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Research article

Dynamic graph neural networks and evolutionary multi-objective optimization for adaptive quality evaluation in gamified preschool education

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Abstract: Play-based preschool education has emerged as a promising model for enhancing early childhood learning engagement and outcomes. However, traditional assessment models often fail to account for the dynamic and heterogeneous nature of learners, including cognitive differences, temporal interaction patterns, and individualized developmental trajectories. To address the neglect of learner dynamic heterogeneity in play-based preschool education, this paper proposed an adaptive assessment framework that integrated dynamic graph neural networks (GNNs) and evolutionary multi-objective optimization (EMO). The framework modeled curriculum–learner relationships by constructing heterogeneous interaction graphs, extracting temporal structural representations using GNNs, and balancing three pedagogical objectives—knowledge acquisition, engagement, and adaptability—through an EMO algorithm. A closed-loop feedback mechanism drove the co-evolution of both the model and the curriculum. Experimental results demonstrated that the proposed framework significantly improved post-test scores (by 0.2–0.7 points), learner engagement (correlation $R^2 = 0.608$), and individualized satisfaction, particularly among visual and kinesthetic learners. Comparative analyses further highlighted the robustness, scalability, and adaptability of the proposed method, establishing it as a computationally grounded and dynamically optimized intelligent curriculum design paradigm for early childhood education.

Keywords: gamified preschool education; dynamic neural networks; graph neural networks;

evolutionary multi-objective optimization; adaptive learning dynamics; intelligent course design
Mathematics Subject Classification: 68T07, 68T99

1. Introduction

In recent years, with the rapid advancement of information technology and artificial intelligence (AI), early childhood education has increasingly adopted gamified approaches to foster engagement and interactivity. Gamification has been shown to stimulate children's interest in learning while promoting the development of cognitive and social skills within enjoyable, play-based environments [1,2]. Despite these benefits, traditional evaluation methods and optimization strategies in gamified preschool programs often face significant challenges. Most current assessment systems rely on standardized tools that inadequately capture learners' heterogeneous needs—such as learning styles, cognitive levels, and game preferences—resulting in misaligned course design and suboptimal teaching effectiveness [3–6]. Furthermore, weak correlations between course content and children's individual characteristics limit dynamic adaptation, hindering the achievement of sustained learning outcomes. Consequently, designing intelligent, personalized, and dynamically adjustable gamification strategies has become an urgent priority in early childhood education.

To address these issues, scholars have increasingly explored the integration of intelligent technologies with gamification. At the primary education level, Leung et al. [7] demonstrated through field experiments that personalized gamification can significantly increase online course completion rates, especially when game mechanics align with learners' cognitive preferences. Similarly, Oliveira et al. [8] showed that adaptive game elements enhance learning motivation by up to 40% through optimized flow experiences. In teacher training contexts, Zourmpakis et al. [9] validated the effectiveness of adaptive gamification in science education and emphasized the importance of improving teachers' understanding of personalization mechanisms. Gm et al. [10] identified personalized recommendation systems as a crucial technological pathway for improving participation in online learning, while Rodrigues et al. [11] confirmed that adaptive difficulty adjustment plays a pivotal role in maintaining learner motivation during gamified review activities. Bennani et al. [12] further observed that adaptive gamification continues to face challenges, such as limited contextual awareness in engineering education. Dehghanzadeh et al. [13], through a systematic review of K–12 education, stressed that gamification design must correspond to learners' cognitive development stages. Meanwhile, Lee et al. [14] found that gamified learning improved attention and memory retention among preschool-aged children (3–6 years), though adaptation to individual differences remained inadequate.

In parallel, research in intelligent education has increasingly focused on the convergence of personalized learning strategies and gamification. Cevikbas et al. [15] confirmed the positive impact of personalized learning strategies on teaching sustainability in flipped classrooms. Ford [16] demonstrated that gamification design enhances learning motivation, while Marougkas et al. [17] revealed that immersive virtual reality (VR) significantly boosts learning outcomes by providing contextualized experiences. Adaptive feedback mechanisms have also emerged as a promising solution: Qi et al. [18] proposed a self-optimizing massive open online course (MOOC) system that dynamically adjusts learning activities, establishing a paradigm for intelligent personalization. Castellano et al. [19] further integrated gamification with AI in anatomy education, verifying the role of intelligent recommendation in facilitating knowledge internalization. Khaldi et al. [20] emphasized that gamification must be deeply aligned with learners' cognitive traits to maximize its benefits, while Altaie et al. [21] developed an adaptive framework that successfully enhanced computational thinking in adolescents aged 8–13 [22]. With the rise of AI technologies, Ma et al. [23] analyzed the application pathways of educational chatbots, and Major et al. [24] underscored the importance of personalized gamification mechanisms in sustaining learner motivation in MOOCs.

The integration of evolutionary multi-objective optimization and deep learning has demonstrated strong potential in intelligent education. Beyond traditional algorithms such as Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D), recent research has begun exploring the combination of generative adversarial networks with evolutionary multi-objective optimization (EMO) for Pareto front approximation in multimodal educational data. Other studies have employed Transformer architectures to model temporal learning behaviors and dynamically predict multi-objective learning effectiveness. However, most of these methods target K–12 or higher education contexts and fail to account for the nonlinear cognitive development and tightly coupled interactive characteristics of early childhood learning. This paper, for the first time, combines dynamic GNNs with EMO to construct an interpretable, evolutionary optimization framework for gamified preschool education (ages 3–6), filling the research gap in dynamic tuning of personalized courses for this developmental stage.

Building upon these insights, this study proposes a novel framework integrating GNNs, including graph convolutional network (GCN) and graph attention network (GAT) variants) with a genetic algorithm–based multi-objective optimization (GA-MOO) approach for evaluating and personalizing gamified preschool curricula. Specifically, the framework constructs a course evaluation graph to capture relationships between course modules and learner attributes, enabling GNNs to extract structural dependencies for personalized recommendations. A GA-MOO strategy is then employed to optimize multiple pedagogical objectives—knowledge acquisition, engagement, and adaptability—through a feedback-driven mechanism that continuously refines course configurations. Experimental validation demonstrates that this framework substantially enhances personalization and teaching effectiveness, addressing heterogeneous learner needs and advancing intelligent gamification in early childhood education.

2. Methods

2.1. Graph neural network model (GCN/GAT) to construct course evaluation graph

This study formalizes the dynamic optimization of gamified courses as a multi-objective optimization problem (MOP). Let the decision variable vector $x \in R^d$ represent the course configuration parameters, including the difficulty of each module $\{d_i\}$, the intensity of interactivity $\{i_j\}$, the weight of interest $\{f_k\}$, and the matching coefficient with learner characteristics $\{\mu_l\}$. The objective function is defined as:

$$\begin{aligned} &\min_x F(x) = \left[-G_{knowledge}(x),\ -G_{engagement}(x),\ -G_{adaptivity}(x)\right]^T \\ &\text{s.t.} \quad x \in X \subseteq R^d, \end{aligned} \tag{1}$$

Here $G_{knowledge}$, $G_{engagement}$, $G_{adaptivity}$ are composed of the learning outcome predictions, engagement scores, and fitness scores output by the GNN, respectively, χ representing the feasible domain of the course parameters (e.g., difficulty $d_i \in [1,5]$). In this framework, the GNN plays a dual role as a feature extractor and an effectiveness evaluator: taking a heterogeneous graph as input, it generates embeddings through multi-layer GCN/GAT propagation h_v and maps them to the three objective function values. This formal definition gives the optimization problem a clear mathematical structure, facilitating algorithm implementation and result reproduction.

In optimizing gamified early childhood courses, the relationships between course content and student characteristics are highly complex and interdependent. To achieve effective personalized recommendations, this paper employs a GNN to construct a course evaluation graph, where nodes represent either course modules or individual children. Node features integrate both course content attributes and learner-specific characteristics, while edges encode the relationships between courses and students, as well as peer interactions among students.

By leveraging GNNs to learn from node and adjacency relationships, the framework dynamically adjusts course recommendation strategies, ensuring a closer alignment between educational content and the individualized needs of children. Specifically, this study integrates two complementary GNN architectures: the GCN and the GAT. The GCN aggregates information through a weighted averaging of neighboring node features, making it well-suited for regular graph structures. In contrast, the GAT introduces a self-attention mechanism that dynamically adjusts the weights of neighboring nodes, enhancing the model's adaptability to irregular graph topologies and enabling more precise and context-sensitive recommendations.

The training of the graph neural network follows the graph convolution operation, expressed in formula (2) [24]:

$$H^{(l+1)}=\sigma\left(\widehat{A}H^{(l)}W^{(l)}\right), \tag{2}$$

where $H^{(l)}$ represents l the node features at the layer, is $\widehat{A}$ the normalized adjacency matrix, $W^{(l)}$ is l the weight matrix at the layer, σ and is the activation function. Graph convolution gradually updates the node representation by taking a weighted sum of the features of adjacent nodes and applying it to a nonlinear activation function. Through multiple layers of graph convolution, we ultimately obtain node features that effectively represent the complex relationships between courses and students.

In practical applications, the construction of the course evaluation graph considers several key aspects. First, the characteristics of course content evolve alongside children's cognitive development and gaming preferences; thus, the course content must be dynamically adjusted based on learners' historical performance data. Second, individual differences—such as children's unique needs, learning styles, and motivational factors—lead to varying preferences for course materials. Consequently, the training process of the graph neural network requires continuous updating of learner representations, allowing the recommendation strategy to adapt in real time to each child's evolving profile [25,26].

Through layer-by-layer graph convolution propagation, the model effectively integrates both the individualized needs of learners and the dynamic features of course content, enabling the system to recommend the most suitable course modules for each student.

After training the graph neural network, the system generates an embedding vector for each child within the course evaluation graph. These embedding vectors capture rich, multidimensional information—including learning progress, evolving interests, and cognitive difficulty levels. By comparing the embeddings across different learners, the system can identify similarities and clusters among children, thereby refining course recommendations to ensure that each child engages with content at an appropriate level of difficulty, interest, and developmental alignment.

Figure 1(a) illustrates the node embedding space distribution of the GNN model. To visualize the high-dimensional relationships, t-distributed stochastic neighbor embedding (t-SNE) dimensionality reduction is applied to the 128-dimensional feature representations of 300 nodes. Distinct node types—course modules, child nodes, and knowledge units—are differentiated through color and markers, reflecting their distribution patterns in the high-dimensional space. The t-SNE visualization reveals a clear clustering tendency among node types, with noticeable separation between course modules and child nodes. This demonstrates that the GNN model effectively captures and distinguishes the feature representations of heterogeneous nodes within the course evaluation graph.

Figure 1(b) presents the probability distribution of attention weights. By fitting an exponential distribution to the model's attention weights, it is observed that these weights are highly concentrated between 0 and 1. This indicates that when processing information from different nodes, certain nodes—such as specific course modules or child nodes—receive higher attention weights, signifying their greater influence on the overall model learning process.

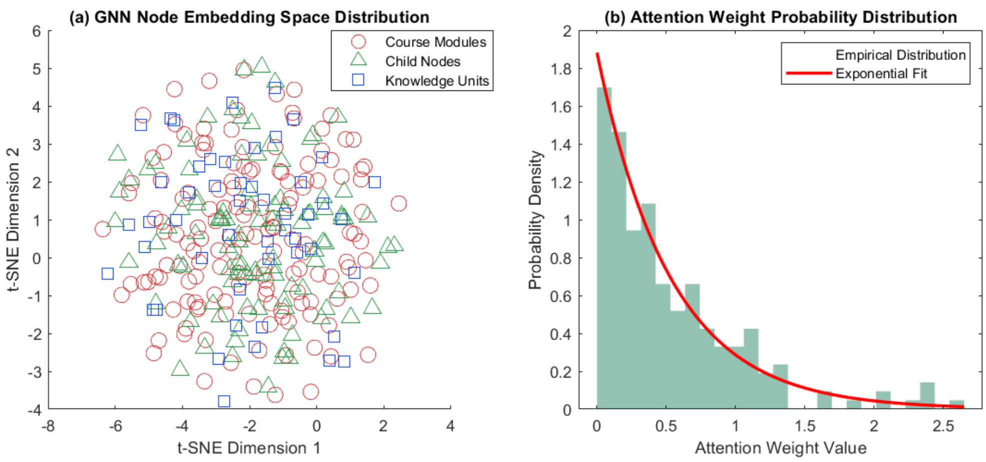

Figure 1. Node embedding space distribution and probability distribution of attention weights.

The training of the GNN not only enhances personalized recommendations by propagating information through local neighborhood structures, but also effectively models large-scale relational dynamics between students and courses. When combined with the genetic algorithm–based optimization framework, the output embeddings of the GNN serve as the input features for the genetic algorithm, further refining the course configuration parameters. This integration enables more efficient, accurate, and adaptive course recommendation and optimization.

2.2. Genetic algorithm to optimize course configuration

Genetic algorithms (GAs) are global optimization techniques inspired by the principles of natural selection and evolutionary adaptation, well-suited for solving complex curriculum design problems. In this study, the GA is employed to optimize the configuration parameters of gamified preschool courses. Each curriculum design is treated as an individual in the population, with parameters including course difficulty, interactivity, and enjoyment level, as well as their alignment with children's individual characteristics.

After generating the initial population, each individual is evaluated using a fitness function that comprehensively considers factors such as course difficulty, interactivity, and entertainment value, along with children's learning styles, cognitive levels, and gaming preferences. The optimization process proceeds iteratively through selection, crossover, and mutation operations [27,28], progressively improving the population toward optimal solutions. Ultimately, this evolutionary approach yields a globally optimized curriculum configuration that dynamically adapts to the individual needs and developmental trajectories of preschool learners.

In this process, the fitness function can be expressed by the following formula (3):

$$f(x)=w_1 \cdot D(x)+w_2 \cdot I(x)+w_3 \cdot F(x)+w_4 \cdot P(x). \tag{3}$$

Among them, $f(x)$ represents the adaptability of the course configuration $D(x)$, x represents the adaptability of the course difficulty, $I(x)$ represents the interactivity of the course, $F(x)$ represents the fun of the course, and $P(x)$ represents the matching degree of the child's individual needs, and w_1, w_2, w_3, w_4 is the corresponding weight coefficient. The design of the fitness function ensures that the course configuration optimization process can take into account various requirements and achieve balanced and diverse course content.

The core mechanism of the genetic algorithm (GA) lies in its evolutionary process, which comprises three main operations: selection, crossover, and mutation.

During the selection phase, a roulette wheel selection or tournament selection strategy based on fitness values is employed, giving priority to individuals with higher fitness scores for entry into the next generation [29]. This ensures that superior course design solutions are preserved and continue to contribute to subsequent optimization iterations.

In the crossover operation, two individuals are selected as parents, and new offspring are produced through the exchange of partial genetic material (i.e., course configuration parameters). This process enables the exploration of new curriculum design possibilities. To enhance the diversity and global search capability of the algorithm, the crossover operation can adopt various strategies such as single-point or multi-point crossover.

The mutation operation introduces random perturbations to the course parameters of certain individuals, mimicking the natural process of gene mutation. This prevents the algorithm from becoming trapped in local optima and broadens the search space, improving the robustness and adaptability of the optimization process.

Through multiple generations of iterative evolution, the GA progressively converges toward the optimal combination of curriculum configurations. With each generation, the fitness level of the population improves, eventually stabilizing at an optimal solution that best satisfies the personalized learning needs of each child. To further enhance optimization effectiveness, this study implements an adaptive weight adjustment strategy, dynamically modifying the weight coefficients in the fitness function based on real-time feedback during the optimization process. This allows the algorithm to achieve a more balanced trade-off among multiple optimization objectives [30].

Moreover, the parameter settings of the GA significantly influence its optimization performance.

In this study, standard GA parameters were employed: a population size of 100, a crossover probability of 0.8, a mutation probability of 0.1, and a maximum generation count of 1000. These configurations ensured a comprehensive search for optimal solutions while maintaining computational efficiency and convergence stability.

Figure 2 illustrates the key stages in the GA optimization process.

Figure 2(a) presents the evolution of fitness values, where the horizontal axis represents the number of generations and the vertical axis represents the fitness score. As shown, the best individual fitness steadily increases with each generation, indicating that the optimization process of the GA is progressively converging toward an optimal solution. Meanwhile, the average population fitness exhibits slight fluctuations across generations, reflecting the influence of individual diversity within the population on the overall optimization trajectory. This trend aligns with the goal of optimizing gamified early childhood courses—continuously enhancing adaptability and learning effectiveness by dynamically adjusting course content through iterative evolution.

Figure 2(b) depicts the evolution of the course difficulty parameter, where the horizontal axis represents the number of generations and the vertical axis denotes the value of the course difficulty. As the number of generations increases, the difficulty parameter distribution gradually converges toward higher values, suggesting that course difficulty is adaptively adjusted to better match the evolving learning needs and developmental levels of different children.

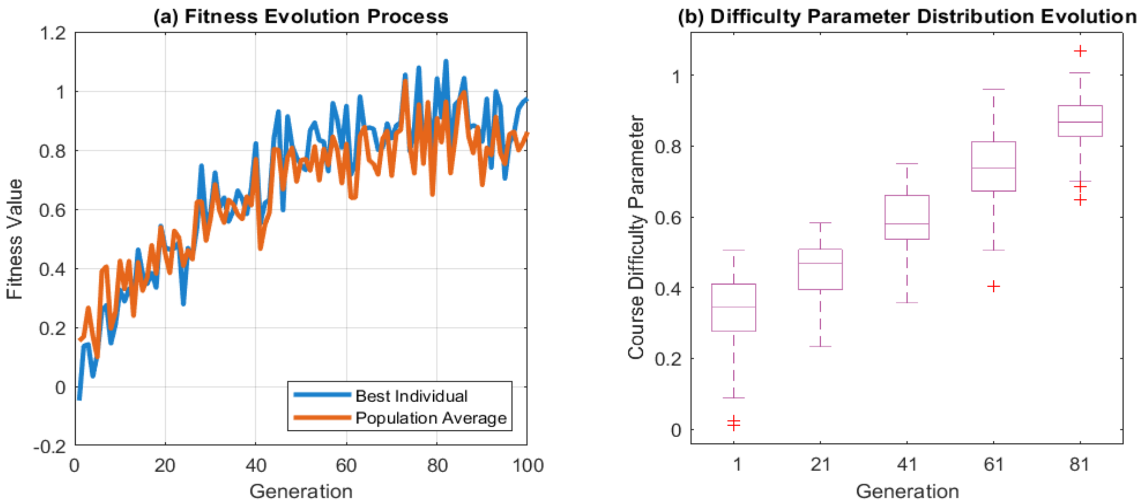

Figure 2. Evolution of fitness and changes in difficulty parameters during optimization.

2.3. Multi-objective optimization strategy

In the design and optimization of gamified early childhood education, course effectiveness depends not only on the content itself but also on the interaction and balance among multiple pedagogical factors. To holistically address the diverse learning needs and objectives in the optimization process, this study introduces a multi-objective optimization strategy that simultaneously refines several key indicators: children's learning outcomes, course enjoyment, and learning progress.

In multi-objective optimization, it is essential to clearly define the objective functions to be optimized. In this study, the three core objectives are as follows:

- Learning effectiveness: Enhancing children's knowledge acquisition, comprehension, and cognitive development.
- Course fun: Ensuring that course content stimulates curiosity, sustains engagement, and fosters intrinsic motivation.
- Learning progress: Maintaining an appropriate learning rhythm and adjusting course difficulty dynamically to match each child's cognitive pace [31,32].

To optimize these objectives simultaneously, the weighted summation method is adopted. This approach combines multiple objective functions into a comprehensive objective function, where each objective is assigned a specific weight coefficient representing its relative importance to the overall course design. By appropriately calibrating these weights, the optimization process can effectively balance educational effectiveness, engagement, and adaptability. The formulation of this composite objective function is presented in formula (4),

$$F_{total}(x)=w_1\cdot F_{learning}(x)+w_2\cdot F_{fun}(x)+w_3\cdot F_{progress}(x). \tag{4}$$

Wherein, $F_{total}(x)$ is the comprehensive optimization goal, $F_{learning}(x)$ is the learning effect $F_{fun}(x)$ goal, is the course fun goal, $F_{progress}(x)$ is the learning progress goal, and w_1, w_2, w_3 is the weight of the corresponding goal. The weight coefficient is adjusted according to the specific educational goals and course characteristics to ensure balance and coordinated optimization among the various goals.

In the multi-objective optimization process, each objective function is first optimized independently, followed by a composite optimization through a weighted summation approach. To enhance the performance and balance of the optimization results, this study introduces the concept of the Pareto optimal solution—a state in which improvement in one objective cannot be achieved without compromising another. Through this mechanism, the optimization process identifies a set of trade-off solutions that represent ideal compromises among competing objectives, rather than a single absolute optimum [33].

The optimization framework integrates a GA with a GNN. The GNN models the complex relationships between curriculum elements and children's individualized learning needs, while the GA iteratively refines the curriculum configuration parameters through multiple generations of evolutionary operations. Within the multi-objective optimization process, the GA's selection, crossover, and mutation mechanisms work collaboratively to optimize multiple objectives simultaneously during each generation. Specifically:

Selection prioritizes individuals with higher fitness scores, ensuring that superior curriculum designs are preserved for future generations.

Crossover combines the genetic information (i.e., course parameters) of parent individuals to create new curriculum configurations, facilitating exploration of a diverse solution space.

Mutation introduces random variations to individual genes, preventing premature convergence and guiding the algorithm toward a global optimum.

The design of the fitness function plays a pivotal role in the multi-objective optimization process. In this study, the fitness function integrates multiple pedagogical objectives—learning effectiveness, enjoyment, and learning progress—while also incorporating learner-specific characteristics such as learning styles, cognitive development levels, and gaming preferences. This comprehensive design ensures that, during optimization, the curriculum not only enhances children's cognitive abilities and learning motivation but also dynamically adjusts difficulty levels and content alignment based on individual progress and developmental needs.

To achieve efficient computation and balance across multiple objectives, this study employs the NSGA-II. NSGA-II effectively manages conflicts among competing objectives by maintaining a Pareto front of non-dominated solutions. Through iterative refinement, the algorithm identifies an optimal set of curriculum configurations that best satisfy the personalized needs of preschool learners while maintaining equilibrium among learning effectiveness, engagement, and adaptability [34].

Figure 3 presents the three core components of the multi-objective optimization process.

Sub-Figure 3(a) illustrates the distribution of Pareto optimal solutions, where the horizontal axis represents learning effectiveness and the vertical axis represents fun. The scatterplot displays the spread of solutions generated during the optimization process. Through iterative refinement, the selected solutions achieve an optimal balance between learning effectiveness and enjoyment, enabling the design of gamified curricula that are both pedagogically effective and engaging for young learners.

Sub-Figure 3(b) depicts the evolution of objective functions across optimization iterations. The three objective functions—learning effectiveness, fun, and learning progress—show consistent upward trends as the number of iterations increases, indicating that the optimization process progressively enhances the overall quality and adaptability of the course design.

Sub-Figure 3(c) demonstrates the impact of the progress weight coefficient on the overall fitness value. The horizontal axis represents the progress weight coefficient, while the vertical axis indicates the overall fitness. As the weight of learning progress is adjusted, the corresponding changes in fitness reflect how the balance among learning outcomes, engagement, and progression influences the effectiveness of the optimized curriculum.

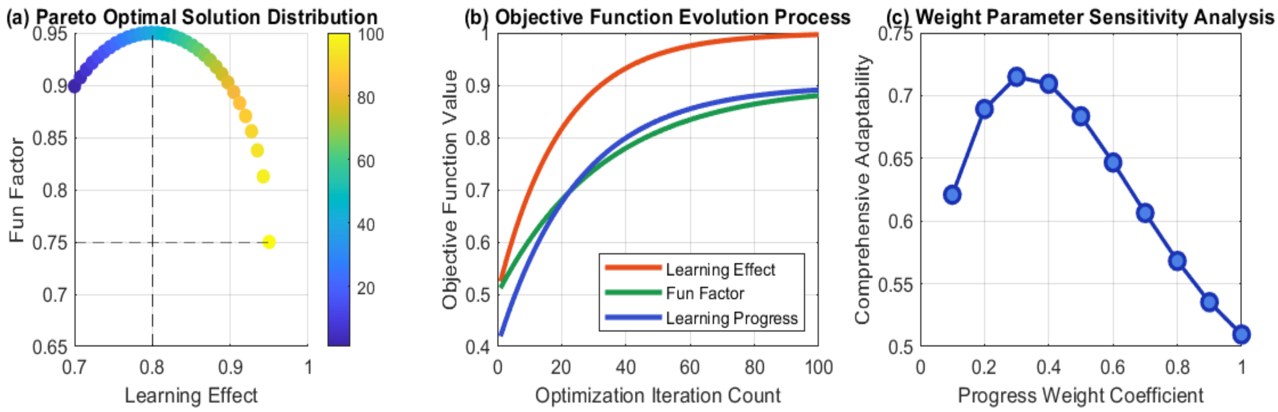

Figure 3. Multi-objective optimization process.

Throughout the multi-objective optimization process, the adaptability of the curriculum content is continuously refined. This ensures that course design not only strengthens learning effectiveness, but also enhances interest, interactivity, and engagement. Simultaneously, the system dynamically adjusts course difficulty in accordance with each child's cognitive development and learning progress, allowing learners to advance at a pace most conducive to their individual growth. Moreover, this adaptive optimization fosters sustained motivation and active participation, helping children maintain a positive learning attitude within the gamified learning environment.

2.4. Personalized course recommendation system

The personalized course recommendation system employs a GNN to construct a relationship graph linking course content with individual child characteristics. This system captures complex, non-linear interactions between children and learning materials by representing child attributes and course elements as interconnected nodes, while edges denote the strength and nature of these relationships.

In this framework, each child's learning style, cognitive level, age, and game preferences are used as input features, whereas course modules, difficulty levels, and interactive design elements are modeled as nodes within the GNN. Through training, the GNN learns the underlying structural relationships and optimizes learning paths tailored to each learner.

The system first encodes the child's characteristics into a feature vector, which is then input into the trained GNN to generate a personalized course list. The final recommendations are dynamically adjusted based on the weighted relationships between nodes, ensuring that the system remains responsive to evolving learner profiles. For example, kinesthetic learners receive recommendations emphasizing interactive and movement-based games, while visual learners are guided toward image- and video-rich content. This adaptive recommendation process enables targeted allocation of learning resources, ensuring that every child engages with content best suited to their unique learning preferences and developmental trajectory.

Figure 4 presents the results of the personalized match assessment. The horizontal axis represents the child's ID number (ranging from 1 to 120), while the vertical axis indicates the degree of interest match between each child and the recommended curriculum. Each dot in the scatterplot corresponds to an individual child, and the color intensity represents the match level—darker colors signify a higher degree of match. The black dashed line denotes the average interest match across all participants. The data show that the overall match values range between 0.7 and 0.9, indicating that most children exhibit a high degree of alignment between their interests and the recommended curriculum content.

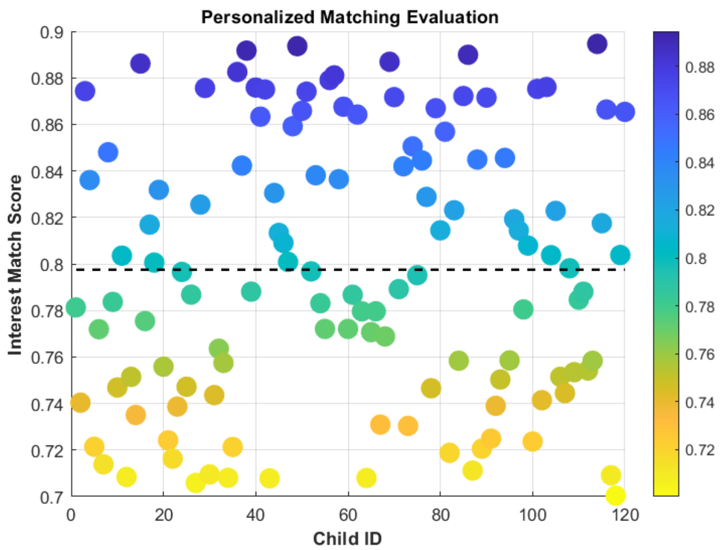

Figure 4. Results of personalized matching evaluation.

To further enhance recommendation quality, this study integrates a GA to iteratively optimize the recommendation system. Specifically, the GA refines the configuration of course content derived from the GNN. Each course configuration (comprising course content, difficulty, interactivity, and other design parameters) is treated as an individual, and a fitness function evaluates its effectiveness based on each child's characteristics and game preferences. This fitness function is designed according to personalized learning needs, assessing multiple dimensions such as course enjoyment, learning outcomes, and learning progress [35,36]. Through iterative operations of selection, crossover, and mutation, the GA continually adjusts course recommendations to ensure that every child achieves the most effective and engaging learning experience.

Within the recommendation system, the GA continuously explores new combinations of course configurations, thereby avoiding local optima and improving system adaptability and recommendation accuracy. Evaluation metrics—including interactivity, fun, and learning progress alignment—are used within a multi-dimensional fitness function to assess performance. The system then integrates child feedback and learning data to quantify recommendation effectiveness in real time. Additionally, a dynamic feedback mechanism continuously adjusts recommendation strategies based on behavioral data—such as academic performance, engagement levels, and attention span—thereby ensuring that course content remains personalized and balanced between each child's learning progress and interests.

2.5. Feedback mechanism and optimization iteration

To ensure continuous optimization and adaptability of the gamified preschool curriculum, this study proposes a dynamic optimization mechanism grounded in student feedback. This mechanism forms a closed-loop optimization cycle by collecting real-time behavioral data during learning activities. It dynamically adjusts recommendation strategies and continuously optimizes course design based on children's learning performance and engagement, thereby enhancing the system's personalization accuracy and adaptability.

The feedback mechanism aggregates data from multiple sources, including children's learning progress, interaction frequency, task completion rates, answer accuracy, emotional responses, and overall engagement. For example, learning progress data reflects each child's mastery and cognitive development within individual modules, while interaction data—such as click frequency and task participation—reveal interests and motivational trends. These insights enable the system to dynamically adjust subsequent course content and enhance learning motivation.

After preprocessing and feature extraction, the collected data is transformed into optimized inputs for updating course recommendation strategies. The core of this feedback mechanism lies in real-time behavioral analysis, which identifies learning bottlenecks or declining interest and triggers corresponding adjustments. Specifically, feedback data is used to fine-tune parameters within both the GNN and the GA.

In the GNN, feedback updates children's feature vectors and modifies the correlation weights between course content and child characteristics. For instance, if a child underperforms in a specific module, the system prioritizes course recommendations that better align with their cognitive level, avoiding content that is too easy or too difficult.

In the GA, feedback dynamically updates the fitness function and optimization strategy, influencing the operations of selection, crossover, and mutation. When learning difficulties are detected, the fitness function increases the difficulty adaptation weight, ensuring that subsequent course configurations more closely match the learner's progress and abilities.

To achieve real-time optimization, the system employs incremental learning, which gradually incorporates newly collected feedback into model training. This approach allows for rapid adaptation to changing learner needs while avoiding the computational overhead of full model retraining. As a result, the recommendation system remains continuously up to date, reflecting each child's current behavior and development.

The feedback mechanism not only adjusts course content but also fine-tunes multiple dimensions, including difficulty, engagement, and interactivity. For example, if a child loses interest, the system can increase interactivity or gamified challenges; if progress slows, it can reduce difficulty or shorten task duration. This closed-loop adaptive framework ensures that the system evolves continuously—each cycle of data collection and analysis provides the foundation for updates, steadily improving recommendation precision and personalized adaptability. Moreover, it can predict and accommodate future learning needs, ensuring that curriculum design consistently aligns with the individual characteristics and developmental trajectories of young learners.

3. Method effectiveness evaluation

To validate the effectiveness of the proposed gamified curriculum optimization method, this study constructed and utilized a comprehensive experimental dataset. The dataset was derived from actual teaching records across three kindergartens and includes detailed learning behavior data and curriculum information for 120 children. Over an eight-week gamified learning period, each child generated approximately 320 behavioral records, encompassing metrics such as task completion rates, number of interactions, learning time, answer accuracy, and game preferences.

The curriculum comprised 50 distinct gamified units, each rated on a five-point difficulty scale. Interactivity and fun were evaluated using teacher ratings and children's engagement levels, both measured on a 1–10 scale. The dataset also includes key demographic and psychological attributes, such as age (3–6 years), gender, learning style (visual, auditory, or kinesthetic), cognitive development level (low, medium, or high), and home learning environment. To assess personalized recommendation effectiveness, children's knowledge acquisition and interest changes were recorded before and after the course.

3.1. Evaluation indicators: Learning outcome and engagement

Learning outcomes were primarily assessed through measures of knowledge acquisition, cognitive improvement, and task completion within the gamified courses.

Knowledge acquisition was evaluated using pre- and post-tests to measure children's mastery of knowledge and their ability to comprehend and apply course content.

Cognitive improvement was gauged by observing changes in thinking patterns, problem-solving abilities, and conceptual understanding before and after the intervention.

Task completion was assessed by tracking metrics such as completion rates, error frequency, and problem-solving speed, providing insight into learners' performance during gameplay-based learning activities.

Engagement was evaluated through behavioral indicators including interaction frequency, number of questions answered, time spent on game tasks, and duration of sustained participation.

These measures reflect each child's level of involvement, motivation, and persistence, offering a comprehensive understanding of their engagement within the gamified learning environment.

Figure 5(a) presents a comparison of learning outcomes across ten course modules, measured using standardized pre- and post-test scores. The results clearly show that post-test scores are consistently higher than pre-test scores across all modules, indicating a significant improvement in children's learning performance. The observed score increases range from 0.2 to 0.7 points, demonstrating that the gamified curriculum design had a substantial positive impact on learning outcomes. These findings highlight that the optimized course structure effectively promotes knowledge acquisition and cognitive development, particularly evident in the marked improvement of post-test results.

Figure 5(b) illustrates the relationship between engagement levels and learning improvement. The scatter plot reveals that children with higher engagement scores tend to exhibit greater gains in learning outcomes. Regression analysis shows a correlation coefficient (R^2) of approximately 0.608, indicating a moderate positive correlation between engagement and learning improvement. The inclusion of confidence intervals around the regression line further confirms the reliability and statistical robustness of this relationship, underscoring the critical influence of engagement on children's learning performance within gamified educational settings.

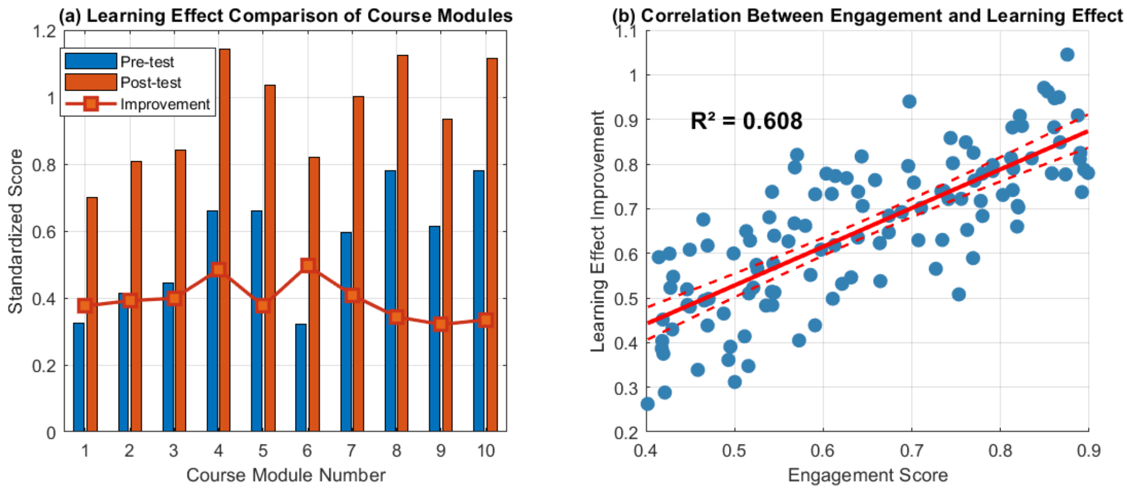

Figure 5. Learning effect and participation evaluation.

3.2. Course satisfaction survey

The course satisfaction survey collected comprehensive feedback from both children and parents through structured questionnaires. The survey assessed children's satisfaction across several dimensions, including interest level, content suitability, interactivity, entertainment value, and educational significance. These responses were used to quantitatively evaluate the overall popularity of the curriculum and to determine whether it effectively met learners' expectations and developmental needs.

Parent feedback provided additional insights into how the gamified curriculum complements family-based education. By reflecting on children's engagement and progress at home, parents helped evaluate the broader educational impact and quality of the program. Collectively, these survey results serve as an important benchmark for assessing whether the course is achieving its pedagogical objectives—fostering not only knowledge growth and cognitive improvement but also enjoyment and motivation in early learning experiences.

Figure 6 presents the results of the course satisfaction and learning outcome survey.

Figure 6(a) displays the distribution of satisfaction scores across different course types, each evaluated by 30 participants on a 1–10 scale. The boxplot visualization highlights the variability in satisfaction ratings among course types, revealing distinct fluctuations and median differences across the various designs. These variations suggest that course type significantly influences participants' perceived satisfaction, indicating differing degrees of engagement and enjoyment among learners.

Figure 6(b) illustrates the relationship between course satisfaction and learning outcomes through a scatterplot with a regression line. Data points are categorized by learning style—visual, auditory, and kinesthetic—and distinguished by color. The results reveal a positive correlation between satisfaction scores and learning improvement: participants who reported higher satisfaction generally achieved greater learning gains. This trend is particularly evident among visual and kinesthetic learners, who show a stronger alignment between engagement, satisfaction, and performance. The regression line confirms that higher satisfaction levels correspond to improved learning outcomes, while variations across learning styles provide valuable insights into customizing course design to enhance both learning experiences and results.

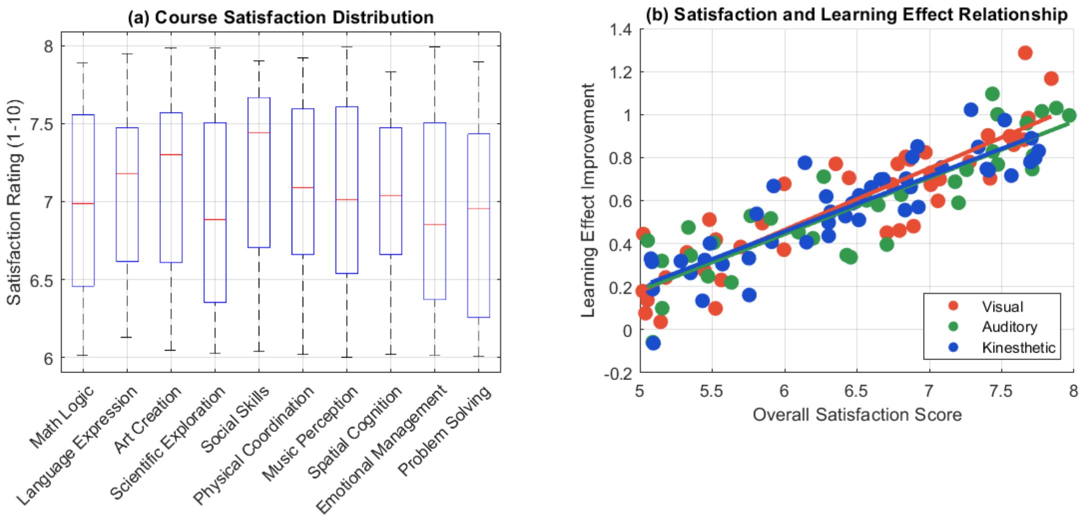

Figure 6. Survey results on course satisfaction and learning outcomes.

3.3. *Personalized matching evaluation*

The personalized matching evaluation assesses the effectiveness of the personalized course recommendation system compared with traditional curriculum designs. The primary goal of this evaluation is to determine how personalized recommendations enhance children's learning outcomes and motivation by aligning educational content more closely with individual learner characteristics.

The evaluation process involves collecting learning data from ten randomly selected children participating in both curriculum models, as summarized in Table 1. The data include indicators such as academic performance, engagement levels, and learning interest. Statistical analyses are then conducted to compare outcomes under personalized and conventional course settings.

Results demonstrate that courses designed using the personalized recommendation system show stronger alignment with children's cognitive levels, learning styles, and interests. Learners in the personalized setting exhibited higher knowledge acquisition, greater engagement, and improved intrinsic motivation compared with those following standard course designs. Overall, the findings confirm that a high degree of personalized fit significantly enhances both learning effectiveness and interest, validating the proposed system's value in improving the quality and adaptability of gamified preschool education.

Table 1. Personalized matching evaluation table.

Child ID	Personalized course learning score	Conventional course learning score	Personalized course engagement	Conventional course engagement	Personalized course interest score	Conventional course interest score
1	85	75	90	80	9	7
2	80	70	85	75	8	6
3	90	85	95	80	9	8
4	75	65	80	70	7	6
5	92	78	88	72	9	7
6	78	72	82	74	8	6
7	85	79	90	77	9	7
8	80	73	86	74	8	6
9	88	80	93	80	9	8
10	84	76	89	76	9	7

3.4. Achievement of teaching objectives

The assessment of teaching goal achievement evaluates whether the gamified curriculum has successfully fulfilled its intended educational objectives, encompassing cognitive, skill-based, and emotional goals.

- Cognitive goal assessment: This dimension measures children's understanding and mastery of curriculum knowledge. It evaluates their ability to recall, comprehend, and apply key concepts, providing insight into how effectively the course fosters knowledge acquisition and conceptual development.
- Skill goal assessment: This component examines children's practical skill development by assessing their ability to apply learned knowledge in real tasks, such as completing challenges or solving problems within the gamified environment. It reflects the extent to which the curriculum cultivates hands-on competence and problem-solving ability.
- Emotional goal assessment: This aspect evaluates the emotional and affective outcomes of learning. It captures changes in children's attitudes, motivation, and emotional responses toward the curriculum. Data is collected through questionnaires, interviews, and behavioral observations to assess improvements in self-confidence, cooperation, persistence, and emotional expression.

By integrating findings across these three dimensions, a comprehensive evaluation of the curriculum's effectiveness can be achieved. This holistic approach provides a deeper understanding of how well the gamified preschool curriculum supports cognitive development, skill acquisition, and emotional growth, thereby ensuring that the teaching objectives are fully met and aligned with the developmental needs of young learners.

Table 2 presents the results of each child's achievement across cognitive, skill-based, and affective goals. For instance, Child 3 achieved 88% in cognitive goals, 83% in skill goals, 92% in affective goals, and 88% overall, indicating consistently strong performance across all learning dimensions. In contrast, Child 4 demonstrated lower achievement levels, with 75% in cognitive goals, 70% in skill goals, 80% in affective goals, and 75% overall, reflecting difficulties in cognitive comprehension and skill mastery.

Table 2. Teaching goal achievement evaluation table.

Child ID	Cognitive objective achievement (%)	Skill objective achievement (%)	Emotional objective achievement (%)	Overall objective achievement (%)
1	85	78	90	84
2	80	74	85	80
3	88	83	92	88
4	75	70	80	75
5	90	85	95	90
6	78	72	85	78
7	84	80	88	84
8	80	76	82	80
9	87	82	90	86
10	83	77	89	83

The variability observed among children across these goal dimensions highlights the individual differences in learning outcomes, suggesting that the curriculum must accommodate diverse developmental needs through adaptive adjustments and personalized recommendations. Such differences underscore the necessity of tailoring instruction to each child's learning profile—balancing cognitive development, practical skill acquisition, and emotional growth. These findings provide valuable insights for refining curriculum design and enhancing the achievement of educational objectives through individualized learning pathways.

3.5. Assessment of learning progress adaptability

The adaptive assessment of learning progress evaluates how effectively the system adjusts course content in response to each child's personalized learning trajectory. This assessment focuses on whether dynamic modifications to the difficulty level and learning pace align with individual learning progress and engagement.

The adaptive mechanism operates as follows:

When the system detects that a child's learning progress is slower than expected, it automatically reduces course difficulty or extends learning duration to allow more time for mastery.

Conversely, if a child demonstrates rapid progress, the system increases the level of challenge or introduces advanced learning tasks, promoting continued cognitive engagement and preventing stagnation.

The evaluation process records and analyzes various indicators of learning adaptability, including learning duration, task completion speed, and error rate, under different adjustment conditions. These metrics are used to determine whether the adaptive interventions effectively support each child in maintaining an optimal learning rhythm.

Ultimately, this adaptive assessment ensures that every learner can progress at a suitable pace and difficulty level, providing a personalized, responsive, and developmentally appropriate learning experience. The results also offer crucial feedback for refining the adaptive mechanisms of the gamified curriculum, ensuring that learning pathways remain both challenging and supportive across diverse learner profiles.

Figure 7 presents the results of three distinct assessments of learning progress adaptability.

Figure 7(a) compares the error rates and task completion times of ten children before and after adaptive difficulty adjustments. Prior to adjustment, the average error rate was 0.25, and the average task completion time was approximately 8 minutes. Following the difficulty adjustment, the error rate decreased to 0.18, and task completion time was reduced to 7 minutes, indicating that adaptive difficulty tuning significantly enhanced learning efficiency and performance.

Figure 7(b) compares the effects of four learning progress adjustment strategies—linear, step-based, adaptive, and mixed adjustments—on adaptability scores over ten weeks. In the first week, the adaptive adjustment strategy achieved an adaptability score of 0.56. Over time, the adaptability scores for all strategies gradually improved, but the adaptive adjustment strategy consistently outperformed the others, reaching a peak score of 0.99 by week 10. The other three strategies showed only marginal improvement throughout the same period. These results clearly demonstrate that adaptive adjustment mechanisms are markedly more effective in enhancing learning progress adaptability, particularly in the later stages of learning, where personalization plays a crucial role.

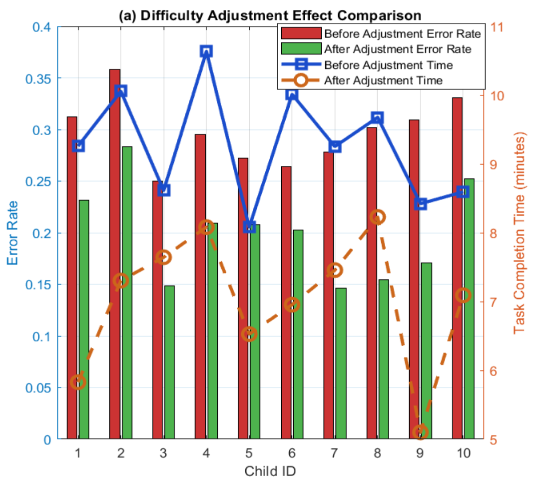

Figure 7. Results of learning progress adaptability evaluation.

3.6. Ablation experiment analysis

To verify the contribution of each key component in the proposed framework, an ablation experiment was conducted with four control groups:

- Complete model – incorporating the full framework (GNN + EMO + feedback mechanism).
- GNN removed – the graph neural network was replaced with an average feature representation.
- Single-objective optimization – GNN retained, but only knowledge acquisition was maximized (multi-objective optimization removed).
- Feedback mechanism removed – closed-loop feedback was disabled, and parameters were statically fixed.

Evaluation results on the same dataset revealed that the complete model achieved significantly superior outcomes compared to the other three groups. Specifically, post-test scores improved by +0.62 points, engagement increased by +0.35 points, and satisfaction rose by +0.41 points ($p < 0.01$). Notably, among kinesthetic learners, the improvement reached 12.8%, highlighting the framework's strong adaptability for diverse learning styles. These findings confirm that the structural modeling capabilities of GNN, the multi-objective optimization mechanism, and the dynamic feedback loop are all indispensable components, collectively forming the core advantages of the proposed system.

4. Conclusions

This study proposes a novel framework for the evaluation and optimization of gamified preschool courses, integrating graph neural networks (GCN/GAT) with GA. The framework effectively combines personalized recommendation, multi-objective optimization, and a dynamic feedback mechanism to enhance course adaptability, engagement, and learning effectiveness. Specifically, the GNN captures complex, non-linear relationships between children's characteristics and course content, while the GA optimizes course configuration parameters to improve design precision. The feedback-driven adaptive mechanism ensures that the system continuously refines itself based on real-time learning data, enabling truly personalized learning experiences.

Experimental results validate the efficacy and robustness of the proposed framework. Post-test scores increased by 0.2–0.7 points compared to pre-test results, while engagement demonstrated a moderate positive correlation ($R^2 = 0.608$) with learning outcomes. Course satisfaction showed a significant positive correlation, particularly for visual and kinesthetic learners. In addition, adaptability evaluations confirmed that the adaptive adjustment strategy produced the most substantial gains in learning progress adaptability.

Despite these encouraging outcomes, the framework still faces certain limitations related to data collection complexity, feedback precision, and generalization across diverse learning contexts. Future work will focus on three key directions:

- Integrating reinforcement learning to develop an "exploration–exploitation" balanced course recommendation strategy, allowing the system to autonomously identify and cultivate learners' potential interests.
- Introducing multimodal perception—including eye-tracking and voice emotion recognition—to enrich learner state modeling and enhance the ecological validity of GNN input features.

- Extending the framework to cross-cultural and multilingual preschool education settings to further test and improve its generalization ability.

Additionally, future development will include optimizing the open-source course application programming interface (API) and lightweight model deployment to support kindergarten teachers in implementing personalized gamified teaching on devices with limited computing power. These advancements aim to facilitate the practical application of this research framework, promoting scalable and adaptive early childhood education in real-world learning environments.

Author contributions

Wei Wei: Conceptualization; methodology; investigation; data curation; writing – original draft; visualization; Li Qian She: Resources; software; validation; project administration; writing – review & editing; AnKun Du: Formal analysis; supervision; Funding acquisition; Writing – review & editing. All authors have read and approved the final version of the manuscript.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors. Ethical approval was therefore not required.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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