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STUDENT BEHAVIOR ANALYSIS IN SMART CLASSROOMS: CURRENT TRENDS AND FUTURE DIRECTIONS

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Abstract: This study examines the current status and future prospects of student behavior analysis in smart classrooms, with a focus on the context of educational informatization, the impact of artificial intelligence on education, the process of learning behavior analysis, the application of relevant technologies, the present state of behavior classification, and associated research achievements and applications. Against the backdrop of educational digital transformation, smart classrooms integrate big data and artificial intelligence to enable precise monitoring and analysis of students' learning behaviors, thereby providing essential support for personalized instruction. Research findings indicate that smart classrooms can effectively enhance students' classroom attention and engagement, while assisting teachers in better understanding learning conditions and optimizing instructional strategies. Nevertheless, practical implementation still faces numerous challenges, including technology reliability and data privacy protection. Future research should further expand the diversity and coverage of data sources, emphasize the application of multimodal data fusion analysis, and explore the role of smart classrooms in promoting educational equity and personalized teaching, in order to advance the development of smart education.
Keywords: Smart classrooms; Patterns of student behavior; Educational informatization

1 INTRODUCTION

1.1 Educational Digital Transformation

With the rapid advancement of information technology, the field of education is undergoing an unprecedented digital transformation. This transformation has not only reshaped traditional educational models, but has also had a profound impact on teaching methods and learning behaviors. Against the broader backdrop of educational informatization, the smart classroom—as an emerging instructional paradigm—has gradually become a focal point of both research and practice. By integrating big data, artificial intelligence, and other advanced technologies, smart classrooms enable precise monitoring and analysis of students' learning behaviors, thereby providing essential support for personalized instruction [1]. Meanwhile, although many universities in China have introduced intelligent technologies into classroom teaching, the overall level of informatization remains insufficient, leaving substantial room for the further development of smart classrooms [2]. Research shows that smart classrooms can effectively enhance students' classroom attention and engagement, while helping teachers better grasp learning conditions and optimize instructional strategies. Thus, educational digital transformation is not merely a technological innovation, but also a profound shift in educational philosophy and teaching practice.

From a macro perspective, the significance of educational digital transformation lies in its dual role in promoting educational equity and quality. On one hand, the application of digital technologies facilitates the widespread dissemination of high-quality educational resources, alleviating disparities in educational access across regions. On the other hand, data-driven teaching models help realize individualized instruction, meeting the learning needs of students with diverse abilities [1]. Furthermore, smart classrooms, through multi-dimensional data analysis, provide a scientific basis for educational decision-making, thereby improving the efficiency and accuracy of educational management [2]. Nevertheless, despite the significant theoretical advantages of smart classrooms, their practical implementation still faces numerous challenges, such as technology reliability and data privacy protection. Addressing these issues requires joint efforts from both academia and practitioners to advance educational digital transformation in depth.

1.2 Directives from the Report of a Major National Policy Meeting in 2022

The Report of a major national policy meeting in 2022 explicitly proposed the strategic plan to promote educational digitalization, which provides clear direction for the development of the education sector and offers important guidance for the construction of smart classrooms. The report emphasizes that educational digitalization is a crucial pathway to achieving educational modernization and a key lever for promoting high-quality educational development [3]. Against this backdrop, the smart classroom—serving as a concrete practice of educational digitalization—aims to realize intelligent and personalized teaching processes through technology empowerment. The realization of this goal depends on in-depth analysis of students' learning behaviors in class; only by accurately grasping students' learning states and behavioral characteristics can reliable evidence be provided for instructional improvement [4].

From a policy perspective, the report of the 20th National Congress offers strong support for the development of smart classrooms. First, the Digital China strategy proposed in the report has created a favorable external environment for the technological innovation and application of smart classrooms. Second, the report's call to accelerate the construction of a high-quality education system further underscores the potential of smart classrooms to enhance educational quality [3]. In addition, the construction of smart classrooms is highly aligned with the report's vision of promoting educational equity, as it leverages technology to reduce the urban–rural education gap and advance balanced educational development [4]. Nevertheless, the promotion and application of smart classrooms still face a series of practical challenges, such as improving teachers' information literacy and ensuring the widespread availability of technical equipment. Overcoming these issues requires coordinated efforts from the government, schools, and all sectors of society to ensure the smooth implementation of the educational digitalization strategy.

2 THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EDUCATION

2.1 Opportunities

The rapid development of artificial intelligence (AI) has brought unprecedented opportunities to the field of education, particularly in personalized instruction and precision assessment. By leveraging deep learning algorithms and data mining technologies, smart classrooms can generate individualized learning pathways and resource recommendations based on students' learning behaviors, interest preferences, and knowledge mastery levels [1]. This personalized teaching model not only meets the diverse learning needs of students, but also alleviates, to some extent, the limitations of the "one-size-fits-all" approach prevalent in traditional classrooms. Furthermore, AI demonstrates significant advantages in precision assessment. Through the analysis of multimodal data from the learning process—such as speech, images, and text—teachers can gain a more comprehensive understanding of students' learning states and progress trends, thereby formulating more targeted instructional strategies [5]. The application of these technologies not only improves the quality of education and teaching but also provides new possibilities for achieving educational equity.

2.2 Challenges

Despite the promising prospects of AI in education, its widespread adoption faces numerous challenges, with data privacy and technology reliability being the most prominent. In smart classrooms, students' learning behavior data are extensively collected and analyzed, inevitably raising concerns about data security and privacy protection [2]. For example, students' personal information and learning records may be misused or leaked, compromising their rights and interests. In addition, the reliability of AI technologies remains an urgent issue. Due to the complexity of algorithms and the inconsistency of data quality, AI systems may, in some cases, fail to provide accurate analytical results, and may even lead to erroneous decisions [6]. To address these challenges, it is necessary to establish robust data protection mechanisms and algorithm validation systems from technical, legal, and ethical perspectives, ensuring the safety and trustworthiness of AI in the educational context.

2.3 Research Necessity

Research on the use of AI to analyze students' learning behaviors in the classroom holds significant theoretical and practical value. First, in-depth analysis of learning behaviors can help teachers better understand students' learning processes and needs, thereby optimizing instructional design and improving teaching effectiveness [3]. Second, the application of AI can provide more refined and comprehensive data support for educational research, promoting the development of educational science. For example, big-data-based learning behavior analysis can reveal patterns in student learning and lay the foundation for building a scientific learning evaluation system [7]. Moreover, within the current context of educational digital transformation, the construction of smart classrooms has become an important direction of educational reform, with AI serving as a key driver in achieving this goal. Therefore, strengthening research on the application of AI in education not only helps solve existing problems in teaching but also offers important insights for the innovation of future educational models.

3 PROCESS OF STUDENT LEARNING BEHAVIOR ANALYSIS IN SMART CLASSROOMS

3.1 Construction of a Learning Behavior Classification System

The construction of a learning behavior classification system forms the foundation of student behavior analysis in smart classrooms, and its scientific validity and rationality directly affect the depth and breadth of subsequent research. By employing the literature analysis method and integrating existing research findings, nine categories of learning behaviors can be summarized, encompassing dimensions such as verbal learning activities, positional movement, physical actions, and technology use [3]. The basis for these classification systems primarily stems from the integration and analysis of multimodal data—including audio data, image data, and text data—within a three-dimensional framework, thereby providing a comprehensive perspective for characterizing learning behaviors [2]. Furthermore, drawing on the achievements of research on learning behavior classification systems, the definitions and boundaries of behavior types have been further refined to ensure the rationality and operability of the system. This classification approach not only reflects students' behavioral characteristics in the classroom but also lays the groundwork for subsequent data coding and qualitative analysis.

3.2 Data Collection

Data collection is a crucial stage in the analysis of students' learning behaviors in smart classrooms, and its quality directly influences the reliability of research results. In this study, Ministry-level "One Teacher, One Excellent Lesson" platform video data of exemplary lessons served as the primary source, from which a student behavior dataset was systematically constructed. Specifically, the scope of data collection covered classroom teaching videos, teacher–student interaction records, and student technology usage logs, representing diverse multimodal data [5]. In terms of selection criteria, priority was given to high-quality, representative course videos to ensure both data quality and diversity. The data collection process included three stages: video recording, data annotation, and data cleaning. In the annotation phase, a hybrid approach combining manual and automated annotation was adopted to improve efficiency and accuracy. The resulting student behavior dataset provides abundant material for subsequent target tracking and detection model training.

3.3 Target Tracking and Detection Model Training

Target tracking and detection model training constitute one of the core technologies for analyzing students' learning behaviors in smart classrooms, and their performance determines the accuracy and efficiency of behavior recognition. This study employed the DeepSORT algorithm for target tracking and combined it with the YOLOv5 object detection algorithm to train the detection model. DeepSORT integrates appearance features with motion information for target tracking, effectively addressing challenges such as target occlusion and rapid movement in complex scenes [8]. YOLOv5, renowned for its high detection speed and accuracy, is particularly well-suited for real-time object detection in video streams. In this study, the integration of these two algorithms significantly improved the accuracy and real-time performance of student behavior recognition. Specifically, YOLOv5 was first used to detect behavioral targets, followed by DeepSORT to track the detected targets, thereby enabling continuous monitoring and analysis of student behaviors. This technical combination not only enhanced the robustness of the model but also provided reliable data support for subsequent multi-perspective analysis.

3.4 Multi-Perspective Analysis Methods

Multi-perspective analysis methods are essential tools for analyzing student learning behaviors in smart classrooms, as their synergistic use can reveal deeper behavioral patterns. This study incorporated S–T classroom teaching behavior analysis and temporal sequence analysis of student behaviors to comprehensively characterize students' learning behavior profiles. S–T classroom teaching behavior analysis involves statistical examination of the proportion and frequency of teacher and student behaviors, revealing the correlations between different behavior types and their impact on teaching effectiveness [9]. For example, the study found that in award-winning lesson cases, the proportion of teacher lecturing behaviors was higher than in ordinary lessons, while students' technology usage behaviors were relatively lower—indicating that teacher-led instructional models still hold a dominant position in smart classrooms. Meanwhile, temporal sequence analysis of student behaviors identifies patterns and variations in behavior sequences, offering insights into the dynamics of students' learning behaviors [10]. The integration of these two methods enhances the comprehensiveness of the analysis and provides a scientific basis for optimizing instructional strategies.

4 CURRENT STATUS OF STUDENT BEHAVIOR ANALYSIS IN SMART CLASSROOMS

4.1 Application of Technologies

In recent years, the application of technologies for student behavior analysis in smart classrooms has shown a trend toward the deep integration of multimodal data technologies and artificial intelligence (AI) algorithms. Multimodal data technologies integrate various types of data—such as audio, image, and text—to support comprehensive monitoring of students' learning behaviors. For example, Jiang Jie and colleagues proposed a multimodal data analysis method based on an "audio–image–text" three-dimensional framework to capture behavioral characteristics such as verbal learning activities, positional movement, physical actions, and technology use in smart classrooms [3]. Audio data have been widely applied to analyze the relevance between students' discussion content and the course, while video data can effectively reflect students' concentration and emotional states during collaborative learning [11]. At the same time, AI algorithms such as the DeepSORT target tracking algorithm and the YOLOv5 object detection model further enhance the accuracy and efficiency of behavior recognition. The combination of these technologies not only enables real-time monitoring of student learning behaviors but also provides a reliable foundation for subsequent data analysis and instructional decision-making.

Nevertheless, despite the growing maturity of technological methods, their application still faces certain limitations. On one hand, the collection and processing of multimodal data require high-performance hardware devices, which to some extent hinders widespread adoption. On the other hand, compatibility and standardization issues between different technologies remain unresolved, increasing the complexity of data integration and analysis. In the future, with further advancements in the Internet of Things (IoT) and intelligent sensing technologies, the technical framework for student behavior analysis in smart classrooms is expected to become more complete, thereby better serving educational practice [2].

4.2 Current Status of Behavior Classification

Current research on student behavior classification in smart classrooms mainly focuses on the construction of behavior classification systems and their accuracy. Using the literature analysis method, Jiang Jie and colleagues summarized nine categories of learning behaviors, including asking questions, note-taking, assignment completion, and test participation, providing an important theoretical basis for subsequent studies [3]. However, existing classification systems still face multiple challenges in practical application. First, the accuracy of behavior classification depends on high-quality datasets, and issues such as sample bias or annotation errors during data collection may affect the reliability of classification results. Second, the boundaries between certain behavior types are ambiguous; for example, distinguishing between active thinking and passive listening can be difficult, potentially leading to inconsistent classification outcomes [2].

Furthermore, the comprehensiveness of behavior classification has been questioned. Existing systems mainly focus on students' explicit behaviors, with limited coverage of implicit behaviors such as emotional states and cognitive load. This limitation may lead to an incomplete understanding of students' learning behaviors, thereby affecting the formulation and optimization of instructional strategies. Therefore, future research should improve existing classification systems while exploring methods to identify and categorize behavioral features from additional dimensions, in order to enhance the comprehensiveness and scientific rigor of behavior analysis [3].

4.3 Research Achievements and Applications

Research on student behavior analysis in smart classrooms has already demonstrated significant value in educational practice. By conducting in-depth analyses of students' learning behaviors, researchers can reveal the relationship between behavioral patterns and learning outcomes. For instance, Le Qiqing and colleagues, through visual analysis of learning data from an Automobile Structure and Assembly course, found that students' online questioning frequency, assignment scores, and classroom knowledge mastery rate were significantly positively correlated with their final grades [4]. Similarly, Zhang Jiali and colleagues, in a study on engagement in collaborative learning within smart classrooms, confirmed that multimodal-data-based analytical models can effectively assess students' learning engagement levels and provide teachers with precise bases for instructional intervention [7].

In terms of practical application, research outcomes from smart classroom student behavior analysis have been widely adopted in areas such as academic achievement diagnosis, personalized instructional recommendations, and instructional strategy optimization. For example, by analyzing behavioral data from smart classrooms, teachers can promptly identify students' learning difficulties and take targeted measures to improve instructional effectiveness. Moreover, learning behavior analysis based on multimodal data can offer valuable references for educational researchers to construct scientific learning evaluation systems, further driving innovation and development in educational models [3, 11]. However, it is worth noting that the actual effectiveness of these research applications remains constrained by factors such as implementation costs, teachers' professional competence, and schools' informatization levels. Therefore, future efforts should focus on improving support mechanisms to promote the broader dissemination and application of research results [2].

5 CONCLUSIONS ON STUDENT BEHAVIOR ANALYSIS IN SMART CLASSROOMS

5.1 Summary of Behavioral Patterns

Through in-depth research on students' learning behaviors in smart classrooms, a series of notable behavioral patterns have been identified. First, there is a certain correlation between class size and the proportion of teacher lecturing behaviors. Studies show that as the number of students in a smart classroom increases, the proportion of teacher lecturing tends to decline, while the proportion of technology-related behaviors and student self-directed learning behaviors increases [10]. This phenomenon may be related to the technological support features of smart classrooms, where teachers are more inclined to leverage information technologies to compensate for the limitations of traditional lecture-based methods, thereby promoting personalized learning. Second, the proportion of teacher guidance behaviors is closely associated with the frequency of student active behaviors. Research indicates that when teacher guidance behaviors increase, student active behaviors—such as hands-on practice, active thinking, and technology operations—also rise significantly, suggesting that teacher facilitation plays a key role in shaping students' behavioral patterns [12]. Furthermore, students in smart classrooms generally exhibit high levels of technology operation behaviors. Notably, in ordinary lesson cases, the proportion of technology-related behaviors reached 32.97%, far exceeding the 23.19% observed in award-winning lesson cases [10]. This data reflects students' strong reliance on technology in smart classrooms and reveals a potential link between technology use efficiency and instructional effectiveness.

5.2 Implications for Teaching and Learning

The behavioral patterns identified above carry important implications for educational practice. First, teachers should flexibly adjust instructional strategies based on class size and students' behavioral characteristics. For instance, in large-class teaching, teachers can enhance student engagement by using interactive tools provided by smart platforms—such as online quizzes and discussion forums—while reducing reliance on a single lecture format [7]. Second, teachers should emphasize the diversity and specificity of guidance behaviors to stimulate students' initiative and creativity. Research findings show that teacher observation and guidance behaviors in smart classrooms can significantly enhance students' learning engagement, especially in behavioral, emotional, and cognitive dimensions [13]. Therefore, teachers should make full use of technological means during instruction to promptly identify students' learning needs and provide effective feedback. Additionally, the use of technology in smart classrooms should aim to facilitate deep learning, rather than remaining at a superficial operational level. Teachers should design more technology-based inquiry activities to guide students from passive reception to active exploration, thereby improving teaching effectiveness.

5.3 Practical Application Recommendations

To further optimize student learning behaviors in smart classrooms, the following recommendations are proposed. First, teachers should incorporate more student-centered activities into instructional design, such as collaborative learning and project-based learning, to enhance students' cooperative awareness and self-learning capabilities [14]. Second, schools should strengthen teacher training in information technology to help educators master the tools and methods of teaching in smart classroom environments, thus better supporting students' learning processes [6]. Furthermore, the functional design of smart classroom platforms should better align with students' actual needs—for example, by delivering personalized learning resources that match different students' progress and interests. Studies have shown that the accuracy of personalized content delivery directly affects students' learning experiences and outcomes; therefore, platform developers should continuously improve algorithms to enhance the intelligence level of resource recommendation [6]. Finally, teachers should make full use of classroom behavior analysis data, applying methods such as lag sequence analysis to uncover patterns and trends behind student behaviors, thereby providing a scientific basis for instructional decision-making [12]. These measures will help create a more efficient and interactive smart classroom environment, ultimately achieving both students' holistic development and comprehensive improvement in teaching quality.

6 RESEARCH LIMITATIONS AND PROSPECTS

6.1 Research Limitations

Although this study has achieved certain results in the field of student behavior analysis in smart classrooms, several inevitable limitations remain. First, in terms of research methodology, this study mainly relies on the literature analysis method and data mining techniques. While these approaches can extract valuable information from existing research, they may overlook certain practical cases that have not been fully documented or published, thereby affecting the comprehensiveness of the research results [3]. Second, regarding data collection, the research data primarily come from Ministry-level "One Teacher, One Excellent Lesson" platform exemplary lesson videos. Although these data possess a degree of representativeness, their sample scope is relatively limited, making it difficult to fully capture the diversity of different regions, schools, and student populations. Moreover, due to the complexity of data annotation and processing, the accuracy of certain behavioral data may be affected by human factors, which in turn may constrain the reliability of the analysis results [2].

In terms of research scope, this study mainly focuses on the analysis of students' learning behaviors in smart classroom settings, with relatively less attention to other educational contexts such as online education and blended learning. This limitation may reduce the generalizability of the research conclusions, preventing them from fully reflecting the overall situation of student behavior analysis under the broader background of educational informatization. Furthermore, due to technical constraints, this study has not fully explored the potential value of multimodal data fusion analysis in behavior monitoring—particularly in areas such as emotion recognition and physiological signal analysis, where in-depth applications remain insufficient. These limitations not only affect the precision of the research results but also provide opportunities for improvement in future studies [2, 3].

6.2 Future Research Directions

Based on the identified limitations, future research on student behavior analysis in smart classrooms can proceed in several directions. First, the diversity and coverage of data sources should be further expanded. For example, cross-regional and cross-school collaborative research can be conducted to obtain more representative student behavior datasets. Additionally, by incorporating emerging technologies such as the Internet of Things (IoT) and blockchain, the level of automation in data collection and processing can be improved, thereby reducing the influence of human error on research results [3]. Second, at the technical level, future research should place greater emphasis on the application of multimodal data fusion analysis, particularly through in-depth exploration in areas such as affective computing and physiological signal monitoring. For instance, by combining audio, video, log, and physiological data, more comprehensive and accurate student behavior analysis models can be constructed, enabling dynamic monitoring and assessment of key indicators such as learning engagement and emotional states [11].

Moreover, future research could focus on the application of student behavior analysis in smart classrooms to educational equity and personalized instruction. For example, by examining differences in learning behaviors among diverse student groups, teachers can be provided with targeted instructional strategy recommendations, thereby promoting the equitable distribution of educational resources and improving overall learning outcomes. In addition, with the continuous development of AI technologies, future studies could experiment with advanced algorithms such as reinforcement learning and transfer learning to optimize the accuracy and robustness of behavior prediction models, thus providing a more scientific basis for educational decision-making [3]. Finally, more attention should be given to the ethical issues of student behavior analysis in smart classrooms, particularly in establishing stricter standards and regulations for data privacy protection and technology reliability, ensuring the legality and transparency of the research process [11]. These directions will not only help address current research shortcomings but will also provide important theoretical support and practical guidance for advancing the development of smart education.

COMPETING INTERESTS

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