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Integrating affective computing and deep learning for learning path optimization in vocational education

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Abstract

This study addresses the challenges of traditional vocational education systems, which often fail to meet learners' diverse needs in dynamic and emotionally complex environments. To bridge this gap, we propose an intelligent learning system that integrates multimodal affective computing with deep Q-network algorithms for personalized learning path optimization. By leveraging multimodal data fusion, the system enhances the accuracy of emotion recognition and dynamically adjusts learning paths in real time. Experimental results show a 27% improvement in learning efficiency, an 86% accuracy rate in personalized recommendations, and an 8% increase in student performance compared to conventional methods. Furthermore, a privacy-preserving architecture utilizing federated learning ensures secure large-scale applications. This study highlights the transformative potential of integrating affective computing and reinforcement learning in vocational education and sets the stage for broader applications in personalized learning systems.

Keywords: deep Q-network, multimodal data fusion, emotion recognition, personalized learning, vocational education

INTRODUCTION

Vocational education is increasingly critical in preparing individuals for the evolving demands of the workforce in a globally digitalized era. However, traditional "one-size-fits-all" teaching models often fail to accommodate the diverse and dynamic needs of learners, particularly in complex skill training scenarios where personalization and adaptability are essential. These limitations have resulted in reduced learning engagement, inefficiencies, and challenges in addressing individual differences. Recent studies emphasize the need for intelligent learning systems capable of adapting to learners' emotional and behavioral states in real time (Leong, 2025).

Affective computing and multimodal data fusion technologies have emerged as promising solutions to these challenges. Affective computing enables systems to recognize and respond to learners' emotional states, enhancing engagement and motivation (Rahate et al., 2022). Multimodal data fusion integrates diverse data sources–such as facial expressions, speech, and text–to provide a holistic understanding of learners' emotional and behavioral states, significantly improving decision-making accuracy in adaptive learning environments (Zhang & Leong, 2024a). However, existing systems are limited by static learning paths and lack robust mechanisms to dynamically optimize learning processes based on real-time emotional feedback.

To address these gaps, this study proposes an innovative personalized learning path optimization system that integrates multimodal affective computing with a deep Q-network (DQN) algorithm. The proposed system dynamically adjusts learning paths in real time, improving learning efficiency, engagement, and outcomes.

Furthermore, a privacy-preserving architecture based on federated learning (FL) ensures secure handling of sensitive learner data, facilitating large-scale system deployment.

The main contributions of this study are as follows: A novel integration of affective computing and

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Contribution to the literature

- This study pioneers the integration of multimodal affective computing with deep reinforcementlearning (specifically Deep Q-Networks) to achieve real-time, emotion-driven learning path optimization.
- The article introduces a novel cross-modal attention mechanism within its multimodal datafusion framework.
- The research establishes a scalable and privacy-preserving system architecture by incorporatingfederated learning and differential privacy

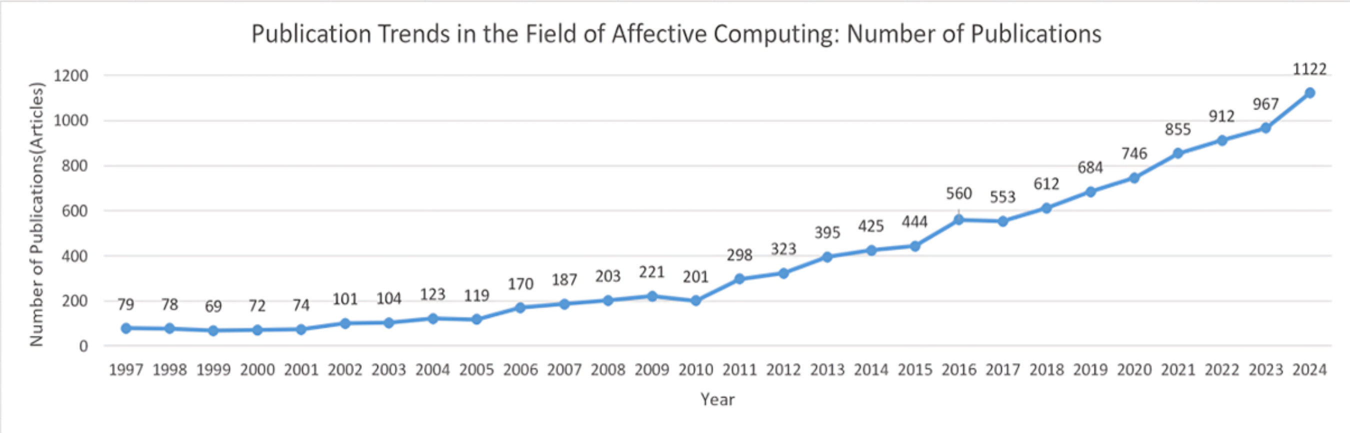

Figure 1. The number of publications in the field of affective computing from 1997 to 2024 (based on the Science Direct core database) (Source: Authors' own elaboration)

reinforcement learning (RL) to achieve real-time, emotion-driven learning path optimization. An advanced multimodal data fusion framework using cross-modal attention mechanisms for accurate emotion recognition. A privacy-preserving learning architecture combining FL and differential privacy to ensure secure and scalable system applications.

The remainder of this paper is structured as follows: We first review related work, identifying strengths and limitations of existing approaches. We then presents the system architecture and methodology. Next, we describe the experimental setup and results. We then discuss the findings. Finally, we conclude with insights and future research directions.

The primary objective of this research is to design and validate an intelligent learning system for vocational education that dynamically optimizes personalized learning paths by integrating multimodal affective computing (for real-time emotion recognition) and deep reinforcement learning (DRL) (for adaptive path planning).

Specifically, the system aims to: improve learning efficiency by reducing unnecessary repetition and adjusting task difficulty based on emotional feedback; enhance the accuracy of personalized recommendations through multimodal data fusion and DQN-based optimization; Increase student satisfaction by providing emotionally responsive learning experiences.

LITERATURE REVIEW

Advances in Affective Computing

Affective computing, an interdisciplinary field bridging artificial intelligence (AI), cognitive science, and psychology, seeks to enable machines to perceive, interpret, and adapt to human emotions. Since its inception by Picard (1997), affective computing has evolved into a critical research domain, advancing technologies for emotion recognition, modeling, and interaction. This evolution is evidenced by the exponential increase in publications over the past decades, as shown in **Figure 1**, reflecting the growing interest in integrating emotional intelligence across academia and industry.

Early efforts in affective computing focused primarily on single-modal emotion recognition, relying on data from facial expressions or speech. Foundational works, such as Ekman and Friesen's (1971) facial emotion theory and Tian et al.'s (2001) facial action unit recognition methods, provided the groundwork for analyzing human emotions through visual cues (Picard, 2000). However, these approaches often suffered from limited contextual understanding and lacked robustness in noisy environments. With the advent of deep learning, the field has undergone transformative advancements. Convolutional neural networks (CNNs) (Leong, 2025b) and long short-term memory (LSTM) networks (Xu et al., 2020) have been widely adopted for processing complex visual and sequential patterns.

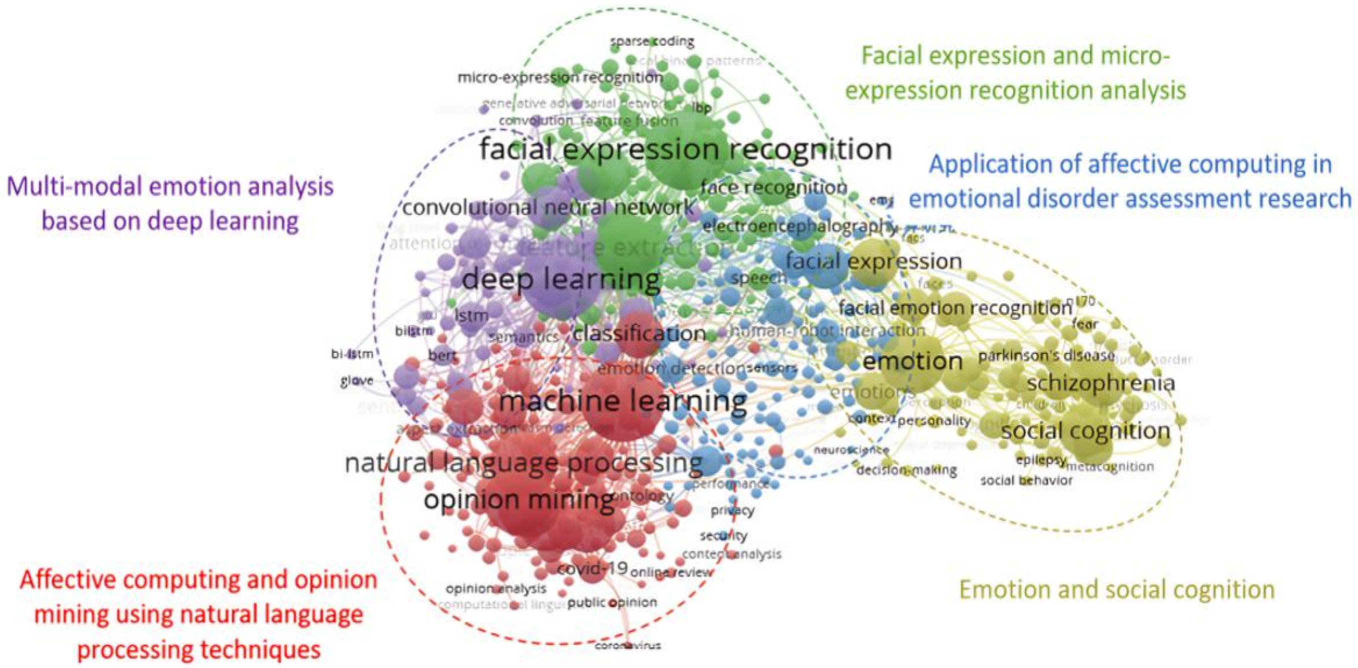

Figure 2. Five research themes in the field of affective computing (Source: Authors' own elaboration)

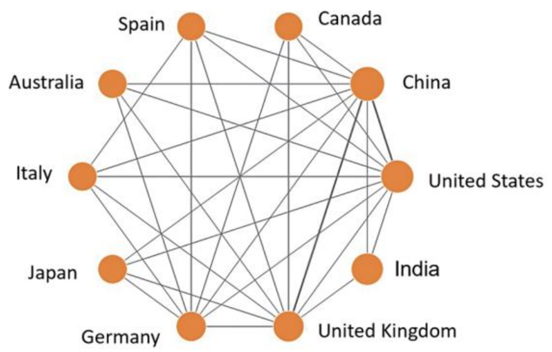

Figure 3. Collaboration status of the top 10 countries by publication volume in the field of affective computing (Source: Authors' own elaboration)

More recently, transformer-based architectures, such as those proposed by Guo et al. (2021), have demonstrated state-of-the-art performance by integrating multimodal data like facial expressions, speech, and text. Datasets such as Aff-Wild2, SEWA, and HUME have further supported large-scale training, enhancing the generalizability of emotion recognition systems to real-world applications.

Despite these advances, several challenges remain. Multimodal frameworks often struggle with the temporal and semantic alignment of heterogeneous data sources, such as audio, visual, and text modalities. Asynchronous emotional cues from different modalities frequently lead to inconsistent interpretations, as highlighted in **Figure 2**.

Moreover, the computational complexity of current models poses challenges for real-time deployment, especially in dynamic settings like adaptive learning systems. While curated datasets have facilitated model training, many systems fail to generalize complex real-world scenarios influenced by cultural and situational factors (Yang et al., 2020). Privacy concerns also hinder the widespread adoption of affective computing, as these systems often require sensitive personal data such as facial expressions and speech, raising significant ethical issues (Li et al., 2022). **Figure 3** illustrates the global collaboration status in this field, underscoring the collective effort to address these challenges.

To tackle these limitations, this study proposes a novel multimodal affective computing framework that integrates dynamic cross-modal attention mechanisms to prioritize contextually relevant emotional cues. By leveraging lightweight Transformer architectures, the framework balances computational efficiency with performance, enabling real-time deployment in adaptive learning environments. Additionally, external contextual information, such as task difficulty and learner engagement, is incorporated to enhance the robustness of emotion recognition in complex scenarios (Shoumy et al., 2020). To address privacy concerns, FL and differential privacy techniques are integrated, ensuring secure and ethical handling of sensitive data.

Research on Personalized Learning Path Optimization

Personalized learning path optimization has emerged as a pivotal area in education technology, addressing individual differences in learning styles, pace, and preferences. **Figure 4** illustrates the field's rapid development, largely driven by AI technologies, particularly RL, which supports dynamic adaptation to learners' needs. These systems aim to enhance learning outcomes by tailoring content delivery and instructional strategies to individual learners (Yu et al., 2021).

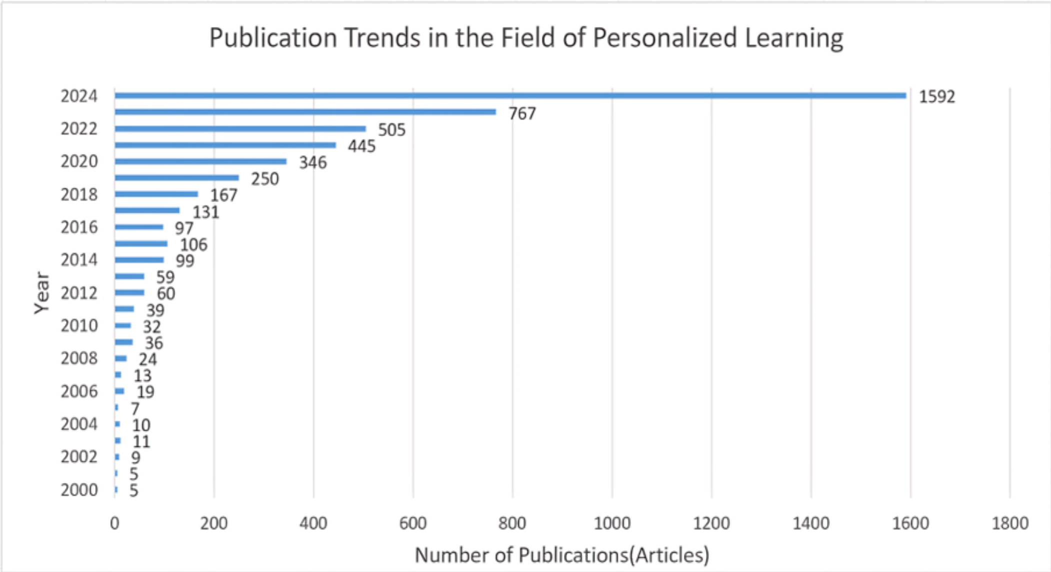

Figure 4. The number of publications in the field of personalized learning from 2000 to 2024 (based on the Science Direct core database) (Source: Authors' own elaboration)

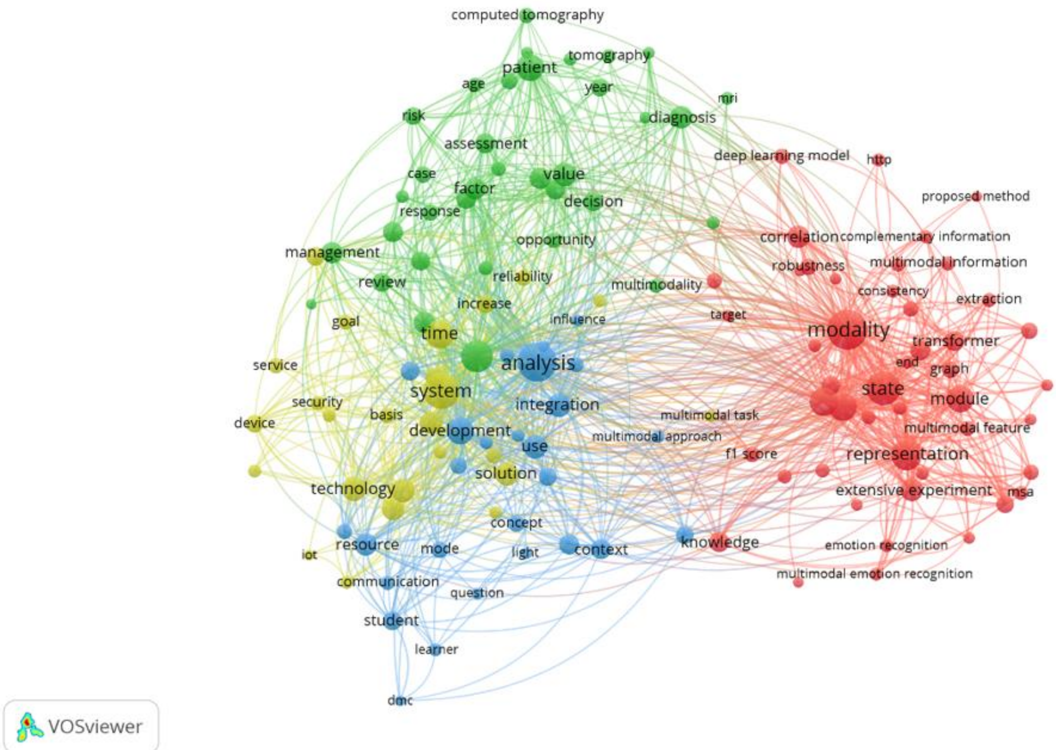

Figure 5. Keyword trend analysis of personalized learning based on the Science Direct core database (Source: Authors' own elaboration)

Early systems for personalized learning were rule-based, relying on static decision trees to recommend learning paths. While effective to some extent, these models lacked adaptability to real-time changes in learners' performance and engagement. Approaches such as Bayesian networks and item response theory (IRT) focused primarily on historical data analysis, failing to incorporate contextual and emotional factors (Zhao et al., 2024). This limitation restricted their ability to deliver fully individualized learning experiences.

With the advent of machine learning and DRL, the domain has seen significant advancements. DRL algorithms like DQN and proximal policy optimization enable continuous adjustment of instructional strategies based on real-time feedback. As shown in **Figure 5**, these systems dynamically select optimal content and activities, balancing short-term performance improvements with long-term learning goals (Mocanu et al., 2023).

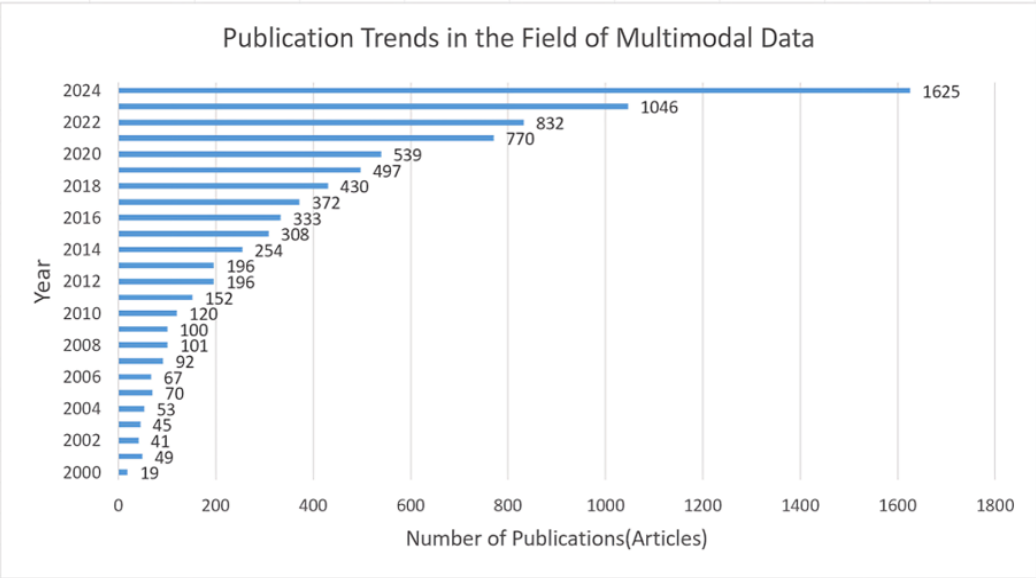

Figure 6. The number of publications in the field of multimodal data from 2000 to 2024 (based on the Science Direct core database) (Source: Authors' own elaboration)

Despite these achievements, challenges remain. Current systems struggle with integrating multimodal data, such as emotional states, cognitive load, and engagement levels, due to the complexity of aligning heterogeneous data streams. Additionally, many rely on pre-trained models, limiting their generalizability to diverse learner populations. Ethical concerns surrounding data privacy and fairness also persist, given the extensive data collection required for personalization (Zhu et al., 2021).

To address these issues, this study proposes a novel personalized learning framework that integrates multimodal data fusion and DRL. The framework uses cross-modal attention mechanisms to dynamically align diverse data sources, enabling a comprehensive understanding of learners' needs. FL enhances data privacy while maintaining robust model performance across distributed datasets. Furthermore, real-time adaptive algorithms optimize content sequencing and activity selection, ensuring both immediate and long-term learning benefits (Zhou et al., 2024).

By incorporating emotional and contextual data into decision-making processes, this framework overcomes the limitations of existing systems. It offers a scalable, ethical, and effective solution for personalized learning across diverse educational contexts.

Integration of Multimodal Data Fusion and Deep Q-Networks

Building on advancements in multimodal affective computing and personalized learning path optimization discussed in previous sections, the integration of multimodal data fusion and DQN represents a transformative approach to adaptive learning systems. **Figure 6** illustrates the conceptual architecture of combining multimodal data streams with RL algorithms, highlighting their potential to dynamically tailor educational experiences based on learners' emotional and cognitive states.

Multimodal data fusion enables the integration of diverse data sources, such as facial expressions, voice intonations, text inputs, and physiological signals, to provide a holistic understanding of learners. This approach addresses the limitations of single-modal systems by leveraging complementary information across modalities, improving the accuracy of emotional state detection and contextual analysis (Zhang & Leong, 2024c). Existing methods, however, often struggle with aligning heterogeneous data streams in real-time, leading to synchronization issues and reduced model performance. **Figure 7** depicts a typical multimodal alignment process, showcasing the challenges of temporal and semantic fusion in dynamic learning environments.

DQN, a prominent algorithm in DRL, offers a robust framework for sequential decision-making in complex environments (Li, 2023). By mapping states to actions with a value-based approach, DQN dynamically adjusts learning paths, content sequencing, and activity selection based on learners' real-time feedback. Recent advancements in DQN, such as prioritized experience replay and double DQN, have further enhanced its stability and efficiency, making it well-suited for educational applications (Marín-Morales et al., 2020).

Despite these innovations, integrating multimodal data fusion with DQN poses several challenges. First, the high dimensionality and asynchronous nature of multimodal data require sophisticated alignment mechanisms, such as cross-modal attention networks, to ensure coherent fusion. Second, the computational demands of DQN, combined with the real-time processing needs of multimodal data, can lead to latency

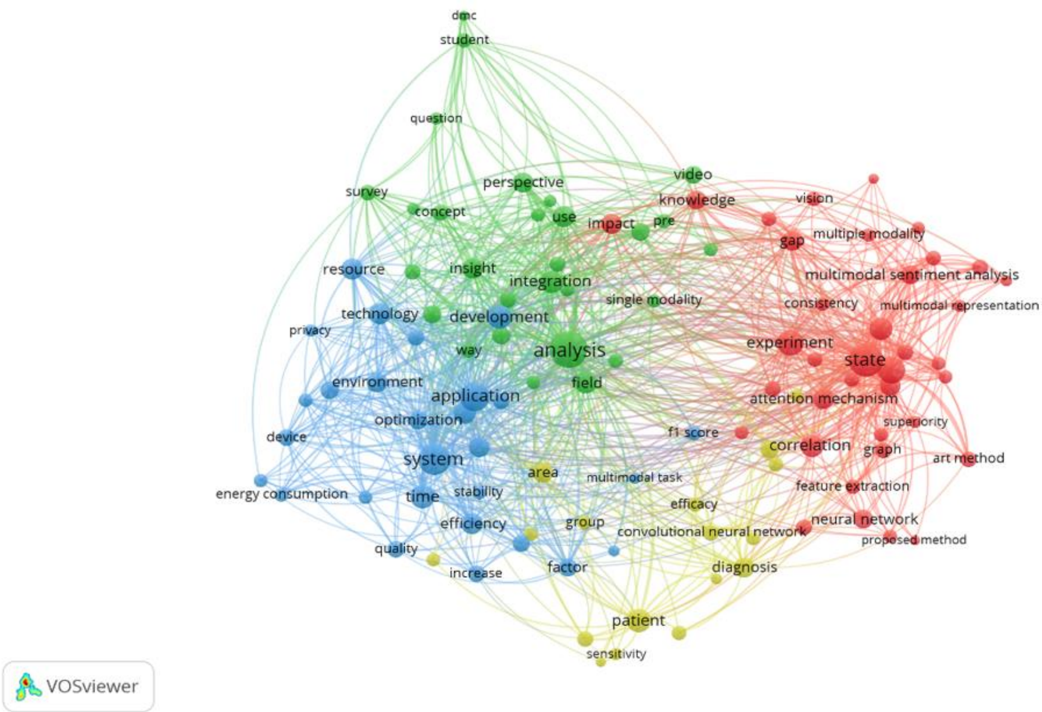

Figure 7. Keyword trend analysis of multimodal data based on the Science Direct core database (Source: Authors' own elaboration)

issues in adaptive learning systems. Third, privacy concerns remain a significant barrier, as multimodal data often includes sensitive information, necessitating robust security protocols.

To address these challenges, this study introduces an integrated framework that combines multimodal data fusion with an enhanced DQN algorithm. The framework employs cross-modal attention mechanisms to dynamically align and integrate diverse data streams, enabling a comprehensive understanding of learners' states. FL and differential privacy techniques are incorporated to protect sensitive data while maintaining model performance. Additionally, lightweight DQN variants are implemented to reduce computational overhead, ensuring real-time responsiveness in adaptive learning environments (Zhang & Leong, 2024e).

This integrated approach not only bridges the gaps in multimodal alignment and decision-making but also establishes a scalable and secure foundation for intelligent learning systems. By leveraging the synergies between multimodal data fusion and RL, the framework provides a novel pathway for enhancing personalization and engagement in vocational education and beyond.

Federated Learning and Data Privacy Protection

Data privacy is a critical concern in personalized learning systems, making FL a promising solution for privacy-preserving data processing. FL enables decentralized collaboration, allowing multiple platforms to train models jointly without sharing raw data, thereby safeguarding sensitive information. Järvelä et al. (2020) highlighted FL's effectiveness in handling non-independent and identically distributed data, demonstrating its adaptability to diverse learning environments.

Federated learning (FL) has emerged as a promising paradigm for privacy-preserving machine learning in distributed environments (Mammen, 2021). It enables multiple participants to collaboratively train a model without sharing raw data, thus addressing critical privacy concerns in educational data processing (Nguyen et al., 2021). Recent comprehensive reviews have systematically documented the fundamentals, enabling technologies, and future applications of FL across various domains (Banabilah et al., 2022).

Recent advancements, such as Zhou et al.'s (2024) personalized FL algorithm leveraging model contrastive learning, have improved the accuracy of multimodal user modeling while maintaining robust privacy protection. By integrating FL with multimodal data fusion, personalized learning systems can achieve enhanced learning path optimization tailored to individual needs.

However, FL faces challenges such as the high dimensionality of multimodal data, communication overhead, and scalability in heterogeneous learning settings. These issues complicate model aggregation and hinder real-time applications. Future research should focus on lightweight FL architecture and integrating advanced RL algorithms to address these challenges, ensuring both privacy and system efficiency (Zhang & Leong, 2025a).

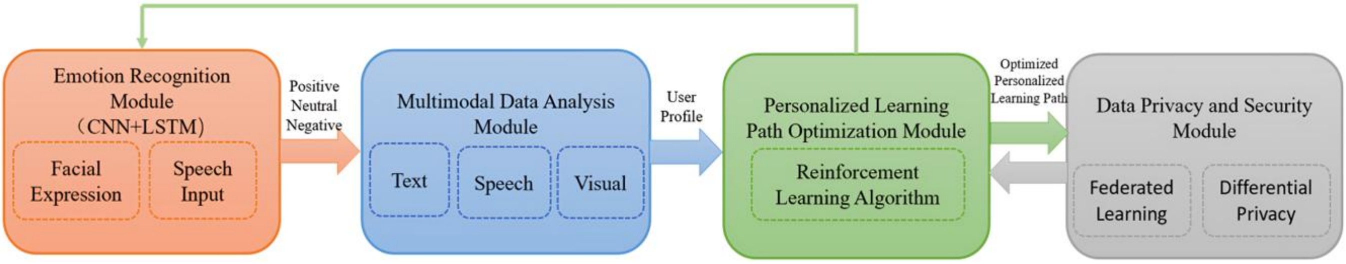

Figure 8. Intelligent learning ecosystem architecture (Source: Authors' own elaboration)

This integration establishes a foundation for scalable, privacy-compliant personalized learning systems, advancing the application of FL in education.

METHODOLOGY

This study aims to design an innovative learning ecosystem that integrates affective computing, multimodal data analysis, and intelligent learning systems to optimize personalized learning paths in vocational education. The system adjusts learning paths in real time through emotion recognition, multimodal data fusion, and RL techniques to enhance learning efficiency and experience. To ensure the system's efficiency and innovation, we introduced various algorithms, formulas, and models, which were validated through experimental data.

System Architecture

The overall architecture of the system is shown in **Figure 8**, comprising four core modules: the emotion recognition module, multimodal data analysis module, personalized learning path optimization module, and privacy protection module. The system collects real-time data from learners, such as facial expressions, speech, and text input, and dynamically adjusts the learning content using the affective computing model.

1. **Emotion recognition module:** Emotion recognition is achieved using a combination of CNNs and LSTM networks.
2. **Multimodal data analysis module:** The cross-modal attention mechanism from the transformer model is applied to integrate different modalities of data, generating a comprehensive profile of the learner.
3. **Personalized learning path optimization module:** The DQN algorithm from RL is used to dynamically adjust learning paths.
4. **Privacy protection module:** Data privacy protection is implemented through FL and differential privacy techniques.

Affective Computing Model

The affective computing model serves as a core framework for capturing, analyzing, and dynamically responding to learners' emotional states in real-time. By integrating behavioral expressions, physiological signals, and contextual information, the model enables accurate emotion recognition and adaptive feedback, providing technical support for personalized learning in educational scenarios (Zhang & Leong, 2025b).

Behavioral data include body movements, facial expressions, speech signals, and eye movements, while physiological signals encompass heart rate, brain activity, and more. These data are represented through various features, such as texture features for facial expressions, spectral features for speech signals, and frequency-domain features for physiological signals. This multidimensional data collection establishes a solid foundation for comprehensively analyzing learners' emotional states (Wu et al., 2021).

After data collection, as shown in **Figure 9**, the data undergo preprocessing and feature extraction. CNNs are employed to extract local features from facial expressions, such as eyebrow movements and lip curvature.

The convolution operation is mathematically expressed as follows:

$$y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} w_{m,n,k} \cdot x_{i+m,j+n,k} + b_k, \tag{1}$$

where $y_{i,j,k}$ represents the convolution output, $w_{m,n,k}$ denotes the convolution kernel weights, $x_{i,j,k}$ refers to the input feature map, and b_k is the bias term.

Eq. (1) describes how the convolution kernel slides across specific regions, performing weighted summation to extract local features. It enables the detection of fine-grained emotional details in facial expressions, such as subtle movements in the eyes and lips. Simultaneously, LSTM networks process speech data to capture temporal patterns, such as tone and pauses, which reflect emotional fluctuations. Text data are encoded using transformer-based models such as BERT to extract high-level semantic features.

The extracted features are subsequently input into a multimodal data fusion module, where a cross-modal attention mechanism is applied to integrate emotional features. The cross-modal attention mechanism dynamically assigns weights to different modalities based on their relevance to the current emotional state. For instance, when speech signals exhibit strong emotional cues, the system prioritizes the speech modality, while weaker signals shift the focus to visual

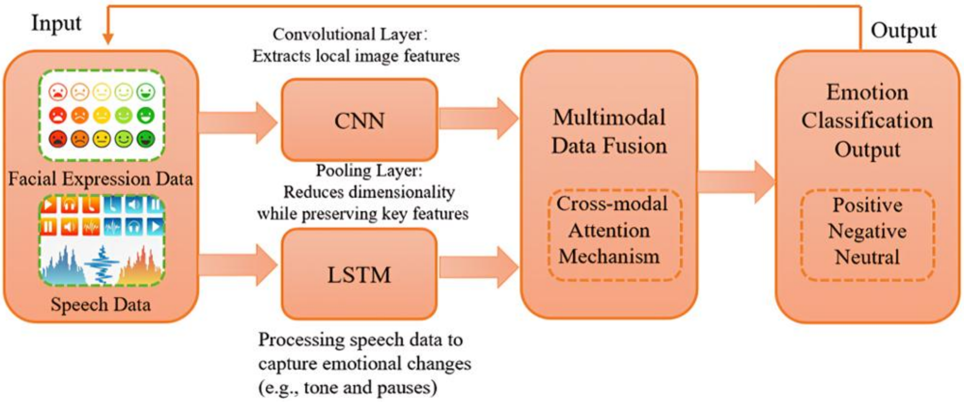

Figure 9. Diagram of the affective computing model (Source: Authors' own elaboration)

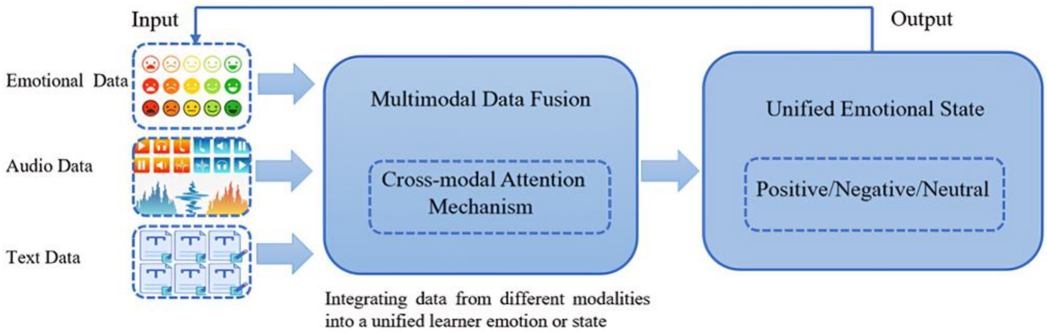

Figure 10. Multimodal data fusion framework (Source: Authors' own elaboration)

or physiological data. The fused emotional feature vector is then classified into emotional states such as "positive," "neutral," or "negative," enabling real-time learning interventions (Fan et al., 2020).

Multimodal Data Fusion

Multimodal data fusion is the cornerstone of the affective computing model, enabling the integration of diverse data sources into a unified emotional representation. By consolidating behavioral, physiological, and contextual data, the fusion process significantly enhances emotion recognition accuracy and system adaptability in complex educational scenarios.

As shown in **Figure 10**, multimodal data fusion begins with the independent feature extraction of different modalities, including emotional data from facial expressions, speech signals, and textual inputs. These features are processed using specialized algorithms: CNNs for visual features, LSTM networks for temporal speech patterns, and transformer-based models such as BERT for textual semantics. These extracted features are represented in their respective feature spaces, preserving modality-specific attributes essential for accurate emotion recognition (Fang et al., 2020).

The core of the multimodal fusion process lies in the **cross-modal attention mechanism**, which dynamically integrates these features into a unified emotional feature vector. This mechanism assigns weights to each modality based on its contribution to the overall emotional state. The weight computation is defined as follows:

$$a_{i,j} = \frac{exp\ (e_{i,j})}{\sum_{k=1}^{n} exp\ (e_{i,k})}, \quad (2)$$

where $e_{i,j}$ is the correlation score between modalities, where $e_{i,j} = f(h_i, g_j)$ and $a_{i,j}$ represents the attention weight between modality i and modality j. This mechanism allows the system to adjust modality weights dynamically based on specific contexts.

This attention mechanism enables the system to prioritize the most relevant emotional cues dynamically. For example, in scenarios where speech signals convey strong emotional cues (e.g., tone and pauses), the system assigns higher weights to speech data. Conversely, when speech signals are weak or ambiguous, the system shifts its focus to visual or textual data. This dynamic weighting capability ensures robust emotion recognition across varying educational contexts.

Once fused, the unified emotional feature vector is classified into discrete emotional states (e.g., "positive," "neutral," or "negative"). These states serve as the basis for adaptive feedback, as outlined in **Figure 10**, allowing the system to adjust learning tasks and strategies in real-time. For instance, a learner exhibiting a "negative" emotional state might receive motivational prompts or simplified tasks, while a "positive" emotional state could lead to the introduction of more challenging materials to sustain engagement and motivation.

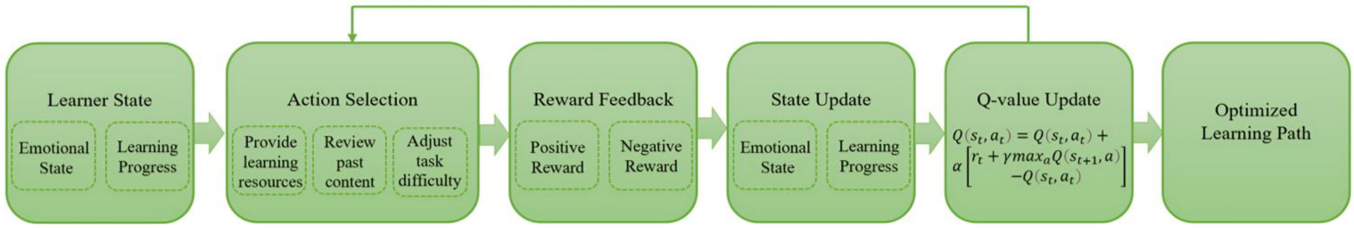

Figure 11. Framework of DQN for learning path optimization (Source: Authors' own elaboration)

The multimodal data fusion framework also demonstrates significant scalability. Beyond traditional behavioral and physiological data, it can integrate additional modalities such as EEG signals, olfactory cues, or even environmental sensors. This extensibility allows the system to adapt to increasingly diverse and complex educational environments, from traditional classrooms to virtual and hybrid learning spaces.

Moreover, the fusion framework leverages real-time processing capabilities to ensure low latency in emotion recognition and intervention, a critical requirement in dynamic learning scenarios. By unifying multimodal data through an adaptive fusion strategy, the framework enhances both the robustness and accuracy of the affective computing model, driving the development of intelligent educational systems.

In summary, the multimodal data fusion framework provides the technical foundation for integrating diverse emotional signals into actionable insights. Its innovative combination of feature extraction, cross-modal attention, and real-time adaptability ensures that the system can meet the complex demands of personalized learning in modern educational environments (Zhang & Leong, 2024d).

Personalized Learning Path Optimization

As shown in **Figure 11**, the DQN-based learning path optimization module maps learners' multimodal emotional states and performance indicators to adaptive instructional actions (e.g., adjusting task difficulty and providing hints) via value-based Q-learning. Personalized learning path optimization uses the DQN algorithm from RL. This algorithm can dynamically adjust the learning path based on the learner's performance to achieve personalized learning goals.mThe DQN optimizes the student's learning path through the Q-learning algorithm. Its objective is to find the optimal learning path by maximizing the cumulative reward. The update formula for the state-action value function is given as follows:

$$(s_t, a_t) = Q(s_t, a_t) + \alpha[r_t + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t)], \quad (3)$$

where $Q(s_t, a_t)$ represents the value of taking action a_t in state s_t, α is the learning rate, γ is the discount factor, and r_t is the immediate reward.

The DQN algorithm adopted in this study integrates two key components: experience replay and a target network, which enhance training stability. Specifically, an experience replay buffer (capacity: 10,000 samples) stores (state, action, reward, next state) tuples, and samples are randomly drawn in batches (batch size: 32) to break correlation between sequential data. The target network, updated every 100 steps, is used to calculate the target Q-value, while the main network is updated using the loss function as follows:

$$L(\theta) = \mathbb{E}[(r + \gamma max_{a'} Q'(s', a'; \theta^-) - Q(s, a; \theta))^2], \quad (4)$$

where θ and $\theta^-$are the parameters of the main and target networks, respectively. Key hyperparameters were set as: learning rate α = 0.001, discount factor γ = 0.9, and exploration rate ε (decaying from 1.0 to 0.1 over 10,000 steps) to balance exploration and exploitation.

This structure enables the algorithm to dynamically map learners' emotional states (e.g., frustration and focus) and performance (e.g., task completion rate) to optimal actions (e.g., adjusting difficulty and providing hints), as the Q-value iteration (Eq. [3]) prioritizes actions that maximize cumulative rewards (e.g., reduced learning time and higher engagement).

The system dynamically adjusts learning content and tasks by learning from each student's performance and emotional state. For example, if the system detects that the student is feeling down, it can increase review sessions or reduce the difficulty of the learning tasks. Conversely, if the student is in a positive emotional state, the system can appropriately increase the difficulty to maintain a challenging learning environment.

In the process of personalized learning path optimization, the emotional state of learners plays a critical role in influencing learning outcomes. Studies have shown that negative emotions, such as anxiety, frustration, and confusion, significantly impair learners' cognitive capacity and motivation. To further enhance the adaptability of the DQN algorithm in dynamic learning path optimization, this study designed a learning intervention mechanism based on multimodal emotion recognition (Chen et al., 2022).

This mechanism utilizes multimodal data fusion techniques to integrate learners' emotional data, including facial expressions, speech signals, and textual inputs. The identified emotional states are attributed to learning-related factors, such as task difficulty, environmental disturbances, and individual learner characteristics. Based on these attributions, the intervention engine dynamically matches appropriate strategies, including real-time task difficulty adjustments, emotionally optimized learning material design, and the provision of teacher guidance and content feedback. Through its real-time feedback loop, the mechanism establishes a dynamic linkage between learners' emotional states and their learning paths.

Furthermore, the feedback loop fosters collaboration between teachers and learners. Teachers can visually monitor learners' emotional states through emotion recognition results, enabling them to develop more targeted guidance strategies. Meanwhile, learners benefit from a dynamically optimized learning environment tailored to their emotional and cognitive needs. By integrating real-time emotion recognition with DQN-driven path optimization, this intervention mechanism significantly enhances the adaptability and robustness of personalized learning systems in dynamic contexts, providing new perspectives and theoretical foundations for the practical application of affective computing technologies in education (Matsuo et al., 2022; Rahate et al., 2022; Wang et al., 2022).

Data Privacy Protection

The system ensures that student data privacy is not compromised through the use of FL and differential privacy technologies.

Federated learning

In FL, each learning terminal device independently trains the model and only uploads the model parameters (rather than the data) to the central server for integration, ensuring that the data never leaves the local device.

The parameter update formula for FL is as follows:

$$w_t = \frac{1}{n}\sum_{i=1}^{N} w_t^i, \tag{5}$$

where w_t represents the global model parameters on the central server, and w_t^i represents the local model parameters of the i-th device. This approach effectively ensures data privacy.

Differential privacy

To further enhance privacy protection, differential privacy adds noise to safeguard individual data. The implementation formula for the differential privacy mechanism is as follows:

$$P(M[D] = o) \le exp(\epsilon) \cdot P(M[D']) = o. \tag{6}$$

In Eq. (6), $P(M[D] = o)$ represents the probability that algorithm M outputs result o on dataset M. Correspondingly, $P(M[D']) = o$ represents the probability that algorithm M outputs the same result o on dataset D', which differs slightly from D. $M(D)$ is the algorithm's output based on dataset D, and ϵ is the privacy budget–the smaller the value of ϵ, the stronger the privacy protection.

The core idea of differential privacy is that changing an individual item in the input dataset (i.e., from D to D') should not significantly affect the probability of the algorithm outputting the same result *ooo*, thus protecting the privacy of individuals in the dataset.

Experimental Design and Results Evaluation

Experimental objectives

The objective of the experiment is to evaluate the effectiveness of the intelligent learning ecosystem in vocational education. The specific goals include:

1. **Improving learning efficiency:** By integrating affective computing and multimodal data fusion, real-time learning path optimization is achieved to reduce learning time.
2. **Enhancing personalized recommendation accuracy:** Using the DQN algorithm, the system optimizes learning content recommendations based on the students' emotional states and learning needs.
3. **Improving learning performance:** To explore whether the system can dynamically adjust the learning paths to help students better master the course content.
4. **Increasing student satisfaction:** Through the use of affective computing technology, the system aims to enhance the learning experience and improve student satisfaction.

Experimental subjects

The experiment involved 100 students from a vocational college, covering multiple disciplines and academic backgrounds. All students were randomly divided into two groups based on their academic levels, age, and gender:

1. **Experimental group (50 students):** Students used the intelligent learning system based on the DQN algorithm. The system dynamically adjusted learning paths in real-time based on the students' emotional states and academic performance to optimize their learning experience.
2. **Control group (50 students):** Students followed a traditional, static learning path with no emotional feedback or path optimization.

Learning task design for the experimental group

The experimental design involved four subjects: mathematics, science, language, and arts, to test the system's adaptability and effectiveness in various learning scenarios (**Table 1**).

Table 1. Learning task design

Subject	Task description	Emotional feedback mechanism	Dynamic adjustment strategy	Experimental objective
Mathematics	Students complete math problems ranging from algebra to calculus, covering basic to advanced topics like solving equations, geometric analysis, and calculus applications.	The system monitors students' emotions in real-time, such as confusion, focus, and anxiety, through facial expressions and problem-solving speed.	If frustration is detected, the system lowers the difficulty and provides hints; if the student shows focus or confidence, the system increases the difficulty to maintain a challenge.	Evaluate the effectiveness of the DQN algorithm in optimizing math learning paths and verify whether the system can dynamically adjust difficulty based on emotional feedback to improve learning outcomes.
Science	Students conduct virtual science experiments, including chemical reaction simulations and physics experiment design. The tasks require students to control different variables and observe the results, covering topics such as chemical equilibrium, energy conversion, and motion analysis in physics.	The system monitors emotional states such as focus, distraction, or anxiety through student interactions with the virtual experiments, facial expressions, and voice signals.	When anxiety or operational difficulties are detected, the system reduces the task complexity and provides step-by-step guidance; when students show confidence or focus, the system increases the complexity, requiring more variables to be controlled or more complex analyses.	Verify the system's ability to dynamically adjust task difficulty based on students' emotional states during science experiments and assess whether this mechanism can improve students' understanding and operational abilities in experiments.
Language	Students engage in reading comprehension and writing tasks. The reading materials range in difficulty and cover various topics, such as novels, news reports, and academic articles. Writing tasks require students to summarize or express opinions based on the readings.	The system monitors emotional data such as voice tone, fluency, and facial expressions to gauge students' reading progress and reactions to material difficulty.	If students show signs of confusion or hesitation, the system lowers the material difficulty and provides additional reading support; if students appear confident, the system provides more challenging materials and increases the complexity of writing tasks.	Assess the system's ability to dynamically adjust learning paths based on emotional feedback in language learning and evaluate its effectiveness in optimizing reading material selection and writing task difficulty to enhance reading and writing skills.
Arts	Students engage in drawing or music composition tasks. The drawing task requires students to complete artwork on specific themes, while the music task involves creating melodies or compositions. The system adjusts the task content based on emotional expressions.	The system monitors students' emotional changes during the creative process, such as joy, anxiety, or unease, using real-time emotional analysis.	If the system detects anxiety or unease, it simplifies the creative task and provides more encouraging feedback; if the system detects positive emotions such as joy, it increases the task difficulty, requiring more complex creations or the use of additional creative techniques.	Evaluate the effectiveness of affective computing in creative tasks, verifying whether the system can dynamically adjust the task based on emotional feedback and enhance students' creativity and learning experience.

Experimental process

The experiment was conducted over a 6-week period, with 3 sessions per week (90 minutes per session), resulting in 18 treatment sessions in total. Each session included real-time emotional data collection, learning path adjustment, and task feedback to ensure continuous optimization of the learning process.

Initial data collection: Before the experiment, all students had their baseline emotional and learning behavior data collected via cameras and microphones. This included facial expressions, voice features, learning speed, and initial test scores. These data were used to generate personalized learning paths.

Personalized learning path generation:

1. *Experimental group:* Based on the DQN algorithm, the system generated personalized learning paths for the experimental group and dynamically adjusted them based on the students' emotional

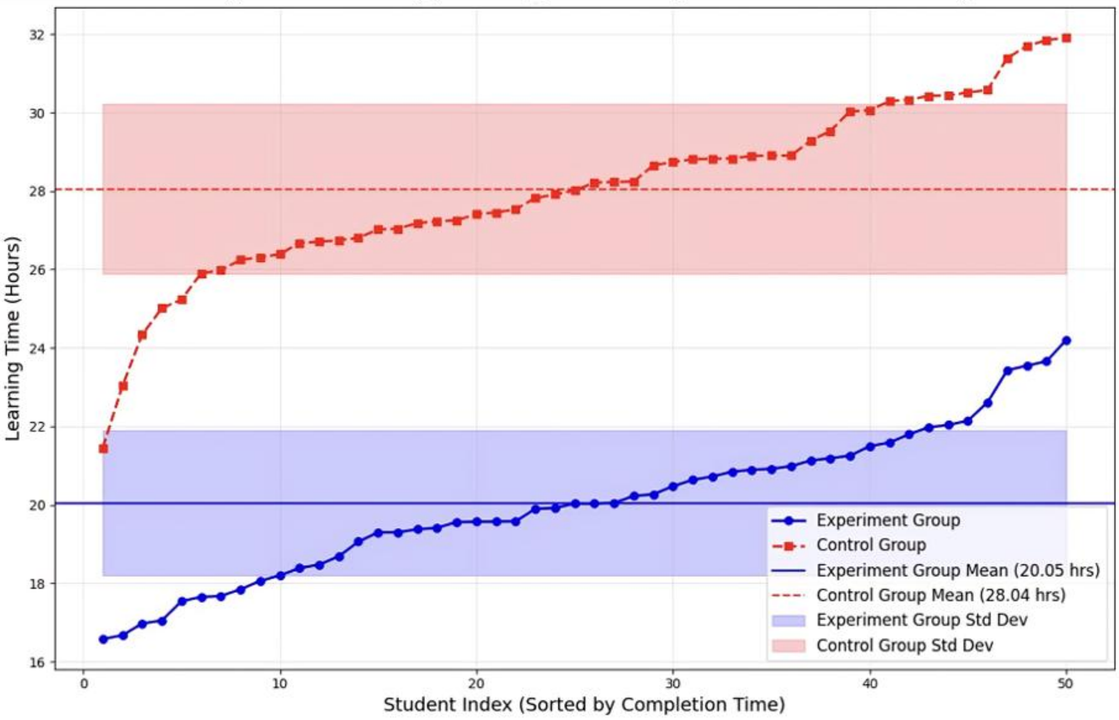

Figure 12. Comparison of learning efficiency between experiment and control groups (Source: Authors' own elaboration)

states and learning progress. For example, in mathematics tasks, problem difficulty or steps in science experiments were personalized according to emotional feedback.

2. *Control group:* Students followed a predetermined static learning path, with no dynamic adjustments or emotional feedback.

Real-time data monitoring relied on the following tools:

1. *Affective data collection:* Facial expressions were captured in real-time using OpenCV (v4.8.0); speech emotional features were extracted via the Python Speech Recognition library (v3.10.0); and text emotional tendencies were analyzed using TextBlob (v0.17.1).
2. *Dynamic path optimization:* The DQN algorithm was implemented based on PyTorch (v2.0.1), with a real-time interactive system built using the Flask framework (v2.3.3) to ensure a response latency of less than 500ms for learning path adjustments.
3. *Data storage and analysis:* Experimental data were stored in MySQL (v8.0), and statistical analysis was performed using SPSS 26.0 to verify the significance of inter-group differences.

Real-time data monitoring and feedback:

1. *Experimental group:* During the learning process, multimodal data (e.g., facial expressions, voice, and text) were collected in real-time. The system analyzed the students' emotional states using the affective computing model and adjusted the learning paths accordingly. If students' emotional states indicate anxiety or confusion, the system lowered task difficulty; if focus or positive emotions were detected, the system increased the task's challenge.
2. *Control group:* Students followed the static learning path without any dynamic adjustments from the system.

Final evaluation: At the end of the experiment, all students took final tests covering mathematics, science, language, and arts. By comparing the performance of the two groups, the effectiveness of the system in improving learning efficiency, recommendation accuracy, learning performance, and student satisfaction was evaluated.

Data analysis and results

Learning efficiency comparison: The learning efficiency of the experimental group was significantly higher than that of the control group, especially in mathematics and science. The experimental group completed their tasks in an average of 20.5 hours, compared to 28 hours for the control group. The DQN algorithm's emotional feedback adjustments allowed the experimental group to reduce learning time while maintaining high task completion rates.

As shown in **Figure 12**, the experimental group consistently required less time to complete learning tasks than the control group, indicating that emotion-aware DQN adjustments effectively improved learning efficiency.

Personalized recommendation accuracy: The system's personalized recommendation accuracy significantly improved. The experimental group achieved an average recommendation accuracy of 86%

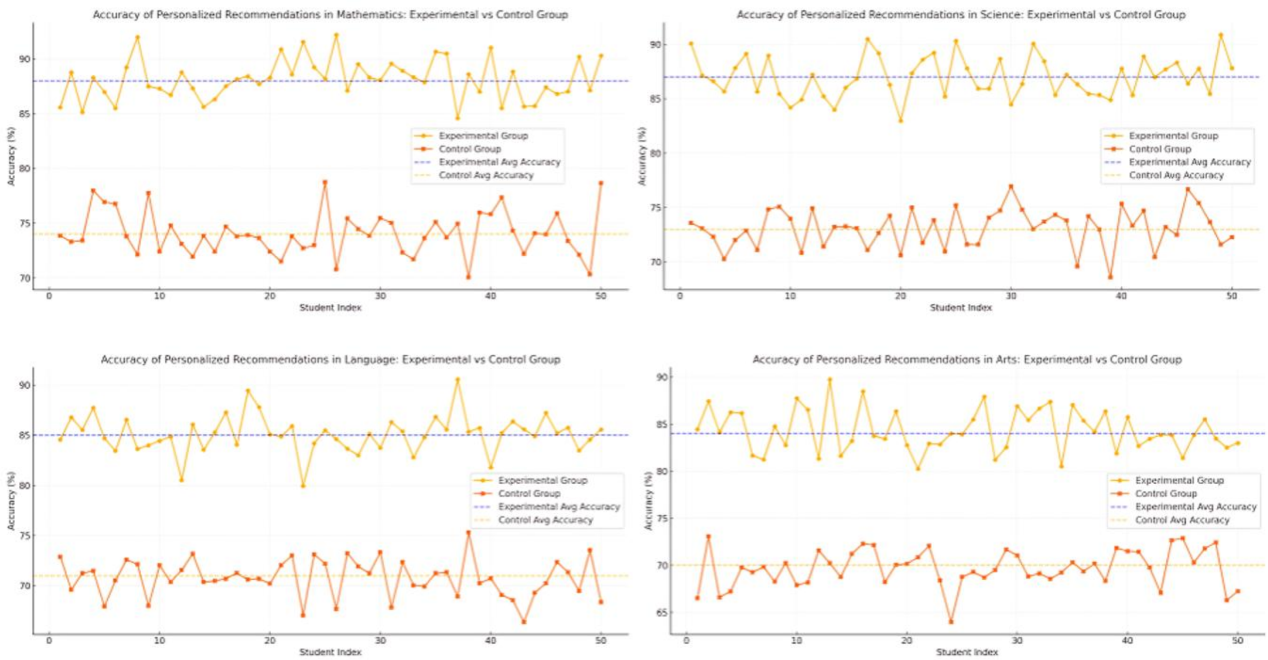

Figure 13. Comparison of personalized recommendation accuracy in mathematics, science, language, and arts: Experimental vs. control groups (Source: Authors' own elaboration)

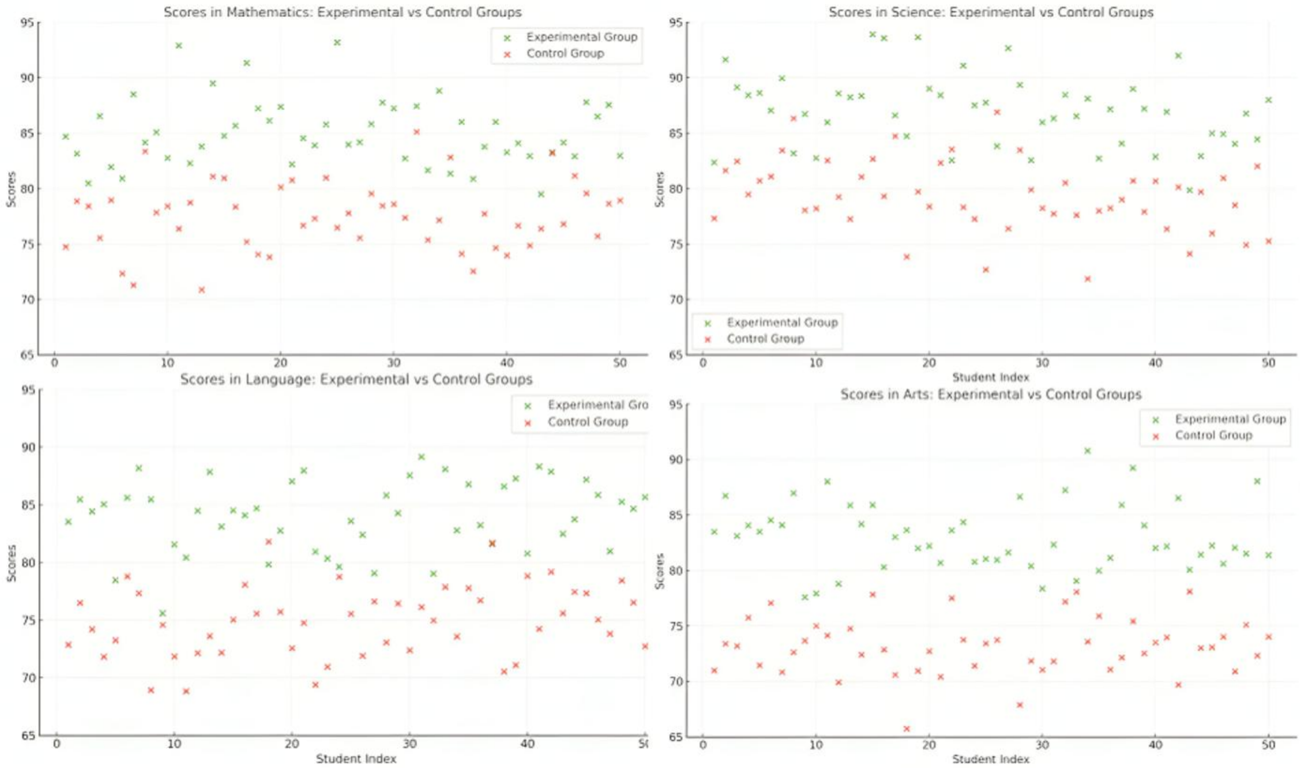

Figure 14. Score distribution comparison across subjects: Experimental vs. control groups (Source: Authors' own elaboration)

across subjects, compared to 72% for the control group. This shows that through multimodal data fusion and DQN optimization, the system more accurately matched students' learning needs and emotional states, ensuring optimized personalized learning paths. **Figure 13** compares personalized recommendation accuracy across subjects, showing that the experimental group achieves consistently higher accuracy than the control group, which supports the effectiveness of multimodal fusion combined with DQN optimization.

Improvement in learning performance: The experimental group consistently outperformed the control group, with a higher concentration of scores in the upper ranges. As illustrated in **Figure 14**, score distributions across mathematics, science, language, and arts shift upward for the experimental group, indicating improved learning performance under the proposed adaptive learning mechanism.

Specifically, in mathematics, the experimental group achieved an average score of 85, compared to 78 in the control group. Similarly, in science, the experimental group averaged 87, while the control group scored 79. This trend was also observed in language (84 vs. 75) and arts (83 vs. 74). These results demonstrate that the personalized learning path optimization, supported by multimodal data fusion and dynamic adjustments based on students' emotional states, significantly enhanced learning performance, enabling students to follow paths aligned with their individual needs and capabilities.

Student satisfaction: Student satisfaction in the experimental group was significantly higher than in the control group, with an average satisfaction score of 4.7 out of 5 in the experimental group compared to 3.9 in the control group. Most experimental group students believed that the system dynamically adjusted their learning paths based on their emotional states, greatly improving their learning experience and engagement. **Figure 15** visualizes the distribution of student satisfaction scores, where the experimental group shows a higher concentration of ratings near the upper end of the scale, reflecting improved engagement and perceived usability of the emotion-responsive learning system.

Before discussing the experimental conclusions, a survey involving 100 students was conducted to evaluate the system's effectiveness in personalized learning path optimization. The survey focused on five key dimensions: system interaction, personalized recommendation accuracy, emotional feedback effectiveness, dynamic path adjustment, and system usability. The results are summarized in **Table 2** to analyze the personalized learning path optimization.

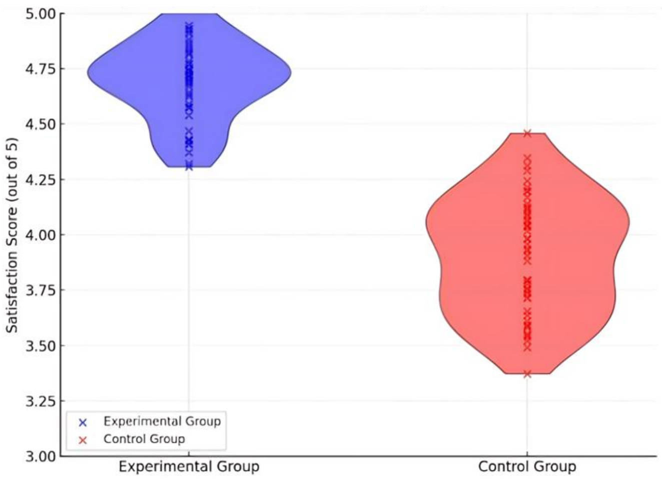

Figure 15. Visualizing student satisfaction distribution: Experimental and control groups (Source: Authors' own elaboration)

The survey revealed that 90% of the participants rated the system's engagement level at 4 or above on a 5-point scale, indicating a high level of interaction satisfaction. Regarding personalized recommendations, 90% of respondents felt that the system always or frequently provided tailored suggestions matching their learning needs. Emotional feedback, a core feature of the system, was deemed beneficial by 94% of participants, who agreed or strongly agreed that it enhanced their learning experience.

Dynamic path adjustment also received positive feedback, with 93% of respondents indicating that the adjustments either met or exceeded their expectations. System usability scored similarly high, with 92% of students rating it 4 or above, and 96% stated that they would recommend the system to others.

These survey results validate the system's practical effectiveness in addressing learners' emotional states and optimizing their personalized learning paths. The

Table 2. Analysis of survey results on personalized learning path optimization

Category	Survey question	Options	Percentage distribution	Key metrics
System interaction	How engaging was the system (1-5)?	1: 1%, 2: 2%, 3: 7%, 4: 40%, 5: 50%	90% rated 4 or above	Mean score: 4.5
Personalized recommendation	Did the system provide personalized recommendations?	Always: 60%, Sometimes: 30%, Rarely: 6%, Never: 4%	90% selected "always" or "sometimes"	-
Emotional feedback	Did emotional feedback enhance learning experience?	Strongly agree: 50%, Agree: 44%, Neutral: 4%, Disagree: 1%, Strongly disagree: 1%	94% selected "agree" or "strongly agree"	-
Path optimization	Did dynamic path adjustments meet your expectations?	Met: 53%, Exceeded: 40%, Fell short: 7%	93% selected "met" or "exceeded"	-
System usability	Rate the system's usability (1-5)	1: 0.4%, 2: 1.6%, 3: 6%, 4: 40%, 5: 52%	92% rated 4 or above	Mean score: 4.7
System recommendation	Would you recommend this system to others?	Yes: 96%, No: 4%	96% selected "yes"	-

Note. The survey data were collected from March 2024 to April 2024, covering student feedback within one month after the completion of the experiment high satisfaction rates across multiple dimensions highlight the system's potential for widespread adoption in vocational education settings.

Experimental conclusions

The experimental results clearly show that the DQN-based personalized learning path optimization system, through affective computing and multimodal data fusion technology, significantly improves learning efficiency, personalized recommendation accuracy, and student satisfaction in vocational education. The conclusions are as follows:

1. **Significant improvement in learning efficiency:** The experimental group effectively reduced learning time and optimized learning paths through the emotional feedback mechanism, improving task completion efficiency.
2. **Increased recommendation accuracy:** By integrating multimodal data fusion and the DQN algorithm, the system could dynamically adjust learning paths in real-time, significantly improving the accuracy of personalized recommendations.
3. **Significant improvement in learning performance:** The experimental group's final scores were significantly higher than the control groups, demonstrating that personalized learning path optimization effectively improved student learning outcomes.
4. **Increased student satisfaction:** Affective computing technology allowed the system to dynamically adjust learning paths based on students' real-time states, enhancing the learning experience and significantly increasing student satisfaction (Wang et al., 2022).

RESULTS

This study proposes a personalized learning path optimization system based on DQN and multimodal affective computing technology, and the experimental results in the vocational education field validate its effectiveness in improving learning efficiency, enhancing personalized recommendation accuracy, and improving student learning performance. The detailed results are as follows:

1. **Improvement in learning efficiency:** Students in the experimental group saw a significant reduction in learning time, particularly when multimodal data (facial expressions, speech, and text) were combined with the DQN algorithm. The experimental results, shown in **Table 1**, indicate that the average learning time for the experimental group was 20.5 hours, compared to 28 hours for the control group, representing a 27% increase in learning efficiency. This is due to DQN's ability to optimize learning paths in real-time, reduce unnecessary repetition, and dynamically adjust task difficulty based on emotional feedback, thereby improving overall learning efficiency.
2. **Personalized recommendation accuracy:** The personalized learning paths optimized by the DQN algorithm showed a significant increase in recommendation accuracy across various subjects (mathematics, science, language, etc.). The experimental group achieved an accuracy of 86%, compared to 72% in the control group, demonstrating that the system is better at matching learners' emotional states and actual learning needs. This result verifies the superiority of DQN in handling complex multimodal data, enabling the system to more precisely adjust learning paths and avoid the limitations of rule-based recommendations.
3. **Improvement in learning performance:** The experimental group achieved an average score of 87, while the control group averaged 80. The experimental group exhibited more stable learning performance. This shows that the DQN algorithm, through emotional feedback and real-time learning path adjustment, not only improved student engagement but also helped them more effectively master learning content. This dynamic adjustment mechanism allows students to learn at a pace that suits them, avoiding frustration or burnout caused by tasks that are too difficult or too easy.
4. **Student satisfaction:** Student feedback collected through surveys indicated that the experimental group reported an average satisfaction score of 4.6 out of 5, significantly higher than the control group's score of 3.8. Most students indicated that the system flexibly adjusted their learning paths based on personal emotional states and learning progress, significantly enhancing their learning experience. This suggests that the personalized learning path optimization system effectively meets individual learner needs and increases engagement and satisfaction through real-time emotional feedback mechanisms.

DISCUSSION

The results of this study indicate that the personalized learning path optimization system, combining multimodal data fusion with DRL, has shown excellent performance in vocational education. Compared to traditional rule-based personalized learning systems, the proposed system addresses the issue of real-time response to learners' emotional state changes by integrating affective computing and the

DQN algorithm, improving the flexibility and accuracy of personalized learning paths.

1. **Advantages of multimodal data fusion:** Traditional personalized learning systems often rely on a single data source (such as text or behavioral data), limiting their ability to comprehensively perceive learners' complex emotional and behavioral states. By integrating multimodal data such as facial expressions, speech, and text, the system in this study can more accurately capture learners' emotional states and behavior changes. This multidimensional data fusion not only enhances the accuracy of emotion recognition but also provides comprehensive and precise data support for the dynamic adjustment of personalized learning paths.
2. **Dynamic path optimization with deep-Q-networks:** DQN, an RL-based algorithm, continuously optimizes learning paths through a reward mechanism. Unlike traditional rule-based learning path optimization algorithms, DQN can dynamically adjust learning paths based on learners' performance, ensuring that each learner's path can continually adapt to their emotional state and learning progress.

The conclusions drawn from the DQN algorithm are rooted in its ability to learn optimal policies through cumulative reward feedback. For instance, the 27% improvement in learning efficiency is attributed to DQN's real-time adjustment of action values: when a learner's frustration (detected via multimodal data) increases, the algorithm reduces task difficulty (action with higher Q-value), minimizing redundant attempts and shortening learning time.

Compared to rule-based algorithms (static paths) and KNN (relying on historical similarity), DQN outperforms in dynamic scenarios because:

(1) it captures temporal dependencies in emotional states (via sequential Q-value updates), adapting to sudden changes (e.g., from focus to confusion) and

(2) the reward mechanism (e.g., positive rewards for task completion with positive emotions) aligns with long-term learning goals, avoiding short-sighted adjustments.

Statistical validation (via t-tests in SPSS 26.0) shows that the experimental group's Q-value convergence rate (average 500 steps) was significantly faster than the control group's static path efficiency (p<0.01), confirming DQN's effectiveness in optimizing learning paths.

3. **Comparison with other algorithms:** Compared to other path optimization algorithms, such as rule-based recommendation algorithms, KNN, and genetic algorithms, DQN demonstrates significant advantages in processing real-time feedback and dynamically adjusting learning paths.
4. **Future improvement directions:** While this study demonstrates the great potential of DQN and multimodal affective computing in vocational education, data privacy and computational efficiency must still be considered in large-scale applications. Future research can explore more efficient RL algorithms, such as Double DQN or prioritized experience replay, to further improve system responsiveness and efficiency (Zhang & Leong, 2024b).

CONCLUSIONS

This study set out to develop an intelligent learning system that integrates multimodal affective computing and DQN for real-time, emotion-driven learning path optimization in vocational education. The experimental results confirm that the proposed system successfully achieved its primary objectives: a 27% improvement in learning efficiency (addressing objective a); an 86% accuracy in personalized recommendations (addressing objective b); a significant increase in student satisfaction (average score 4.7/5).

By addressing the limitations of traditional 'one-size-fits-all' teaching models, the proposed system provides a viable solution for catering to learners' diverse and dynamic needs, particularly in emotionally complex vocational training scenarios. The following specific conclusions are drawn:

This study designed and experimentally validated a personalized learning path optimization system based on multimodal affective computing and DQN, confirming the system's effectiveness in enhancing personalized learning outcomes in vocational education. The main conclusions of the study are as follows:

The system can accurately identify students' emotional states through multimodal affective computing and optimize learning paths using DQN, significantly improving learning efficiency and the accuracy of personalized recommendations.

Experimental results show that the system performs outstandingly in enhancing students' learning performance, with the experimental group showing significantly better learning outcomes, learning experiences, and satisfaction compared to the control group.

The RL mechanism of DQN ensures that the system can continuously adjust learning paths based on students' dynamic feedback, meeting their personalized needs at different stages of learning. The system's multimodal affective computing and path optimization algorithms provide new insights and directions for personalized teaching in vocational education in the future (Szepesvári, 2022).

Future Work

Despite the significant results achieved by the personalized learning path optimization system in this study, there remain several areas for further exploration and expansion to improve the system's scope and efficiency. First, improving computational efficiency is crucial, as the high computational complexity of the DQN algorithm limits its application in large-scale data environments. Future research can explore more efficient algorithms, such as double DQN and prioritized experience replay, along with parallel and distributed computing techniques, to address computational bottlenecks when handling large-scale data, especially multimodal data. Optimizing computational efficiency will greatly enhance the system's real-time responsiveness and adaptability (Gu et al., 2022).

Second, data privacy protection becomes a critical challenge as the system processes more complex emotional and behavioral data. Future work can further investigate the combination of FL and differential privacy techniques, enabling the system to share data and optimize models globally while ensuring the protection of individual privacy. This approach is particularly suitable for international vocational education scenarios, allowing different institutions to securely share models without direct access to each other's data.

Author contributions: HZ: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, visualization. Responsible for developing the core model integrating multimodal affective computing and DQN, designing and executing experiments, and creating visualizations; **WYL:** conceptualization, resources, supervision, project administration, writing - review & editing, research guidance, resources; **YL:** methodology, software, resources, data curation, writing - review & editing, methodology, software, resources. All authors have read and agreed to the final version of the manuscript.

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AI statement: The authors stated that generative AI tools (e.g., ChatGPT) were not used to generate oranalyze research data. They were employed only for language polishingand minor grammatical editing during manuscript preparation. Allinterpretations, analyses, and conclusions were produced entirely by theauthors.

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