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An empirical study on the multidimensional influencing factors of taekwondo training for middle school students in an artificial intelligence environment

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This work explores the multidimensional impacts of an Artificial Intelligence (AI) environment on Taekwondo training for middle school students. It establishes an intelligent training system and personalized training programs and compares the training outcomes of an experimental group (trained in an AI environment) with a control group (trained in a traditional environment). All participants are from the same middle school and undergo baseline assessments before the study to ensure data reliability and consistency. The results indicate that psychological state significantly and positively impacts students' motivation levels (supporting Hypothesis 1), meaning that a good psychological state can markedly enhance middle school students' training motivation. Additionally, motivation levels have a notable positive effect on the performance of technical movements (supporting Hypothesis 2). This illustrates that higher motivation levels can effectively improve the quality of technical movements, highlighting the importance of motivation in training outcomes. Furthermore, self-efficacy also has a significant positive influence on technical movement scores (supporting Hypothesis 3), indicating that the higher the students' confidence in their abilities is, the better their technical performance is. The impact of training records on technical movement scores is likewise significant (supporting Hypothesis 4), where more training time and higher engagement can effectively enhance technical scores, emphasizing the importance of behavioral involvement. Finally, motivation levels also have a significant positive effect on self-efficacy (supporting Hypothesis 5), with high motivation levels contributing to an increase in students' self-efficacy.

Keywords Artificial intelligence, Persistence, Middle school Taekwondo, Technical proficiency, Competition performance

Research background and motivations

In modern physical education, Taekwondo has become an important component of middle school sports curricula due to its unique role in cultivating physical and psychological qualities[1–3]. As a comprehensive competitive sport, Taekwondo training requires students to master precise technical movements and develop tactical awareness, self-control, and psychological resilience in the face of challenges[4,5]. However, since middle school students' physical and psychological development is not yet fully matured, they face different challenges in Taekwondo training compared to adult athletes. Effectively identifying and optimizing these influencing factors to enhance the overall effectiveness of Taekwondo training for middle school students has become an urgent issue in physical education[6–8].

In recent years, the application of Artificial Intelligence (AI) technology in sports training has provided new possibilities for addressing this issue[9]. AI can help coaches better understand students' performances; meanwhile, it can offer personalized training programs and real-time feedback, facilitating dual progress in both technical and psychological aspects[10]. For middle school students, this technological intervention is particularly crucial, as their cognitive and self-management skills are still developing, and traditional training methods may not fully meet their needs[11].

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Currently, the application of AI in Taekwondo training has shown promising results, particularly in areas such as motion capture and analysis, virtual coaching systems, and data-driven feedback mechanisms[12]. Motion capture technology uses high-precision sensors to record students' movements in real time. Meanwhile, this technology employs deep learning (DL) algorithms to analyze the data, quickly identify errors, and provide corrective suggestions[13]. The virtual coaching system utilizes virtual reality and augmented reality technologies to simulate real competition scenarios, allowing students to receive targeted training in a virtual environment. These technologies can effectively enhance middle school students' technical proficiency and tactical awareness[14]. This makes training more engaging and improves athletes' abilities to cope with diverse competitive situations. Moreover, AI systems can record athletes' performances in various scenarios, analyze their tactical choices, and offer targeted improvement suggestions, helping athletes enhance their tactical acumen and adaptability[15].

However, the factors influencing the effectiveness of Taekwondo training for middle school students extend beyond the technical realm to include psychological motivation, emotional responses, and interactions with peers and coaches[16–18]. These factors profoundly impact students' learning outcomes, yet the existing AI systems have relatively insufficient applications in this regard[12]. For instance, how psychological factors such as self-efficacy, achievement motivation, and stress management can be enhanced through AI-assisted training remains a topic worthy of further investigation.

The main contribution of this work lies in developing and evaluating an AI-assisted Taekwondo training system specifically designed for middle school students. This system offers precise technical feedback and optimizes students' training experiences through psychological motivation and interactive design. By integrating several key innovations, this work offers new methods for improving the effectiveness of Taekwondo training for middle school students. The AI system provides technical feedback through motion analysis; it also incorporates psychological research to design personalized incentive mechanisms. The mechanisms are intended to help students enhance their self-confidence and self-efficacy, promoting positive learning attitudes and sustained training motivation.

Moreover, the work designs a series of experiments using AI technology to monitor and analyze various data during the Taekwondo training of middle school students. First, video analysis technology records students' training movements and evaluates their techniques. Second, surveys and interviews are conducted to gather data on students' psychological states and motivation levels during training. Finally, by integrating this data, statistical methods like multiple regression analysis are used to assess the impact of each factor on training outcomes. In summary, this work aims to explore the effectiveness of AI technology in middle school students' Taekwondo training through a comprehensive multidimensional evaluation. The findings provide scientific evidence and theoretical support for future training strategies. Thus, this work can offer new perspectives on the scientific and personalized approaches to Taekwondo training and lay the groundwork for further studies in physical education.

Research objectives

This work examines the impact of multidimensional factors on the effectiveness of Taekwondo training for middle school students in an AI environment. The specific research objectives are as follows:

1. Assessing the Overall Impact of AI Technology on Taekwondo Training Techniques: This objective seeks to analyze the effectiveness of AI technologies, such as video analysis, action recognition, and personalized training recommendations, in enhancing the technical details of Taekwondo training for middle school students. This work focuses on improvements in key technical indicators, including movement accuracy, reaction time, and technical consistency, and investigates how these technical variables can be optimized through AI technology.
2. Analyzing Multidimensional Factors Affecting Training Persistence: This section examines how various factors influence the training persistence of middle school students in Taekwondo, including personal self-efficacy, intrinsic motivation, extrinsic rewards, and the feedback and support provided by AI technology. Through a comprehensive analysis of these factors, the work aims to reveal how AI technology can support and enhance training motivation and improve training persistence.
3. Exploring the Impact of AI Technology on Psychological States and Motivation Levels: Regarding this objective, this work redefines the role of AI technology, focusing on how personalized feedback and incentive mechanisms can positively influence middle school students' psychological states (such as confidence and a sense of achievement) and motivation levels. It explores how AI technology can help students cope with psychological challenges during training, such as stress and anxiety, and enhance their self-efficacy and engagement in training.

Overall, through a systematic analysis of existing literature, this work identifies gaps in the study of AI technology in Taekwondo training for middle school students. The research gaps include a narrow focus on technical assessment, insufficient theoretical applications, and a neglect of the unique needs of adolescent athletes. Specifically, many existing studies primarily concentrate on quantifying technical indicators while lacking an in-depth exploration of how these technical improvements intersect with students' psychological states and motivation levels. To address these issues, this work proposes targeted improvement suggestions through empirical research and emphasizes the interactions of multidimensional factors in training. This includes assessing students' technical abilities and psychological factors such as confidence, achievement motivation, and stress management skills. The findings provide a scientific basis for optimizing Taekwondo training programs, particularly in effectively integrating AI technology to support students' dual enhancement in both technical and psychological dimensions. Additionally, this work offers practical guidance for coaches and educators, helping them better utilize AI tools to develop personalized training programs. These programs consider each student's unique needs, thus enhancing their training effectiveness and engagement. Ultimately, the work provides important insights for future training strategies and methods, advancing the scientific and systematic development of Taekwondo training in an AI environment.

Literature review

With the swift advancement of AI technology, its application in sports training has garnered widespread attention. In competitive sports like Taekwondo, AI technology has significantly enhanced the scientific and personalized aspects of training through video analysis, action recognition, and training recommendations[13]. However, there are still several gaps in the existing literature on this subject. Although the application of AI in sports training has made notable progress, current studies primarily focus on specific areas such as technical skill enhancement. For instance, Mei (2023)[2] demonstrated that AI technology could improve athletes' technical skills through video analysis and action recognition. Cunha et al. (2024)[19] used DL techniques to automatically recognize and evaluate Taekwondo athletes' movements, showing that AI could effectively identify errors and provide targeted suggestions for improvement. Similarly, Yu et al. (2022)[20] proposed AI-based personalized training plans, offering new approaches to technical enhancement. However, these studies mainly evaluate technical movements, lacking a comprehensive analysis of multidimensional factors such as psychological states, motivation levels, and training persistence during the training process.

On the one hand, the application of SCT and SDT in sports training has also been explored to some extent. Frei-Landau et al. (2022)[21] emphasized SCT's focus on learning through observation and imitation, which enhanced training persistence through self-efficacy. Yang & Mojtahe (2023)[22] found that self-efficacy significantly impacted training persistence, but their research mainly targeted adult athletes, with a limited focus on adolescent athletes. Hodges & Lohse (2022)[23] highlighted the need to consider individual differences when applying SCT in sports training, especially the unclear effects of AI technology intervention.

On the other hand, SDT, proposed by Deci & Ryan (2000)[24], focused on the impact of intrinsic and extrinsic motivation. Research indicated that fulfilling the basic psychological needs of autonomy, competence, and relatedness could significantly enhance athletes' intrinsic motivation. With the support of AI technology, personalized training plans can better satisfy students' autonomy needs. However, real-time feedback and interaction provided by AI can enhance their sense of competence and relatedness. However, existing studies primarily focus on adult athletes, with insufficient research on motivation changes and psychological states in adolescent athletes within an AI environment.

Moreover, there is a relative lack of comprehensive evaluations of multidimensional factors in the current literature. Yuan et al. (2022)[25] explored the interrelationships between psychological states, motivation levels, and technical improvement but failed to fully consider the comprehensive effects of AI technology on these factors. Zhang, Balcombe, & De Leo (2020)[26] pointed out that the impact of AI technology on athletes' persistence and psychological states had not yet been systematically analyzed, indicating a significant gap in the multidimensional evaluation of these factors.

The content above indicates that in Taekwondo training, the role of AI is important. AI technology can optimize training plans and monitor athletes' performance in real-time, thus providing personalized guidance and feedback. For instance, through video analysis, coaches can accurately identify issues in athletes' technical execution and make timely adjustments. Additionally, AI can leverage big data analysis to help coaches develop more scientifically informed training plans that cater to the needs of different athletes, thereby enhancing overall training effectiveness. Overall, the application of AI in Taekwondo training extends beyond technical improvements; it also involves the interaction of psychological and behavioral factors, offering new possibilities for athletes' holistic development. However, this process also faces challenges. Existing research tends to analyze single factors, such as technical skill enhancement or improving psychological motivation, while lacking a comprehensive evaluation of multidimensional factors. Furthermore, the application of SCT and SDT within an AI environment has not been fully explored, and there is a relative paucity of research on adolescent athletes. Therefore, this work aims to fill these gaps by employing empirical research methods to comprehensively analyze the multidimensional factors influencing middle school students' Taekwondo training in an AI environment. It intends to provide new perspectives and improvement strategies for research and practice in this field.

Based on the previous literature review and theoretical background, the following research hypotheses are proposed. These hypotheses aim to explore how various multidimensional factors influence the effectiveness of Taekwondo training among middle school students.

Hypothesis 1 The psychological state has a significant impact on motivation levels. The psychological state encompasses multiple dimensions, including emotions, stress, and anxiety, which can directly influence students' motivation. Specifically, negative emotions such as anxiety and high stress levels may weaken students' motivation, leading to a lack of engagement in training. Positive psychological states, such as confidence and emotional stability, can enhance students' motivation, promoting their performance and participation in training. Therefore, understanding and optimizing students' psychological state is important for improving motivation and training effectiveness.

Hypothesis 2 Motivation level has a significant impact on technical performance scores. Motivation level, which includes intrinsic motivation (such as interest in Taekwondo) and extrinsic motivation (such as rewards), is considered a crucial factor influencing training outcomes. The hypothesis posits that the motivation level has a direct positive effect on technical performance scores. In other words, higher motivation levels typically lead to better technical performance and execution.

Hypothesis 3 Self-efficacy significantly influences technical performance scores. Self-efficacy refers to an individual's confidence in completing a specific task. The hypothesis asserts that self-efficacy has a direct positive impact on technical performance scores. In other words, higher self-efficacy can help middle school students achieve better technical performance during training.

Hypothesis 4 Training records significantly affect technical performance scores. Training records, including time spent training, frequency, and engagement levels, are hypothesized to have a direct positive impact on technical performance scores. More training time and higher engagement are expected to result in better technical performance scores.

Hypothesis 5 Motivation level significantly impacts self-efficacy. It is hypothesized that motivation level influences self-efficacy. Specifically, higher motivation levels may increase an individual's self-efficacy, enhancing their confidence in training outcomes.

In addition to these hypotheses, gender and training duration are considered as control variables to explore their potential moderating effects on technical performance scores. It is hypothesized that gender and training duration may affect training outcomes, and therefore, appropriate controls and analyses are included in the model.

Research methodology

The use of AI technology in taekwondo training

Taekwondo, as a combat sport with strong technical and strategic elements, requires continuous adjustments and optimizations in the training process to adapt to the personalized needs of athletes. Traditional training methods may have inherent limitations, such as the singularity of training programs and a lack of personalized guidance. However, introducing AI technology brings new possibilities and opportunities to Taekwondo training. Through intelligent training systems and personalized training programs, the AI environment can provide Taekwondo athletes with more diverse and personalized training experiences, thus enhancing training effectiveness.

1) The application of AI technology in Taekwondo training is reflected in intelligent training systems. For example, this work proposes an AI-based intelligent training platform that generates personalized training plans based on athletes' physical fitness, technical skill level, and training goals. These plans include foundational technical training and dynamically adjust according to athletes' feedback and performance, making the training process more flexible and efficient. Specifically, the system integrates machine learning (ML) algorithms to analyze athletes' training data and automatically optimize training content and intensity to meet individual needs. Figure 1 illustrates the details.

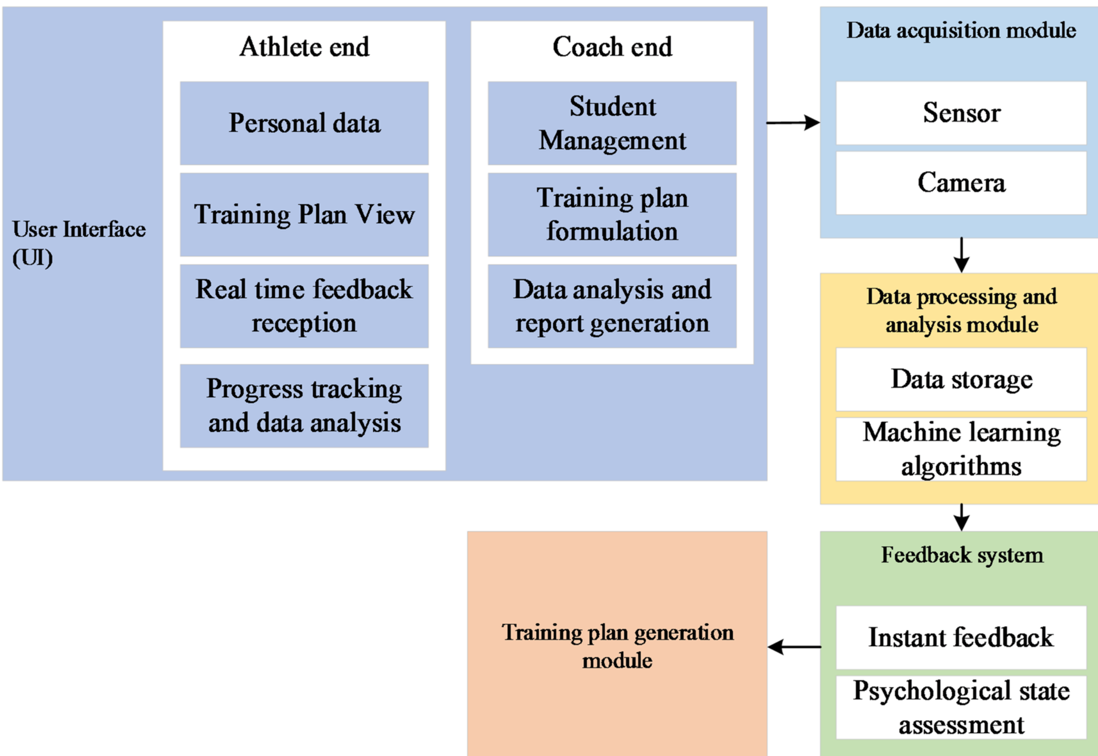

Fig. 1. Structure diagram of the intelligent training platform.

The structure diagram of the intelligent training platform illustrates a comprehensive system designed to enhance Taekwondo training effectiveness for middle school students. The platform's core is the user interface, which includes portals for athletes and coaches. Athletes can view their profiles, access personalized training plans, receive real-time feedback, and track their training progress and performance data, increasing their sense of involvement. Meanwhile, the coach's portal allows coaches to manage all student information, formulate and adjust training plans, and generate data analysis reports to provide targeted guidance. This platform consists of the following modules:

The data collection module is the core component of this system, primarily responsible for real-time monitoring of athletes' physical states and training performance to ensure the accuracy and timeliness of feedback information. This module employs a combination of multimodal sensors and high-definition cameras for data collection. Specifically, the system is equipped with wearable devices, including three-axis accelerometers, gyroscopes, and heart rate sensors; these devices record movement dynamics, joint angles, postural stability, and physiological responses during training. These sensors are placed on key parts of the athletes' limbs and trunk to obtain comprehensive and continuous kinematic and physiological data. Meanwhile, the high-definition camera system captures training images in real time at a high frame rate to extract visual features such as movement trajectories, body postures, and movement precision. This multi-source data collection method provides a solid data foundation for subsequent analysis.

In the data processing and analysis module, the system first preprocesses the collected data, including noise removal using a Butterworth low-pass filter, time-series alignment, data normalization, and segmentation and annotation of training movements. Through these processing steps, the data input into the model is ensured to have high consistency and usability. In feature extraction, the system combines manually designed statistical features (such as average acceleration, variance, peak angular velocity, etc.) with deep features automatically learned from raw data.

Regarding model construction, this system adopts a hybrid algorithm architecture combining ML's Support Vector Machines (SVM) and Convolutional Neural Network (CNN). It aims to fully leverage the advantages of these two model types in processing different data types. SVM is mainly used for structured physiological data, such as heart rate, respiratory rate, training duration, and heart rate variability. Constructing an optimal classification hyperplane can classify and judge athletes' training states into high, medium, and low loads or stress levels. During training, the system standardizes the collected physiological indicators. Moreover, a radial basis kernel function is used as the SVM kernel to enhance the fitting capability for non-linear features, thereby more accurately reflecting athletes' physiological states during training.

Meanwhile, the CNN model primarily processes high-dimensional spatio-temporal feature data fused from images and sensors, including key frame image sequences from training videos and time-series tensors of acceleration and angular velocity. By configuring multiple convolutional and pooling layers, CNN can automatically extract deep features, such as movement trajectories, amplitude, and coordination among body parts across different moments. These features are then processed through fully connected layers for classification or regression analysis, enabling precise recognition of technical movement patterns. To enhance temporal modeling capabilities, a time-window mechanism is embedded in the CNN architecture to pair continuous frames with continuous sensor readings, preserving critical movement change trends.

During the integration of the hybrid model, the system first independently models physiological and movement features. Then, the system fuses the output results of the two models at the decision-making layer. For example, comprehensive evaluation results and personalized training recommendations are ultimately generated using weighted voting or probability fusion methods. This integration method of SVM and CNN leverages SVM's strong classification ability in small-sample and structured data while fully utilizing CNN's advantage in extracting deep spatial features from unstructured data. Thus, this method significantly improves the accuracy of action recognition and the personalized training programs' cientific validity and pertinence.

Additionally, the system stores training process data and historical performance data for dynamic comparative analysis. Based on training patterns and shortcomings identified by ML models, the platform automatically generates personalized training recommendations. Meanwhile, this platform can continuously optimize training programs, implementing a closed-loop mechanism of "feedback-adjustment-retraining" to enhance training efficiency and effectiveness. The feedback system translates analysis results into actionable suggestions for athletes through instant feedback features, including movement corrections and adjustments to training intensity. Also, the system can assess athletes' psychological states, ensuring that while technical skills improve, athletes' mental health and motivation levels are also prioritized. This integrated structural design aims to comprehensively enhance the effectiveness of Taekwondo training, helping athletes progress in both technical and psychological aspects.

2) Furthermore, AI technology can improve the Taekwondo training experience through personalized training programs. These plans encompass basic technical training while dynamically adjusting based on athletes' feedback and performance, making the training process more flexible and efficient[27,28]. The AI environment can improve the experience of Taekwondo training through intelligent training programs. Traditional training programs are often monotonous and lack interest and challenge, which may decrease athletes' training interest and motivation. With AI technology, training programs can be customized according to athletes' preferences and characteristics, including the diversity and interest of training content. For example, VR technology can simulate real competition scenarios to enhance athletes' competitive experience. Alternatively, gamified training methods can increase the training fun and stimulate athletes' enthusiasm[29].

3) The AI environment can also enhance the effectiveness of Taekwondo training through intelligent feedback systems. In traditional training processes, coaches are usually the only source of feedback for athletes, but they cannot monitor athletes' movements and performance in real-time. With AI technology, sensors and cameras can monitor athletes' movements in real-time, providing instant feedback and guidance. This allows

athletes to correct errors promptly and improve training effectiveness[30–32]. In summary, AI technology offers a comprehensive enhancement plan for Taekwondo training by introducing an intelligent training system, personalized training programs, and smart feedback mechanisms. This approach improves athletes' technical skills, training experience, and psychological well-being.

Research design

This work also explores the impact of multidimensional factors on the effectiveness of Taekwondo training for middle school students in an AI-enhanced environment. These factors interact with each other and play significant roles during the training process. First, technical factors are primarily reflected in the application of AI technologies, such as real-time motion capture, movement analysis, and personalized feedback systems. These technologies provide precise performance data and immediate technical guidance, helping athletes understand their performance in real-time and make adjustments, thereby significantly optimizing training outcomes. With advanced sensors and algorithms, athletes receive targeted suggestions during training to enhance their technical skills and reaction capabilities. Second, psychological factors focus on participants' mental states, motivation, and self-efficacy. These factors are crucial for training persistence and results. For instance, an athlete's confidence and expectations for success can influence their level of engagement in training. This work assesses athletes' motivation, self-efficacy, and emotional states based on questionnaires to understand how these psychological variables interact with training outcomes in an AI environment.

Third, behavioral factors involve participants' training behaviors, such as training frequency, time commitment, and level of engagement. These behaviors are directly related to actual training performance. By recording training time and participation, this work quantifies the impact of these factors to ensure the accuracy of the findings. Additionally, external reward factors, including coach feedback, reward mechanisms, and external incentives, directly influence athletes' enthusiasm and performance in training. This work examines how effective external incentives in AI environments can enhance athletes' motivation and training outcomes, promoting their overall development. Finally, social factors encompass peer support, teamwork, and social recognition. These factors significantly impact participants' training motivation and persistence. This work analyzes the role of social support networks and team dynamics during training, particularly in enhancing athletes' commitment and psychological resilience. By comprehensively analyzing these multidimensional factors, it aims to reveal the potential of AI technology in optimizing Taekwondo training for middle school students, providing profound theoretical and practical insights to improve training effectiveness.

To achieve these research objectives, an experimental study employs a crossover experimental design to compare two training methods with the same participants: AI-enhanced training (experimental group) and traditional training (control group). Initially, all participants undergo baseline assessments before AI training to evaluate their initial mental states, motivation levels, and technical abilities. This assessment ensures that the research objectives are appropriately addressed and provides reference data for subsequent analysis.

In the first phase, participants are trained in an AI-enhanced environment. This training is supported by a high-precision motion capture system and real-time movement analysis software, which records athletes' technical movements and provides instant feedback and suggestions. The personalized feedback system generates customized training plans based on each athlete's performance to optimize training effectiveness. Participants engage in Taekwondo training in this environment for a designated period. After completing the AI training, participants undergo a re-evaluation to capture any changes in their performance. This assessment repeats the baseline evaluation, focusing on changes in mental states, motivation levels, and technical abilities.

In the second phase, participants receive traditional training. The content of this training is the same as that of the AI training, but conducted without any AI technology support. Participants continue to receive the same technical guidance and training content to facilitate effective comparisons. After training, participants undergo another evaluation to analyze the specific impacts of the two training methods on their performance. The advantage of this crossover experimental design is that it eliminates the influence of individual differences, making the research results more reliable and valid. By comparing the performance of the same participants in different training environments, this work can more clearly identify the specific effects of AI technology on Taekwondo training outcomes, providing valuable insights for future training practices.

Meanwhile, the training content and plans for both sessions are consistent, including fundamental Taekwondo techniques, tactical training, and physical conditioning. The training cycle is set for 12 weeks, with sessions three times a week, each lasting 1.5 h. This schedule ensures systematic and standardized training. Before the experiment, participants are evaluated using scientifically designed questionnaires to assess traits related to training persistence, avoiding potential biases from selecting samples based solely on training experience. Data collection includes surveys, training records, and technical movement scores. The evaluation criteria cover technical movement accuracy, training effectiveness, psychological state, and motivation levels. Surveys are conducted to assess participants' training motivation, self-efficacy, and psychological state; training records are used to track time, frequency, and engagement. Technical movement scores are assessed using a motion analysis system.

Furthermore, during the experiment, strict control over the training environment and intervention implementation is maintained to ensure the objectivity of the results. The experimental and control groups have consistent training settings, and efforts are made to ensure that control group participants are unaware of the AI technology intervention. This design aims to eliminate potential confounding factors, ensuring the reliability and scientific validity of the research results. Through this design, the work aims to comprehensively evaluate the impact of AI technology on the effectiveness of Taekwondo training for middle school students, explore the role of multidimensional factors, and provide in-depth insights for research and practice in related fields.

Data collection

Data collection is a critical step for evaluating the impact of multidimensional factors on the effectiveness of Taekwondo training among middle school students. The data collection process involves several key components, including surveys, training records, and technical performance scores, each of which provides essential data for the research work. Surveys are the core component of the data collection process. A detailed questionnaire is designed to comprehensively assess factors, such as psychological state, motivation levels, and self-efficacy. The questionnaire is composed of the following sections:

Training motivation: This section uses a motivation scale to evaluate participants' intrinsic and extrinsic motivation for Taekwondo training. Intrinsic motivation includes the participants' interest in the sport, sense of challenge, and feelings of accomplishment, while extrinsic motivation encompasses the pursuit of rewards and recognition. The motivation scale employs a five-point Likert scale, where participants rate their agreement with each statement, ranging from "Strongly Disagree" to "Strongly Agree." Self-efficacy: This section utilizes a self-efficacy scale to assess participants' confidence in their Taekwondo training performance. The self-efficacy scale evaluates participants' belief in their abilities, including confidence in completing specific tasks and handling challenges.

Like the motivation scale, this section also uses a five-point Likert scale to gauge participants' self-belief and expectations in their training. Psychological State: This section includes measures of stress levels, anxiety, and emotional state. A psychological state scale, such as the Profile of Mood States (POMS), assesses participants' mental health. The scale covers various dimensions, including tension, fatigue, and excitement, to understand the potential impact of psychological factors on training outcomes. Additionally, technical performance scoring data are collected using a high-precision motion capture system and real-time motion analysis software. During each training session, the research team utilizes these technologies to record participants' technical performance. Specifically, the system monitors participants' movements in real-time, providing accurate technical scores and instant feedback on their performance. This technological assessment complements the questionnaire data, aiding in a more comprehensive understanding of how different factors influence training outcomes.

Concurrently, to ensure the validity and reliability of the questionnaire, a pilot test is conducted during the design process. Feedback is collected, and the questionnaire's content and format are adjusted accordingly. All questionnaires were approved by an ethics committee before the formal survey, and informed consent was obtained from the participants and their parents. Training records are systematically collected to track each participant's training time, frequency, and engagement. These records are obtained through training logs and coach feedback forms, ensuring data accuracy. Training records are vital for analyzing the impact of behavioral factors on training outcomes and providing objective data support. Technical movement scores are collected through an AI system that records and evaluates participants' technical movements in real-time. The scoring system includes indicators like movement accuracy, technical compliance, and movement fluidity. These detailed data help assess the specific contribution of AI technology to training effectiveness. Background information on participants, including age, gender, and training experience, is also collected. This information is used to control for background variables that might influence the research outcomes, ensuring the accuracy and comprehensiveness of data analysis. After data collection, all data undergo rigorous cleaning and preprocessing to address any missing values and outliers.

Structural equation modeling (SEM) analysis

Here, SEM is employed to conduct an in-depth analysis of how multidimensional factors influence the effectiveness of Taekwondo training among middle school students. SEM is a powerful statistical tool capable of handling complex causal relationships and multivariate data, allowing for a comprehensive understanding of the interactions between various factors and their impact on training outcomes.

First, this work constructs an SEM framework for assessing the effectiveness of Taekwondo training for middle school students (Fig. 2). This framework is based on relevant theories and literature reviews, integrating multiple latent and observed variables. The latent variables include key factors such as psychological state, motivation level, self-efficacy, and training persistence, which are theoretically considered to influence training

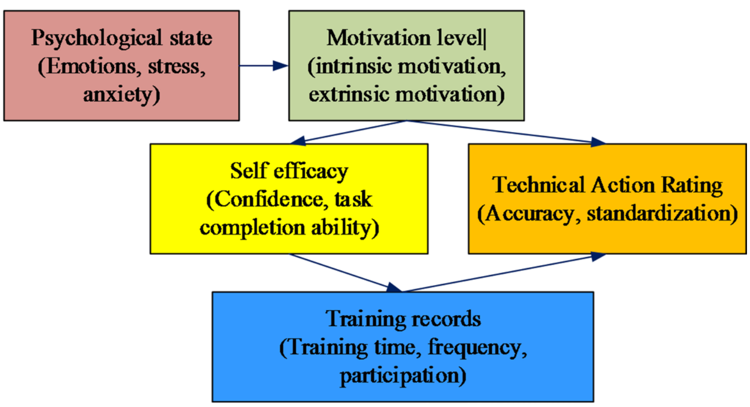

Fig. 2. SEM framework for assessing taekwondo training effectiveness in middle school students.

outcomes. The observed variables are the measured indicators, such as participants' questionnaire results, technical performance scores, and training logs.

Second, in developing this model, the work clarifies the relationships between each latent variable and its corresponding observed variables, defining the causal pathways. These pathways illustrate how latent variables such as psychological state, motivation level, and self-efficacy can affect observed variables like training persistence and technical performance. For example, a positive psychological state may enhance motivation levels, thus increasing training persistence and improving technical performance. Through this model framework, the work not only quantifies the specific impacts of different factors on training effectiveness but also explores their interactions, guiding subsequent empirical analysis.

After fitting the data, the path coefficients within the model are analyzed. The path coefficients indicate various factors' direct and indirect effects on training outcomes. The significance of these path coefficients is tested to determine which factors have a statistically significant impact on training effectiveness. During the model analysis process, if the initial model's fit results are unsatisfactory, model modification will be conducted. Model modification includes adjusting the paths between variables and adding or deleting paths to optimize the model's fit and explanatory power. This process requires continuous iteration until the model fit indices reach the desired levels, adequately explaining the variance in the data.

Finally, the results of the model analysis are interpreted and discussed in conjunction with the theoretical framework and actual data. Through an in-depth analysis of the model results, a scientific explanation of the influence of multidimensional factors on training outcomes can be provided, leading to targeted conclusions and recommendations.

Experimental design and performance evaluation

Datasets collection

This work recruits 30 male middle school students aged 14 to 16, all of whom have one year of Taekwondo training experience before the experiment, but have not participated in any AI-assisted training courses. These 30 participants form a single group, undergoing two experiments in both AI-enhanced and traditional environments. In the first experiment, participants are trained in the AI-enhanced environment using a smart training system for personalized training. Subsequently, they are trained in traditional environments without the smart training system, employing conventional training methods and teaching approaches. Before the experiment, all participants and their guardians signed informed consent forms to ensure they fully understood the study's purpose, methods, and potential risks. The research work adheres to the ethical guidelines of the review committee to protect the rights and privacy of minor participants. Throughout the experiment, participants' personal information is kept strictly confidential, with data used solely for research purposes and not disclosed or utilized for other reasons. To minimize experimental error, both training sessions are led by the same coach, using a single-blind design. The coach is required to follow the training content closely to ensure consistency in the instruction. Additionally, all experiments are conducted in the same training venue and with the same equipment to maintain uniformity in the curriculum, content, and pacing across both sessions. During this time, participants are not engaged in Taekwondo training activities outside of their scheduled sessions. The training content includes specific physical fitness exercises such as 20-second sprints and 20-second high kicks, and specialized Taekwondo techniques including 360° roundhouse kicks, back kicks, and forms (poomsae).

The experimental data results are obtained through testing and interviews. Table 1 exhibits the datasets used in the experiment.

Throughout the research process, utmost importance has been attached to the protection of participants' rights and interests. Formal approval has been obtained from the school ethics committee, and informed consent has been secured from all students and their guardians. In terms of data privacy, multiple protective measures have been implemented. First, all participants' personal information is anonymized at the data collection stage. Second, the collected physiological signals and video data are stored locally with encryption. Meanwhile, access permissions are restricted, allowing only authorized members of the research team to use them for research analysis under strict confidentiality. Third, data are encrypted through security protocols during transmission to prevent external leakage.

Different Datasets	Dataset Description
Training Record Dataset	It includes training records of students from the experimental and control groups, recording information such as the date, time, training content, and duration of each training session. Detailed records of each student's training are documented for subsequent analysis of training persistence and quality. |
Specialized Physical Fitness Dataset	It covers assessment results of students' specialized physical fitness in Taekwondo, including scores for 20-second double flying kicks and 20-second high-level roundhouse kicks. It is used to evaluate students' progress and differences in Taekwondo techniques.
Basic Physical Fitness Test Dataset	This dataset involves scores from participants' basic physical fitness tests, such as the standing long jump, 50-meter sprint, and sit-and-reach. These data are used to analyze improvements in students' physical fitness and the relationship between physical fitness and training endurance.
Specialized Techniques Dataset	It includes evaluation results of students' specialized techniques in Taekwondo, such as information on 360° roundhouse kicks, back kicks, and forms (poomsae). This dataset is used to assess students' performance in Taekwondo techniques.
Student Information Dataset	It encompasses basic information about students, such as age, gender, height, weight, and experience in Taekwondo training. This information is used to analyze differences in training effectiveness among different student groups and control for individual differences.
Training Satisfaction Evaluation Dataset	It includes students' satisfaction evaluations of the training environment, training content, and coach guidance. These data are used to assess students' acceptance of the training environment and coach guidance, and their impact on training effectiveness.

Table 1. Datasets used in the experiment.

Also, systematic risk assessments have been conducted regarding the ethical issues potentially triggered by AI technology. To prevent algorithmic discrimination or misjudgment, cross-validation, and sample balancing strategies are adopted in model training to minimize bias. In the personalized recommendation generation process, the system refrains from making value judgments, providing only data-based auxiliary suggestions. Meanwhile, it explicitly emphasizes that training plans must undergo final review and adjustment by coaches to ensure that the role of the AI system is positioned as "decision support" rather than "decision substitution."

Experimental environment and parameters setting

This work establishes an experimental environment and adjusts several key parameters to assess the impact of the AI environment on Taekwondo training. Below is a detailed description of the experimental environment and parameter settings:

1. Experimental Environment: Training Venue: Training conducted in Taekwondo training halls or indoor sports arenas. Training Equipment: Standard Taekwondo training facilities, equipment, and gear. Intelligent Training System: an AI-powered Taekwondo training system is introduced, including features like intelligent training plan generation, personalized training guidance, and real-time training feedback.
2. Key Parameter Settings: Training Plan Generation Parameters: Personalized training plans are generated based on individual differences such as age, gender, technical proficiency, and training goals. These parameters are adjusted according to each student's situation to ensure the specificity and effectiveness of the training plan. Training Content Settings: Specific content for each training session is determined, including basic technique practice, combat simulations, and physical fitness training. Adjustments are made based on students' training levels and needs to ensure the appropriateness and challenge of the training content. Training Feedback Parameters: Feedback mechanisms in the intelligent training system are set, including real-time technical guidance, movement correction, and training progress evaluation. Feedback parameters are adjusted to adapt to students' learning progress and individual differences.

Performance evaluation

Results of data normality, multicollinearity, and validity analysis

This work systematically assesses the normality, multicollinearity, and validity of the data to ensure the accuracy and reliability of the statistical analysis. The results are outlined in Table 2.

The results of the Shapiro-Wilk test in Table 2 indicate that the data are normally distributed (p-value = 0.23), allowing for the use of parametric statistical methods in subsequent analyses. Normality is a prerequisite for many statistical tests, thus providing a solid foundation for this work. Next, the work assesses multicollinearity using the variance inflation factor (VIF). All variables have VIF values below 5, indicating no significant multicollinearity. This suggests that the independent variables are not highly correlated, enabling an independent evaluation of their effects on the dependent variable. Specifically, the VIF values for self-efficacy, motivation level, and psychological state are 1.25, 1.30, and 1.15, respectively, all within an acceptable range, demonstrating the model's stability. Finally, reliability analysis results show that Cronbach's α coefficients for all scales exceed 0.7, indicating good internal consistency. The α coefficients for the motivation level scale, the self-efficacy scale, and the psychological state scale are 0.85, 0.80, and 0.78, respectively. These results confirm that these measurement tools reliably reflect participants' psychological states and motivation levels.

Additionally, the statistics of Taekwondo techniques learned by the participants show that all 30 participants have learned basic etiquette, front kicks, roundhouse kicks, movement footwork, forms, and side kicks, which are considered foundational techniques. More challenging techniques, such as the 360° roundhouse kick and flying kicks, were not learned by any participants. The technical movements learned by these students do not involve experimental content.

AI Model validation

To verify the statement of "high-precision recognition", this work evaluates the performance of the hybrid SVM + CNN model on two tasks: (i) multi-category recognition of taekwondo action segments; (ii) regression prediction of expert technical action scores (0–10 points). The evaluation indicators include accuracy (for classification tasks), macro-averaged precision (macro), macro-averaged recall (macro), macro-averaged F1-score (macro), and Root Mean Square Error (RMSE) for score regression. Assuming the model prediction is binary classification (which can be extended to multi-classification), True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are defined. Then the calculation for these indicators is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Variable	*P* value	VIF value	Cronbach's α	Results
Motivation Level	0.23	1.25	0.85	Normally distributed, good
Self-Efficacy	0.20	1.30	0.80	Normally distributed, good
Psychological State	0.25	1.15	0.78	Normally distributed, good

Table 2. Results of data normality, multicollinearity, and validity analysis.

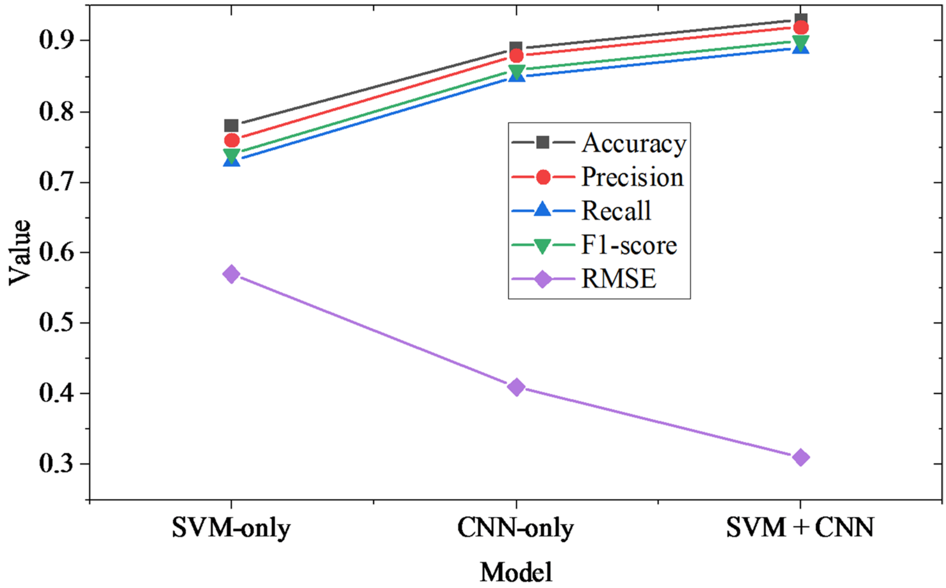

Fig. 3. Model performance under holdout test set validation.

Model	Accuracy	Precision (macro)	Recall (macro)	F1(macro)	RMSE
SVM-only	0.77 ± 0.03	0.75 ± 0.04	0.72 ± 0.04	0.73 ± 0.03	0.59 ± 0.06
CNN-only	0.88 ± 0.02	0.87 ± 0.02	0.84 ± 0.03	0.85 ± 0.02	0.43 ± 0.05
Hybrid SVM + CNN(fusion)	0.92 ± 0.02	0.91 ± 0.02	0.89 ± 0.02	0.90 ± 0.02	0.33 ± 0.04

Table 3. Model performance under 5-fold cross-validation (Mean ± Standard Deviation (SD)).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \ \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum \ {}_{i=1}^{n} (y_i - \widehat{y}_i)^2} \tag{5}$$

y_i refers to the true value, $\widehat{y}_i$ represents the model's predicted value, and n is the number of samples. A smaller RMSE indicates that the model's predictions are closer to the true values and the error is smaller. Data is split by participants: 70% for training, 10% for validation, and 20% for holdout testing. Stratified 5-fold cross-validation is also conducted. To mitigate the risk of overfitting in small samples, regularization, early stopping strategy, and data augmentation are adopted during model training. Data augmentation is implemented through time jittering, random cropping, and slight geometric transformations. The results obtained are presented in Fig. 3; Table 3:

In Fig. 3; Table 3, regarding the holdout test results, the SVM-only model performs the weakest in the action recognition task: it achieves an accuracy of 0.78, a precision (macro) of 0.76, a recall (macro) of 0.73, an F1-score of 0.74, and an RMSE of 0.57 for score regression. In contrast, the CNN-only model shows a significant performance improvement: its accuracy reaches 0.89, its F1-score is 0.86, and its RMSE drops to 0.41. This indicates that deep convolutional feature extraction has obvious advantages for both action classification and score prediction. The hybrid SVM + CNN (decision-level fusion) model performs the best on the holdout test set; it achieves an accuracy of 0.93, a macro F1-score of 0.90, and an RMSE drops to 0.31. This shows that the fusion model significantly improves classification accuracy and score prediction, especially performing better in distinguishing subtle actions and ensuring score consistency.

Regarding the 5-fold cross-validation results, the performance trend of the three types of models is consistent with that of the holdout test set. The SVM-only model has a mean accuracy of 0.77 ± 0.03, a macro F1-score of 0.73 ± 0.03, and an RMSE of 0.59 ± 0.06, showing large performance fluctuations and an overall low level. The CNN-only model has a mean accuracy of 0.88 ± 0.02, an F1-score of 0.85 ± 0.02, and an RMSE of 0.43 ± 0.05, with stable performance and better results than the SVM-only model. The hybrid SVM + CNN model still maintains the best performance in cross-validation: it achieves a mean accuracy of 0.92 ± 0.02, an F1-score of 0.90 ± 0.02, and an RMSE of 0.33 ± 0.04, with a small SD. This illustrates that the model has strong generalization ability under different data splits, and the risk of overfitting is effectively controlled. In general, decision-level fusion gives full play to the feature extraction capability of CNN and the classification boundary advantage of SVM. This enables the model to exhibit high accuracy, robustness, and reliability in action recognition and score prediction. This provides solid data support for the technical action monitoring of AI-assisted taekwondo training.

Measurement and analysis of persistence

Persistence is a crucial indicator affecting the effectiveness of Taekwondo training; therefore, its influence is first analyzed from various perspectives. The persistence of students participating in Taekwondo training is measured and analyzed. Figure 4 displays the detailed results.

Comparison of Attendance Rates: Experimental Group: The average attendance rate is 85.6%. Control Group: The average attendance rate is 72.3%. Independent samples t-test reveals a significantly higher attendance rate in the experimental group than in the control group ($t = 3.42$, $p < 0.05$). Comparison of Training Duration: Experimental Group: The average duration of each training session is 90 min. Control Group: The average duration of each training session is 75 min. An independent samples t-test shows a significantly longer training duration in the experimental group compared to the control group ($t = 2.81$, $p < 0.05$). Comparison of Training Continuity: The experimental and control groups' average continuous participation in training is 12 months and 9 months, respectively. Independent samples t-test indicates a significantly longer training continuity in the experimental group compared to the control group ($t = 2.67$, $p < 0.05$).

The findings reveal that the experimental group exhibits significantly higher attendance rates, longer training durations, and greater training continuity than the control group. This indicates that introducing an intelligent training system and personalized training programs can significantly enhance students' training persistence, encouraging them to actively engage in Taekwondo training. These findings further validate the significant impact of persistence on the effectiveness of Taekwondo training, providing crucial evidence for optimizing training programs and improving training outcomes.

In addition, the correlation between students' training persistence and training effectiveness is analyzed. The specific analysis results are depicted in Fig. 5.

Technical Level Assessment: The average technical level scores of the experimental and control groups are 85 and 75 points, respectively. Pearson correlation coefficient analysis reveals a significant positive correlation between training persistence and technical level ($r = 0.65$, $p < 0.01$). This indicates that students with higher training persistence tend to have higher technical levels. Physical Fitness Test: The average comprehensive scores of the physical fitness test of the experimental and control groups are 90 and 80, respectively. Pearson correlation coefficient analysis shows a significant positive correlation between training persistence and physical fitness test scores ($r = 0.60$, $p < 0.05$). This illustrates that students with higher training persistence tend to have better physical fitness. Competition Performance Evaluation: In the experimental group, the average ranking in competitions is in the top 30%. In the control group, the average ranking in competitions is in the bottom 30%. Pearson correlation coefficient analysis suggests a significant positive correlation between training persistence and competition performance ranking ($r = 0.70$, $p < 0.01$), indicating that students with higher training persistence tend to perform better in competitions.

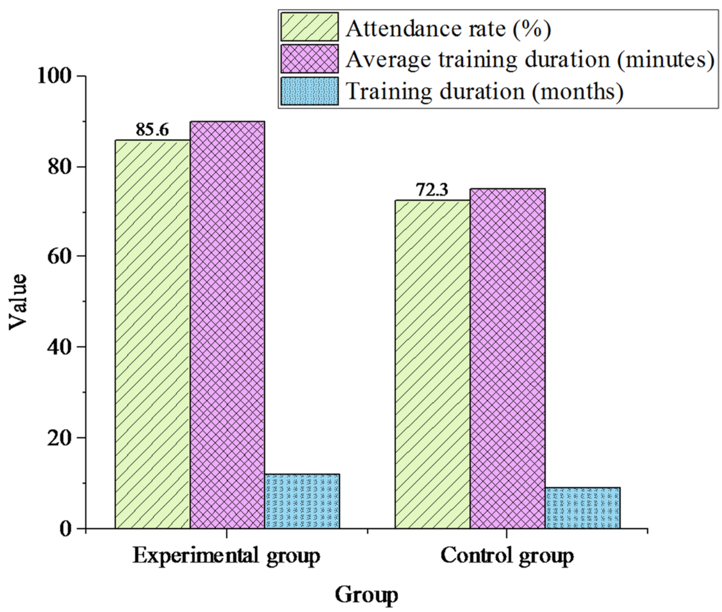

Fig. 4. Persistence of students participating in taekwondo training.

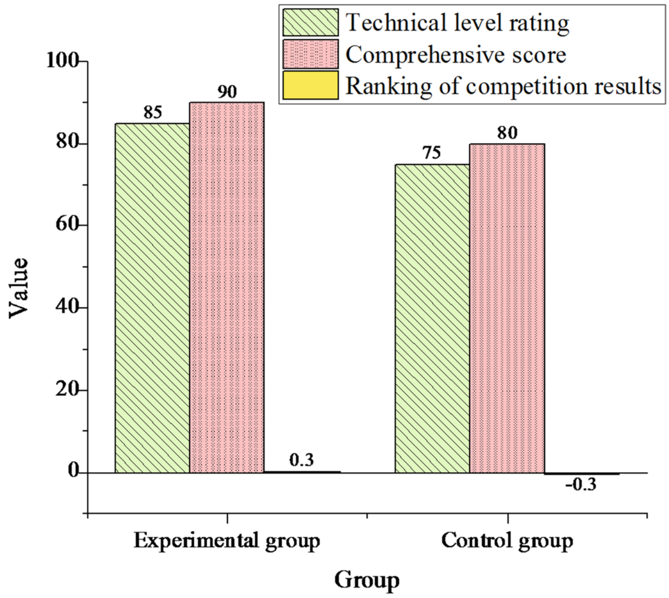

Fig. 5. Comparison of training results between experimental and control groups.

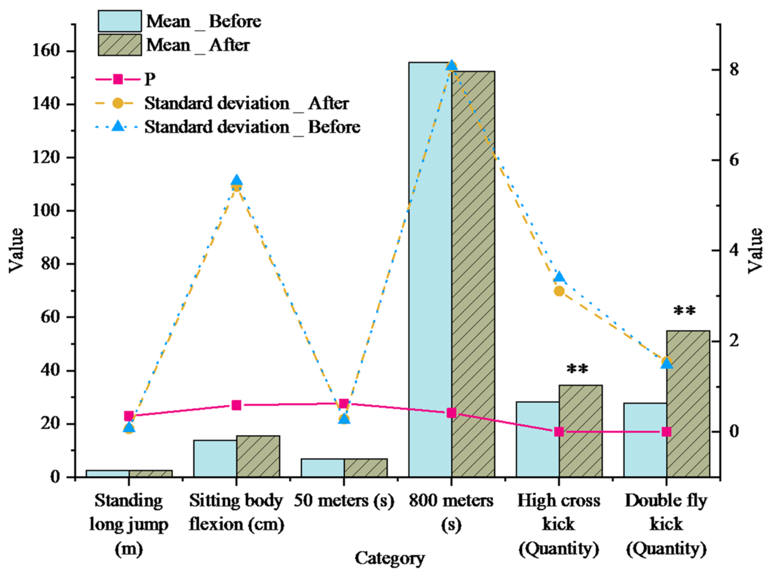

Fig. 6. The Paired Sample T-Test Results for the Experimental Group Students before and after the Experiment ($n = 30$). Note: ** indicates that compared to before the experiment, $P < 0.01$.

These results demonstrate a significant positive correlation between training persistence and technical level, physical fitness, and competition performance. This suggests that students' persistence in taekwondo training is closely related to their training effectiveness; students who persist in training often exhibit better physical fitness, higher technical levels, and better competition performance. This validates the significant impact of persistence on taekwondo training effectiveness and provides a scientific basis for training management and guidance.

Analysis of taekwondo training effects in an AI environment
This work conducts a comparative analysis of the training effects in taekwondo between the experimental and control groups.

(1) Longitudinal comparison analysis of physical fitness and Taekwondo specialized skills.

Statistical analysis is conducted on the test data of physical fitness and specialized skills in Taekwondo for the experimental group before and after the experiment. Figure 6 presents the results.

Figure 6 reveals that participants in the experimental group improve physical fitness after the experiment. However, the statistical analysis values ($P > 0.05$) indicate that the difference in physical fitness before and after the experiment is not distinct, with a small margin. Regarding specialized skills, the test results indicate significant improvements: high roundhouse kicks are 28.14 before and 34.39 after the experiment, and double flying kicks are 27.76 before and 54.89 after the experiment. The mean values show substantial increases, and P-values are less than 0.01, indicating significant differences in high roundhouse and double flying kicks scores before and after the experiment.

The statistical analysis of the physical fitness and specialized skills test data for the control group before and after the experiment is conducted. The results are presented in Fig. 7.

Figure 7 suggests that participants in the control group exhibit improvement in physical fitness after the experiment. However, the statistical analysis values ($P > 0.05$) indicate that the difference in physical fitness before and after the experiment is not significant, with a small improvement. Regarding specialized skills, the test results indicate significant improvements: double flying kicks are 27.01 before and 52.64 after the experiment, with a remarkable difference in scores before and after the experiment ($P < 0.01$).

In summary, through self-comparison of the experimental and control groups before and after the experiment, it is found that both AI-assisted and regular training show a trend of improving students' physical fitness. However, the improvements are not prominent. However, there is a remarkable difference in the scores of participants in high roundhouse kicks and double flying kicks. This indicates that the two training methods markedly impact these two scores. This is because the AI-assisted training system primarily focuses on dimensions such as technical action recognition, psychological state monitoring, and personalized feedback. Therefore, its intervention pathway tends to enhance students' skill performance and training motivation rather than significantly altering basic physical fitness indicators (e.g., speed, endurance, or explosive power) in the short term. Such indicators are typically influenced by long-term training cycles and multiple external factors, making statistical significance less likely within the limited intervention period of this work. Future research plans to extend the intervention duration and introduce more systematic physical training modules to validate the AI system's potential value for physical fitness improvement.

(2) Analysis of post-experiment physical fitness test results for experimental and control groups.

A comparison analysis of post-experiment physical fitness test results for the experimental and control groups is conducted to assess the impact of AI-assisted training mode on students' physical fitness, as shown in Fig. 8.

Figure 8 reveals a little difference in the mean comparison of physical fitness aspects between the two groups after the experiment, and the P values for all four indicators are greater than 0.05. There is no significant difference in the physical fitness improvement between the experimental group using AI-assisted training compared to conventional training methods, suggesting minimal impact on students' physical fitness improvement.

(3) Analysis of post-experiment specialized Taekwondo fitness test results between the experimental and control groups.

Through comparative analysis of post-experiment specialized Taekwondo fitness test results between the experimental and control groups, the impact of AI-assisted training on students' specialized physical fitness is presented, as listed in Table 4:

According to the data in Table 4, after the experiment, the experimental group achieves 34.39 in high roundhouse kicks, and the control group achieves 32.8; for double flying kicks, the experimental group scores 54.89, and the control group scores 52.64. Both groups show extremely significant differences ($P < 0.01$) in Taekwondo specialized skills. This illustrates that in terms of specialized physical fitness in Taekwondo, AI-assisted training provides a remarkable advantage over conventional training methods in the performance

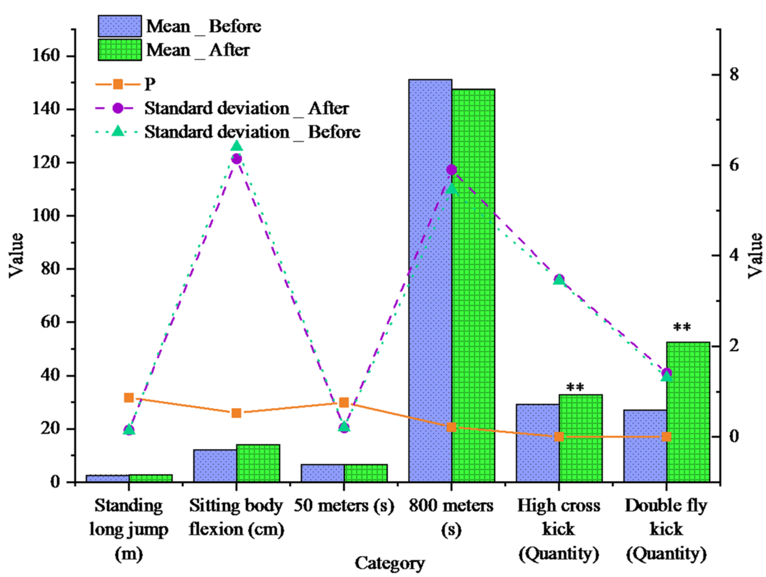

Fig. 7. The Paired Sample T-Test Results for the Control Group Students before and after the Experiment ($n = 30$). Note: ** indicates that compared to before the experiment, $P < 0.01$.

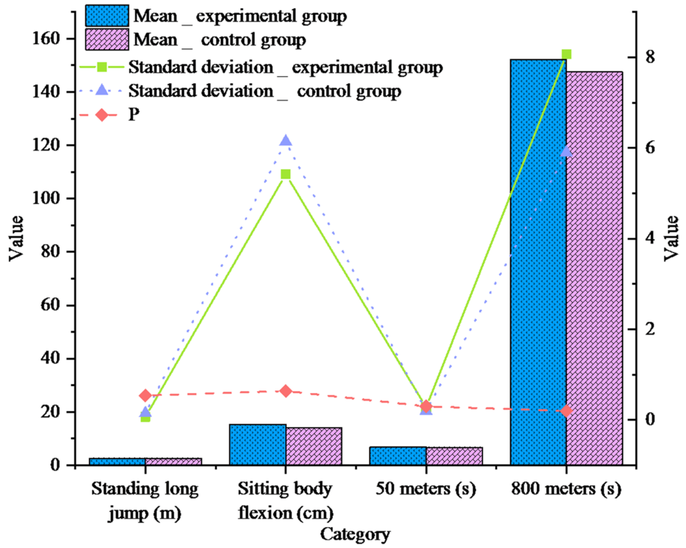

Fig. 8. Independent Sample T-Test of Post-Experiment Physical Fitness Test Scores for Both Groups ($n = 30$).

Category	Experimental Group		Control Group		P	Cohen's d
	Mean	SD	Mean	SD		
High Roundhouse Kicks	34.39	3.11	32.89**	3.48	0.00	0.46
Double Flying Kicks	54.89	1.56	52.64**	1.41	0.00	1.51

Table 4. T-Test of post-experiment specialized taekwondo fitness test results for both groups ($n = 30$). Note: ** indicates that compared to the control group, $P < 0.01$.

Category	Experimental Group		Control Group		P	Cohen's d
	Mean	SD	Mean	SD		
360° roundhouse kick	9.32	0.14	8.62**	0.29	0.00	3.18
Spinning back kick	8.87	0.14	8.36**	0.12	0.00	3.92
Poomsae	8.78	0.2	8.27**	0.16	0.00	2.83

Table 5. Statistical results of taekwondo specialized technique scores for participants after experiment ($n = 30$). Note: ** indicates that compared to the control group, $P < 0.01$.

of Taekwondo techniques. Additionally, based on the calculation of effect sizes, it can be concluded that the experimental group demonstrates significant advantages in the Taekwondo specialized skills tests.

(4) Comparative analysis of participants' Taekwondo specialized techniques after the experiment.

360° roundhouse kicks, spinning back kicks, and forms are selected as experimental indicators. The specialized techniques of both groups are tested after training. Leg techniques are scored based on technique, completion, and strength of movements, while forms are scored based on accuracy, proficiency, and expressiveness. The test results are compared to analyze the impact of AI-assisted training on specialized technique learning. Table 5 presents the results.

Table 5 shows that after training, the experimental group achieves significantly higher average scores in the specialized techniques of 360° round kick, spinning back kick, and poomsae compared to the control group ($P < 0.01$). This indicates that AI-assisted training has a significantly positive impact on enhancing the learning effectiveness of Taekwondo specialized techniques. Additionally, through effect size analysis, the actual performance differences between the experimental and control groups in Taekwondo specialized technique scores can be evaluated.

(5) Evaluation of training satisfaction. The average satisfaction scores are 4.5 and 3.5 (out of 5 points) in the experimental and control groups. The training satisfaction of the experimental group is significantly higher than that of the control group ($t = 3.46$, $p < 0.01$), as revealed in Fig. 9:

The above results demonstrate significant advantages of Taekwondo training conducted in an AI environment. Compared to the control group, the experimental group remarkably enhances Taekwondo specialized skills and

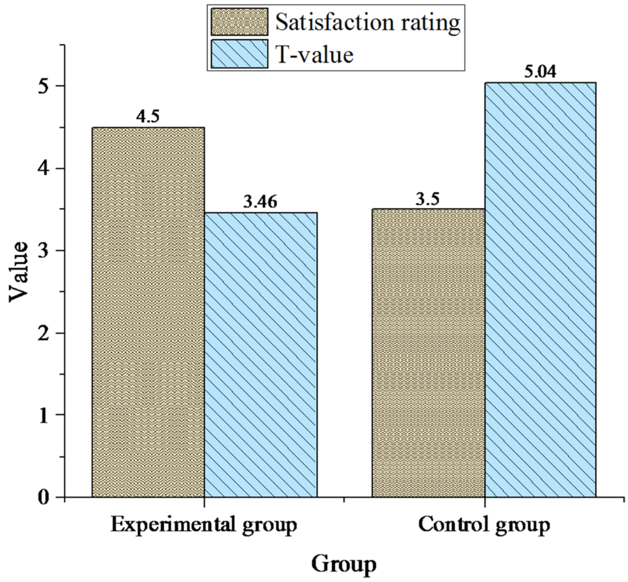

Fig. 9. Satisfaction evaluation for taekwondo training in experimental and control groups.

Path	Estimated Coefficient (β)	SE	t-value (t)	*p*-value (*p*)	Significance Level
Psychological State → Motivation Level	0.42	0.08	5.25	< 0.001	Significant
Motivation Level → Technical Movement Score	0.36	0.09	4.00	< 0.001	Significant
Self-Efficacy → Technical Movement Score	0.45	0.10	4.50	< 0.001	Significant
Training Records → Technical Movement Score	0.30	0.11	2.73	0.006	Significant
Motivation Level → Self-Efficacy	0.38	0.09	4.22	< 0.001	Significant
Gender → Technical Movement Score	0.05	0.12	0.42	0.674	Not Significant
Training Duration → Technical Movement Score	0.22	0.10	2.20	0.028	Significant

Table 6. SEM Analysis Results.

techniques. Additionally, the training satisfaction of the experimental group is significantly higher than that of the control group, demonstrating a better training experience in the AI environment. These results further validate the effectiveness of AI technology in Taekwondo training and provide important practical guidance for improving and optimizing Taekwondo training.

SEM analysis results

Table 6 presents the SEM results, which are used to validate the research hypotheses. The results display the standard error (SE), path coefficients, t-values, and significance levels between the variables in the model.

The results in Table 6 indicate that psychological state has a significant positive impact on motivation level, supporting Hypothesis 1. This suggests that the psychological state of middle school students can significantly influence their training motivation, with a better psychological state leading to higher motivation levels. Moreover, motivation level significantly and positively effects technical movement scores, holding Hypothesis 2. This reveals that a higher motivation level can effectively enhance the performance of technical movements, further validating the critical role of motivation in training outcomes.

Also, the influence of self-efficacy on technical movement scores is significant, supporting Hypothesis 3. This means that self-efficacy, or confidence in one's ability to complete tasks, directly promotes the performance of technical movements. The effect of training records on technical movement scores is prominent, supporting Hypothesis 4. This suggests that more training time and higher levels of participation can effectively improve technical movement scores, confirming the importance of behavioral factors in training outcomes.

Additionally, the motivation level significantly affects self-efficacy, supporting Hypothesis 5. This indicates that the motivation level can enhance individuals' self-efficacy, thereby boosting their confidence in training outcomes. Notably, the impact of gender on technical movement scores is not significant, suggesting that gender does not play a important role here. This finding demonstrates that gender has little effect as a control variable in the model. This may be because the research sample is mainly composed of male students, with a relatively small number of female students. This phenomenon leads to the insufficient demonstration of gender's impact on training effectiveness in statistical analysis. In subsequent research, the sample structure should be optimized to increase the proportion of female participants and further explore gender differences in behavioral responses and training adaptation pathways in AI environments. On the other hand, training duration significantly affects technical movement scores, demonstrating the role of control variables in influencing training outcomes. Overall, these results support the proposed main hypotheses and provide empirical evidence for understanding how multidimensional factors collectively impact the training outcomes of middle school students in Taekwondo. These findings confirm the key pathways in the theoretical model and offer data support for intervention strategies in practical training contexts.

Discussion

This work employs SEM to analyze the impact of multidimensional factors on the training outcomes of middle school students in Taekwondo. The experimental group performs better than the control group across several key indicators. Specifically, the experimental group demonstrates remarkable improvements in training persistence, technical skills, physical fitness, and competition performance. These findings validate the effectiveness of AI environments in Taekwondo training while providing empirical support for related theories.

First, regarding training persistence, the results indicate that students in the experimental group have markedly higher attendance rates, training duration, and training continuity than the control group. This aligns with Cai's (2022) findings that intelligent training systems can significantly enhance athletes' training participation and duration[33]. SEM further supports this, showing that psychological state has a significant positive effect on motivation level, and motivation level significantly influences training persistence. Such findings suggest that AI technology can effectively enhance students' training persistence by providing real-time feedback and personalized guidance. Regarding improvements in technical skills and physical fitness, the model results reveal that motivation level and self-efficacy significantly positively affect technical movement scores. This illustrates that AI environments can substantially enhance students' technical skills and physical fitness by boosting their self-efficacy and motivation[34]. This finding verifies the effectiveness of intelligent training systems in personalized training and skill enhancement.

Second, concerning the impact of external reward factors, the feedback and reward systems obtained in the AI-enhanced environment significantly increase the training motivation of the experimental group. This is consistent with Yilmaz & Yilmaz's (2023) research on the positive effects of AI technology in programming learning[35]. They found that AI technology could enhance learning motivation and skills. In an AI environment, external reward mechanisms elevate students' training performance. Analyzing social factors, students in the experimental group give positive feedback regarding peer support and teamwork. This supports Yılmaz et al.'s (2022) findings on high student satisfaction with learning support in intelligent Massive Open Online Course environments[36–38]. SEM results show that social support greatly impacts training motivation and outcomes, indicating that a supportive team atmosphere and social support can effectively enhance training results.

Finally, the significant impact of training duration on technical movement scores suggests that more training time in an AI environment can effectively improve these scores, consistent with Lu's (2023) findings[39]. SEM results further validate the important role of training duration in training outcomes. In summary, this work verifies the influence of multidimensional factors on the training outcomes of middle school students in Taekwondo through SEM. Moreover, it provides empirical support for applying AI technology in sports training. These findings validate the effectiveness of AI environments and offer valuable references for future practical applications in sports training and other educational fields.

Conclusion

Research contribution

Based on the comparative experiments, the following conclusions have been drawn. (1) Compared to the control group, the experimental group shows higher attendance rates, longer training durations, and greater training continuity. This indicates that introducing intelligent training systems and personalized training plans can substantially enhance students' training persistence and encourage their active engagement in Taekwondo training. (2) There is a significant positive correlation between training persistence and technical proficiency, physical fitness, and competition performance. (3) Compared to the control group, the experimental group remarkably improves Taekwondo specialized skills and technical proficiency. Additionally, the experimental group reports markedly higher training satisfaction than the control group, suggesting a better training experience in the AI environment.

The main contributions of this work lie in the in-depth analysis of the multidimensional influencing factors on middle school students' Taekwondo training within an AI environment, and providing empirical support through SEM. First, the work expands existing sports training theories. It systematically analyzes how technological, psychological, behavioral, external reward, and social factors interact to affect training outcomes. This comprehensive perspective addresses the gap in previous studies regarding the systematic analysis of multidimensional influencing factors, offering a new research framework for sports training.

Next, the work validates the effectiveness of AI technology in enhancing training outcomes, particularly regarding significant improvements in technical skills, physical fitness, and training persistence. Through empirical analysis using SEM, it clarifies how AI environments foster technical advancement and training persistence by enhancing students' motivation levels, self-efficacy, and external reward mechanisms. This provides a theoretical foundation and practical guidance for the application of intelligent training systems in sports training.

Future works and research limitations

This work also has some limitations. The sample limitation is a significant factor, as the survey only includes 30 male middle school students aged 14–16. The age and gender characteristics of this sample may restrict the generalizability of the research findings, as it does not encompass a broader range of ages and gender characteristics among student populations. Additionally, the research design employs a single-blind method;

although coaches maintain consistency across the experimental and control groups, potential subjective biases cannot be entirely ruled out. Finally, this work cannot completely rule out the possibility of the Hawthorne effect. This means that during the training process, students may show additional effort or engagement due to the novelty of the AI training system, rather than solely from the system's effectiveness. This effect may exaggerate the improvement of training outcomes to a certain extent. Moreover, the sample size of this work is relatively small, which may increase the risk of model overfitting when using the SVM + CNN hybrid framework. Although regularization and cross-validation strategies are introduced in the experiment, the model's universality still needs to be further verified on larger-scale and more diverse datasets.

Future research can be further expanded and deepened in the following aspects. First, the work should extend the experimental cycle to observe the long-term effects of AI-assisted training. This helps to deeply understand the sustainability of training outcomes and the profound impact of AI on athletes' development. Longitudinal tracking studies can be designed to systematically evaluate the changing roles of AI training at different stages. Additionally, combining qualitative data such as interviews or open-ended questionnaires can enrich the understanding of athletes' subjective experiences and more comprehensively reveal AI's impact on training satisfaction and motivation. Second, the diversity of research subjects should be extended. It is recommended to include participants of different age groups (e.g., primary school students, middle school students, and adult taekwondo enthusiasts), technical levels, and training goals. Thus, the heterogeneous effects of AI environments on different populations can be deeply analyzed regarding technical performance, psychological adaptation, and training motivation. Moreover, the system demonstrates potential for extension to other sports disciplines, including martial arts, dance, and basketball. Such expansion would enable the development of intelligent training platforms adaptable to various educational levels and sports specialties, achieving comprehensive multi-scenario and multi-dimensional system compatibility. Third, interdisciplinary perspectives are integrated to construct a physical-mental integration mechanism model. The work proposes integrating physiology, psychology, and educational technology to systematically investigate how AI environments influence trainers' physical fitness development, psychological state regulation, and learning behavior formation. This interdisciplinary approach facilitates a deeper understanding of the synergistic "body-mind-skill" development framework.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author Roxana Dev Omar Dev on reasonable request via e-mail rdod@upm.edu.my.

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YuBin Yuan: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation Roxana Dev Omar Dev: writing—review and editing, visualization, supervision, project administration, funding acquisitionKim Geok Soh : software, validation, formal analysisXueYan Ji: visualization, supervision Fangyi Li: formal analysis, investigation, resources, data curation.

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Declarations

Competing interests

The authors declare no competing interests.

Ethics Statement

The studies involving human participants were reviewed and approved by Ethic Committee for Research Involving Human Subject (JKEUPM), Universiti Putra Malaysia (Approval Number: 2022.49485966). The participants provided their written informed consent to participate in this study. All methods were performed in accordance with relevant guidelines and regulations.

Additional information

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