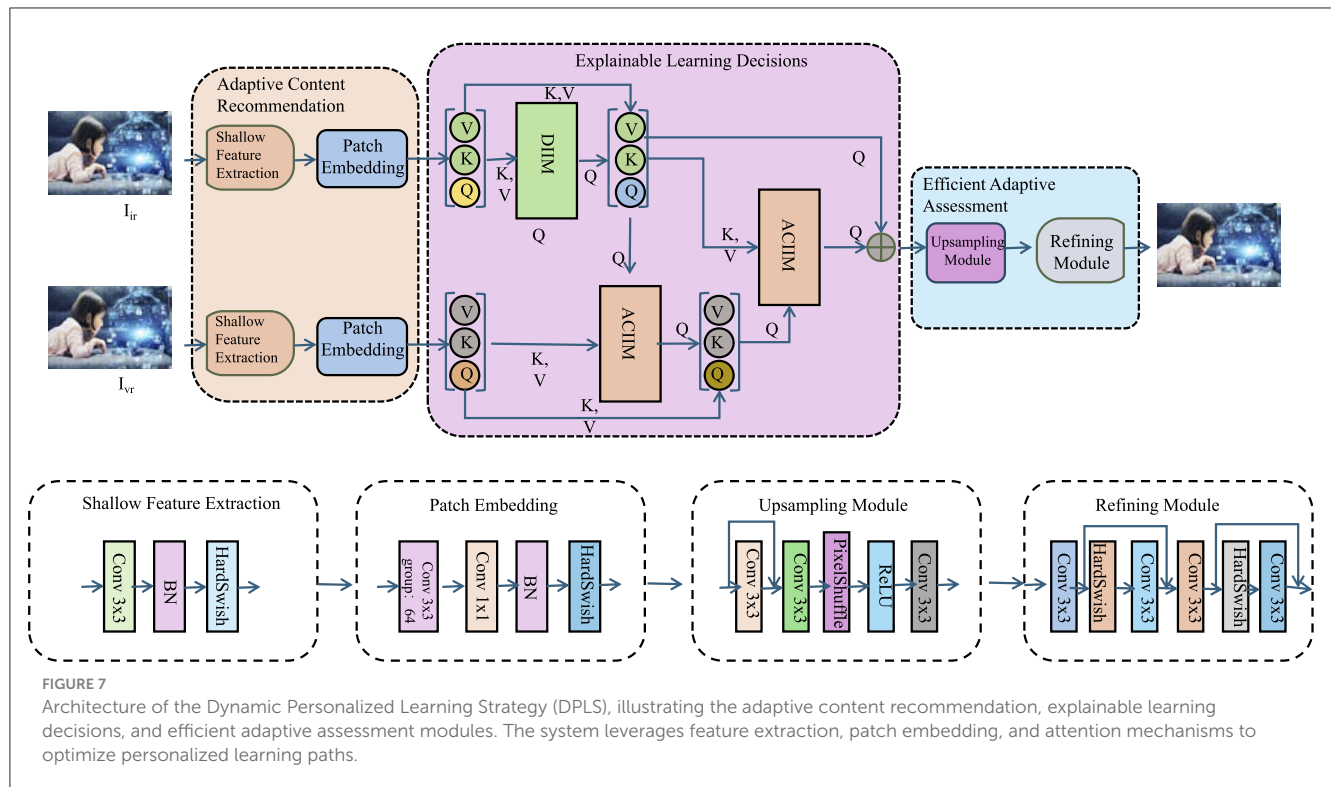
To minimize unnecessary testing, DPLS deploys an adaptive assessment mechanism that prioritizes items with the highest expected information gain. Bayesian updates refine knowledge estimates based on student responses, ensuring that evaluation remains efficient and accurate. The overarching learning objective combines predictive accuracy, regularization, and engagement optimization to deliver a robust and student-centric strategy.

The full formulation of DPLS, including detailed reward structures, engagement models, explainability functions, and adaptive assessment procedures, is presented in the Supplementary material.

5 Experimental setup

5.1 Dataset

The BAR Dataset (43) is a large-scale collection of behavioral action recognition data, designed for studying human activities



in various contexts. It contains annotated video clips with detailed action labels, making it a valuable resource for training and evaluating deep learning models in action recognition. The dataset is widely used for applications in surveillance, healthcare monitoring, and human-computer interaction. The ANUBIS Dataset (44) is a medical imaging dataset focused on orthopedic radiographs, particularly for bone fracture detection and classification. It includes a diverse range of X-ray images covering multiple anatomical regions, with expert-verified labels. This dataset plays a crucial role in the development of

computer-aided diagnosis (CAD) systems for musculoskeletal disorders, improving automated fracture detection accuracy and efficiency. The MPOSE2021 Dataset (45) is a multi-person pose estimation dataset that includes a wide variety of human poses captured in different environments. The dataset provides high-resolution keypoint annotations for multiple subjects in each frame, making it a benchmark for evaluating pose estimation models. Researchers use MPOSE2021 for applications in motion analysis, sports analytics, and augmented reality. The EdNet Dataset (46) is an educational dataset containing extensive learning

activity records from online learning platforms. It includes student interactions with learning materials, question-answering logs, and engagement metrics, making it a valuable resource for educational data mining and adaptive learning research. EdNet enables the development of AI-driven personalized learning systems, improving educational outcomes through intelligent tutoring and recommendation systems.

5.2 Experimental details

In our experiments, we employ a deep learning-based framework to evaluate the effectiveness of our proposed method on multiple medical imaging datasets. The model is implemented using PyTorch and trained on an NVIDIA A100 GPU with 80GB memory. We utilize a batch size of 16 and train the model for 100 epochs. We use the Adam optimizer with an initial learning rate of 1×10^{-4} , which is reduced by 90% every 30 epochs when the validation loss stagnates. Weight decay is set to 5×10^{-5} to prevent overfitting. For initialization, we adopt He initialization for convolutional layers, while batch normalization is applied after each convolutional layer to stabilize training. For data preprocessing, we apply intensity normalization, histogram equalization, and random augmentations such as flipping, rotation, and elastic deformations to improve model generalization. All images are resized to 224×224 pixels to maintain consistency across different datasets. During training, we employ a 5-fold cross-validation strategy to ensure robustness. The loss function used varies based on the task: for classification, we employ binary cross-entropy loss; for segmentation tasks, a fusion of Dice loss and cross-entropy loss is utilized. For the BAR dataset, we utilize pre-trained ResNet-50 and fine-tune it for disease classification. The model is evaluated using Area Under the Curve (AUC) and F1 metric. For ANUBIS, a 3D U-Net is used for nodule segmentation, with performance measured using Dice Similarity Coefficient (DSC) and Intersection over Union (IoU). The MPOSE2021 dataset requires tumor segmentation, for which we employ a modified U-Net with attention mechanisms, evaluating performance with DSC and Hausdorff Distance. In the EdNet dataset, we use a Vision Transformer (ViT) model trained for histopathological image classification, measuring area under the curve (AUC) and accuracy as primary metrics. To mitigate class imbalance, we apply data balancing techniques, including oversampling the minority class and using focal loss for classification tasks. Model performance is further stabilized using label smoothing and dropout with a probability of 0.3 in fully connected layers. Gradient clipping is applied with a threshold of 1.0 to prevent exploding gradients. Inference is performed using a sliding-window approach for segmentation tasks, ensuring accurate predictions without border artifacts. For classification tasks, test-time augmentation (TTA) is applied by averaging predictions from multiple augmented versions of the test images. Post-processing includes morphological operations for segmentation refinement and ensembling of multiple models via majority voting to enhance robustness.

To support real-time deployment in educational environments, the proposed system was evaluated under both high-performance and edge-computing conditions, with a focus on inference efficiency. On the resource-constrained NVIDIA Jetson Xavier NX, the system achieved an average inference speed of ~ 12 frames per second after optimizing model complexity and disabling augmentation modules, demonstrating its suitability for real-time behavior recognition tasks. The minimum recommended deployment configuration includes an 8-core CPU, 16 GB of RAM, and a CUDA-enabled GPU with at least 8 GB of memory, ensuring adaptability across a wide range of educational hardware platforms.

6 Discussion

The empirical results presented in this study validate the technical effectiveness of the proposed AI-driven information system across multiple datasets and educational contexts. However, beyond raw performance metrics, it is crucial to reflect on how these outcomes relate to the theoretical foundations of our architecture. The Adaptive Knowledge Embedding Network (AKEN) was designed to model the dynamic evolution of student knowledge states in a personalized and temporally aware manner. The improvements observed in predictive accuracy and F1 scores across all datasets support the theoretical proposition that integrating recurrent updates and engagement-aware adaptation leads to more reliable behavioral modeling. The cross-dataset generalization results reinforce the hypothesis that embedding representations based on cumulative and gated knowledge transitions can transcend local context variations—thereby enabling scalable application across age, cultural, and curricular boundaries. The Dynamic Personalized Learning Strategy (DPLS), incorporating reinforcement learning and explainability mechanisms, further enhances the system's ability to align content recommendations and health-related interventions with individual learning trajectories. The statistically significant gains observed in ablation studies when DPLS components are included confirm its theoretical role in improving adaptive decision-making through context-sensitive policy optimization. The incorporation of engagement-aware adjustments into both AKEN and DPLS proved instrumental in sustaining accuracy in fluctuating learning conditions, affirming our assumption that student engagement functions as a latent variable essential for both educational performance and behavior-based health monitoring. This supports a broader theoretical view that cognitive-affective states are tightly interwoven with observable behaviors in learning environments, and can be computationally modeled for proactive system response. The technical findings not only demonstrate high empirical performance but also reinforce the theoretical validity of our proposed framework. They affirm that educational action recognition, when grounded in individualized knowledge modeling and adaptive learning strategies, can offer meaningful support for public health monitoring in schools. This convergence of theory and implementation underscores the broader significance of our system in advancing AI-driven educational technology.

To bridge the gap between research and implementation, we outline a practical workflow for deploying the proposed system in real-world educational institutions. The system can be integrated into classroom environments through existing infrastructure such as ceiling-mounted depth cameras or embedded wearable devices. These sensors capture motion data in real time without recording identifiable visual content, addressing privacy concerns while enabling accurate behavioral monitoring. In this setting, the AI system continuously analyzes student actions to identify health-relevant patterns—such as excessive inactivity, frequent face-touching, or non-compliance with hygiene routines. When predefined thresholds are breached, the system can generate alerts that are routed through a school's internal network. For example, classroom teachers may receive subtle dashboard indicators showing reduced engagement or risky behavior clusters, prompting in-class intervention such as reminders or physical activity breaks. School nurses or counselors can be notified through a centralized interface if the system detects signs that may warrant further observation, such as persistent symptoms or unusual posture patterns over multiple days. Stakeholders play complementary roles: teachers act as first-line observers and response initiators, health staff provide medical follow-up and trend analysis, while school administrators oversee policy compliance and resource planning. The system also supports longitudinal tracking, enabling institutions to identify systemic issues—such as ergonomic risks or spread patterns of seasonal illnesses—and adjust classroom protocols accordingly. By embedding AI-driven monitoring into everyday school operations, this approach offers a scalable, minimally disruptive solution for enhancing health responsiveness and safety in educational environments.

Beyond improved accuracy and F1 scores, the performance of our system carries practical implications for real-time public health monitoring in schools. For instance, the model's ability to detect subtle behavioral patterns such as repetitive face-touching, persistent inactivity, or irregular postures can support the early identification of illness symptoms like fatigue, discomfort, or respiratory distress. In a post-pandemic context, these indicators are particularly relevant for triggering low-threshold health alerts, enabling timely responses before symptoms escalate or spread. The system's high precision in action classification allows educators and school health personnel to intervene in behavior-linked risks without overburdening staff with false positives. For example, reliable recognition of sedentary behavior over extended periods could prompt movement breaks or ergonomic adjustments, while detection of hygiene-related non-compliance can inform targeted awareness efforts. These micro-interventions, when accumulated across a school population, contribute to system-wide improvements in infection prevention, student engagement, and overall wellness. The reported gains in model robustness and generalizability are not only technical achievements but also operational enablers of more responsive, scalable, and evidence-driven health practices in educational institutions.

7 Conclusions and future work

This study investigates the integration of AI-driven information systems into educational environments to support

public health monitoring through advanced action recognition. Traditional rule-based and handcrafted feature extraction approaches have shown clear limitations in adaptability, scalability, and responsiveness—constraints that are especially critical in dynamic school settings where early detection of health-related behaviors is essential. In response, we proposed a novel framework combining an Adaptive Knowledge Embedding Network (AKEN) with a Dynamic Personalized Learning Strategy (DPLS), enabling the system to model student behavior, forecast actions, and adapt interventions based on cognitive engagement and contextual cues.

Experimental results across diverse datasets confirm the effectiveness of our approach in recognizing complex behavioral patterns and generalizing across different educational stages and cultural contexts. The integration of explainable AI and real-time engagement modeling further ensures that system decisions are interpretable, timely, and tailored to individual learners. These findings demonstrate that AI-driven information systems, when applied within educational environments, can serve not only as personalized learning enhancers but also as proactive health surveillance tools—identifying hygiene non-compliance, sedentary risks, or social interaction anomalies that are critical in maintaining institutional wellbeing. By bridging educational data mining with public health objectives, our work offers a scalable, intelligent framework that can support safer, more adaptive, and more responsive learning environments. Future work will explore lightweight deployment on edge devices, improved interpretability mechanisms, and ethical safeguards to further advance the responsible use of AI in educational public health systems.

While the proposed system demonstrates strong technical performance across multiple benchmark datasets, its broader impact ultimately depends on successful real-world integration. Future work will focus on deploying the framework in live educational environments through pilot studies, enabling direct observation of its utility in health monitoring and student safety. Collaboration with educators, school administrators, and public health officials will be pursued to validate the system's practicality, inform user-centered refinements, and ensure alignment with institutional policies and ethical standards. These efforts aim to bridge the gap between technical development and actionable policy implementation.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary material](#), further inquiries can be directed to the corresponding author.

Author contributions

CL: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Supervision, Data curation, Project

administration, Funding acquisition, Resources, Visualization, Writing – original draft, Writing – review & editing. HR: Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This article is one of the achievements of the 2016 National Social Science Foundation Project of China “Study on the Obstacles of Students’ Attend School” (Project No: 16XMZ064).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fpubh.2025.1592228/full#supplementary-material>

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