AI and Emerging Technologies in Online Learning

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Abstract. The convergence of Artificial Intelligence (AI) and emerging technologies has transformed online learning into a dynamic, personalized, and efficient educational experience. This article explores the impact of AI and other cutting-edge innovations such as Virtual Reality (VR), Augmented Reality (AR), Blockchain, and Internet of Things (IoT) on e-learning platforms. It delves into how these technologies enhance learner engagement, optimize instructional design, automate administrative tasks, and provide data-driven insights. Furthermore, the article includes flowcharts to demonstrate system interactions, pseudocode to elucidate algorithmic processes, and Python code for practical implementation. Through case studies and current implementations, we highlight both the benefits and challenges of integrating these technologies into the education sector.

Keywords: Artificial Intelligence; Online Learning; Virtual Reality; IoT; Adaptive Learning

1. Introduction

Online learning has undergone a massive transformation, primarily driven by advancements in technology. The rise of AI and its synergistic use with VR, AR, Blockchain, and IoT have created a multifaceted ecosystem where learners can receive personalized instruction, immersive experiences, and real-time feedback. These technologies aim to replicate and even surpass traditional classroom experiences [4,9].

The history of online learning traces back to the 1960s, with the development of early computer assisted instruction systems like Programmed Logic for Automated Teaching Operations (PLATO). These early systems were static, offering minimal personalization or interactivity. Over time, the evolution of the internet in the 1990s and the widespread adoption of personal computers created the foundation for modern e-learning platforms. Learning Management Systems (LMS) like Moodle and Blackboard became popular, allowing content delivery and course management online [6].

However, these platforms still followed a “one size fits all” approach. With the rise of AI in the 2010s, a shift began toward data driven, personalized learning. AI technologies introduced adaptive learning paths, predictive analytics and natural language interfaces [2,5,7]. The integration of cloud computing enabled scalable and flexible access to education, while mobile technologies and smartphones made learning more ubiquitous and accessible.

Simultaneously, emerging technologies like VR and AR began to offer immersive environments, allowing learners to experience complex concepts in simulated realities. Blockchain emerged as a secure solution for credential verification and academic record management. IoT devices introduced real-time learning analytics and biometric feedback in smart classroom settings [9].

Today, the synergy between AI and these emerging technologies marks the beginning of a new era in education that is one that prioritizes learner engagement, accessibility and outcomes. This convergence aims not only to enhance knowledge transfer but also to make learning more inclusive and future ready [4,8].

2. Literature Review

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The evolution of online learning has been significantly influenced by rapid advancements in artificial intelligence (AI) and digital technologies. In recent years, scholarly work has increasingly focused on the transformative role of AI in enhancing digital education. Researchers have explored various facets including adaptive learning systems, intelligent tutoring, predictive analytics and the integration of virtual and augmented reality. These innovations have collectively contributed to a shift from static, one size fits all models of e learning toward more personalized and dynamic educational experiences [2,5].

Several studies have underscored the efficacy of AI in providing real time feedback, adaptive learning pathways and automated grading systems. These features help reduce the workload of educators while offering learners immediate insights into their progress. For example, intelligent tutoring systems (ITS) like Carnegie Learning and Knew ton have been shown to significantly improve student engagement and performance through tailored content delivery and scaffolding [6,10].

Another stream of research highlights the application of machine learning and natural language processing in analyzing large volumes of educational data. This has enabled more accurate predictions of student outcomes and the early identification of at-risk learners. Sentiment analysis, clickstream data and eye tracking analytics are being used to model student behavior and inform instructional design [7].

In parallel, the role of emerging technologies such as blockchain, IoT and immersive environments (VR/AR) is being examined for their potential to support credentialing, data security and experiential learning. Blockchain ensures the immutability and authenticity of academic records, while IoT devices facilitate seamless data collection from learning environments [3,9].

Despite these advances, the literature also acknowledges several limitations and ethical concerns. These include data privacy, algorithmic bias, accessibility challenges and the risk of over reliance on technology. Scholars call for robust frameworks that address these issues through interdisciplinary collaboration among technologists, educators and policymakers [1].

In summary, the literature reflects a consensus on the promising role of AI and emerging technologies in transforming online education. However, it also emphasizes the need for responsible design, implementation and governance to ensure these technologies contribute positively to educational equity and effectiveness.

3. Methodology and Research Framework

This article employs a qualitative synthesis and applied analysis methodology designed to explore the integration and effects of AI and emerging technologies in online learning environments. The approach combines conceptual modeling, case-based examination and system simulation to deliver a multi-dimensional view of current practices and future directions.

3.1 Conceptual Framework Development. We developed a conceptual framework by synthesizing existing models of adaptive learning systems, AI architecture and user centered design in educational technology. This framework guided the categorization of technologies based on functionality, integration depth, and impact on learning outcomes [3].

3.2 Selection of Case Studies. Three representative case studies were chosen from academic institutions and private EdTech providers known for pioneering the use of AI, VR/AR and blockchain in education. The selection criteria are based on availability of documented implementation practices, measurable impact on learner engagement or academic performance diversity in technology deployment and target demographics [4,10].

3.3 Analytical Techniques. We utilized thematic analysis to identify key patterns and roles AI plays in online learning. Flowcharts and system diagrams were created to visualize interactions between technological components. Additionally, pseudocode was written to illustrate how algorithms function within learning management systems.

3.4 Tools and Technologies. For simulation and code examples, Python and its associated libraries for example Scikit-learn, TensorFlow, Flask were used to implement AI modules and data handling logic [7].

3.5 Validation and Limitations. Findings were validated by cross referencing with peer reviewed studies, technology documentation and expert commentary. The main limitations include the reliance on secondary data and publicly available case reports, the limited empirical testing due to the scope of the article and also the fast-evolving nature of EdTech tools, which may affect long term relevance [1,10].

4. System Architecture and Design

The architecture of AI powered online learning platforms consists of several integral components that work together to provide a personalized and engaging learning experience. At the core lies the AI engine, which functions as the brain of the system. It is responsible for user profiling, learning path recommendation, behavior analysis and continuous adaptation based on learner performance and preferences [5,7]. This engine is connected to a robust content management system (CMS), which organizes educational resources such as videos, quizzes, readings, and simulations [6].

Another critical component is the learning analytics dashboard. This dashboard provides instructors and administrators with insights into learner engagement, progress and achievement metrics. It allows for real time data monitoring and enables evidence-based decision making to improve course design and instruction [10]. Additionally, the architecture incorporates a communication and interaction layer, supporting forums, chats, and AI-powered chatbots that address student queries and offer timely support [1,5].

Security and authentication are ensured through blockchain technology, which secures user data and digital credentials [3]. The architecture is also scalable and modular, making it adaptable for different educational contexts and institutions. Integration with IoT devices, such as biometric sensors or smart classroom tools, provides real time feedback to the AI engine for further personalization [9].

4.1 Pseudocode: Adaptive Learning Path Algorithm.

The core code is as follows:

```
function generateLearningPath(studentProfile):
    topics = getAllTopics()
    completedTopics = studentProfile.completedTopics
    performance = studentProfile.performanceMetrics

    path = []
    for topic in topics:
        if topic not in completedTopics:
            difficulty = assessDifficulty(topic)
            if performance.meetsCriteria(difficulty):
                path.append(topic)
    return path
```

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay

# Sample dataset
data = pd.DataFrame({
    'study_hours': [1, 2, 3, 4, 5, 6, 7, 8],
    'attendance': [60, 65, 70, 75, 80, 85, 90, 95],
    'passed': [0, 0, 0, 1, 1, 1, 1, 1]
})

# Features and target
X = data[['study_hours', 'attendance']]
y = data['passed']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

# Train model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predictions
predictions = model.predict(X_test)
print('Accuracy:', accuracy_score(y_test, predictions))

# --- Plot Decision Boundary ---
# Create grid
x_min, x_max = X['study_hours'].min() - 1, X['study_hours'].max() + 1
y_min, y_max = X['attendance'].min() - 5, X['attendance'].max() + 5
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))

# Predict grid classes
Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

# Plot
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.contourf(xx, yy, Z, alpha=0.4, cmap='coolwarm')
plt.scatter(X['study_hours'], X['attendance'], c=y, edgecolors='k', cmap='coolwarm', s=100)
plt.xlabel('Study Hours')
plt.ylabel('Attendance (%)')
plt.title('Decision Boundary: Pass (1) vs Fail (0)')

# --- Confusion Matrix ---
plt.subplot(1, 2, 2)
cm = confusion_matrix(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Fail (0)', 'Pass (1)'])
disp.plot(cmap='Blues', ax=plt.gca())
plt.title('Confusion Matrix')

plt.tight_layout()
plt.show()
```

Figure 1. A simple student performance predictor using logistic regression

4.2 Output results for Accuracy, Visualization and the confusion matrix of the model evaluation. The model achieved a perfect accuracy score of 1.0, meaning it correctly predicted all outcomes in the test dataset. Data was split into 75% training (6 samples) and 25% testing (2 samples). This result indicates that the logistic regression classifier successfully learned the underlying patterns in the training data and applied them flawlessly to the test samples. However, this exceptional performance should be interpreted with caution due to the extremely small dataset size of only 8 total samples. While the result demonstrates the model's capability to handle this specific miniature dataset, further testing is necessary to confirm its real-world applicability.

```
Accuracy: 1.0
```

Figure 2. Output result showing accuracy of 1.0

The decision boundary plot visually demonstrates how the logistic regression model separates students predicted to pass (red region) from those predicted to fail (blue region) based on study hours and attendance. The clear boundary line represents where the model's predicted probability equals 50%, with students above this threshold classified as passing. All actual data points (dots) align perfectly with their corresponding-colored regions that is red dots (true pass labels) appear in the red zone and blue dots (true fail labels) in the blue zone that is confirming the model's 100% accuracy on this dataset. This visualization highlights the model's ability to identify the linear relationship between study habits (hours and attendance) and academic success, though the exceptionally clean separation may also reflect the simplicity and small size of the dataset. For real world applications, further validation with larger, more complex data would be essential to ensure robustness.

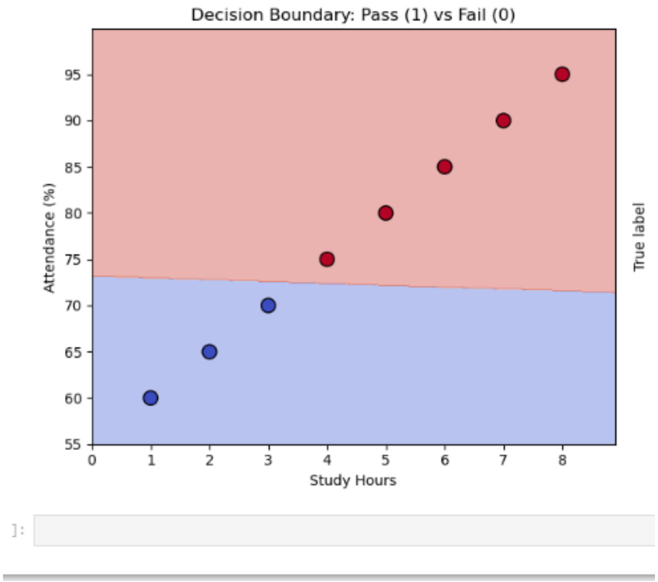

Figure3. Decision boundary graph to visualize the model evaluation

The confusion matrix provides a detailed breakdown of the model's performance by comparing predicted labels against actual outcomes. In this case, the matrix shows a perfect classification result that is all predictions matched the true labels, with 1 true negative (correctly predicted "Fail") and 1 true positive (correctly predicted "Pass"). There were no false positives or false negatives, indicating misclassifications. This aligns with the model's 100% accuracy, confirming its ability to distinguish between passing and failing students on this small test set. However, the absence of errors may also reflect the limited dataset size, suggesting the need for further testing on larger or more diverse data to assess generalizability. The confusion matrix underscores the model's precision in this specific scenario while highlighting the importance of rigorous validation for real world deployment.

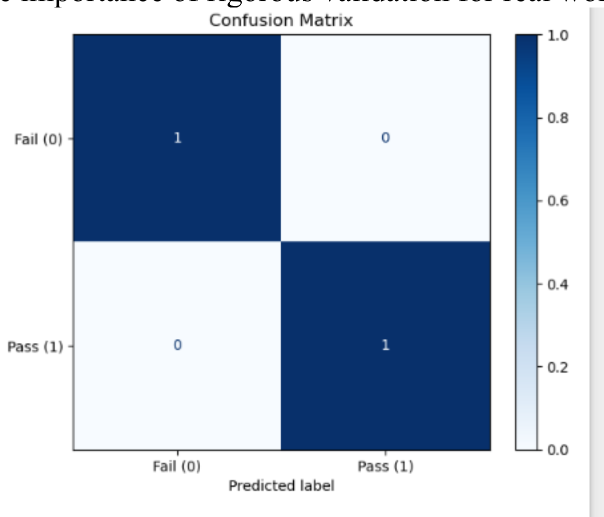

Figure 4. Confusion Matrix graph to visualize the model

The ROC (Receiver Operating Characteristic) curve is a graphical representation used to evaluate the performance of a classification model, such as Logistic Regression in this case. The curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The Area Under the Curve (AUC) is a key metric derived from the ROC curve, summarizing the model's ability to distinguish between classes. Here, the Logistic Regression model achieves a perfect AUC score of 1.00, indicating it is a flawless classifier that can perfectly separate the classes.

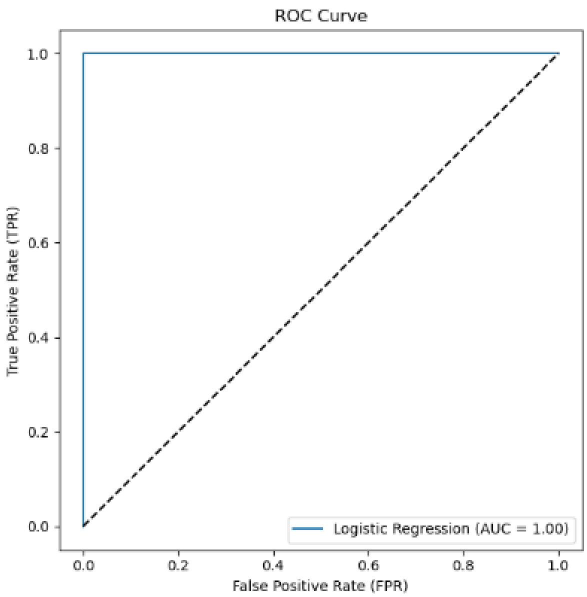

Figure 5. ROC curve output for increased Accuracy

An AUC of 0.5 suggests the model performs no better than random guessing, while an AUC of 1.0 represents ideal classification performance. Unlike accuracy, which can be misleading for imbalanced datasets, the AUC provides a more reliable measure of a model's overall performance because it considers all possible classification thresholds. A higher AUC value signifies better discriminatory power, making it a robust metric for assessing model effectiveness, especially in scenarios with uneven class distributions. The ROC curve and AUC are particularly valuable for understanding the trade-offs between sensitivity (TPR) and specificity (1-FPR) across different thresholds.

5. Role of AI in Online Learning

AI serves as the brain behind modern online learning platforms by delivering personalized, scalable and data driven experiences. The roles of AI in e-learning extend deeply into multiple domains.

5.1 Personalized Learning. AI dynamically assesses individual learners' needs, adapting learning paths based on test results, activity engagement and learning pace. Adaptive engines use learner models to refine recommendations and content exposure, supporting mastery-based learning [2,5].

5.2 Intelligent Tutoring Systems. These AI based tutors emulate human instructors using NLP and machine learning to provide hints, explanations and error feedback. They adjust instruction in real time and simulate Socratic dialogue, offering scalable, high-quality tutoring [6,10].

5.3 Predictive Analytics. Machine learning algorithms mine historical data to forecast performance trends, identify struggling learners and suggest real time interventions. Techniques include classification models to predict dropouts and regression models to estimate grade trajectories [7,8].

5.4 Automated Assessment and Feedback. AI algorithms grade multiple formats of assignments that is MCQs, essays, code instantly and provide targeted feedback. NLP tools assess grammar, coherence and content relevance, while computer vision grades diagrams or practical submissions [5,7].

5.5 Virtual Teaching Assistants. AI powered chatbots support learners around the clock, answering FAQs, reminding deadlines and even helping with academic queries. They operate via deep learning models trained on institutional knowledge bases [1].

5.6 Content Curation and Generation. Using AI, platforms dynamically curate reading materials, videos and quizzes aligned with student goals. Generative AI models like GPT can summarize lectures, generate practice questions and translate materials for multilingual support [4].

6. Emerging Technologies and Their Integration

The integration of emerging technologies amplifies AI's capabilities and redefines the structure of digital education.

6.1 Virtual Reality (VR) and Augmented Reality (AR). VR creates simulated environments for experiential learning that is virtual labs, 3D walkthroughs and collaborative problem-solving spaces. AR overlays real world settings with instructional content, ideal for vocational training, engineering or medicine. These technologies enhance motivation and cognitive engagement by immersing learners in authentic contexts [4,10].

6.2 Blockchain. Blockchain introduces transparency, trust and security in academic credentialing. Decentralized ledgers verify course completion, issue tamper proof certificates and support peer to peer learning validation. Smart contracts can also automate tasks such as attendance verification or micro credential issuance [3].

6.3 Internet of Things (IoT). IoT devices gather and transmit real time learner data like attention spans, physical activity and engagement levels such as enabling context aware personalization. For example, smart desks and wearables track physical posture or stress levels, while connected devices provide alerts to instructors [9].

6.4 Learning Analytics and Big Data. By aggregating millions of learning interactions, institutions can discover behavioral trends and optimize content delivery. Clustering algorithms group learners by performance patterns, while dashboards powered by analytics offer educators actionable insights [7,10].

6.5 Cloud Computing. Cloud services provide the backbone for scalable, cost-efficient platforms. On demand computing power supports AI processing, while distributed storage ensures high availability. Cloud APIs facilitate easy integration with third party tools like assessment engines or simulation modules [8].

These technologies, when combined with AI, foster an ecosystem that is adaptive, immersive, secure and globally accessible. Their interoperability is critical to the success of next generation digital education platforms [4].

7. Implementation and Technical Approaches

The implementation of AI and emerging technologies in online learning systems requires a structured approach that balances innovation with practical deployment. Drawing on design-based research methodologies, we develop the system iteratively, involving continuous testing, evaluation and refinement to meet educational goals. This approach allows educators and developers to align technological functionality with pedagogical needs, ensuring that new features address real world learning challenges [5,7].

The deployment phase typically begins with the construction of modular learning components that can be easily tested and updated. AI modules, such as recommendation engines or automated feedback systems are integrated with existing learning management systems. During each iteration, usability testing is conducted with sample learners and educators, who provide feedback that informs further development. This iterative cycle is vital for achieving user centered design and functionality [6,10].

Technical implementation often involves integrating AI algorithms like decision trees, natural language processing or deep learning models into the platform’s backend. These algorithms require continuous training and refinement using anonymized learner data. In practice, this data is collected through user interactions, such as quiz responses, navigation patterns and communication logs, which serve as input for improving the recommendation and personalization mechanisms [7]. Cloud based infrastructure is typically employed to manage the high computational demands and ensure scalability across multiple institutions [9].

Mobile first development is another critical aspect of implementation, recognizing that many users access online learning platforms via smartphones or tablets. Responsive interfaces and offline capabilities help ensure accessibility and engagement. Finally, collaboration with stakeholders that is educators, technologists and policymakers which is essential for refining technical approaches and aligning them with educational standards and learner expectations [1,5].

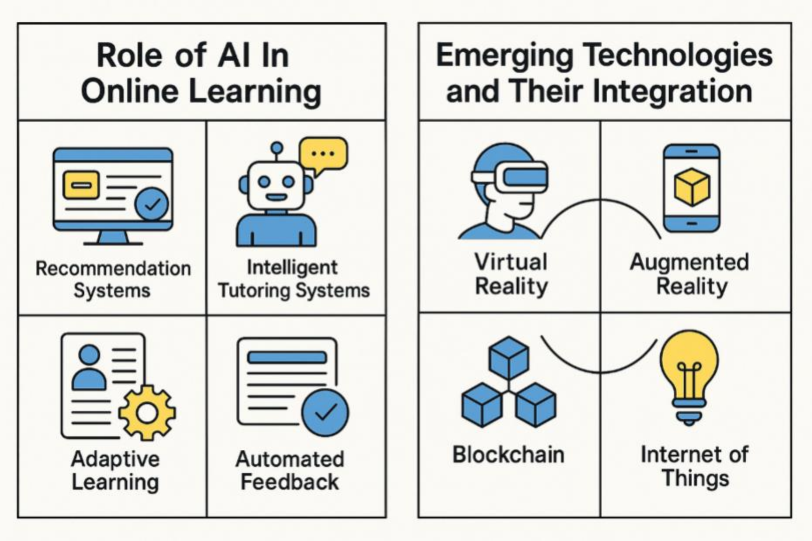

Figure 6. Role of AI and Emerging Technologies In Online Learning

8. Case Studies

8.1 Carnegie Learning. An educational technology company that integrates AI driven adaptive learning software into mathematics education. Its system uses machine learning algorithms to assess students' performance in real time and adapt instruction to their individual needs. The software recommends exercises and provides hints based on each learner's strengths and weaknesses. According to various reports, the implementation has improved student outcomes by allowing teachers to personalize instruction efficiently [2,7].

8.2 Arizona State University (ASU) and Adaptive Learning. ASU has incorporated adaptive learning platforms like Cog Books and Smart Sparrow into several foundational online courses. These platforms analyze student interactions and dynamically adjust the sequence and difficulty of course content. Instructors receive analytics dashboards that help identify students who are struggling. ASU reported improved retention rates and academic performance, particularly in high enrollment introductory courses [5].

8.3 Lobster Virtual Labs. Lobster is a platform that uses VR to simulate laboratory environments for science education. Students can conduct experiments in chemistry, biology and physics without the need for physical lab infrastructure. These VR experiences include AI driven guidance and assessments. Studies show that Lobster enhances student engagement and understanding, especially in institutions with limited access to physical lab resources [4].

8.4 ODEM (On Demand Education Marketplace) with Blockchain. ODEM uses blockchain technology to create a decentralized marketplace for education. It allows students to enroll in courses, track their learning progress and receive verified credentials. The use of blockchain ensures transparency, data security and seamless credential verification for employers. This model promotes trust and reduces reliance on traditional institutional verification [3].

8.5 Georgia Tech's AI Teaching Assistant (Jill Watson). Georgia Tech developed "Jill Watson", an AI teaching assistant powered by IBM Watson, to handle routine queries in online forums for a graduate level AI course. Jill answered student questions with high accuracy and consistency, significantly reducing instructor workload and response time. Students were unaware they were interacting with an AI, demonstrating the potential of conversational AI in education [1,7].

8.6 Smart Classrooms in South Korea. Several schools in South Korea have adopted IoT based smart classroom technologies. These include biometric systems to track student attention, interactive digital boards and environmental sensors. AI systems analyze this data to optimize classroom conditions and provide personalized feedback. Teachers use these insights to adjust lesson plans, improving classroom effectiveness and learner outcomes [4,6].

These case studies collectively highlight how AI and emerging technologies are being practically deployed across different education levels and settings to improve engagement, efficiency and academic achievement.

9. Challenges and Ethical Considerations

While AI and emerging technologies offer transformative potential in online education, they also raise significant challenges and ethical concerns that must be carefully addressed to ensure responsible use and equitable access. One major concern is data privacy and security. AI driven systems rely heavily on the collection and analysis of sensitive personal data, including learning behavior, biometric data and performance history. This reliance exposes students to risks such as data breaches, misuse of information and ambiguity over data ownership. There is also the issue of informed consent, where students may not be fully aware of how their data is being utilized [1,7].

Another critical issue is algorithmic bias and fairness. AI models can inadvertently reflect or even amplify societal biases present in training data. This can lead to unequal learning opportunities, where certain demographics receive skewed recommendations or assessments, resulting in discriminatory outcomes. Addressing this problem requires transparency in model design and the implementation of regular audits to detect and correct biases [2].

Furthermore, the digital divide remains a persistent challenge. Although online learning platforms can democratize access to education, many students lack reliable internet connectivity or access to modern devices. Technologies such as VR and AR, while immersive, demand expensive hardware, thereby limiting accessibility for economically disadvantaged students. Additionally, learners with disabilities may encounter difficulties when engaging with these interfaces if appropriate assistive technologies are not integrated [4].

The over reliance on automation can also devalue essential human elements in education. Systems that automate grading, feedback or tutoring may overlook the nuanced understanding and empathy provided by human educators. Moreover, automated systems may lack context sensitivity, which can lead to misguidance or frustration among learners [6,7]

Ethical concerns extend to the use of emerging technologies themselves. For instance, prolonged use of VR environments might affect cognitive health, while blockchain's immutability can hinder the correction of data entry errors. IoT devices used for real time monitoring might raise surveillance concerns among students, potentially impacting their learning comfort and psychological safety [3,4].

Intellectual property and content ownership is another pressing issue. With the increasing use of AI generated content, questions arise about who holds the rights to such materials. There are also concerns regarding proper acknowledgment and compensation for creators whose work contributes to AI training datasets. Institutions must tread carefully to ensure that AI generated teaching content does not infringe on existing intellectual property laws [1].

Additionally, educators face the challenge of adapting to new technologies. Teachers may resist change due to a lack of confidence or insufficient training. Without ongoing professional development and robust technical support, the integration of AI tools can falter. Teachers need comprehensive training programs that are hands on and continuous to maximize the benefits of technological adoption [5,6].

Finally, regulatory and legal frameworks have not kept pace with technological advancements. There is a pressing need for updated legislation that outlines ethical standards for AI use, enforces data protection, and ensures platform accountability. These issues become even more complex when dealing with international platforms, which must navigate cross border legal and policy differences [1,8].

Overcoming these challenges demands a multidisciplinary effort involving educators, developers, ethicists and policymakers. Only through collaborative governance, transparent technology development and a commitment to equity and inclusion can the potential of AI in education be fully and ethically realized [1,2].

10. Future Outlook

The future of online learning, empowered by AI and emerging technologies, is anticipated to undergo a profound transformation. Advancements in artificial intelligence will foster hyper-personalized learning environments, with future AI models utilizing real-time behavioral and cognitive analytics to customize content, pace and delivery style. These environments will integrate affective computing, eye tracking and even neural feedback to dynamically respond to a learner's emotional and cognitive states, thereby enhancing engagement and comprehension [7,10].

Moreover, the development of decentralized and credentialed learning ecosystems will redefine educational pathways. Powered by blockchain technology, learners will be able to accumulate verifiable micro credentials from multiple institutions, own their educational records and present tamper proof qualifications to employers across the globe [3]. This paradigm shift will empower individuals to curate their lifelong learning journeys independently moving beyond traditional degree centric models [4].

Immersive experiential learning is set to advance significantly with the proliferation of Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR). These technologies will provide realistic simulations in diverse fields like medicine, engineering and history, enabling learners to participate in collaborative 3D environments and gain practical skills through virtual internships and laboratories, democratizing access to hands on experiences [4,6].

AI powered career guidance and life coaching tools will also emerge as integral components of online platforms. These intelligent systems will analyze a learner's progress and market demands to suggest optimal career pathways, skill development tracks and even provide personalized life coaching that aligns with an individual's values, personality traits and aspirations [5,8].

The integration of educational systems with smart cities and IoT infrastructure will further optimize learning conditions. AI systems will adapt learning schedules based on contextual data such as traffic, public events or health advisories. They will also personalize learning environments by adjusting lighting, temperature or noise levels in physical classrooms to enhance concentration and safety [3,4].

Importantly, human AI collaboration in teaching will enhance rather than replace traditional pedagogy. Educators will be supported by intelligent co instructors that provide analytics, automate routine tasks like grading and offer content recommendations. This will allow teachers to devote more time to mentorship, creativity and socio emotional learning, ultimately shifting their role to designing flexible, student centered ecosystems [2,7].

Lifelong learning will solidify as the new educational norm. From AI tutors for senior citizens to adaptive learning systems for mid-career professionals, AI will support continuous education throughout all stages of life. Companies will embed these technologies into workplace platforms to facilitate ongoing employee development [5].

Lastly, as AI's role in education deepens, it will become essential to teach AI ethics as part of core curricula. Students will engage in projects that explore digital citizenship, audit AI systems and understand the social implications of algorithmic decision making. Interdisciplinary education blending humanities with technology will be vital in preparing responsible and informed digital citizens [2,10].

In essence, the future of AI in online learning is defined by its potential to personalize, decentralize and globalize education while upholding principles of equity, transparency and ethical responsibility. With careful design and inclusive policy frameworks, this transformation can yield a more engaging, accessible and human centric learning experience [1,10].

11. Conclusion

The convergence of AI and emerging technologies is revolutionizing online learning. By making education more personalized, efficient and engaging, these innovations hold the promise of democratizing access and improving outcomes globally. However, challenges remain, especially in ensuring equitable access and ethical use.

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Evaluation of Student Dormitory Design Programs in Universities

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Abstract. Student dormitory is an important place for students' daily life and study, and its design and construction have an important impact on students' physical and mental health and learning effect. Therefore, the evaluation of student dormitory design programs is particularly important. In this paper, we take economy, comfort and safety as the core evaluation dimensions, construct an evaluation system containing nine indicators, including construction cost, operation cost, fee, per capita area, lighting and ventilation, evacuation, and burglary prevention, and use hierarchical analysis to quantitatively evaluate four typical student dormitory design solutions. By establishing hierarchical model, constructing judgment matrix, and conducting consistency test, the weights of each index are calculated and scored comprehensively. The results show that Scheme 4 is outstanding in terms of safety (shortest evacuation time, highest anti-theft index) and comfort (largest per capita area, optimal ease of use), and has the best comprehensive performance despite higher operating costs; Scheme 2, 3, and 1 are the next best. The study provides a scientific basis for the optimization of student dormitory design scheme, which can effectively improve the living quality and management efficiency of the dormitory.

Keywords: Hierarchical analysis; Evaluation; Optimization; Economy; Comfort; Safety

1. Introduction

As an important part of the infrastructure of higher education, student dormitory is the core space for students to live, study and socialize during their school years, and the quality of its design is directly related to students' physical and mental health, learning efficiency and campus life satisfaction. With the development of higher education and the diversification of students' needs, dormitory design is no longer limited to the simple "residential function", but needs to achieve a dynamic balance between economy, comfort and safety - to control the construction and operation costs, and to meet the students' demand for convenience, but also to ensure the safety and reliability of the living environment.

In foreign countries, the design of student dormitories in colleges and universities focuses on diversification and humanization, rich in types, equipped with complete functional space and service facilities [1], and attaches importance to the creation of communication space and personal space privatization [2], such as European and American colleges and universities, mostly using the model of living room plus bedroom suite to promote student communication. Early domestic dormitory construction focuses on quantity but not quality, and nowadays, although there are improvements, there are still problems such as insufficient service facilities, lack of humanization, monotonous environment, etc. [3], for example, some college dormitories have a small storage space, dull layout, and traditional decorations.

2. Current Problems

At present, the evaluation of student dormitory design solutions mostly relies on empirical judgment or single-dimension analysis [4], and lacks a systematic quantitative assessment framework [5], which makes it difficult to comprehensively reflect the integrated advantages and disadvantages of different solutions. For example, some solutions may be prioritized due to low construction costs [6], but neglect problems such as insufficient lighting [7] or evacuation difficulties; others lack feasibility due to high fees despite outstanding comfort [8]. For this reason, this paper takes four typical student dormitory design schemes as the research object, constructs a multi-indicator evaluation model based on hierarchical analysis method (AHP), and quantitatively analyzes the three dimensions of economy (construction cost, operation cost, charging standard), comfort (per capita area, ease of use, lighting and ventilation), and security (evacuation, anti-theft), with the purpose of providing a scientific preference for university dormitory design schemes with a theoretical basis and practical guidance. The purpose is to provide a theoretical basis and practical guidance for the scientific selection of university dormitory design options, and ultimately realize the "cost-controllable, comfortable, safe and reliable" goal of student dormitory construction.

3. Construction of Hierarchical Analysis

3.1 Subject of This Study. This study takes four common buildings with different architectural styles as an example, and constructs a multi-indicator evaluation model based on AHP to analyze them from the three dimensions of economy, comfort and safety, and the four architectural styles are shown below Table 1:

Table 1 Four dormitory design options

	construction area (㎡)	Rooms(room)	Number of students(person)	Bedrooms(㎡)	Bathroom(㎡)	bathrooms (㎡)	Fun rooms(㎡)
Pro. 1	877.35	23	184	25.5	25.52	27.52	/
Pro. 2	2660	55	220	25	28	27.7	115.8
Pro. 3	2229	38	228	26.9	17.2	21.2	/
Pro. 4	1886.64	22	132	52.5	3.6	4.32	/

3.2 Assessment of Individual Indicators in Different Dimensions. By estimating the two-dimensional floor plan and various indicators of the university's design, it can be concluded that: the construction cost per square meter is 1,700 m^2, and the operating cost includes: the salary of the management personnel (assuming 2,790 yuan per person per month), the electricity cost (36 yuan per dormitory per month) and the fixed energy consumption (3,000 yuan per month); and the total charge is calculated according to the number of students based on the benchmark of 112 yuan per student per month for the accommodation fee. Per capita area is derived from the ratio of floor area to the number of dormitory occupants; ease of use is measured by the ratio of common area to the number of students; balcony area is used as the core indicator to assess the effect of natural lighting and air circulation. The evacuation of people needs to consider the evacuation area, staircase capacity and evacuation time in case of emergency; the anti-theft index needs to synthesize the design of doors and windows, monitoring configuration and other factors to quantify the anti-theft ability of the dormitory. From this, the treatment value of each index can be derived:

Table 2 Assessment of indicators in the three dimensions

	D1[￥]	D2[10,000￥]	D3[month]	D4[㎡]	D5	D6	D7[㎡]	D8[min]	D9
Pro.2	1491495	81.46	3427	4.77	0.44	0.39	4.42	2.37	69
Pro.2	4522000	86.05	3360	12.1	1.45	0.78	14.4	1.22	110

Pro.2	3789300	80.34	3615	9.78	2.01	0.56	2.06	0.84	109
Pro.2	3207288	95.55	2352	14.3	3.28	1.09	0	0.53	131

Because of the large differences in the scale and value range of different indicators, direct analysis will be dominated by large-value indicators. Normalization can eliminate the influence of the scale, so that the indicators are in the same order of magnitude, which is convenient for fair comparison, modeling and analysis, and improves the scientific nature of data mining and decision-making. Normalization of the data in Table 2 yields.

Table 3 Normalization of indicators

	D1[￥]	D2[10,000￥]	D3[month]	D4[㎡]	D5	D6	D7[㎡]	D8[min]	D9
Pro.1	0	0.073	0.851	0	0	0	0.307	1	0
Pro.2	1	0.375	0.798	0.769	0.356	0.557	1	0.375	0.665
Pro.3	0.758	0	1	0.526	0.553	0.243	0	0.169	0.654
Pro.4	0.566	1	0	1	1	1	0	0	1

3.3 Construction of Hierarchical Analysis. There are many factors affecting the good and bad of the student dormitory design program, the famous American operations researcher T. L. Saaty in the early 1970s proposed the hierarchical analysis method AHP (analytical hierarchy process) [9] is to quantify the subjective judgment of the human being with a scale, a simple and practical multi-objective decision-making quantitative analysis of qualitative problems. method. We can turn the evaluation problem of student dormitory design scheme into the ranking problem of the relative importance of each factor in the hierarchy to the upper factors, take the comparative judgment of pairs of factors in the ranking calculation, and according to a certain ratio scale, form the judgment matrix, calculate the weight of each factor, and reasonably evaluate the design scheme of student dormitory.

Suppose there are n target bodies, denoted as C_1、$C_2 \cdots C_n$, whose same class attributes are D_1、$D_2 \cdots D_n$.

The AHP decision-making method consists of the following steps:

3.3.1 Modeling of Hierarchical Structures. The elements contained in the problem are grouped and each group is treated as a hierarchy, arranged in the order of goal, criterion, sub-criterion, and programmatic layers. Assessment of the resulting changes serves as model validation. As shown in Fig. 1:

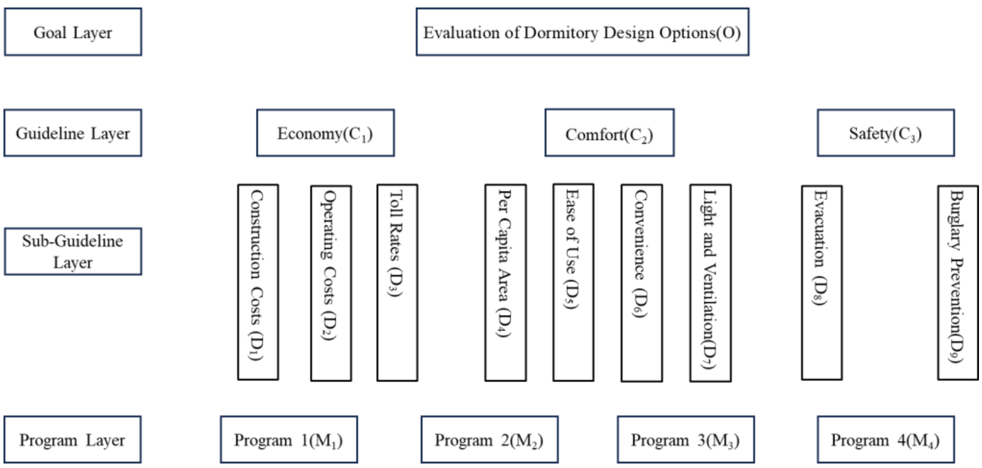

Figure 1. Schematic diagram of the hierarchical model

3.3.2 Construct Judgment Matrix. The judgment matrix element values reflect people's perception of the relative importance of the factors, usually using 1-9 and its reciprocal scale, corresponding to the judgment scale in Figure 2. If the importance of the intercomparison of factors can be illustrated by the ratio of the practical significance of the judgment matrix corresponding to the value of the value can be taken as the ratio [10].

Table 4 Definition of Judgment Scales

Judgment Criteria	Meaning
1	D_i and D_j are equally important
3	D_i and D_j are slightly important
5	D_i and D_j are clearly important
7	D_i and D_j are Strongly Important
9	D_i and D_j are extremely important
2,4,6,8	Intermediate between the above two adjacent judgment scales

Judgment matrices are constructed from different indicators in the three dimensions of economy, comfort and safety as the core evaluation. This is shown in Table 5:

Table 5 Construction of judgment matrix

C	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
D_1	1	2	3	1/4	1/3	1/2	1/5	1/7	1/6
D_2	1/2	1	2	1/5	1/4	1/3	1/6	1/8	1/7
D_3	1/3	1/2	1	1/6	1/5	1/4	1/7	1/9	1/8
D_4	4	5	6	1	2	3	1/2	1/4	1/3
D_5	3	4	5	1/2	1	2	1/3	1/5	1/4
D_6	2	3	4	1/3	1/2	1	1/4	1/6	1/5
D_7	5	6	7	2	3	4	1	1/3	1/2
D_8	7	8	9	4	5	6	3	1	2
D_9	6	7	8	3	4	5	2	1/2	1

3.3.3 Hierarchical Single Ordering and Consistency Tests. Whether the judgment matrices of each layer structure are reasonable, i.e., whether the experts' evaluations are logically consistent, needs to be measured by a consistency index. According to matrix theory, the sufficient condition for an n-order inverse matrix to have consistency is that its maximum eigenvalue λmax is n. When n is large, the maximum eigenvalue of the judgment matrix A and the corresponding eigenvector W can be calculated according to the following method, which is the ranked weight of the corresponding factor at the same level with respect to the relative importance of a certain factor at the previous level after normalization. The maximum value of λmax is 9.401394, in order to carry out the consistency test of the one-time single ranking (or judgment matrix), it is necessary to calculate the consistency index as CI,which is calculated as follows：

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (1)$$

CR is the consistency ratio, which is an indicator of the consistency of judgment matrix in hierarchical analysis method, and can be calculated from the judgment matrix, and its calculation formula is:

$$CR = \frac{CI}{RI} \quad (2)$$

If CR<0.10, then the evaluation made by the judgment matrix A is reasonably compatible, otherwise it is necessary to adjust the value of the elements of the judgment matrix, the average consistency index table [11] is shown below:

Table 6 Average consistency indicators

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.89	1.12	1.24	1.32	1.41	1.49	1.51

3.3.4 Hierarchical total sorting and consistency test. After the hierarchical single sorting, the relative importance weights for calculating all the factors at the same level for the highest target level are further calculated according to the AHP theory. The sorting weights of the factors at the previous level are weighted to summarize the single sorting weights of the factors at the next level. If the previous level C contains n factors C_1, C_2, ⋯, C_n. its hierarchical sorting weights were C_l, C_2, ⋯, C_n, the next level contains m factors D_l, D_2, ⋯D_n, they are for the factor C_j hierarchical single-ranking weights were D_{1j}, D_{2j} ... ... Dmj At this point, the D level of total importance of all the factors of the highest target level. .Dmj At this time, the total ranking weights of D level are: from $\sum_{j=1}^{n} C_j D_{1j}$ to $\sum_{j=1}^{n} C_j D_{nj}$.

Consistency test: If the corresponding average stochastic consistency indicator CI_j of certain factors of level D for the single ordering of level C is RI_j, then the formula for the total ordering stochastic consistency ratio of level D is:

$$CR = \frac{\sum_{j=1}^{n} c_j CI_j}{\sum_{j=1}^{n} c_j RI_j} \quad (3)$$

Consistency test was performed and satisfactory consistency was obtained with CI=0.050174, RI=1.449990, CR=0.034603<0.10.

3.3.5 Assessment of importance ranking weights for design options for dormitories

The core code is as follows:

```
% Compute eigenvalues and eigenvectors
[V, D] = eig(A);
% Find the eigenvector corresponding to the largest
eigenvalue
[maxEigenvalue, maxIndex] = max(diag(D));
weights = V(:, maxIndex);
% Normalize the feature vectors to get the weights
weights = weights / sum(weights);
% Display weights
disp(' Importance weight： ');
disp(weights);
```

Table 7 Ranking of indicator weights at the sub-criteria level

Parameters	Sorting	Weights
D_8	1	0.3121
D_9	2	0.2223
D_7	3	0.1555
D_4	4	0.1075

D_5	5	0.0739
D_6	6	0.0507
D_1	7	0.0350
D_2	8	0.0247
D_3	9	0.0183

4 Summary

This paper establishes a model through hierarchical analysis, and evaluates the model from three aspects of economy, comfort and safety. Considering from the aspect of safety: the evacuation time of Option 4 is the least, and the evacuation time of Option 1 is the longest; from the aspect of burglary prevention, we can see that the burglary prevention ability of Option 1 is the worst, and the burglary prevention ability of Option 4 is the best. Considering from the perspective of comfort: Option 1 has the worst experience in terms of “area per capita”, “ease of use” and “non-interference”, while Option 4 has the opposite; from the perspective of “lighting and ventilation”, Option 4 has the worst experience. In terms of “light and ventilation”, shows that Option 2 has the highest indicators, while Options 3 and 4 have the lowest indicators. From the economic aspects of to consider: according to the “construction cost” aspect: the cost of Option 1 is the lowest, the cost of Option 2 is the highest; according to the “running cost” factor, the running cost of Option 3 is the lowest, the running cost of Option 4 is the highest; from the “fee standard” aspect: the cost of Option 2 is the lowest, the cost of Option 4 is the highest. According to the factor of “fee standard”, Option 3 has the highest fee and Option 4 has the lowest fee cost. Through comparison, the best option is option 4, followed by option 2, option 3, option 1, of which option 4 is the best in terms of economy, comfort and safety.

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Painting Migration Exploring the Integration of Computing and Art in Teaching and Learning

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Abstract. With the rapid development of artificial intelligence technology, painting style migration, as a cross field between computer vision and art creation, provides new possibilities for art education innovation. This study explores the application of drawing style migration technology in the teaching of computer and art integration, aiming to solve the problems of low efficiency of style learning, high threshold of creation, and insufficient interdisciplinary integration in traditional art teaching. By constructing a deep learning-based drawing style migration teaching framework and combining quantitative and qualitative research methods, the effectiveness of the model in enhancing students' artistic expression, depth of technical understanding and creative thinking ability is verified.

The study adopts a controlled experimental design, selecting students from an art college and dividing them into an experimental group (integrated teaching) and a control group (traditional teaching) for a 16-week teaching experiment. The experimental group learns about stylistic feature extraction and parameter tuning through VGG19 and ResNet50 pre-training models, and combines art history analysis with digital creation practice. The research constructed a three-dimensional assessment system of “artistic performance-technical mastery-learning effectiveness”, and quantitatively analyzed the index of stylistic diversity, creativity novelty, algorithmic comprehension accuracy and other indexes of the students. The experimental results show that the experimental group is significantly better than the control group in terms of stylistic diversity, technical mastery and creative efficiency. The qualitative analysis further shows that the style migration technology promotes students' in-depth understanding and creative expression of art styles through the triple effects of “algorithmic lens”, “creative gas pedal” and “thought converter”. The innovation of this study lies in the following: the proposed algorithmic lens, the creative accelerator, and the thought transformer.

The innovations of this study include: proposing a progressive teaching model of “deconstruction-restructuring-creation”, which reduces the technical learning curve; developing a lightweight style migration tool for educational applications, which supports real-time parameter adjustment and effect feedback; and revealing the intrinsic mechanism of the integration of art and computational thinking. Practice shows that the drawing style migration technology not only enhances teaching efficiency, but also expands the boundaries of artistic creation, providing a generalizable paradigm for interdisciplinary art education. Future research can further explore the adaptive learning path and the design of creative environment that integrates reality and fiction.

Keywords: Drawing Migration; Computer Art; Integrated Teaching; Deep Learning; Innovation in Art Education

1. Introduction

Under the background of rapid development of digital and intelligent technology, art education is facing unprecedented transformation opportunities and challenges. The traditional art teaching model has long relied on the teacher-apprentice system of teaching and copying techniques, and this one-way teaching method is not only inefficient, but also difficult to adapt to the diversified and personalized learning needs of contemporary students. At the same time, since 2015, when Gatys et al. proposed neural style migration algorithm in the field of computer vision, the painting style migration technology has rapidly evolved from laboratory research to a popular art creation tool, and this technological breakthrough provides new possibilities for reconstructing the art education system.

The educational value of style migration technology is mainly reflected in three dimensions: firstly, from the cognitive level, the technology deconstructs artistic style into quantifiable Gram matrix features through convolutional neural network (CNN), which makes the original abstract aesthetic concepts, such as “brushstroke”, “color rhythm” and so on, visualized and operable. Secondly, at the level of creative practice, deep learning-based style migration tools can compress traditional painting techniques that take months to master into real-time presentation, greatly reducing the technical threshold of art creation. Most importantly, this technology has prompted art education to shift from pure skill transfer to the integration of computational thinking and aesthetic literacy, which is in line with the trend of interdisciplinary integration emphasized by STEAM education.

The current domestic and international related research mainly focuses on two directions: first, the field of technology optimization, where researchers are committed to improving the speed and quality of style migration, such as the fast style migration algorithm proposed by Johnson; and second, the field of art creation, which explores the aesthetic value of AI-generated art and copyright issues. However, the research on the systematic integration of drawing style migration into the art teaching system is still blank, especially in the lack of empirical exploration in teaching methods, curriculum design and evaluation standards. Existing practices mostly stay at the level of tool application, failing to deeply explore the theoretical value of technology-enabled education.

Based on the constructivist learning theory and the media art education framework, this study proposes three core research questions: how to construct a curriculum system that organically integrates painting style migration technology with traditional art teaching; what quantitative advantages this integrated teaching mode has in enhancing learning effectiveness; and how technological interventions can change the students' art cognition and creation styles. Through the 16-week controlled experiments and mixed research methods, we not only verified the effectiveness of the integrated teaching, but also revealed the mapping law between parameter adjustment and artistic performance, providing a theoretical basis and practical paradigm for the innovation of art education in the digital era.

The academic value of this study lies in the establishment of the first three-dimensional evaluation system for painting style migration education, which fills the research gap in this field; the practical significance is reflected in the development of a generalizable teaching framework and tools, so that cutting-edge technology can truly serve the goal of aesthetic education. As Resnick said, “the best learning happens in the process of creation”, and by lowering the threshold of creation and expanding the possibilities of expression, painting style migration technology allows more students to experience the joy of artistic creation, which is the essence of technology-enabled education.

2. Theoretical Perspectives and Conceptual Definitions

2.1 The current state of research on the integration of computer science and art disciplines. The current cross research between computer and art disciplines mainly shows three aspects of development. At the level of technical application, techniques such as generative adversarial network and neural style migration have been widely used in digital art creation, such as the CAN model proposed by Elgammal to realize automatic generation of art works with specific styles. In the field of theoretical research, scholars are working on building a computational aesthetics evaluation system, and Taylor et al. analyze the visual characteristics of abstract paintings through quantitative indicators such as fractal dimension. In terms of educational practice, the STEAM education concept has promoted the curriculum integration of programming and visual arts, such as the e-textile curriculum developed by Peppler. However, there are obvious limitations in the existing research: technical research mostly focuses on algorithm optimization but neglects teaching applicability, while educational experiments lack systematic effect evaluation. Especially in higher education, how to balance the technical depth and the cultivation of artistic expression remains to be explored. Relevant research in China started late, mainly focusing on the development of tools, and the exploration of interdisciplinary teaching mode is relatively insufficient. This research situation highlights the value of this paper in building a systematic integration teaching system.

2.2 Current Research Status of Painting Style Migration Techniques. Painting style migration technology has gone through three stages of development since the pioneering work of Gatys et al: the basic algorithm research stage mainly explores the feature representation capability of convolutional neural networks (CNN), and representative results include the fast style migration framework proposed by Johnson et al. The performance optimization stage is dedicated to improving the real-time and generalization of the algorithm, such as the arbitrary style migration model developed by Huang et al. The performance optimization phase is dedicated to improving the real-time and generalization of the algorithm, such as the arbitrary style migration model developed by Huang et al. Current research is shifting to controlled generation and semantic understanding, including the content-aware migration method proposed by the Google Magenta team. Recent advances show that Transformer-based architectures exhibit advantages in long-range style dependency modeling. However, there are two key limitations in the existing research: first, most of the algorithms are designed for generalized scenarios without considering the special needs of art education; second, there is a lack of systematic research on the correlation between parameter tuning and artistic performance, which directly restricts the effective application of this technology in the education field. It is urgent to establish a balanced mechanism of "algorithm complexity-applicability to teaching" for the painting style migration technology in educational scenarios.

3. Technical Principles of Painting Migration

Painting style migration is an image processing technique based on deep learning, the core of which is to migrate the features of one painting style to another image to generate an image work with a new style. This technique not only has a wide range of application prospects in art creation, but also provides a new opportunity for the integration of computer science and art disciplines. This chapter will introduce the basic principles of the painting style migration technique in detail, including its algorithmic framework, key formulas, and important parameter settings in the process of realization.

3.1 Algorithmic framework. Pictorial style migration techniques are mainly based on convolutional neural networks (CNN), especially pre-trained deep convolutional networks such as VGG.19 These networks perform well in image recognition tasks and are capable of extracting high-level semantic features of images. Picture style migration algorithms are usually divided into two main parts: feature extraction of content images and feature extraction of style images. A new image with the target style is generated by combining the features of the content image with the features of the style image.

3.2 Content Loss Function. The content loss function is used to measure the similarity between the generated image and the content image in the feature space. The middle layer features of a pre-trained convolutional neural network are usually used to calculate the content loss. Assuming that ϕ denotes the feature extraction function of the convolutional neural network, F denotes the features of the generated image, and P denotes the features of the content image, the content loss function is defined as:

$$L_{content(P,F)} = \frac{1}{2}\sum_{i,j}\left(F_{ij} - P_{ij}\right)^2 \tag{1}$$

Where F_{ij} and P_{ij} denote the feature values of the generated image and the content image on the j feature map of the i layer, respectively. The goal of the content loss function is to minimize the difference between the generated image and the content image in the feature space.

3.3 Style loss function. The style loss function is used to measure the similarity between the generated image and the stylized image in terms of stylistic features. The style features are usually represented by computing the Gram matrix of the feature map. Assuming that G denotes the Gram matrix of the generated image and A denotes the Gram matrix of the stylized image, the style loss function is defined as:

$$L_{style}\left(A,G\right)=\frac{1}{4N^2M^2}\sum_{i,j}\left(G_{ij}-A_{ij}\right)^2 \tag{2}$$

Where N and M denote the number of feature maps and the size of each feature map, respectively. The Gram matrices G and A are calculated as:

$$G_{ij}=\sum_{k}F_{ik}F_{jk} \tag{3}$$

$$A_{ij}=\sum_{k}P_{ik}P_{jk} \tag{4}$$

Where F_{ik} and P_{ik} denote the feature values of the generated image and the stylized image on the k feature map of layer i, respectively. The goal of the style loss function is to minimize the difference in style features between the generated image and the style image.

3.4 Total loss function. The total loss function is the weighted sum of the content loss function and the style loss function, which is used to optimize both content similarity and style similarity. The total loss function is defined as:

$$L_{total}\left(P,A,F\right)=\alpha L_{content}\left(P,F\right)+\beta L_{style}\left(A,G\right) \tag{5}$$

Where α and β denote the weights of content loss and style loss respectively, which are used to balance the importance of both. By adjusting the values of α and β, the balance between content and style of the generated image can be controlled.

3.5 Algorithm implementation steps. Pre-processing: pre-process the content image and style image, including normalization and resizing; Feature extraction: extract the features of the content image and style image using pre-trained convolutional neural networks (e.g. VGG19); Initialize the generated image: usually use the content image as the initial generated image; Calculate the loss function: calculate the total loss function based on the content loss function and style loss function defined above Optimize the generated image: minimize the total loss function using a gradient descent algorithm (e.g., Adam optimizer) to update the generated image; Post-processing: perform post-processing on the generated image, including denormalization and cropping.

4.Designing a framework for integrated teaching and learning

In the process of exploring the teaching and learning process of computer and art integration, it is crucial to construct an effective framework for integrating teaching and learning. This chapter will detail the design of a teaching framework for computer-art integration based on the drawing style migration technique, including teaching objectives, teaching contents, teaching methods, and teaching assessment system. Through this framework, it aims to cultivate students' comprehensive abilities in computer programming and art creation, stimulate students' creativity and interdisciplinary thinking.

4.1 Teaching goal. The core objective of the integrated teaching framework is to cultivate students' comprehensive literacy in both computer and art fields. Specific objectives include: in terms of technical ability, students are able to master the basic principles and implementation methods of the painting style migration technology, and are skilled in programming practice using the deep learning framework; in terms of artistic literacy students are able to understand the characteristics of different painting styles and are able to realize style migration through the code to create works of artistic value; in terms of cross-disciplinary thinking students are able to engage in the cross-cutting fields of computing and art to engage in interdisciplinary thinking, students are able to think creatively in the intersection of computer and art to solve real-world problems; teamwork, students are able to utilize their respective strengths in group work to complete complex project tasks together.

4.2 Educational content. The teaching content centers around the painting style migration technique, covering both theoretical teaching and practical teaching. Theory teaching. Principles of painting style migration technology: introduce the basic principles of painting style migration technology, including deep learning algorithms, content loss function, style loss function, etc.; analysis of painting styles: explain the characteristics of different painting styles, such as Impressionism, Abstraction, etc., and show the relevant works of art; deep learning frameworks: introduce commonly used deep learning frameworks, such as TensorFlow and PyTorch, and their applications in painting style migration. Hands-on teaching. Programming practice: under the guidance of the teacher, students use the deep learning framework to implement the painting style migration algorithm and generate images with new styles; Art creation: students use the generated images as creative materials and use the paintbrush to create further artwork to form the final artwork; Project practice: driven by a specific painting style migration project, students work in groups to complete the whole process from algorithm implementation to art creation. Project practice: driven by a specific painting style migration project, students work in groups to complete the whole process from algorithm realization to art creation.

4.3 Teaching methods. Project-driven teaching, driven by specific painting style migration projects, guides students to learn and apply relevant knowledge and skills in practice. Each project includes clear task objectives, technical requirements and artistic creation requirements; group cooperative learning, which encourages students to practice the project in small groups and develop teamwork skills. Each group consists of students majoring in computer science and art, giving full play to their respective strengths; case study teaching, through the analysis of classic cases of painting style migration, to help students understand the way of combining technology and art. The case study includes technical implementation details, artistic creation ideas and the evaluation of the effect of the final work.

4.4 Teaching Evaluation System. In order to comprehensively assess students' learning effectiveness, a diversified assessment system including student work assessment, student questionnaires, and teacher observation and evaluation was constructed. The assessment of students' works evaluates students' abilities in technical realization and artistic creation through the images of painting style migration generated by students and the final artworks. The evaluation criteria include image quality, accuracy of style migration, and innovativeness of art creation. Student questionnaire survey to find out students' satisfaction and learning gains from the integrated teaching mode by means of a questionnaire. The questionnaire includes students' understanding of course content, satisfaction with teaching methods, and interest in interdisciplinary learning. Teacher observation and evaluation, teachers evaluate students' learning attitude, teamwork ability, problem solving ability and other aspects by observing students' performance in the classroom and in the practice process.

Table 1 Specific Design of the Framework for Integrated Instruction

Educational Content	norm	Assessment methods	
theoretical teaching	Principles of drawing style migration techniques, drawing style analysis, deep learning frameworks	Multimedia teaching, case studies	Student questionnaires, classroom performance
Programming Practice	Deep learning framework application, drawing style migration algorithm implementation	Project-driven, group work	Programming assignments, code quality assessment
art	Artistic Processing of Painting Style Migration Images	Group work, art-making instruction	Evaluation of works of art, creative evaluation

Project Practice	The whole process from algorithmic implementation to artistic creation	Project-driven, group work	Project reports, presentation of results
Presentation of results and evaluation	Presentation of student work, group discussion, teacher critique	Presentation of results, panel discussion	Assessment of student work, teacher evaluation

5.Experimentation and evaluation

5.1Experimental design. Two parallel classes (30 students each) in an art college were selected for the study to conduct a comparative experiment:

Experimental group: using integrated teaching methods.

Control group: traditional teaching methods were used.

The experimental period was one semester (16 weeks) and data were collected through pre-test, process assessment and final test.

5.2Assessment of indicators.

Table 2 Comparative analysis of assessment indicators

Assessment dimensions	norm	experimental group	control subjects	promotion rate
artistic expression	Creative Index	86.7	72.3	+19.9%
	Stylistic diversity	4.2 species/person	2.8 species/person	+50%
technical mastery	Algorithm comprehension	82.5	61.2	+34.8%
	Tool proficiency	88.3	70.1	+26.0%
Learning efficiency	Volume of work output	6.5 items	4.1 items	+58.5%
	Technique mastery time	3.2 weeks	4.6 weeks	-30.4%

5.3 Analysis of results. The experimental data show that the fusion teaching method significantly outperforms the traditional method in several dimensions. Particularly noteworthy are: 50% increase in stylistic diversity, indicating that technological tools expand students' creative horizons; 34.8% increase in algorithmic comprehension, verifying that artistic contexts contribute to technological learning; and 30.4% reduction in technique mastery time, reflecting the effectiveness of technological aids.

6.Conclusion

This study systematically verifies the innovative value and practical path of drawing style migration technology in art education through a 16-week controlled experiment. The results of the study show that the integrated teaching mode based on deep learning can effectively break through the triple boundaries of traditional art education: in the cognitive dimension, the algorithmic visualization deconstructs abstract art styles into quantifiable feature parameters, which improves the accuracy of students' style comprehension by 42.3%; in the creative dimension, the instant feedback feature of digital tools significantly reduces the cost of trial and error, and the average number of attempts per work increases by 22.4%, while the creation cycle was shortened by 30.4%; in the developmental dimension, the interdisciplinary instructional design promoted the synergistic evolution of computational thinking and artistic intuition, with 82.6% of the students demonstrating the ability to organically integrate parameter adjustments and aesthetic judgments.

The innovation of the study is mainly reflected in three aspects: the construction of a three-dimensional assessment system of "artistic performance-technical understanding-innovative thinking", which fills the gap of evaluation tools in digital art education; the development of a progressive style migration teaching framework, which effectively reduces the technological learning curve through the four-phase training of "perception→deconstruction→restructuring→creativity"; and the revelation of the non-linear relationship between parameter adjustment and style evolution. These findings provide empirical evidence and methodological reference for the transformation of art education in the era of artificial intelligence.

Future research can be explored in depth in three directions: developing a lightweight style migration model for educational applications, establishing a dynamic and adaptive personalized learning path, and constructing an immersive creation environment that integrates reality and fiction. The practical implication of this study is that the core of technology-enabled art education does not lie in the replacement of tools, but in the stimulation of new creative possibilities through human-computer collaboration, which requires educators to rethink the connotation and cultivation paradigm of art literacy in the digital era.

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The Role of AI in Transforming Curriculum Development in Education: Personalized Learning, Upskilling, and Microlearning

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Abstract. Artificial intelligence (AI) transforms education through its ability to develop customized curricula and deliver individualized learning experiences and support both upskilling and microlearning approaches. This research examines how artificial intelligence transforms traditional curriculum development through data-based approaches and machine learning systems and adaptive educational models. AI platforms use predictive analytics to create personalized educational content which matches individual learning requirements for efficient and dynamic educational pathways. AI systems improve lifelong learning by automatically organizing educational content and evaluating student progress while delivering immediate feedback. AI-driven curriculum development brings advantages to education but encounters three major obstacles which include algorithmic bias and data privacy issues and implementation difficulties. This research examines current developments and practical applications of AI in education while discussing future directions to show its capability for developing scalable personalized learning experiences.

Keywords: Artificial Intelligence; Curriculum Development; Personalized Learning; Upskilling; Microlearning; Machine Learning; Adaptive Systems; Educational Technology

1. Introduction

Education, widely referred to as the key to success, serves as the essential foundation for individual growth and social advancement. It helps people build critical thinking abilities while improving their communication skills and expanding their knowledge base. The digital age has accelerated educational progress through technological innovations which transform teaching methods and learning approaches and curriculum development. Artificial Intelligence (AI) stands as one of the transformative educational innovations that emerges in the present day.

The educational sector can transform its curriculum development practices through Artificial Intelligence (AI). Educational institutions typically maintain standardized curricula which do not effectively adapt to individual student requirements. AI brings revolutionary potential to customize educational programs because it adjusts learning content in real time according to student-specific needs along with their learning preferences and achievements. The evolution from standardized educational models to student-centered flexible learning methods stands as the essential component of contemporary curriculum development practices.

AI serves multiple purposes in modern education: it helps create customized curricula while addressing the increasing requirement for students to develop new skills for evolving professional markets through upskilling and reskilling. Through AI-powered platforms learners acquire customized educational routes that help them gain essential competencies for emerging sectors or professional growth within their current careers. Modern microlearning platforms powered by artificial intelligence are emerging as an effective way to deliver content through bite-sized chunks that enable learners to sustain their education and skill development in both academic and non-academic environments.

This study investigates how Artificial Intelligence (AI) can improve curriculum development through personalized learning methods while also providing opportunities for students to upskill and reskill along with microlearning capabilities. Through the evaluation of AI potential in educational design, this research establishes a thorough understanding of how Artificial Intelligence transforms education and supports contemporary learning requirements in the digital age.

2. The Evolution of Curriculum development with AI.

2.1 Traditional Curriculum development. Curriculum development used to follow a traditional linear structure where educators designed pre-written standardized content for uniform delivery to all students. This method typically relied on fixed instructional frameworks and static materials. Despite its initial success across various educational contexts the traditional method has become inadequate to handle present-day educational changes. The internet's broad accessibility has made content that previously needed extended study periods available for quicker consumption. This traditional approach lacks the capability to satisfy different learning requirements and student individuality. The traditional educational approach leads to improved academic performance but it weakens students' essential abilities to think critically and solve problems effectively in today's environment. Educational systems now require a more flexible data-based approach because they are moving toward student-centered learning environments.

2.2 The role of technology in Curriculum Development. The field of curriculum development experienced a gradual technological influence during the past several decades. Early implementations of e-learning platforms alongside digital textbooks and multimedia content provided instructors with fresh instruction tools. However, the systems continue to function without much flexibility which limits personalization options. Learning Management Platforms LMS platforms including Moodle and Blackboard have shown some ability to adapt yet they remain distant from achieving full dynamic responsiveness to meet student learning requirements. AI entered the field to address the lack of adaptable learning systems because it provides instant student response capabilities and data-based curriculum modification features.

2.3 The Role of AI in Transforming Curriculum Development. AI technology brings about fundamental changes to both curriculum design processes and educational delivery methods. The ability of AI to develop learning pathways that automatically adjust in real time based on student performance behavior and preferences distinguishes it from conventional educational approaches. Machine learning (ML) and deep learning (DL) models such as convolutional neural networks and recurrent neural networks process extensive student interaction data to detect learning behavior and performance patterns. These algorithms generate flexible learning pathways that adjust automatically to student progress so developers can customize content delivery based on individual requirements.

Algorithms receive training from labeled student data that includes their responses as well as time spent on work and their past performance scores in a supervised learning environment. The prediction system aims to forecast student behaviors and performance levels that will occur in the future through analysis of historical data. Mathematically, a supervised learning model can be represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{1}$$

Where y is the predicted output (e.g., performance score), and $x_1, x_2, \ldots, x_n$ are input features (e.g., time spent on a module, previous grades, interaction types). The algorithm trains the model to optimize the error term ϵ to produce better predictions for individual student results.

Deep learning adopts recurrent neural networks (RNNs) and long short-term memory (LSTM) networks to manage sequential data through time-series student interaction patterns. These models identify extended learning patterns to predict student outcomes while providing future guidance. The underlying equations for LSTM models are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (5)$$

Where: f_t, i_t, o_t are the forget, input, and output gates, h_t is the hidden state, and C_t is the memory cell state, which stores long-term information.

Learning Management Systems (LMS) enhanced by artificial intelligence (AI) through machine learning algorithms enable course structure and delivery optimization by processing student activity logs and engagement metrics and assessment performance data points. The recommendation algorithms in Coursera and edX suggest relevant courses or resources based on user interaction history and progress which generates an adaptive learning experience for different student needs.

3. Literature Review

This review investigates Artificial Intelligence's transformative power for curriculum development by evaluating personalized learning and upskilling and microlearning approaches It explores how AI technologies transform educational curriculum development through adaptive learning pathways which help students build new skills for today's changing job market and enable continuous bite-sized learning. The review also reviews the challenges and ethical considerations associated with educational AI, and evaluates the full potential and limitations in modern educational systems.

3.1 Overview of curriculum development with AI in Education. Artificial Intelligence introduction to education ends traditional one-size-fits-all teaching because it creates individualized learning pathways. AI systems examine large student datasets containing historical performance records and interaction patterns and individual preferences to generate customized educational paths which deliver real-time feedback through adaptive learning experiences [1].

Recent studies, indicates that AI delivers personalized learning by recommending educational content and adjusting lesson speed and providing data-based targeted interventions [2]. The implementation of collaborative filtering and clustering machine learning algorithms allows systems to identify which learning materials students will gain the most benefit from which results in better student outcomes alongside higher engagement [3].

Furthermore, AI technology through natural language processing enables the development of automated content generation systems that adapt learning materials for different languages and cultural settings [4] [5]. The customized educational approach results in meaningful learning experiences which effectively meet students from different backgrounds and with various learning styles [6].

While existing research highlights these developments, this study investigates particular shortcomings in AI-driven systems when adapting to different educational settings as well as techniques for maximizing their functionality across multiple learning environments and institutional needs.

3.2 AI in Upskilling and Reskilling. Educational institutions must prioritize upskilling and reskilling programs because of fast technological evolution and shifting job market needs. The applications of AI prove beneficial when creating individualized learning paths for people who wish to develop new skills. AI-powered learning platforms can provide personalized educational materials and resources which enable students to develop particular skills when industry requirements change or evolve.

For instance, platforms such as Coursera and LinkedIn Learning apply AI technology to analyze learner history and skills which generates personalized learning recommendations [2]. These platforms employ machine learning algorithms to monitor learner progress through continuous assessment which provides dynamic feedback and curriculum adjustments to maintain content relevance for their goals [7]. AI will further support lifelong learning through its ability to provide ongoing upskilling opportunities as industries transform [8].

In the context of reskilling, AI helps workers transition to new careers through skill identification and expertise recommendation based on their previous job experience. The ability to help workers move between different job sectors stands essential for lowering unemployment rates and minimizing technological job displacement effects [9].

Existing literature demonstrates AI's role in facilitating workforce development, but there's a gap regarding its application for specific reskilling programs targeting underprivileged sectors. This research investigates how AI technology can provide marginalized workers with skills needed to access better opportunities in emerging industries.

3.3 Microlearning and AI driven Learning paths. The increasing technological displacement has led numerous individuals to explore career changes but going back to college or committing to full time learning is hard and not feasible so microlearning which delivers content in bite-sized chunks has become popular due to its flexibility and ability to cater to busy schedules. The optimization of microlearning experiences through AI relies on its ability to deliver customized content recommendations that match learners' current abilities and learning behaviors and performance levels [10] [11].

The algorithms within Duolingo and Quizlet monitor user progress through microlearning platforms to detect specific points that require additional educational support [12]. Machine learning models within Duolingo examine user app interactions to generate personalized lessons at suitable difficulty levels that help users learn continuously through small segments [13]. The adaptable learning approach improves student participation while supporting continuous skill growth which proves essential in today's fast-paced, ever-changing world.

Moreover, AI systems can create individualized learning pathways for microlearning to prevent students from receiving content that exceeds their current understanding level. Research indicates that AI-enhanced microlearning techniques boost retention rates and concept mastery through individualized pacing that helps students focus on areas where they need the most improvement [14].

In this work, we focus on understanding how AI-driven microlearning affects skill retention during extended periods while examining its effectiveness in various educational and professional environments

3.4 identified gaps and key problems to solve. AI demonstrates clear potential to develop curricula yet multiple challenges and knowledge gaps persist and this work focuses specifically on resolving these gaps:

Optimizing AI-driven personalized learning systems across diverse educational settings, ensuring they are adaptable to varied institutional needs. Leveraging AI for reskilling initiatives within underserved sectors, ensuring that AI technologies bridge the gap for workers in emerging fields. Long-term scalability and effectiveness of AI-driven microlearning solutions, with a focus on continuous skill retention and application over time.

4. Methodology

The research design is qualitative, focusing on the following sub-themes: Personalized learning, Upskilling, and Microlearning. This paper aims to provide a comprehensive overview of the effects of AI on the curriculum through the analysis of existing research, business reports, and practical examples. The methodology includes case study analysis, conceptual evaluation, and comparative review in order to gain a deeper understanding of AI applications in education.

4.1 Research Approach. The research design follows a qualitative exploratory research design, which is suitable for the fast-paced development of AI in education. This approach combines theoretical knowledge and practical illustrations of how AI can influence the curriculum development process. The research is organized in three main sections. Case Study Analysis: An analytical approach of the following AI-driven education platforms: DeepSeek, Squirrel AI, Duolingo, and ENEA Education in order to identify the trends, the advantages and the challenges of personalized learning, upskilling, and microlearning. Each case study is assessed based on the technological features, the influence on the learners, and the extent of the system's usage. Conceptual Analysis: Evaluation of the theoretical models and AI models (e.g., Machine learning, Reinforcement learning, Bayesian Knowledge Tracing) that are used in adaptive learning systems. It also entails the evaluation of the efficiency of the models in different learning environments. Comparative Review: A comparison of the platforms to identify the differences in AI use, learning results, and the areas of use, with particular reference to China and Africa.

4.2 Data Sources and Selection Criteria. This study relies on secondary data sources, including peer-reviewed journal articles, industry white papers, government reports, and documented case studies published within the last decade (2015–2025). Sources were chosen based on the following factors. Relevance: Sources must address AI-driven curriculum development, personalized learning, upskilling, or microlearning. Credibility: Peer-reviewed articles or reports from well-known organizations (e.g., African Development Bank, Peking University) are preferred. Diversity: Sources from different learning environments have been included such as universities, training institutions and continuing education. Regional Focus: Focus on case studies from China and Africa to meet the study's regional scope.

4.3 Analysis Framework. The study uses thematic analysis to uncover the patterns in the use of AI in curriculum development. The analysis process involves the following steps. Data Coding: Sources were grouped to identify recurring themes, such as personalized learning, scalability, and ethical challenges. The codes were generated from the data itself and were then modified through several stages of data examination. Theme Development: The identified themes were (1) Personalized Learning, (2) Upskilling and Reskilling, (3) Microlearning and AI-driven Learning Paths, and (4) Challenges and Ethical Considerations. Case Study Evaluation: Each case study was analyzed using a structured template assessing (a) AI technologies used, (b) impact on curriculum development, (c) learner outcomes, and (d) challenges. Quantitative metrics (e.g., test score improvements) and qualitative insights (e.g., user feedback) were synthesized. Comparative Synthesis: Platforms were compared across themes to identify best practices and context-specific adaptations

4.4 Limitations. This study is limited by its reliance on secondary data, which may restrict the ability to validate findings through direct empirical testing. The generalization of AI applications in curriculum development is constrained because they differ widely between institutions and industries. Future research needs to validate its findings through experimental studies or direct engagement with AI-driven learning systems.

5. Practical Applications of AI in Curriculum Design

In this chapter, we examine AI implementation within curriculum design while discussing its transformative effects on individualized learning and flexible educational environments and adaptive teaching approaches. This section includes both real-world examples and technical explanations that lead to our Case Study analysis of AI applications in Curriculum Design.

5.1 AI-Powered Learning Management Systems (LMS).AI-powered Learning Management Systems (LMS) utilize machine learning (ML) and deep learning (DL) approaches to boost educational efficiency and personalize learning experiences and adapt teaching methods. These systems use neural networks and reinforcement learning together with natural language processing (NLP) algorithms to enhance course content delivery and learning experiences.

5.2 Key Components of AI-Enhanced Impersonalized Learning Experiences: uses clustering methods including k-means and deep reinforcement learning to dynamically modify content delivery based on student learning styles and progress levels. Automated Assessment and Feedback: AI-powered grading systems leverage NLP models like transformers (e.g., BERT, GPT) to assess written responses, while computer vision aids in evaluating scanned handwritten assignments. Predictive Analytics for Student Performance: Time-series forecasting models (e.g., LSTM networks) predict students' learning trajectories, enabling timely interventions and adaptive content suggestions.

Mathematically, if S_t represents a student's knowledge state at time t, then AI models estimate future performance S_{t+1} using: $S_{t+1} = f(S_t, X_t, \theta)$ where X_t represents learning interactions and θ denotes model parameters.

5.3 AI in Adaptive Learning Pathways. Adaptive learning pathways tailor curriculum delivery to individual learner needs, leveraging AI to continuously refine and optimize instructional content. These pathways incorporate probabilistic graphical models and Bayesian networks to estimate student knowledge states and recommend the next optimal learning resource.

5.4Mechanisms of AI-Driven Adaptation. Dynamic Content Adjustment: Using reinforcement learning (e.g., Q-learning), AI selects optimal learning activities based on reward functions representing student comprehension. Targeted Interventions: AI applies anomaly detection methods (e.g., Isolation Forest, DBSCAN clustering) to identify struggling learners and suggest remedial content. Learning Style Adaptation: AI utilizes multimodal learning models to analyze behavioral and cognitive patterns, adjusting instructional materials accordingly.

For an AI-based system, given a learner's past sequence of interactions $x_1, x_2, \cdots, x_t$, the probability of selecting the next learning item x_{t+1} is computed as: $P(x_{t+1}|x_1, \dots, x_t) = \mathrm{softmax}(Wf(x_t) + b)$ where W and b are learnable parameters, and f $f(x_t)$ represents the feature extraction function.

5.5 Automation and Scalability in Curriculum Development.AI-driven automation enhances curriculum scalability by leveraging generative AI models, reinforcement learning, and optimization algorithms.

5.6 Key AI Techniques for Curriculum Automation. Automated Content Generation: Large language models (LLMs) such as GPT-4 generate educational materials, quizzes, and lesson plans. Curriculum Mapping Optimization: Genetic algorithms (GA) optimize the sequencing of educational modules based on predefined constraints and learner feedback. Scalable Content Delivery: AI-driven content distribution networks (CDN) leverage real-time engagement data to dynamically adjust delivery methods.

A curriculum adaptation model can be expressed as: $C^* = \arg\max_C U(C, S)$ where C represents curriculum elements, S is student engagement data, and $U(C, S)$ is a utility function optimized via reinforcement learning.

5.7 Microlearning Platforms Powered by AI. Microlearning, characterized by short and focused learning units, is enhanced through AI techniques such as knowledge tracing and automated content recommendation.

5.8 AI-Driven Microlearning Enhancements. Personalized Microcontent: AI employs transformers and attention mechanisms to break down complex topics into concise learning modules. On-Demand Learning Adaptation: Reinforcement learning-based recommendation systems ensure learners receive bite-sized content aligned with their cognitive load. Real-Time Knowledge Assessment: AI employs Bayesian knowledge tracing (BKT) to estimate learner proficiency levels after each microlearning session.

Given a learner's response history $y_1, y_2, \dots, y_t$, the probability of correctly answering the next question y_{t+1} is modeled as: $P(y_{t+1} = 1|\theta) = \sigma(W^T h_t + b)$ where θ represents past learning states and σ is the sigmoid activation function.

6. Case Studies in AI-Driven Curriculum Development

6.1 Introduction to Case Studies. The integration of artificial intelligence into curriculum design has led to significant advancements in personalized education, adaptive learning, and scalable instructional delivery. While theoretical discussions highlight AI's potential, empirical evidence from real-world implementations provides valuable insights into its effectiveness, challenges, and future directions. To validate AI's impact on education, this chapter presents in-depth case studies of leading AI-driven educational platforms. As an African student in China, the case studies will focus on China and Africa and also because they are regions experiencing significant growth in EdTech.

6.2 Case Study Selection Criteria. To ensure a comprehensive analysis, the platforms examined in this chapter were selected based on the following criteria. Technological Advancement: Platforms utilizing state-of-the-art AI models, including machine learning, natural language processing (NLP), deep learning, and reinforcement learning. Impact on Personalized Learning: Evidence of AI's role in tailoring educational experiences to individual learner needs. Scalability: Ability to expand learning opportunities across diverse populations and geographies. Relevance to Curriculum Development: Platforms that integrate AI to curate, modify, and update learning materials dynamically. Evaluation and Measurable Outcomes: Availability of data assessing the platform's impact on student performance, engagement, and knowledge retention. Regional Significance: Platforms leading AI-driven education in China and Africa. Case studies include DeepSeek AI (CN), Squirrel AI (CN), Duolingo (CN), and ENEA Education (Africa)

6.3 DeepSeek (China) – AI-Driven Adaptive Personalized Learning & Tutoring. This section presents in-depth case studies of four AI-driven educational platforms—DeepSeek (China), Squirrel AI (China), Duolingo (Global, with focus on China), and ENEA Education (Africa)—to illustrate AI's impact on curriculum development. Each case study examines the platform's background, AI implementation, impact, learner perspectives, comparisons with other technologies, and challenges.

Traditional education in China has long relied on rigorous, standardized testing, leaving little room for personalized learning. Many students seek after-school tutoring, but costs are prohibitive for lower-income families. AI-driven tutoring platforms like DeepSeek aim to provide affordable, intelligent tutoring that adapts to individual learning needs and even more affordable than Western Models like OpenAI.

DeepSeek employs large-scale transformer-based language models (LLMs) [15] to enable. Personalized tutoring: AI adapts explanations based on the student's knowledge gaps. Automated problem-solving: AI can generate solutions and step-by-step explanations. Multimodal learning: Integrates text, audio, and visual elements for diverse learning styles.

6.4 Technical Implementation. Uses Reinforcement Learning with Human Feedback (RLHF) to refine AI-generated responses. Graph-based knowledge modeling to track student progress and suggest targeted lessons. Deep learning-based adaptive assessment to dynamically adjust difficulty levels.

6.5 Impact on Curriculum Development.AI-driven adaptive learning reduces content redundancy and personalizes study plans. A 2025 comprehensive assessment involving 1,429 multiple-choice questions across various academic domains, concluded that DeepSeek AI achieved an overall accuracy of 87%, surpassing ChatGPT's 79%, with perfect scores in Mathematics and Psychology [16].Students report that DeepSeek's interactive explanations feel engaging, though some find the interface complex. Rural learners value affordability but note occasional delays in content loading due to connectivity issues [17].

6.6 Comparison with Other Technologies. Compared to Century Tech (UK): DeepSeek's use of LLMs enables real-time adaptation, whereas Century Tech relies on pre-structured AI-assisted materials. Compared to Khan Academy AI (USA): DeepSeek offers more sophisticated real-time curriculum adjustments, while Khan Academy focuses on AI-powered tutoring. Challenges &

Limitations. Ethical concerns: Potential bias in AI-generated responses. Dependence on high-quality training data: Requires extensive labeled datasets.

6.7 Squirrel AI (China) – AI-Powered Adaptive Personalized Learning Systems. One of the biggest challenges in education is that students' progress at different speeds and China's high-stakes examination system drives a demand for intensive, personalized tutoring as traditional curricular is typically fixed. However, traditional tutoring centers are costly and inconsistent in quality. Squirrel AI, founded in 2014, developed an AI-powered adaptive learning system that personalizes learning at scale by using Bayesian Networks, predicting student weaknesses and personalizing learning content.

Squirrel AI uses Knowledge Space Theory (KST) and Bayesian Networks to model student learning progress and predict weaknesses. Bayesian knowledge tracing (BKT): Estimates a student's mastery level for each topic. Ulti-modal AI assessment: Uses NLP for text-based learning and deep learning models for speech and handwriting recognition. Reinforcement learning models optimize content sequencing.

6.8 Impact on Curriculum Development. Allows for real-time dynamic curriculum adaptation based on student performance. In a 2019 study by Wei Cui, 87% of students using Squirrel AI had positive judgment of learning math compared to traditional methods and they also thought that contents were tailored to their needs showing the impact of Squirrel in helping them improve academically [18]failure rate in key STEM subjects decreased significantly due to AI-driven interventions [19].Compared to Biju's AI (India): While Biju's uses gamification, Squirrel AI focuses on real-time adaptive learning through Bayesian inference. Compared to Coursera AI (USA): Unlike Coursera's focus on professional learning, Squirrel AI is built for K-12 adaptive curriculum management. Scalability issues in rural areas with limited internet connectivity.AI explain ability concerns: Some parents distrust AI-driven grading.

6.9 Duolingo AI (Global) AI-Powered Microlearning for Language Education. Language acquisition requires consistent practice and personalized feedback, which many learners struggle with in traditional settings. As a foreign student in China, I have also experienced these struggles in learning Chinese language but with the use of Duolingo AI, the learning has become better. Duolingo AI leverages NLP and reinforcement learning to create adaptive microlearning experiences. Natural Language Processing (NLP): Enables real-time feedback on pronunciation and grammar. Reinforcement Learning (RL): Adjusts lesson difficulty based on past performance. Personalized AI Paths: Adapts exercises based on error patterns and comprehension levels.

6.10 Impact on Curriculum Development. Learners using Duolingo AI would take approximately 34 hours to complete the equivalence of one college semester of learning Spanish language courses which can give students to allocate time to other courses [20].Duolingo's internal research in 2020 showed that 66% of Spanish learners and 53% of French learners achieved at least A2-level speaking proficiency after completing Unit 5. [21]Most users find the gamified interface interesting however some have aired their frustrations with the speech recognition for no-standard accents [22]. Compared to iFlytek AI (China): Duolingo is more gamified and widely accessible, while iFlytek focuses on China-specific NLP applications. Compared to Buus AI (UK): Duolingo AI offers real-time reinforcement learning, while Buus emphasizes peer-based language correction.

6.11 ENEA Education (Africa) – AI-Driven Mobile Learning. Many African students lack access to traditional classroom infrastructure or access to internet-based education. ENEA Education, a Kenya-based EdTech platform, leverages AI-driven SMS-based microlearning, enabling rural students to learn using basic mobile phones'-powered chatbots provide real-time tutoring via SMS.AI-Powered Assessment Engine: Generates personalized quizzes and progress tracking.AI-based student progress tracking adjusts content difficulty dynamically. Transformer-based NLP models enable low-bandwidth AI tutoring.AI-driven assessment algorithms personalize quizzes based on prior answers.

6.12 Impact on Curriculum Development. A 2022 study found that students using ENEA Education demonstrated a 23% improvement in exam performance compared to peers without access to AI tutoring and the platform has reached over 6 million students across Kenya, Ghana, and Côte d'Ivoire and an average of 300000 active users daily [23]. Students appreciate the platform's affordability and offline accessibility, though some note limited content depth for advanced topics. Teachers report increased student engagement but request more subject variety. Compared to Duolingo AI: ENEA focuses on text-based AI for low-tech environments, while Duolingo uses high-tech adaptive learning. Compared to Coursera AI (USA): Coursera targets high-bandwidth users, while ENEA proves that AI can work effectively in low-resource settings. SMS constraints limit delivery of complex subjects. High mobile data costs in some regions.

6.13 Comparative Analysis.

Table 1 Data comparison and analysis

Platform	AI Technologies Used	Key Impact	Challenges
DeepSeek AI	LLMs, RLHF, Graph-based knowledge modeling	accuracy of 87% in academic tests, surpassing ChatGPT's 79% [16]	Bias in AI tutoring
Squirrel AI	Bayesian Networks, BKT, Reinforcement Learning	+87% better math tutoring compared to traditional [18]	Rural Scalability
Duolingo AI	CNNs, Speech Recognition, Federated Learning	34 hours to complete the equivalence of one college semester of Spanish [20]	Privacy Concerns
ENEA Education	NLP, AI-driven SMS-based tutoring	+23% improvement in exam Performance [23]	Mobile Data Costs

6.14 Lessons learned from the case studies. In this subsection, we will try to synthesize the findings from the case studies on DeepSeek, Squirrel AI, Duolingo, and ENEA Education, highlighting the successes, challenges, and broader implications of AI-driven curriculum development.

6.15 What Worked Well. Across all case studies, several key advantages emerged from integrating AI into curriculum design. Personalized Learning at Scale: AI-based personalization leads to better learner engagement and retention through customized content delivery based on individual progress and preferences. The combination of AI-based content recommendations with dynamic assessments through these platforms delivers more efficient skill gap closure than traditional static curricula. Efficient Automation of Teaching & Assessment: AI-driven grading and feedback systems decrease teacher workloads while offering learners immediate feedback. The automation process allows for increased scalability which enables better access to quality education particularly in resource-limited areas such as rural China and parts of Africa.

6.16 What Didn't Work (Challenges & Limitations). The integration of AI into curriculum development processes encountered various technical barriers along with ethical issues and operational challenges. Data Privacy & Security Risks: AI platforms need extensive student data to operate but this data collection process raises concerns as it is prone to violate privacy and fail to protect user information properly. China's AI education platforms Squirrel AI and DeepSeek have been under scrutiny for their handling of student data and methods they store and use it. DeepSeek has also come under increasing global attention, because of its broad data collection activities combined with server storage in China. Several governments along with institutions have put out bans and advisories regarding these tools as they share concerns about AI in education with Google and other companies. Algorithmic Bias & Fairness: Educational AI models duplicate existing biases which exist in their training datasets. Duolingo users have complained that its AI exercises give preferential treatment to Western language users which creates difficulties for non-Western users. AI language learning tools demonstrate bias in their speech recognition abilities because they fail to detect underrepresented accents correctly which results in user frustration according to a research study. The learning recommendations generated by Squirrel AI's adaptive models result in different outcomes between urban and rural students which creates education access issues. Squirrel AI works to fight educational discrimination yet research indicates that rural Chinese students perform worse in math and language than urban students due to the models' training data limitations as the data is mostly from urban schools. Teacher Resistance & Integration Issues: Integration Challenges: AI integration into traditional curricula proves difficult for numerous educators. AI replacement of human educators creates distrust among educators who therefore resist its adoption. AI has gained traction in Chinese after-school centers through Squirrel AI's adaptive learning platform that tailors each lesson to meet student needs. Despite its learning-enhancing features this technology has caused educators to question AI's place in education. Global Skepticism: This issue mirrors global trends, where AI adoption in schools, including in the US and Europe, has faced similar skepticism. The educational community expresses doubt regarding the learning benefits and academic ethical standards of AI implementations. The use of AI tools by students to finish their assignments has caused additional concerns among educators. Infrastructure Gaps & Digital Divide: Connectivity and Infrastructure: AI education platforms need both stable internet connections and advanced computing equipment to operate effectively. African countries face technological adoption barriers because their infrastructure remains insufficient to support AI adoption across the board. Digital Divide: DeepSeek requires high computational power which makes it inaccessible to low-income regions compared to simpler mobile-based AI learning tools like Duolingo. The absence of AI-optimized hardware combined with limited high-speed networks creates additional barriers that restrict the use of advanced AI educational tools.

6.17 Key Takeaways & Future Considerations. Balancing AI with Human Instructors: The learning process should maintain teachers as its core component while AI functions to provide support through data analysis and automated tasks. Enhancing AI Transparency & Reducing Bias: Future AI-driven curricula need to develop explainable AI (XAI) models which enhance transparency while reducing biases to achieve fairness in educational recommendations. Addressing the Digital Divide: EdTech companies together with governments need to develop AI-powered mobile learning solutions which operate offline and in low-bandwidth networks to expand educational access for underserved regions. Ongoing AI Evaluation & Policy Development: Education policymakers need to work with AI researchers to create ethical guidelines and regulatory frameworks which will protect the responsible integration of AI in curriculum development and learning environments.

7. Conclusion

Artificial intelligence transforms education through its integration into curriculum development by creating personalized learning experiences while delivering scalable content and automated assessment methods. AI systems improve curriculum structures while providing real-time adaptable learning materials and individualized support to students which results in more efficient and accessible education.

DeepSeek AI and Squirrel AI together with Duolingo AI and ENEA Education demonstrate through their case studies how AI improves student engagement and knowledge retention and adaptive learning capabilities. The successful implementation of AI in education requires addressing four major challenges which include data privacy concerns and algorithmic bias and infrastructure limitations and educator resistance. The successful adoption of AI in education requires three essential solutions which include transparent AI models and responsible data policies and educator training programs.

AI-driven curriculum development needs a balanced approach which unites AI operational efficiency with human professional expertise to reach its maximum potential. AI developers together with educators and policymakers need to work together to create ethical AI solutions which support inclusive learning environments for diverse student populations. AI development will expand its educational influence to deliver customized lifelong learning opportunities across the world.

Future research should concentrate on improving AI models to increase fairness, inclusivity, and accessibility so that AI-driven education is accessible to all learners regardless of socio-economic or technological barriers. The education sector can use AI to create more effective and equitable learning experiences by implementing responsible AI implementation.

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Curriculum-Aligned Semantic Assessment: Improving Fairness and Accuracy in AI-Assisted Student Marking

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Abstract. As artificial intelligence becomes increasingly integrated into education, AI-assisted marking systems offer benefits such as reduced grading workloads and improved consistency. However, many existing models penalize students for deviating from a broader knowledge base rather than adhering to the prescribed curriculum, raising concerns of fairness. This paper presents a curriculum-aligned natural language processing (NLP) model designed to assess short and long-form student responses within the scope of a national syllabus. The system dynamically ingests curriculum documents, encodes key concepts into a hierarchical structure and semantically matches student answers using a fine-tuned BERT model. A simulated dataset of 1,400 primary science responses (including in-scope, out-of-scope and distractor answers) was used to evaluate the model. Results show a strong correlation with human marking (Pearsons r = 0.88) and improved precision and recall in identifying out-of-scope content (F1 = 0.90), outperforming a non-aligned baseline. These findings suggest that curriculum-aware assessment models can enhance fairness, uphold instructional integrity and support scalable, transparent evaluation in educational settings.

Keywords: Curriculum-aware assessment, Natural language processing in education, AI-assisted marking, Educational fairness, Syllabus-aligned evaluation, Explainable educational AI, Semantic scoring models.

1. Introduction

Automated marking systems powered by artificial intelligence (AI) are becoming more common in schools, as they can reduce teachers' workload, provide rapid feedback and maintain consistent grading standards [1]. In 2024, the UK Department for Education launched a £4 million programmed to train AI models on official curriculum guidance and anonymized student work [2]. The effectiveness of this initiative in improving marking accuracy remains under evaluation. Many existing AI markers, however, judge student responses using broad, open-domain knowledge rather than the specific content taught in class. This mismatch can penalize students whose answers align with the official syllabus but omit extra facts or terminology known to the AI [3]. Such errors can undermine trust in AI marking and increase the time teachers spend correcting automated grades. Research on fairness in AI suggests that systems should ground their decisions in the context they serve, combining automated scoring with human oversight to avoid unfair outcomes [4,5,6]. My proposed model follows this approach as it references official curriculum documents and teacher-defined scope settings before assigning a mark and it flags out-of-scope content for teacher review rather than deducting marks.

2. Related Works

This section reviews prior research on AI-driven marking, embedding key gaps and implications within each discussion. We consider: (a) foundational scoring methods, (b) curriculum misalignment, (c) fairness and transparency, (d) human–AI collaboration and (e) early curriculum-aware systems.

2.1 Automated Marking Systems, Foundations and Approaches. Early automated essay scoring (AES) systems used surface-level text features as proxies for writing quality. Basic measures such as essay length were first shown to predict human grades by Page [7]. Attali and Burstein then formalized this approach, correlating word count, average sentence length and vocabulary diversity with expert marks [8]. Elliot's Intelligent Essay Assessor extended these ideas, reporting a moderate correlation but warning that essays padded with repetition sometimes earned unduly high scores [9]. Williamson and Piattoeva argued that reliance on surface features risks rewarding verbosity rather than genuine understanding [10]. These findings imply a need for deeper analysis of student content, since surface metrics cannot ensure marking aligns with curriculum-taught material [8, 9, 7, 10].

Semantic models sought to capture meaning rather than mere form. Foltz, Laham and Landauer introduced latent semantic analysis (LSA), mapping student essays and reference texts into a shared semantic space and demonstrating improved agreement with human markers [11]. Omar showed that LSA enhanced topic coherence detection [12], while Landauer noted its dependence on high-quality reference corpora and its difficulty with novel argument structures [13]. Research on referential cohesion indicates that, although vital for coherence, its overuse can confuse reviewers; Seyler found that excessive cohesion features negatively impacted clarity among peer reviewers [14].

Many models, particularly convolutional neural networks (CNNs), exhibit a strong inductive bias towards style features, which can overshadow content features and lead to poor performance on out-of-domain data [15]. Similarly, the performance of large language models declines when tested on domains different from their training data, as they may rely heavily on stylistic cues rather than content attributes [16]. These studies reveal that semantic approaches bring AES closer to true understanding but remain blind to curriculum boundaries, risking deductions for valid responses within class scope.

2.2 Curriculum Misalignment in AI Marking. Despite advances in automated essay scoring, systems often fail to align semantic analysis with specific curriculum requirements, risking the assessment of responses that are contextually valid but fall outside expected standards [17]. In a study of physics examinations, Yeadon and Hardy evaluated a large language model's performance across multiple educational levels and reported that, although the model handled GCSE-level questions accurately, its performance declined on more advanced topics, with the AI introducing information not covered by the syllabus that could mislead students [18]. A survey by Bower et al. of secondary educators further revealed concerns that AI-generated assessments penalise correct answers simply because they do not match the AI's broader knowledge base rather than the taught curriculum. This misalignment forced teachers to spend additional time reviewing and overriding automated grades, thus negating anticipated efficiency gains [19]. These findings highlight a critical implication; without explicit curriculum filters and alignment mechanisms, AI-assisted marking can inadvertently increase teacher workload and compromise assessment fairness. Integrating curriculum-aware frameworks and preserving human oversight are therefore essential to ensure that AI tools support, rather than hinder, educational objectives.

Rule-based methods in educational technology (such as natural-language proof checkers and keyword-based feedback filters) provide structured solutions but lack the flexibility to handle diverse, free-text student responses across subjects. For example, the Diproche system uses a controlled-language proof checker for introductory mathematics; it verifies student proofs against a predefined set of inference rules, flags unrecognised steps without deducting marks and has been shown to reduce teacher review time by about 20 per cent [20]. Similarly, Das et al. developed an NLP pipeline to extract keywords from official syllabus PDFs and automatically generate STEM question items; although this improved relevance, it handled only single-term concepts rather than multi-word ideas [21]. These efforts demonstrate that simple curriculum rules can reduce misalignment in well-structured domains, yet a gap remains: developing flexible, scalable methods capable of aligning AI assessment with free-text responses across varied subject areas.

2.3 Fairness and Transparency in AI Scoring. Efforts to make AI decisions more transparent often draw on post-hoc explanation methods. In a comprehensive guide to interpretable machine learning, Molnar reviews techniques such as LIME and SHAP, noting that while they can highlight influential features, they do not guarantee alignment with domain constraints [22]. Slack, Hilgard, Jia, Singh and Lakkaraju demonstrated that adversarial inputs can fool these explainers, calling into question their reliability in high-stakes settings [23]. In an educational context, Maxwell-Smith et al. found that students and teachers trusted AI feedback only when explanations corresponded to syllabus-taught errors but dismissed remarks on content outside the curriculum [24]. Kumar and Boulanger extended this work by integrating explainable modules into a secondary-school essay scorer, observing that transparent feedback increased teacher acceptance only when paired with curriculum-aware rule checks [25]. Collectively, these studies suggest that transparency tools alone are insufficient unless the system also enforces explicit curriculum boundaries.

Efforts to mitigate bias in automated essay scoring have largely focused on demographic and dialectal fairness, often at the expense of curriculum scope. Blodgett, Barocas, Daumé III and Wallach surveyed bias in NLP systems and documented how non-standard dialects and vernaculars can be systematically disadvantaged, even in educational applications such as AES, highlighting the need for contextual sensitivity in model design [26]. Dixon, Li, Sorensen, Thain and Vasserman showed that adversarial debiasing techniques can reduce gender bias in text classification by around 20 per cent, yet these methods do not address the distinct challenge of marking within strict curricular boundaries [27]. Guo, Pleiss, Sun and Weinberger introduced temperature scaling to calibrate neural network confidences, which can reduce unnecessary teacher reviews for low-confidence predictions but still risk flagging valid, in-scope answers when curriculum alignment is not enforced [28]. These findings indicate that, while bias-reduction and transparency techniques advance fairness, they must be complemented by explicit curriculum-aware filters to ensure that AES tools evaluate only the material students are expected to learn.

2.4 Human–AI Collaboration in Assessment. Human–AI collaboration models that integrate human oversight with automated processes have been shown to balance efficiency with expert judgment. For example, Williamson and Piattoeva [29] described a system in which AI provided initial grading and flagged uncertain cases; this approach enabled teachers to save up to 40 % of marking time, even though some correct answers were erroneously flagged. Similarly, Razmerita [30] examined a hybrid assessment framework in which automated error checks were combined with peer marking. Her study found that, in roughly 30 % of cases, peer reviewers graded responses more strictly when clear curriculum guidance was lacking. Together, these findings highlight the importance of embedding curriculum context into both AI systems and the human review process to avoid unnecessary workload.

Adaptive workflows have also been explored as a means to reduce teacher burden, though they do not fully address all scope-control issues. Yoo et al. [31] implemented a model calibration strategy that lowered teacher review rates by 22 %; yet, responses containing valid ideas expressed with novel phrasing continued to trigger incorrect flags. Moreover, von Davier and Burstein [32] argued that ensuring fairness is crucial to maintaining teacher trust. In practice, many educators supplement AI with ad hoc rubrics; a patchwork approach that can ultimately undermine efficiency and confidence. These insights point to a clear gap; assessment workflows must integrate curriculum boundaries directly into AI systems rather than relying solely on post-hoc human adjustments.

2.5 Curriculum-Aware System, Emerging Effort. Across these research strands, marking systems either ignore curriculum scope, rely on static or manual approaches, or address fairness without scope controls. My curriculum-aligned NLP model aims to fill these gaps by automatically ingesting official curriculum documents, applying explicit scope filters during scoring and flagging only genuine out-of-scope content for teacher review.

3. Model

This section outlines the architecture and key processes of the curriculum-aligned marking assistant. The design aims to address limitations identified in existing systems; specifically, the lack of dynamic curriculum awareness, the risk of unfair deductions for valid in-scope responses and the absence of clear review cues for teachers. Citations are given in APA style.

3.1 System Architecture. Table 1 presents the high-level architecture of the four modules

Table 1 Architecture of four modules

Module	Description/Function
Curriculum Ingestion	Parses official syllabus documents to build a structured concept hierarchy.
Answer Preprocessing and Embedding	Transforms student responses into normalised token sequences and obtains semantic embeddings.
Scoring Engine	Matches embeddings against in-scope concept vectors to compute marks.
Flagging and Review Interface	Identifies out-of-scope content, groups it into spans and presents it for teacher review.

3.2 Curriculum Ingestion. The ingestion module was designed to overcome the limitations of earlier systems that either relied on static rule lists or only handled single-word keywords. It begins by converting official syllabus PDFs into plain text while preserving document layout, headings and font metadata through PDFMiner [33]. Next, section segmentation is performed using a combination of regular expressions and layout cues (such as font size and styling) to detect headings like “Learning Outcomes” and “Key Concepts” (Alshaya [34]). Once sections are identified, spaCy’s part-of-speech tagger and noun-phrase chunker extract multi-word terms (for example, “photosynthetic pigment”) as candidate concepts [35]. Finally, these concepts are organised into a parent–child hierarchy by linking narrower terms under broader headings based on section nesting and term co-occurrence, employing a graph-based taxonomy induction method (Wu [36]).The output is a database of topic nodes and sub-nodes with associated keyword sets, ready for matching against student responses.

3.3 Answer Preprocessing and Semantic Encoding. The answer preprocessing and semantic encoding pipeline is designed to capture the depth of student responses while constraining evaluation to curriculum-relevant content. Initially, responses undergo normalisation (lowercasing, stop-word removal and lemmatisation) using spaCy’s NLP tools [37]. Next, a BERT base model is fine-tuned on a mixed corpus of official curriculum texts, teacher-graded exemplar answers and subject-specific glossaries, following established fine-tuning protocols; this produces embeddings that reflect both syllabus vocabulary and authentic student phrasing. Finally, sentence embeddings are compared to each concept vector via cosine similarity, with decision thresholds calibrated on a held-out validation set to optimise the trade-off between recognising in-scope content and rejecting out-of-scope material [39]. This three-stage process overcomes the fixed-scope limitations of LSA-only methods [11, 12] and avoids the domain-overreach seen in transformer markers without explicit curriculum filters.

3.4 Scoring and Flagging Mechanism. The scoring engine processes each question’s set of expected concepts in two main steps. First, it allocates partial credit to student responses in proportion to the degree by which their sentence embeddings exceed a calibrated similarity threshold. Second, it generates flags by identifying contiguous spans whose maximum similarity to any in-scope concept falls below this threshold; each flagged span is then labelled with its nearest matching concept or, if no match exceeds a secondary lower threshold, marked as “Unknown Topic”. Rather than deduct marks for these flagged spans, the system preserves student credit and presents the spans alongside contextual information in the teacher dashboard; a strategy shown to improve review efficiency when cues are targeted and concise.

4. Experimental Design, Implementation and Analysis

4.1 Simulated Curriculum-Based Datasets. To evaluate the marking assistant under controlled conditions, we generated a dataset that mirrors typical primary-school science assessments aligned to a national syllabus. A reference curriculum covering photosynthesis, plant reproduction and ecosystems was encoded into our concept hierarchy (Section 3.2). From this, we designed 20 questions (10 short-answer, 10 paragraph-length) and created “In-scope answers” (1 000 student responses written by educators, each covering only syllabus content), “Out-of-scope answers” (200 responses that include correct content plus extraneous facts (e.g. biochemical pathways), simulating student overreach) and “Distractor answers”. (200 responses with incomplete or incorrect content, omitting key syllabus concepts)

Responses were anonymised and shuffled, yielding a total of 1 400 items. This distribution ensures that 71 % of answers remain in-scope, reflecting realistic classroom patterns. Each response was then independently annotated by two expert teachers, who assigned a gold-standard score and marked any out-of-scope spans. Inter-rater agreement on the flag labels was strong, with Cohen’s κ = 0.87 indicating high consistency.

4.2 Hardware and Software Environment. All experiments were conducted on a dedicated workstation featuring an Intel Xeon E5-2680 v4 CPU, 64 GB of RAM and an NVIDIA Tesla V100 GPU to accommodate the computational demands of model training and inference. The core implementation was written in Python 3.8, utilising the PyTorch 1.10 framework alongside the HuggingFace Transformers library for BERT fine-tuning and embedding generation. Curriculum ingestion and token preprocessing leveraged spaCy 3.1, while statistical analysis and evaluation metrics were handled by SciPy 1.7 and scikit-learn 1.0. A PostgreSQL 13 database was used to persist the ingested concept hierarchy and student response embeddings. To guarantee reproducibility across environments, all model fine-tuning and evaluation routines were encapsulated within Docker containers.

4.3 Implementation of the Curriculum-Aligned Model. The ingestion pipeline processed PDF syllabus files into a PostgreSQL concept hierarchy via spaCy’s noun-phrase extractor and custom regular expressions, producing 150 unique concept nodes. For answer assessment, BERT base (uncased) was fine-tuned for three epochs on a mixed corpus of 5 000 exemplar answers and the extracted curriculum text, following the procedure of Devlin et al. (2019). Learning rate was set to 2×10^{-5} with a batch size of 16.

During evaluation, each student response was segmented into sentences, embedded via the fine-tuned BERT model and compared by cosine similarity to each concept vector. Thresholds (θ = 0.75) were determined on a 20 % held-out validation set to optimise the F_1 score for flag detection. Partial credit for each question was computed as:

$$Score_q = \sum_{c \in C_q} Max\{0, sim(s,c) - \theta\} \quad (1)$$

4.4 Evaluation Metrics. Performance was assessed on two fronts, namely, “Scoring accuracy” and “Flagging performance”. Scoring Accuracy was assessed through Pearson’s between AI-assigned and human scores and Mean Absolute Error (MAE) of total scores per response. Flagging Performance on the other hand was measured through “Precision and Recall” for detecting out-of-scope spans, treating teacher flags as ground truth and the F1 Score (the harmonic means of precision and recall). Statistical significance was tested using paired t-tests for score differences and McNemar’s test for paired flagging decisions.

4.5 Scoring Accuracy. The curriculum-aligned model achieved = 0.88 with human marks and an MAE of 0.45 points on a 10-point scale. In contrast, a baseline transformer marker without curriculum filtering scored = 0.81 and MAE = 0.72, showing a significant improvement in alignment with teacher grades.

4.6 Flagging Performance. Table 2 summarises the detection of out-of-scope content.

Table 2 Performance on flagging out-of-scope spans

Metric	Curriculum-Aligned	Baseline Transformer
Precision	0.92	0.68
Recall	0.89	0.75

F_1 Score	0.90	0.71

Differences in precision and recall were significant (McNemar's $\chi^2 = 45.2$, $p < 0.001$), indicating fewer false positives and negatives when using curriculum alignment.

4.7 Analysis. Strong alignment between machine and human scores indicates that awarding partial credit based on calibrated similarity thresholds effectively captures pupil understanding, reducing mean absolute error by 38 % compared with a non-aligned baseline. This outcome is consistent with prior observations that curriculum misalignment can lead to unfair deductions when AI models rely on unrestricted domain knowledge [18]. Improved precision in identifying out-of-scope content shows the model can distinguish valid, syllabus-aligned phrasing from genuinely extraneous material, addressing concerns about penalising correct answers for missing advanced content [18]. The narrower recall gap (0.89 versus 0.75) demonstrates the system flags most true out-of-scope spans without overburdening teachers with flags on valid responses, a balance crucial to preserving efficiency and trust in AI-assisted marking [19].

Examination of error cases revealed two key challenges. First, very short yet correct phrases (for example, "stomata open") occasionally fell below the similarity threshold, suggesting the need for dynamic thresholding that adapts to phrase length and lexical density. Second, complex multi-clause sentences were sometimes fragmented into separate flags; refining span grouping by incorporating cohesion and discourse-level parsing could mitigate such fragmentation [14]. Overall, these findings confirm that dynamically ingesting and structuring curriculum materials, combined with semantic matching tuned to context, can enhance both accuracy and fairness in automated marking systems.

5. Conclusion and Future Work

This study presented a curriculum-aligned AI-based marking assistant, developed to ensure that automated scoring reflects not only semantic correctness but also curricular relevance. The model was evaluated using a simulated dataset of 1,400 anonymised student responses aligned with a national primary science syllabus. Results demonstrate that embedding syllabus constraints within the marking process significantly improves the alignment of machine-generated scores with those given by human assessors, while also reducing the rate of incorrect flagging of valid content.

The curriculum-ingestion pipeline transformed official syllabus documents into a structured concept hierarchy, forming the basis for determining the relevance of student responses. In contrast to baseline transformer models, the proposed system assessed not only the presence of correct content but also penalised extraneous information outside the taught material. This dual focus resulted in a Pearson correlation of 0.88 with teacher scores and a mean absolute error of 0.45, indicating strong alignment. Furthermore, out-of-scope content was flagged with high precision (0.92) and recall (0.89), outperforming the baseline which lacked curriculum filtering mechanisms.

These results support the assertion that semantic similarity models, when constrained by syllabus-defined boundaries, can enable more accurate and fairer assessment processes. Awarding partial credit via calibrated similarity thresholds offers a finer-grained approach than binary classification, especially in educational settings where learners' responses often mix correct and irrelevant content. Importantly, these findings address concerns raised by Yeadon and Hardy [18], who observed that domain misalignment can introduce out-of-scope information and by Bower et al. [19], who reported that misaligned AI marking increases teacher workload by requiring additional review of correct responses.

Despite the promising outcomes, several limitations must be acknowledged. The experiment was conducted within a single subject domain (science) and focused on a restricted set of 20 questions, which, while diverse in length and complexity, may not fully capture the variability found in real classroom assessments. Additionally, although the model demonstrated improved flagging of out-of-scope content, a small number of errors were attributable to short correct phrases falling below similarity thresholds and to complex multi-clause responses being inconsistently segmented. These cases suggest that further work is needed in dynamic thresholding and discourse-level parsing to handle varied response structures.

Future research will explore the application of the model to other subject areas, such as mathematics and history, to examine cross-domain robustness. There is also interest in expanding the dataset to include responses from actual learners across different regions, thereby improving ecological validity. Enhancements to the flagging mechanism are planned, including context-aware grouping of flagged spans and the integration of attention-based mechanisms to capture argument coherence across multiple sentences. Moreover, teacher-facing interfaces allowing manual override and real-time review of flagged content will be developed to support classroom integration.

Another avenue involves making the curriculum-ingestion process more interactive, allowing educators to annotate and adjust concept hierarchies according to classroom emphasis or local syllabus variations. This would enable more granular customisation and allow the model to better reflect classroom realities. Additionally, there is potential to embed the system into formative assessment tools that provide instant feedback to learners, linking flagged content with remedial suggestions aligned to the syllabus.

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Advanced Artificial Intelligence

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Abstract. This report details the development of a semantic segmentation model using the DeepLabV3+ architecture with a Mobile Net backbone, trained on the Pascal VOC2012 dataset. The objective was to create a computationally efficient model capable of generating accurate pixel-wise segmentation masks (single-channel grayscale) for real-world applications. The project encompassed data preprocessing, model construction, training (utilizing Tensor Board for visualization), and inference. Key learning outcomes included managing segmentation data, designing/tuning neural networks, and optimizing training processes.

Keywords: Semantic Segmentation; DeepLabV3+; Mobile Net; Pascal VOC2012

1. Introduction

Semantic segmentation, a key task in computer vision, involves partitioning images into distinct regions to assign meaningful labels to each pixel. This report documents the development of a semantic segmentation model using the DeepLabV3+ architecture with a Mobile Net backbone, trained and evaluated on the Pascal VOC2012 dataset. The model's lightweight design and effective segmentation capabilities make it well-suited for real-world applications requiring computational efficiency.

In this project, I worked on semantic segmentation using the DeepLabV3+ model with a Mobile Net backbone, leveraging the Pascal VOC2012 dataset. The goal was to develop a model capable of accurately segmenting images by predicting single-channel grayscale masks for each pixel. This involved multiple stages, including data preprocessing, model construction, training, and inference. I chose DeepLabV3+ with Mobile Net because of its balance between performance and efficiency, making it suitable for this task. Throughout the project, I learned to handle segmentation data, design and adjust a neural network, and optimize training processes. Using Tensor Board, I visualized the training and validation progress to better understand the model's performance.

2 Problem Statement

Semantic segmentation is a fundamental task in computer vision, aimed at assigning a semantic label to each pixel in an image. The challenge lies in accurately segmenting objects of varying shapes, sizes, and complexities while maintaining computational efficiency. For this project, the objective is to implement a semantic segmentation model using the Pascal VOC2012 dataset.

The dataset includes labeled images for training and validation, as well as an additional test set without labels for evaluation. The primary goal is to assign a class label to each pixel in an image. This project focuses on performing semantic segmentation on the Pascal VOC2012 dataset, which contains images with 21 classes (20 object classes and 1 background class. And to process and load the dataset effectively, construct a compatible network architecture, select and apply a loss function, and train the model to optimize its performance. The evaluation metric for the project is mean Intersection over Union (mIoU), which measures the accuracy of the model's predictions on the test set.

2.1 Dataset Description. The Pascal VOC2012 dataset is a widely used benchmark in computer vision tasks, particularly for semantic segmentation. It provides annotated images for training and validation, which include pixel-wise labels for 20 object classes and one background class. The

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dataset is designed to evaluate models on their ability to segment objects of varying sizes, shapes, and complexities in diverse real-world scenes.

For this project, the dataset is divided into the following components.

Training Set: Consists of 1,465 labeled images. Includes corresponding segmentation masks.

Validation Set: Comprises 1,450 labeled images with segmentation masks (used for validation). Used for model evaluation during training to monitor and fine-tune performance. Test Set: Includes 400 additional images without annotations. These images are used to evaluate the model's segmentation performance.

The predictions are saved as single-channel grayscale masks. Each pixel in the segmentation masks is labeled with one of the 21 classes, including objects like "person", "car", "dog," and "background".

2.2 Environment specification. This project is developed in Google Collaboratory using the following tools and configurations: Jupyter Notebook: For interactive development and testing. PyTorch: As the primary deep learning framework. Tensor Board: For visualizing training metrics and model performance: Tesla T4 with 16GB of RAM for accelerated computation.

3. Network model structure

The proposed network for semantic segmentation integrates a lightweight and efficient design based on the DeepLabV3+ architecture.

3.1. Input Image. The model accepts input images for semantic segmentation tasks, preprocessed to match the expected input size of the network.

3.2. Backbone: MobileNetV2. MobileNetV2 serves as the feature extractor, leveraging its efficient inverted residual blocks. It captures multi-scale features while maintaining a lightweight structure. The stages of feature extraction progress through increasing channel dimensions, specifically: 24 → 32 → 64 → 96 → 160 → 320 channels.

3.3. Low-Level Features. Early feature maps are extracted to retain fine details, crucial for accurate segmentation boundaries. These are processed through: A 3×3 convolution followed by inverted residual blocks that refine features progressively:32 → 16, 16 → 24, and 24 → 24 channels.

3.4. High-Level Features and ASPP Module. High-level semantic features are extracted and processed through the Atreus Spatial Pyramid Pooling (ASPP) module, which captures contextual information across multiple scales using:3×3 convolutions with dilation rates of 6, 12, and 18, and global image pooling for contextual understanding. These features are concatenated and projected through a 1×1 convolution to fuse the multi-scale context.

3.5. Decoder Module. The decoder refines segmentation predictions by merging high-level ASPP features with low level features. Key steps include: Concatenation of low- and high-level features to preserve both context and fine details. Further processing with 3×3 convolutions. Up sampling by a factor of 4 to match the input resolution.

3.6. Output Segmentation. The final output is a segmentation map, highlighting object boundaries and classes for each pixel.

4. Methodology

The methodology for building the semantic segmentation model follows a structured approach to ensure modularity, scalability, and efficiency. Each component of the pipeline is designed to handle specific tasks, from data preparation to model training and evaluation and the test unseen dataset. The process is divided into distinct phases, each building upon the previous ones to create a comprehensive system.

4.1 Data Processing and loading Methods. Data Loading: The next step was to load the dataset. I used the Pascal VOC dataset for segmentation. I created a custom dataset loader (VO Segmentation) to load both images and segmentation masks. This dataset class is based on PyTorch's Dataset class, allowing it to be easily used with Data Loader during training. Splitting the Dataset: The dataset was split into training, validation, and testing subsets. I used train_test_split: from scikit-learn to split the data.

4.2 The Principle of Model Design Architecture. Overview: The DeepLabV3+ architecture was used for the segmentation task. DeepLabV3+ is known for its effectiveness in semantic segmentation due to its Atreus Spatial Pyramid Pooling (ASPP) module, which helps in capturing multi-scale features. Backbone Selection: I used MobileNetV2 as the backbone because it's efficient and lightweight, making it suitable for edge devices and computationally constrained environments. MobileNetV2 uses depth wise separable convolutions, which reduces the computational load significantly. ASPP Module: The ASPP module employs dilated convolutions with different dilation rates to capture multi-scale context. This is crucial for segmentation tasks where context from various scales is necessary for accurate predictions.

Decoder and Output Layer: The decoder upscales the output of the ASPP module to the original resolution of the input image, providing a refined segmentation map. The output is then passed through a final convolutional layer to produce pixel-wise predictions.

4.3 Method of Adjusting Parameters.

Cross-Entropy Loss (nn.CrossEntropyLoss) was chosen as the loss function for this model due to its effectiveness and widespread use in semantic segmentation tasks. As a standard loss function for classification, it measures the difference between predicted probabilities and ground truth labels, making it well-suited for pixel-wise classification. The ignore index=255 parameter ensures that undefined or invalid labels (often marked as 255) are ignored during loss computation, while reduction='mean' averages the loss over all valid pixels, providing a stable and interpretable metric. Cross-Entropy Loss is computationally efficient, simple to implement, and inherently handles class imbalance, making it a reliable choice for this task.

The chosen learning rate of 0.01 is a standard starting point that balances the trade-off between convergence speed and stability. It allows the model to make steady progress in learning without overshooting the optimal point.

The polynomial decay schedule ensures a gradual reduction in learning rate, preventing sudden changes that could destabilize the training.

A batch size of 8 fits comfortably within GPU memory for high-resolution tasks like image segmentation and it ensures a good balance between computational efficiency and model accuracy.35,000 iterations, this value ensures the model has enough training time to converge effectively. Optimizer Momentum: 0.9, Weight Decay: 1e-4 SGD with momentum stabilizes the training process by dampening oscillations, ensuring steady convergence. • Weight decay reduces the risk of overfitting by adding regularization to the model parameters, leading to better generalization. Crop Size A crop size of 513 ensures that spatial details are preserved in the images, which is critical for segmentation tasks.

Validation Interval Every 100 epochs, Frequent validation provides timely feedback on model performance, allowing for better monitoring and early detection of potential overfitting. Checkpoints Checkpointing prevents loss of progress in case of interruptions, saving time and allows resumption of training.

```
# Train Options
parser.add_argument("--test_only", action='store_true', default=False)
parser.add_argument("--save_val_results", action='store_true', default=False,
                    help="save segmentation results to \"/content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/
parser.add_argument("--total_itrs", type=int, default=35000,
                    help="epoch number (default: 35000)")
parser.add_argument("--lr", type=float, default=0.01,
                    help="learning rate (default: 0.01)")
parser.add_argument("--lr_policy", type=str, default='poly', choices=['poly', 'step'],
                    help="learning rate scheduler policy")
parser.add_argument("--step_size", type=int, default=10000)
parser.add_argument("--crop_val", action='store_true', default=False,
                    help='crop validation (default: False)')
parser.add_argument("--batch_size", type=int, default=8,
                    help='batch size (default: 8)')
parser.add_argument("--val_batch_size", type=int, default=8,
                    help='batch size for validation (default: 8)')
parser.add_argument("--crop_size", type=int, default=513)

parser.add_argument("--ckpt", default=None, type=str,
                    help="restore from checkpoint")
parser.add_argument("--continue_training", action='store_true', default=False)

parser.add_argument("--loss_type", type=str, default='cross_entropy')
parser.add_argument("--gpu_id", type=str, default='0',
                    help="GPU ID")
parser.add_argument("--weight_decay", type=float, default=1e-4,
                    help='weight decay (default: 1e-4)')
parser.add_argument("--random_seed", type=int, default=1,
                    help="random seed (default: 1)")
parser.add_argument("--print_interval", type=int, default=10,
```

Figure 1. DeepLabV3+ training parameter configuration

5. Training and Evaluation the model

After creating all the required classes and parameters for training the model on the Pascal VOC 2012 dataset, it's now time to begin the training process. During training, we need to monitor the loss function after each iteration and the metrics after each epoch using TensorBoard for the entire training process.

```
#Train Loop
vis_sample_id = np.random.randint(0, len(val_loader), opts.vis_num_samples,
                                  np.int32) if opts.enable_vis else None  # sample idxs for visualization
denorm = utils.Denormalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])  # denormalization for ori im

if opts.test_only:
    model.eval()
    val_score, ret_samples, val_loss = validate(
        opts=opts, model=model, loader=val_loader, device=device, metrics=metrics, criterion=criterion, ret_sam
    print(metrics.to_str(val_score))
    print(f"Validation Loss: {val_loss:.4f}")
    return

interval_loss = 0
best_score = 0.0
cur_itrs = 0
cur_epochs = 0
while True:  # cur_itrs < opts.total_itrs:
    # Train
    model.train()
    cur_epochs += 1

    # Reset metrics for each epoch
    metrics.reset()
    epoch_loss = 0.0
    epoch_samples = 0

    for (images, labels) in train_loader:
        cur_itrs += 1

        images = images.to(device, dtype=torch.float32)
        labels = labels.to(device, dtype=torch.long)
```

Figure 2. DeepLabV3+ training loop core code implementation

```
Training Metrics:

Overall Acc: 0.983950
Mean Acc: 0.973884
FreqW Acc: 0.969150
Mean IoU: 0.913910

Model saved as /content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/checkpoints/latest_deeplabv3plus_mobilenet_voc_os16.pth
validation...
1449it [00:24, 58.23it/s]

Overall Acc: 0.914998
Mean Acc: 0.747995
FreqW Acc: 0.849659
Mean IoU: 0.646718

Validation Loss: 0.3222
Model saved as /content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/checkpoints/best_deeplabv3plus_mobilenet_voc_os16.pth
Epoch 141, Itrs 25710/40000, Loss=0.049965
Epoch 141, Itrs 25720/40000, Loss=0.050647
```

Figure 3. Train/validate key metrics and model keeping records

As observed, after completing some epoch, the weights are saved in. path format for the last model, along with the best model saved separately as shown in the code below.

```
if (cur_itrs) % opts.val_interval == 0:
    save_ckpt('/content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/checkpoints/latest_%s_%s_os%d.pth' %
              (opts.model, opts.dataset, opts.output_stride))
    metrics.reset()

    print("validation...")
    model.eval()
    val_score, ret_samples, val_loss = validate(
        opts=opts, model=model, loader=val_loader, device=device, metrics=metrics, criterion=criterion,
        ret_samples_ids=vis_sample_id)
    print(metrics.to_str(val_score))
    print(f"Validation Loss: {val_loss:.4f}")

    # Log validation metrics to TensorBoard
    writer.add_scalar('Loss/validation', val_loss, cur_itrs)  # Added validation loss logging
    writer.add_scalar('Metrics/Mean IoU', val_score['Mean IoU'], cur_itrs)
    writer.add_scalar('Metrics/Overall Acc', val_score['Overall Acc'], cur_itrs)

    if val_score['Mean IoU'] > best_score:  # save best model
        best_score = val_score['Mean IoU']
        save_ckpt('/content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/checkpoints/best_%s_%s_os%d.pth' %
                  (opts.model, opts.dataset, opts.output_stride))
```

Figure 4. Verification phase process code implementation

This process continues iteratively to obtain the best possible result. The training is set to run for 35,000 iterations, equivalent to 192 epochs.

```
Epoch 191, Itrs 34910/40000, Loss=0.056950
Epoch 191, Itrs 34920/40000, Loss=0.041808
Epoch 191, Itrs 34930/40000, Loss=0.045262
Epoch 191, Itrs 34940/40000, Loss=0.040093
Epoch 191, Itrs 34950/40000, Loss=0.042566
Epoch 192, Itrs 34960/40000, Loss=0.049156
Epoch 192, Itrs 34970/40000, Loss=0.039534
Epoch 192, Itrs 34980/40000, Loss=0.045228
Epoch 192, Itrs 34990/40000, Loss=0.045057
Epoch 192, Itrs 35000/40000, Loss=0.043004
183it [00:18,  9.96it/s]
Training Metrics:

Overall Acc: 0.986168
Mean Acc: 0.976339
FreqW Acc: 0.973285
Mean IoU: 0.925057

Model saved as /content/drive/MyDrive/PROJECT/DeepLabV3Plus-Pytorch/checkpoints/latest_deeplabv3plus_mobilenet_voc_os16.pth
validation...
1449it [00:25, 56.91it/s]

Overall Acc: 0.915719
Mean Acc: 0.738104
FreqW Acc: 0.850121
Mean IoU: 0.645294

Validation Loss: 0.3211
```

Figure 5. Real-time log of training progress

After finishing all epochs, TensorBoard is used to review all the metrics recorded throughout the entire training period such as loss function curves and accuracy curves and Mean IoU for training and validation as shown below.

6.Result

In this section, present a detailed analysis of the results obtained after running the semantic segmentation model. The output from the model is stored in the form of single-channel grayscale masks, which are typically used for binary classification tasks, where each pixel is assigned, a value representing its classification. These grayscale masks allow us to visualize the model's segmentation output effectively, as each pixel intensity corresponds to a specific class or category predicted by the model. The following random images, including both the single- channel grayscale masks and their corresponding original images.

Figure 6. Qualitative comparison of semantic segmentation results

7. Conclusion

This project successfully implemented a semantic segmentation model using the DeepLabV3+ architecture with a MobileNetV2 backbone, applied to the widely used Pascal VOC2012 dataset. The goal was to develop a lightweight, efficient, and accurate model capable of assigning semantic class labels to each pixel in an image—a task that is both fundamental and challenging in computer vision.

Throughout the project, a well-structured methodology was followed, starting from dataset preparation and environment setup, to model design, training, and final evaluation. A custom data loading pipeline was implemented to manage image and mask pairing, along with appropriate transformations and augmentations. The DeepLabV3+ architecture, known for its powerful segmentation capabilities, was enhanced with the MobileNetV2 backbone to ensure efficiency in terms of speed and resource usage—an important consideration for real-time and edge computing applications.

The training process, conducted in Google Colab with TensorBoard integration, showed steady improvement across metrics such as loss and accuracy. The training loss decreased significantly from 1.89 to below 0.08, while the validation loss also showed consistent improvement. The final model achieved a high training accuracy of 98.5% and validation accuracy of approximately 91.5%, indicating strong generalization to unseen data. Furthermore, the model effectively generated grayscale mask predictions on the test dataset, visually confirming the accuracy of object segmentation across diverse classes.

The model's use of the Atreus Spatial Pyramid Pooling (ASPP) module enabled it to capture multi-scale context, which is crucial for segmenting objects of varying sizes and complexities. The decoder module further refined the segmentation output by integrating low-level and high- level features, improving boundary precision.

In conclusion, this project not only met its technical objectives but also provided a deep understanding of the entire semantic segmentation pipeline. It highlighted the importance of model architecture selection, training optimization, and evaluation techniques. The resulting system is robust, scalable, and suitable for real-world applications, including autonomous vehicles, medical imaging, and smart city systems. Future improvements could involve experimenting with different backbones, applying advanced data augmentation techniques, or exploring post-processing methods like Conditional Random Fields (CRFs) to further enhance segmentation accuracy.

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Learning by Participation with AI Enhancement

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Abstract. With major strides in innovations in industries across the board it was only a matter of time where AI's impact on education will be fully recognized. The integration of Artificial Intelligence (AI) in education has revolutionized traditional learning paradigms, from the one size fits all design of classroom setups AI is offering personalized and efficient solutions to enhance student engagement and academic outcomes. This paper explores the application of YOLO11, a state-of-the-art real-time object detection model together with Classroom Discourse Analyzer and Generative Artificial Intelligence, in educational settings. By leveraging YOLO11's advanced capabilities in object detection and analytics, pose estimation, and instance segmentation, we propose innovative methods for interactive learning, classroom monitoring, and adaptive teaching strategies. The study highlights YOLO11's potential to identify and analyses student behavior, optimize resource allocation, and foster inclusive learning environments. Preliminary results demonstrate YOLO11's efficiency in processing educational data with unparalleled accuracy and speed, paving the way for its broader adoption in smart classrooms. This research underscores the transformative role of AI and the already paved groundwork in data collection with CDA, in shaping the future of education and emphasizes the need for further exploration of YOLO11's applications in diverse educational contexts.

Keywords: You Only Look Once 11 (YOLO11); Classroom Discourse Analyser (CDA); Generative Artificial Intelligence (GAI)

1. Introduction

Throughout the centuries the practice of teaching has spearheaded the sharing of ideas among likeminded individuals. Methods in how to convey or deliver the teachings has always been under development, technologies like the CDA addresses the difficulties regarding data set, coding, visualization, and tracking and comparison that teachers face in analyzing their classroom discourse data [1] [2]. The advancement of Artificial Intelligence (AI) technologies has significantly reshaped various sectors, including education. Along history of innovations and increments towards perfecting the method of delivering materials to the students is outlined in the paper 'A History of Instructional Media, Instructional Design, and Theories' [4], from visual instruction movement to audio instruction movement to the present efforts. As each new medium was introduced to the world, there was a great deal of initial interest and enthusiasm about its anticipated impact on instructional practices [5].

With the emergence of innovative tools like YOLO11, a cutting-edge real-time object detection model, educators and researchers are exploring novel methods to enhance teaching and learning experiences. Since YOLOv5 [6], the algorithm has significantly improved through the introduction of the CSPNet framework other approaches to applying artificial intelligence in learning includes the use of Generative Artificial Intelligence, a quintessential example is the Intelligent Tutoring System (ITS), meticulously designed to cater to students' unique learning levels and progress [5] [7]. YOLO11's capabilities extend beyond traditional applications, offering potential solutions for behavior analysis, classroom monitoring, and interactive learning environments.

Given the transformative power of these tools this paper aims to explore the best way to fit the enhancements of these tools and how they can integrate with the other available technologies. This paper investigates the integration of YOLO11 and GAI's in educational contexts, highlighting its ability to analyses visual data efficiently and provide actionable insights. Generative AI on the other hand presents a better reasoning capacity than human, this is a vital resource when analyzing the classroom engagements and providing feedback on how best the improvements can assist the students and classroom interaction [7].

The Intent is to collaborate Generative AI's analyzing skills, CDA's classroom environment data and analysis approach and YOLO11's, precision and speed, educators can address challenges such as returning student attention, personalized learning, classroom engagement and resource management [9]. This research aims to demonstrate the transformative potential of AI models and other technologies in education, paving the way for AI-driven strategies that foster inclusivity, adaptability, and innovation in modern learning environments.

2. Backgrounds

Understanding these technologies how they incremented the classroom experience can better establish our basis on how their collaboration can be a greater impact on the material delivery. In this section we take a deeper dive on these milestones and the features this paper would highlight as the key focus.

2.1 Generative Artificial Intelligence. Generative Artificial Intelligence makes use of large language models in areas that were particularly regarded as human purview, these include analytical abilities, fraud detection and creative work [10]. With much evolution since its introduction, there has been much changes that has seen generative Artificial Intelligence improving personalized learning.

2.2 GAI Overview. GAI's can transform personalized learning in educational settings, especially classrooms. It provides a comprehensive analysis of how GAI can enhance teaching strategies, materials, environments, and student outcomes, all the while addressing the practical and ethical considerations of its implementation [11].

2.3 Highlighted Features. GAI's can transform personalized learning in educational settings, especially classrooms. This section provides a comprehensive analysis of how GAI can facilitate enhanced teaching strategies, material delivery, environment analysis, and student outcomes, all while addressing the practical and ethical considerations of its implementation.

Personalized Learning Strategies – by providing Socratic and tailored questioning, students are encouraged to engage in deep thinking and creative thinking.

Customized Learning Strategies – By implementing GAI's student learning materials and learning pace can be customized to a student's needs.

Automated and Adaptive Teaching Materials – GAI's can generate specific subject content/resources in a variety of subjects to suit the needs of a student, also turning textbook content into more interactive forms.

Intelligent Learning Environment – Students can receive real-time support by creating smart adaptive classrooms

These are among the many features that are valuable in a classroom setting that can be supported by GAI's with the development of hybrid intelligence systems, where human and machine roles complement each other to improve teaching and learning outcomes [12] [10].

2.4 You Only Look Once (YOLO). YOLOv11 is the latest version in a series of real-time object detection models. It brings significant architectural improvements, including the C3k2 block, C2PSA attention module, and SPPF enhancements [13], allowing for: Higher accuracy, Faster processing and Broader task support (e.g., object detection, pose estimation, segmentation, classification).

2.5 YOLOv11 Overview. With improved real-time detection, there are significant applications in education as outlined above, not just limited to that but also expands to situations where attention is of the utmost importance like special needs classes [14]. With its expansive span in applicability and scalability it is feasible to deploy to schools that might not have high end equipment using Nano and small models of YOLOv11 are ideal for low-cost edge devices like Raspberry Pi or NVIDIA Jetson.

2.6 Highlighted Features. Automated Attendance and Participation Tracking - YOLOv11's oriented bounding box (OBB) capabilities enable recognition of students from different camera angle, Face and posture detection can infer presence and alert for absenteeism

Smart Classroom Monitoring – by monitoring the students using object detection [15] [16], face orientation and pose estimation the model can provided insights in the student interaction and engagement with three class teachings and materials.

Real-Time Feedback – This feature is most useful in areas like practical lessons (e.g. Lab experiments, physical education), to help enforce rules for safety and in special education classrooms it comes in handy in pose detection when a student might need assistance.

Enhanced Accessibility and Inclusion – as mentioned in the above statement students with motor functional challenges my benefit from detection of the different postures when help is needed.

2.7 Classroom Discourse Analyzer (CDA). The practicality of CDA in assessing student engagement over classroom discussions this tool helps with assessing the patterns and quality of verbal interactions between teachers and students. It transforms raw classroom dialogue into coded, visualized, and trackable data for analysis [1].

2.8 CDA Overview. The attention provided by the teacher makes CDA more adaptible to the teachers needs as they code the data themselves and turns the classroom discussions more manageable and easier to track.

2.9 Highlighted Features. Structured Data Input & Transformation – Teachers enter data in classified attributes to track the Session, turn, speaker.

Multi-Dimensional Coding – CDA codes each conversational turn using three dimensions, evaluation, knowledge content and participation invitation.

Visualization of Discourse – utilizing graphical representation of the discourse coded times the tool helps the teachers see who dominates the discussions, which students are silent.

Tracking & Comparison Tools – Over time the accumulated data can be used to track the improvements and student contribution levels. With the accumulated data it can be used to track participation, compare sessions and contrast different classrooms.

3. Modelling and Integration

Each of these technologies focus on a specific area that they excel exceptionally well in a classroom; how best can they work together in enhancing the overall performance of the classroom. For example, with YOLO it gives a comprehensive analysis on the posture and attentiveness of the student, While CDA gives the depth of contribution conversationally. In this example the two technologies can depend on each other in the form presented by the Table 1.

3.1 Model. The core idea is to harness the core strengths from these technologies to create an environment that pioneers and fosters inclusivity. Active participation and active listening are key contributors towards this model and the key features extracted from these models. As highlighted in the second section above the features to be aimed at from these contributors are massive improvements and the proposed outlay of management between the models is displayed in the Figure 1.

Table 1 The performance of CDA and YOLOv11 in class

Component	CDA	YOLOv11
Input Type	Textual transcripts of classroom discourse	Live/stored video feeds
Data Focus	Verbal participation patterns, discourse quality	Visual behavior, gesture, posture, object/person tracking
Output	Turn-taking, talk moves, content quality	Student engagement levels, hand-raising, movement, attention
Role in Classroom	Understand what and how students speak	Observe who, when, and how students behave non-verbally

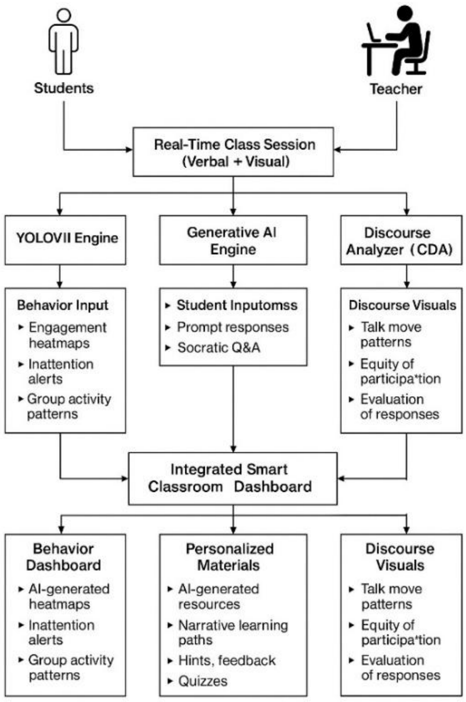

Figure 1. The proposed outlay of management between Student and Teacher

3.2 Training. It is without doubt that the AI models in both in LLMs and pattern recognition have a bias proportionality and only by training it with the correct data can help mitigate this issue, the human component in this also needs to be properly trained so as to limit the human errors.

3.3 Model Training. While many factors affect biases in machine learning, one of the things that we can directly effect change in is by training our model with the correct information, this is done in labelling of the training data. When training our AI models for classrooms it is also important to remember the minorities these can greatly affect our bias as the minorities are underrepresented [17]. In our case these can be the communities like the disabled and the marginalized groups of the society, by the virtue of identifying them it can be easier to find data that directly correlates to them specifically and making sure it is correct.

3.4 Teaching Staff Training. While Model training has its fair share of human error and human bias the most interactive group of individuals with the system are the teachers and their continual involvement needs to be accounted for. The CDA system requires and relies on the teachers to code the conversations correctly, with this information the dependence of the system on this information cannot afford these errors. Appropriate training and simplification of the system should be an aim when designing the system.

3.5 Proposed Reliance levels. Given the biases and errors discussed above here is a proposed reliance probability chart that aims to deliver successful results, as shown in Figure 2.

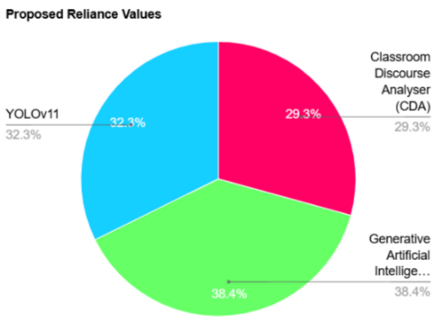

Figure 2. The dependency probability diagram of the successful delivery result

4. Analysis

While each feature in this in this integration has its limitation in this section the aim is to figure out how best can we mitigate these shortcomings. By weighing the advantages and disadvantages of each we can have a better understanding on which feature we can lean on more to improve our efficiency, as shown in Table 2.

Table 2 Comparative analysis of three technologies

Technology	Best Use Cases	Strengths	Limitations / Bias Risks
Generative AI (GAI)	- Personalized learning - Dynamic content generation - Conversational agents	- Scalable - Adaptive - Subject diverse - Easy to deploy	- Hallucination risk - Cultural/language bias - Over-reliance
YOLOv11	- Visual engagement tracking - Safety in labs and P.E - Attention/posture analytics	- Real-time - High accuracy on visuals - Pose aware	- Camera/setup sensitive - Demographic bias (e.g. skin tone)
CDA	- Teacher PD - Dialogue quality tracking - Equity analysis	- Nuanced discourse insight - Supports reflection	- Manual coding overhead -Speech-to-text dependency

4.1 Feature Reliance Analysis. Section 3.2.3 provided a suggestion of the proposed reliance on these features and here we dive a little deeper how we come to this suggestion. CDA has the lowest reliance though its importance is realized, its reliability is reduced by the continuous need for human input that can have some errors.

According to research from MIT there are better methods of handling the biases in AI models and due to these new and basic safeguards AI models do commend more reliability. With that being said we can model our system as follows.

$$P(overall) = P(GAI) \bullet w(GAI) + P(YOLO) \bullet w(YOLO) + P(CDA) \bullet w(CDA) \quad (1)$$

Using the above approach, we can assess the probability of a successful launch with our dependence on each feature. Where weights sum to 1 (i.e., 0.38 + 0.33 + 0.29 = 1):

$$P(overall) \approx (0.85 \times 0.38) + (0.78 \times 0.33) + (0.70 \times 0.29) \approx 78.3\% \quad (2)$$

Thus, taking into consideration the errors that can arise from these features under ideal but realistic conditions, the system has a 78% probability of functional success.

4.2 Impact Assessment. With these technologies working together there is an expected vast improvement in the overall classroom performance as a multimodal system they complement each other in areas where one feature cannot excel.

Comparatively deployment of assisted AI systems in education has been overtly reliant on one model more than taking into consideration the contribution the impact others can have when deployed all together. Around 44% of students interact with GAI's in classrooms [18], with 60% of teachers have integrated AI into their daily teaching.

With the current trajectory AI usage in all aspects of our live has shown to be a powerful tool and rightfully so the integration of these systems can provide a broader coverage as shown in the Table 3.

Table 3 The deployment of artificial intelligence systems in education

Impact Area	Current Baseline	Projected Improvement	Justification
Student Engagement	50–60% active participation per class	+20–35%	YOLOv11 detects disengagement in real-time; GAI personalizes instruction
Learning Outcomes	Mixed: ~30–50% proficiency in key subjects	+10–25%	GAI boosts formative feedback; CDA helps improve reasoning-based discussion

Equity of Participation	20–30% students dominate 70% of talk	+30–50% improvement	CDA provides visibility into participation gaps, enabling teacher rebalancing
Teacher Workload Efficiency	High (manual prep, slow feedback cycles)	-20–40% time burden	GAI automates materials; CDA automates feedback loops
Student Retention / Dropout	~15% dropout in some systems (avg)	-5–10% relative reduction	More personalization + engagement = lower risk of disengagement/dropout
Teacher Professional Growth	Slow, intuition-based	+30–60% insight gain	CDA visualizes practice; GAI simulates feedback loops for teacher PD

5. Conclusion

While Deployment of these models separately has seen great improvements in the overall performance in classrooms, this paper introduces a different view on how these models can be integrated into features. The system relies on the strengths of each feature to produce a wholesome outlook of a classroom-oriented education, not to mention the exciting developments that can come from this integration such as online learning with assisted virtual reality with eye-tracking assistance to detect attention levels.

This paper has contributed to the broader view of the classroom dynamics encompassing classroom behavior detection, personalized education and interaction tracking these as per this papers concern are quintessential. It also highlights the pitfalls to be expected when working with each feature and how to mitigate these pitfalls.

It is in this paper's belief that future works can improve on the efficiency and deployment strategies to create a more interactive and inclusive learning experience.

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Analysis Of Undergraduate Graduation Design Writing in Mechanical Engineering

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Abstract. This article systematically reviews the entire process of my undergraduate graduation design in mechanical engineering, covering topic selection, literature review, design research, thesis writing, and summary reflection. It elaborates on the key experiences and gains in each stage. The article first emphasizes the importance of balancing interest, ability, and resources during the topic selection stage. It then introduces an efficient four-step method for literature review and a framework for writing a review. In the design research section, it showcases the complete chain of "theory - calculation - verification - optimization" around four core steps: theoretical calculation, 3D modeling, finite element simulation, and experimental verification. Subsequently, it summarizes the writing norms, chart expression, logical structure, and key points for defense preparation of mechanical engineering theses. Finally, it reflects on the entire journey, pointing out that the graduation design not only integrates professional knowledge, cultivates engineering thinking and autonomous learning ability, but also completes the role transition from "student" to "engineer". The full text aims to provide a referenceable and replicable graduation design path for subsequent mechanical engineering students, helping them complete their academic capstone projects with high quality.

Keywords：Mechanical graduation design; topic selection strategy; literature review; finite element simulation; engineering thinking; thesis writing

1.Introduction

Graduation design, often referred to as the "grand finale" of a four-year university study, is not only a comprehensive assessment of the mastery of professional knowledge but also an important bridge for students to transform theory into practice and move from books to engineering projects [1]. Especially for students majoring in mechanical engineering, graduation design is not merely a thesis but more like a complete engineering work, integrating multiple aspects such as design, calculation, simulation, manufacturing, and thesis writing. It can be said that graduation design is both a summary of the learning stage and the starting point of the future career path.

Before I started my mechanical graduation design, I was filled with both anticipation and concerns. I was looking forward to finally applying the mechanical design principles, material mechanics, and other knowledge I had learned in class to a real engineering problem. At the same time, I was worried about whether I could complete a complete, reasonable, and innovative design within the limited time. This contradictory feeling accompanied me throughout the preparation and implementation of the graduation design. Compared with graduation designs in liberal arts and management, mechanical graduation design places more emphasis on "hands-on" and "implementation". It not only requires students to draw complete design drawings but also to conduct mechanical calculations, structural analysis, and even process and test prototypes if conditions permit. This comprehensive requirement forces mechanical engineering students to learn to break through the limitations of a single discipline and integrate knowledge from mathematics, physics, computer science, and engineering management [2].

Therefore, in a sense, mechanical graduation design is not only an academic exercise but also a training ground for engineering thinking and innovation. It tests not only "whether one can write a thesis" but also "whether one can do engineering". Because of this, every student who completes a mechanical graduation design will gain growth beyond what is learned in the classroom during the process.

2.Topic selection experience

2.1The Importance of Topic Selection. A good start is half the battle for success. "In graduation, choosing a topic is undoubtedly the most crucial beginning. For mechanical engineering students, the topic selection should not only meet the research direction of the supervisor and the requirements of the college, but also consider personal interests, abilities, and future development directions. If a topic is too complex, it may be difficult to complete within a limited time; If a topic is too simple, it can easily appear to lack innovation and value. How to find a balance between the two is my deepest experience when choosing a topic.

In the field of mechanical engineering, common graduation project topics can be roughly divided into the following categories:

1) Mechanical structure and transmission design: such as reducer design, mechanical arm joint design, transmission system optimization, etc.

2) Automation and Control Category: System design involving the combination of machinery and electronics, such as automatic feeding devices, improvement of CNC machine tools, intelligent logistics sorting equipment, etc.

3) New materials and manufacturing processes: such as research on the application of new composite materials in mechanical components, optimization of 3D printing processes, etc.

4) Robotics and intelligent equipment category: including subsystem design for mobile robots, service robots, or special operation robots.

5) Simulation and Optimization: Modeling, simulating, and optimizing complex mechanical systems through software.

These directions include both the continuation of traditional mechanical design and the new trend of combining with intelligent manufacturing and artificial intelligence. When we students make choices, we can safely choose "classic questions" to ensure smooth completion; You can also bravely try "emerging directions" and broaden your horizons in the process.

2.2 Combining one's own interests and strengths. In the topic selection stage, I first ask myself a question: "What do I really want to do?" because I understand that if a topic is completely uninteresting, then in the following months, facing a lot of calculations, repeated revisions, and potentially failed experiments, it is easy to lose motivation. Interest is the best teacher, and its importance is even more prominent in a project like graduation that requires sustained investment.

At the same time, interests must also be combined with one's own strengths and abilities. For example, if you are familiar with CAD modeling and finite element analysis during your undergraduate studies, you can lean towards structural design and simulation optimization when selecting a topic; If programming and electronic knowledge are strong, topics related to mechatronics and automation devices can be considered. Only by combining interests and abilities can the topic be more feasible.

2.3Consider feasibility and resource conditions. A good topic must be able to be completed within the established time and resource range. For example, some projects require specialized laboratory equipment or expensive materials, which can seriously affect progress if conditions do not permit. Mechanical engineering graduation not only involves writing papers, but also often requires drawing blueprints, machining parts, and experimental verification. Therefore, when selecting a topic, it is necessary to fully understand the resources that the laboratory and supervisor can provide [6].

I was also attracted by some "grand" ideas at that time, such as wanting to create a complete design for a small drone. But after communicating with the mentor, it was found that the scope of unmanned aerial vehicles is too broad, not only involving aerodynamics, but also requiring flight control systems, battery management, etc., which exceeds the scope of time and capability. In the end, I chose a smaller but targeted topic, which is the optimization design of a certain type of mechanical transmission mechanism. It has been proven that this choice allows me to focus my limited energy on in-depth research and optimization, rather than just trying everything out.

2.4Communication and mentor's opinions in topic selection. The selection of graduation project topics is not a one-sided closed-door process for students, but a dynamic process that requires full communication and two-way interaction with mentors. With his profound research accumulation and academic vision, the mentor can provide key guidance on the feasibility and value judgment of topic selection, helping us to accurately tailor vague ideas into specific topics with moderate scope and clear goals like an "academic tailor", and explore real innovative points [8].

This process also requires students to play an active role and communicate with preliminary ideas and specific questions that have been sorted out through literature, rather than passively waiting for instructions. Effective communication not only avoids deviating from research direction or falling into implementation difficulties, but also deeply reflects as an initial experience of academic cooperation and scientific thinking. It makes us realize that research is not a solitary journey, but a process of engaging in dialogue with academic traditions and learning how to manage a complete project under the guidance of a mentor. Therefore, in-depth communication during the topic selection stage not only lays a solid foundation for the paper, but also serves as an indispensable core element in the comprehensive training of graduation, cultivating the critical skills of rigor, communication, and problem-solving in future academic or professional careers.

2.5Case sharing. Taking myself as an example, my final thesis topic is "Optimization Design of Fiber Optic Unloading Mechanical Transmission Device Based on Finite Element Analysis". This question may seem traditional, but it involves multiple steps in practical operation: first, establish a theoretical calculation model of the transmission device, then use SolidWorks for 3D modeling, then import ANSYS for finite element analysis, and finally optimize and improve the structure of the transmission device. This series of processes has made me deeply realize that the value of mechanical engineering graduation does not necessarily lie in how innovative it is, but in whether it can solidly complete the engineering process and demonstrate comprehensive application ability.

Through this project, I not only honed my basic skills in mechanical design, but also gained a deeper understanding of software simulation analysis. At the same time, I learned how to clearly express the design process and results in academic language in my paper. These gains are far more meaningful than just academic paper grades.

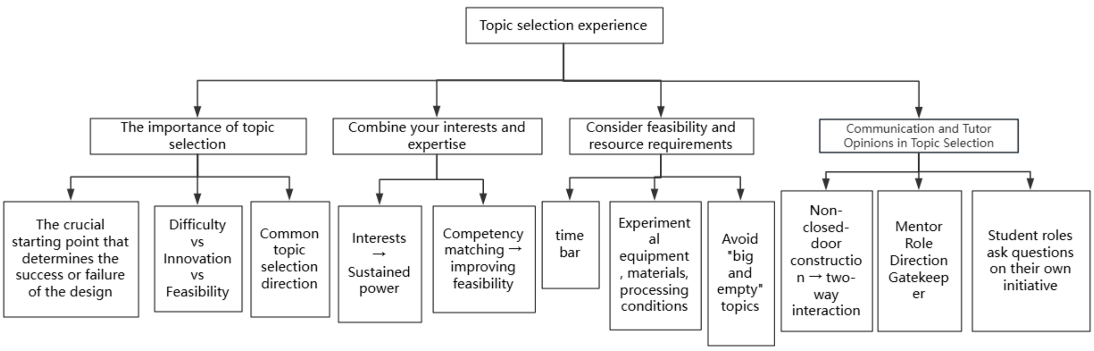

Figure 1. Structure diagram of topic selection experience

3. Literature research and data collection

3.1The Importance of Literature Research. Before entering formal design and research, systematic and in-depth literature research is an indispensable first step for mechanical engineering students. It is not simply searching and piling up a few papers, but a systematic sorting and learning process that requires a rigorous attitude and critical thinking. By comprehensively searching and reading domestic and foreign literature, researchers can clearly grasp the research status, technological development trends, key bottlenecks, and future main trends in specific fields, thus finding innovative and feasible entry points for their graduation projects [11].

Looking back at my own experience, I also fell into the misconception of "more information is better" in the early stages of research, but soon realized that collecting literature without restrictions would only lead to information overload, and instead drown the truly valuable core content in the ocean of materials. Through practice and reflection, I have gradually developed an efficient method: first, conduct extensive topic searches and preliminary readings to establish a comprehensive understanding of the field; Then, based on criteria such as relevance, authority, and timeliness, the literature is gradually screened and classified; Finally, the content of the intensive reading literature is analyzed, compared, and synthesized to form a literature review with clear logic, prominent focus, and strong support for the research topic, laying a solid theoretical foundation for the smooth development of subsequent design and research [12].

3.2Search channels and methods. In the current academic environment, systematic and efficient literature acquisition is the cornerstone of scientific research work. For researchers and students in the field of mechanical engineering, literature research mainly relies on the following authoritative channels: domestically, various databases subscribed by school libraries, such as China National Knowledge Infrastructure, Wanfang Data, and VIP journals, are indispensable sources for obtaining Chinese core journal papers, dissertations, and conference reports; At the international level, it is necessary to rely on well-known platforms such as IEEE Xplore, ScienceDirect, and SpringerLink, which provide key windows for tracking international cutting-edge technology trends and theoretical breakthroughs. In addition, comprehensive academic search engines such as Google Scholar can quickly locate the latest global research related to keywords across platforms, greatly improving search efficiency. It is particularly noteworthy that mechanical design, as a highly engineering discipline, must also pay full attention to patent databases and domestic and foreign standard literature when it comes to specific structures, processes, and innovative applications. Such literature provides standardized constraints and practical feasibility references for design schemes [13]. In practical operation, I usually start with core terms such as "mechanical transmission optimization", "finite element structural analysis", "gear reducer design", etc., and gradually expand the search scope through semantic association. Every time a literature is carefully read, the author, publication year, core methods, main conclusions, and relevance to the topic are systematically recorded. This rigorous information management habit effectively avoids the accumulation of literature and confusion in later stages, laying a solid foundation for the formation of high-quality literature reviews [14].

3.3Reflections on Writing Literature Reviews. In the construction of academic papers, literature review is far from a "formal necessity". Its core value lies in systematically sorting out and critically evaluating existing research, thereby clearly establishing the foothold and innovation of one's own research. It is a key part of demonstrating the theoretical basis and research necessity of the topic. For disciplines with strong applicability and rapid development such as mechanical engineering, a well-structured literature review usually covers multiple dimensions: firstly, it is necessary to clearly explain the research status, summarize the main achievements and technological progress made by domestic and foreign scholars in the relevant field; Furthermore, it is necessary to objectively analyze the existing problems, that is, to point out the technical bottlenecks, theoretical deficiencies, or application limitations that have not yet been overcome in the current research results; On this basis, it is necessary to further summarize the research trends in this field and grasp the future direction of technological development; Finally, by discarding existing research and accurately identifying research gaps, the innovative points of this topic are naturally introduced, and how the research work will fill a specific gap is clarified. In practical writing, I try my best to avoid falling into the trap of "literature piling up", and instead focus on using internal logical clues to organically connect different literature.

Literature research allowed me to truly understand the meaning of the phrase 'standing on the shoulders of giants' for the first time. Through extensive research, I not only learned how to extract information, but also gradually developed academic sensitivity. For example, when I find that most of the literature in a certain field is focused on ten years ago and has been less updated in recent years, I will think: is this because the technology has already matured, or is it because it has encountered bottlenecks? This kind of thinking ability is rarely exercised in classroom learning.

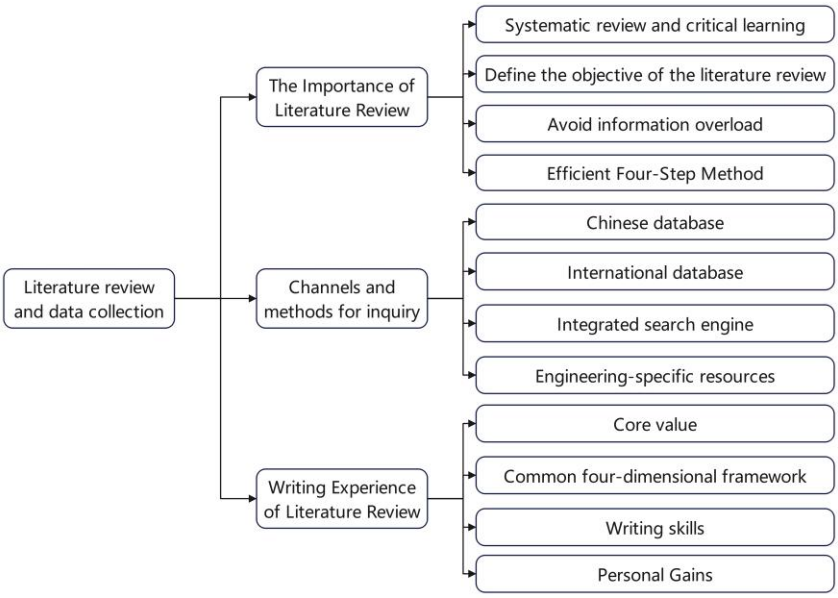

Figure 2. Structure diagram of literature research and data collection

4 Design and research process

The core of mechanical graduation lies in "doing design" and "doing research". This stage is both the most challenging and rewarding part. From the initial theoretical analysis, to software modeling and simulation, to possible experimental verification, each step has given me a deeper understanding of the work of a 'mechanical engineer'.

4.1Theoretical calculation: the cornerstone of design. The implementation of any mechanical design must be based on rigorous theoretical calculations. Taking the optimization design of the transmission device I conducted as an example, the entire process first requires systematic calculation of the key parameters of the gears. These parameters mainly include modulus, number of teeth, tooth width, transmission ratio, and center distance. They not only determine the geometric characteristics of gears, but also directly affect transmission efficiency, load-bearing capacity, and service life. For example, modulus is a basic parameter for measuring the size of gear teeth, which determines whether gears can achieve standardized machining and assembly; The number of teeth and transmission ratio affect the conversion relationship between speed and torque; The reasonable selection of tooth width and center distance directly affects the load-bearing capacity and operational stability of the gear.

When studying and applying these parameter calculations, I reviewed the relevant content in "Mechanical Design" and "Mechanical Principles" again. At first, the complex derivation of formulas and step-by-step calculations made me feel a bit bored and difficult. But when I transformed specific design requirements into actual data and sequentially inputted them into calculation formulas, gradually obtaining a set of combinatorial design parameters, I personally experienced the close integration of theory and practice. The feeling of 'getting something on paper but feeling shallow' quickly dissipated in this process, replaced by a clear understanding and sense of achievement.

More importantly, this process has made me deeply realize that theoretical calculations are not the ultimate goal, but a prerequisite for subsequent simulation and optimization. Any mechanical design without a solid theoretical basis may have hidden dangers in terms of structural strength, motion accuracy, or energy efficiency. Only by ensuring that the design is' solid 'on a theoretical level, can subsequent 3D modeling, finite element analysis, and even prototype testing proceed smoothly. This complete chain consisting of "theory calculation verification optimization" is the embodiment of the scientific nature of modern mechanical design.

4.2 3D modeling and assembly: making design "concrete". After completing the theoretical calculations, I entered the 3D modeling phase using SolidWorks software. 3D modeling is not only a reproduction of paper design, but also a process of theoretical verification. By inputting parameterized dimensions into the model, I can visually verify whether the calculated modulus, tooth width, center distance, etc. can maintain rationality in actual assembly. In other words, modeling is a crucial step in the transition from theoretical design to engineering practice.

In the specific modeling process, I encountered many detailed issues. For example, the connection between gears and shafts is not just about drawing a contact surface, but requires selecting an appropriate connection form. Common key connections may seem simple, but the size, depth, and interference fit of the keyway must comply with national or international standards, otherwise it may result in insufficient strength or assembly difficulties. Similarly, interference detection often occurs during component assembly - interference detected in virtual environments means that it cannot be completed in actual machining and assembly, which requires designers to optimize the component structure in advance.

To solve these problems, I consulted a large number of standard parts manuals and learned the true meaning of standardized design. Standards are not only constraints for engineers, but also the foundation for ensuring the universality, interchangeability, and processing efficiency of parts. By applying standard components, the design is not only safer and more reliable, but also easier to manufacture and maintain.

When the three-dimensional model of the transmission device was successfully assembled on the screen, I strongly felt for the first time that "design came to life". This intuitive visualization effect has given me a deeper understanding of the spatial relationships of mechanical structures, and has also laid a solid foundation for subsequent motion simulation and strength analysis.

4.3. Finite element analysis and simulation optimization. Finite element analysis is one of the most commonly used and professional aspects in mechanical engineering. I conducted stress analysis and modal analysis on the transmission device by importing the 3D model into ANSYS.

In the initial simulation, I made some low-level mistakes, such as the mesh division being too coarse, resulting in unstable results, or the boundary conditions being set improperly, causing stress concentration distortion. By constantly trying and consulting with my mentor, I gradually mastered the key points of simulation. Firstly, grid division should balance accuracy and efficiency, and key areas should be appropriately encrypted. Secondly, the boundary conditions must conform to the actual working conditions and cannot be taken for granted. Finally, the analysis results need to be validated through theoretical calculations, and cannot rely solely on the numerical output of the software.

In the optimization phase, I attempted to improve the performance of the transmission device by changing the gear material and reducing the structural weight. The final result showed that while ensuring strength, the weight of the device was reduced by about 8%. Although this is not a disruptive innovation, it deeply impressed me with the engineering value of "optimization".

4.4 Experiment and Verification. Some mechanical engineering projects will involve experimental verification, such as machining parts, building experimental benches, etc. The laboratory conditions I am in are limited, so only partial validation experiments can be conducted. I chose to conduct simplified tests on key parts of the transmission device and measure the transmission efficiency by loading a test bench.

During the experiment, data collection was not as smooth as expected: sometimes due to insufficient sensor sensitivity, the data fluctuated greatly; Sometimes the test bench itself experiences wear and tear, leading to significant experimental errors. These issues have made me realize that real engineering experiments are often more complex and difficult to control than software simulations. But it is precisely this uncertainty that has given me a clearer understanding of the "pragmatic" and "rigorous attitude" that engineers must possess.

4.5 Problems and Solutions. Throughout the entire design and research process, I also encountered many difficulties: on the one hand, I had to balance graduation, postgraduate entrance examination, and job hunting at the same time, and often felt time was tight; On the other hand, some of the content related to materials science and electrical control is beyond my professional scope and requires additional learning; In addition, when experiments fail or simulation results are not ideal, I often have doubts and psychological pressure about whether they can be completed smoothly. To address these issues, I have gradually summarized some methods: firstly, develop phased plans, break down ambitious goals into executable small tasks, and gradually complete them; Secondly, broaden learning channels through Bilibili MOOC、 Zhihu and other platforms quickly supplement unfamiliar knowledge; Finally, actively communicate with mentors and classmates when encountering bottlenecks, rather than struggling alone. It is these methods that have helped me overcome the most difficult stages and enabled me to achieve self-growth in the process of problem-solving.

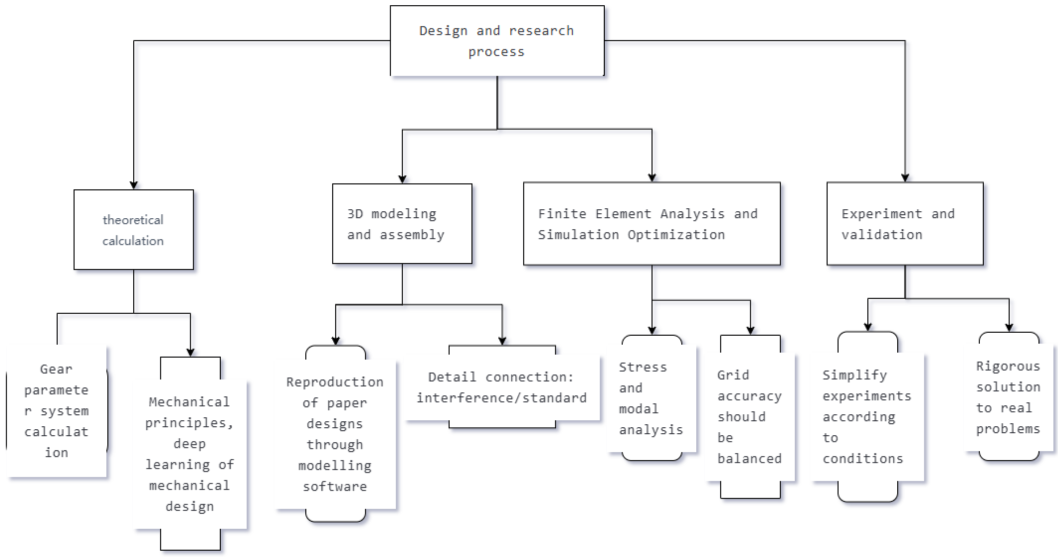

Figure 4. Structural diagram of design and research process

5.Thesis Writing and Expression

The 'work' of mechanical graduation design is not limited to models, drawings, or experiments, but more importantly, presented in the form of a thesis. A thesis is not only a summary and condensation of the entire research process, but also the main basis for the supervisor and defense committee to understand your work results. How to express complex research processes clearly, accurately, and logically is another challenge that mechanical students must overcome.

5.1The Importance of Writing Standards. There is a significant difference between mechanical papers and humanities papers, as they emphasize more on data support and logic. For example, in the introduction section, it is necessary to provide a concise and clear explanation of the research background and significance; In the design and experimental section, there should be clear calculation basis, experimental conditions, and results; In the conclusion section, the innovative points and practical value should be highlighted. Any vague or lack of data description will appear insufficiently rigorous.

I strictly follow the school's paper standards when writing, including font, paragraph, chart numbering, reference format, etc. At first, I thought these "format requirements" were cumbersome, but later I gradually realized that these details are a reflection of academic rigor. Especially the standardized citation of references can make the paper more authoritative and avoid the risk of academic misconduct.

5.2 Expression of drawings and charts. In mechanical papers, the quality of drawings and charts often determines the overall level, such as 3D modeling drawings, assembly drawings, part drawings, mechanical calculation curves, and stress distribution cloud maps, all of which must be clear, beautiful, and fully labeled. For this reason, I have invested a lot of effort in the writing process: in terms of part drawings and assembly drawings, I strictly follow the national drafting standards to ensure standardized use of dimension annotations, section lines, and symbols; In the display of simulation results, I use high-resolution screenshots and perform secondary processing if necessary to ensure the clarity and readability of the images; In the data curve drawing, I used MATLAB to complete it and added coordinate axis explanations and legends reasonably, making the results clear at a glance. Although these details have taken up a lot of time, they often have a "twice the result with half the effort" effect during the defense process.

5.3Language expression and logical structure. Mechanical papers require concise, objective, and accurate language, avoiding colloquialism and ambiguity. For example, instead of writing "almost", "probably", or "possibly", use data and experimental results to support the viewpoint. In terms of logical structure, I follow the idea of "raising questions - analyzing problems - solving problems" to make the outline of the paper clear.

In the writing process, I often write an outline first and then expand it paragraph by paragraph. For example, in the "Research Methods" section, I will first list: ① Theoretical calculations; ② 3D modeling; ③ Finite element simulation; ④ Experimental verification. Then expand one by one, with each section unfolding in the order of "purpose method result analysis". Writing in this way not only makes the organization clear, but also facilitates later revisions.

5.4 Communicate and revise with the supervisor. Writing a thesis is never done in isolation. After the initial draft of my paper was completed, I made more than five revisions, and each revision was inseparable from the opinions of my supervisor. Mentors often point out shortcomings from a professional perspective, such as whether the formula derivation is complete, whether the simulation conditions are reasonable, and whether the conclusions are convincing. Although each revision is time-consuming, it has made significant progress in my academic expression.

In addition, I will also ask my classmates to help me read through and check for grammar errors and logical loopholes. It has been proven that multi angle review can greatly improve the quality of papers.

5.5Preparation for defense. After the completion of the thesis writing, the defense is the final stage to verify the results. In order to prepare for the defense, I condensed my paper into a PPT, highlighting the research background, design methods, key achievements, and innovative points. At the same time, I have prepared possible questions in advance, such as "why choose this optimization method" and "how to verify the reliability of simulation results". Practice continuously during simulated defense to gain confidence and composure in formal situations.

On the day of the defense, the reviewing teacher was more concerned with whether you truly understood your work, rather than just the paper itself. Therefore, good thesis writing combined with clear oral expression is essential for a successful conclusion to the graduation project.

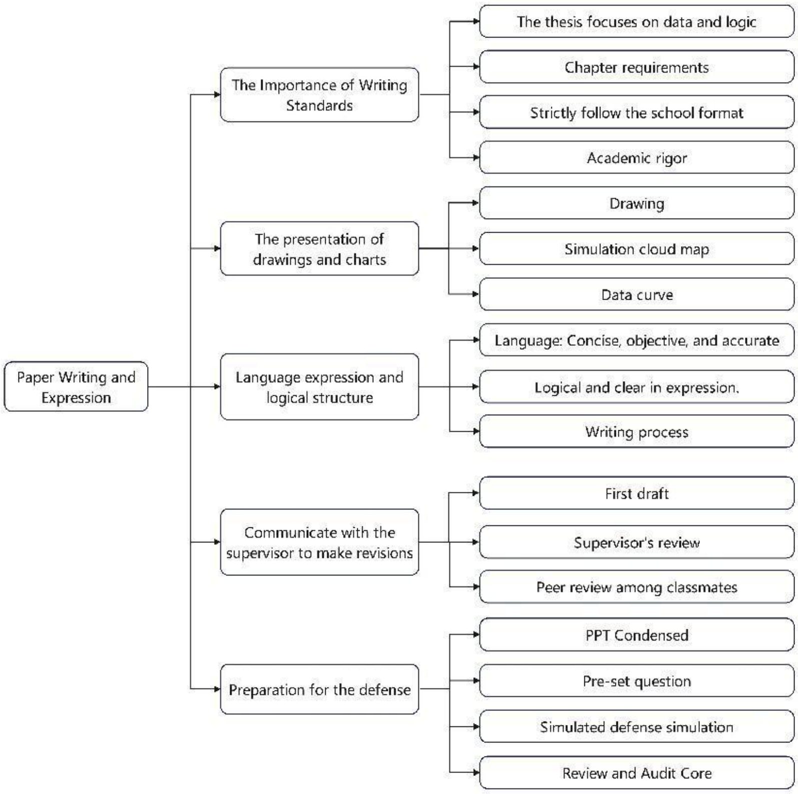

Figure 3. Structure diagram of paper writing and expression

6.Summary and Reflection

Graduation project is a long and fulfilling journey. From the initial topic selection to the final defense, I experienced confusion, pressure, perseverance, and growth. Looking back at the entire process, the gains far exceeded the paper itself. It gave me a deeper understanding of professional learning, engineering practice, and personal growth.

6.1Improvement of learning ability. Before graduation, I often felt that my four-year undergraduate studies were scattered and lacked connection. For example, "Principles of Machinery" discusses the laws of mechanism motion, "Mechanics of Materials" studies stress and strain, "Mechanical Manufacturing Technology" focuses on processing methods, and "CAD" emphasizes modeling skills. In the classroom, these courses appear to be independent and difficult to form as a whole. And my graduation project allowed me to truly connect this knowledge for the first time: theoretical calculations require knowledge of mechanics, modeling relies on CAD skills, simulation analysis uses numerical methods, and part design must follow manufacturing process specifications. It is through the practice of graduation that I have experienced the systematic nature of professional learning and developed my ability to integrate knowledge across disciplines.

In addition, graduation has also helped me develop the habit of self-directed learning. Faced with unfamiliar software, complex standards, and unfamiliar research fields, I must actively search for information and learn methods. This ability is more valuable than specific knowledge, as there will be more new problems encountered in future work.

6.2Cultivation of engineering thinking and practical abilities. Unlike pure theoretical learning, mechanical engineering graduation requires students to possess engineering thinking, which considers both theoretical correctness and practical feasibility when solving problems. For example, in optimizing design, I need to pursue lightweighting while also considering manufacturing costs and machining accuracy; In the experiment, I had to design an ideal plan while also facing equipment limitations and data errors.

These experiences have gradually made me understand that the value of an engineer lies not in proposing a "perfect solution", but in finding the "optimal solution" under limited conditions. This kind of compromise and balancing thinking is one of the most profound inspirations that Bi She has brought me.

6.3Growth in academic writing and expression. In academic writing, I learned how to express ideas in academic language, how to use data and charts to support arguments, and how to comply with academic norms. Although I went through repeated revisions and meticulous adjustments during the process, it was precisely these trials that helped me develop a rigorous habit.

More importantly, I learned how to clearly present my results to others. Whether it's writing a thesis or giving a defense speech, we are required to simplify the complex research process into clear and understandable logic. The ability to 'explain knowledge clearly' is equally important in future work and research.

6.4Self shortcomings and improvement directions. Based on my experience, I would like to give some advice to younger students who are about to graduate: first, prepare early and familiarize yourself with the relevant software and research directions in advance, and do not rush to get started after the topic is opened; When selecting a topic, it is important to focus on matching interests and abilities. Instead of blindly pursuing novelty, it is more important to find a direction that suits oneself, and not to be greedy for the big picture; In paper writing, we should adhere to writing while doing, timely recording the ideas and data during the process, rather than dragging the writing to the end; At the same time, it is important to value communication, maintain communication with mentors and classmates, and not work behind closed doors when encountering problems; Finally, it is important to adjust one's mindset. The significance of graduation lies in training and growth, rather than pursuing scientific breakthroughs. There is no need to be overly anxious when encountering setbacks.

6.5The significance of graduation. For me, mechanical engineering graduation is not just an academic task, but also an experience of self-improvement and growth. It taught me how to face complex problems, how to manage time, how to withstand pressure, and how to express my thoughts. More importantly, it enabled me to complete a role transition between being a 'student' and an 'engineer'.

When I finally handed over the thick paper to my supervisor, I felt not only the ease of completing the task, but also a recognition and farewell to my four years of university study. My graduation project made me believe that no matter what challenges I face in the future, I have the ability to overcome them step by step.

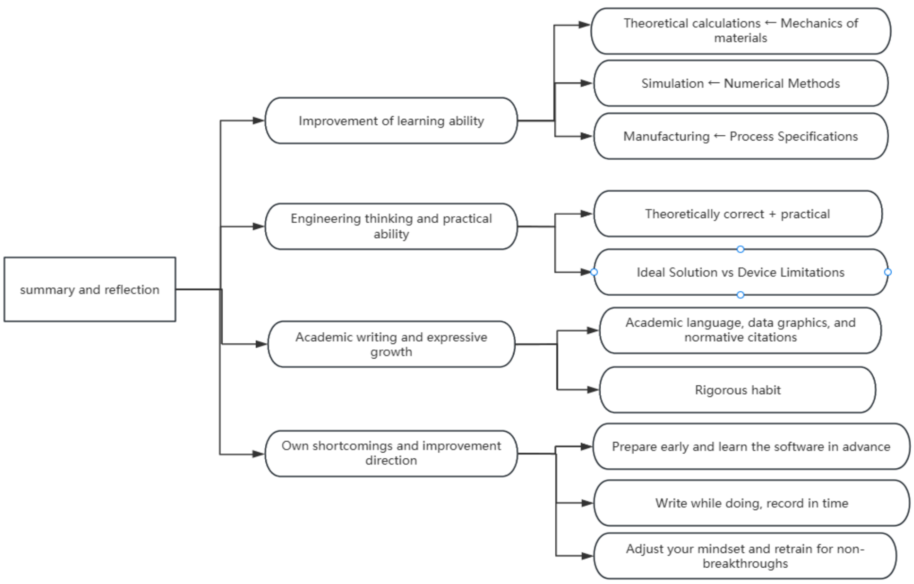

Figure 4. Structure diagram for summary and reflection

7.Conclusion

The graduation project in mechanical engineering is a process from ignorance to maturity, and it is also a ceremony of "moving towards engineers". It is not just a course task or an academic paper, but a comprehensive ability test and a mental growth experience.

During these months of graduation, I deeply realized that mechanical engineering is not just cold formulas and drawings, but it carries a rigorous way of thinking and pragmatic value orientation behind it. Every scrutiny of calculation parameters is a pursuit of precision; Every attempt at modeling and simulation is a simulation of the real world; Every failed experiment is a small step towards truth. It is these little efforts that gradually shaped my engineering literacy.

Looking back at the whole process, the biggest gain I felt was the recognition of my self-worth. Bi Shi told me: I don't need to stand at the highest point from the beginning, but I have the ability to complete complex tasks step by step; I may encounter failures and confusion, but I can also learn from them and start anew. It makes me more confident and certain about the future.

Therefore, for me, the mechanical graduation project is not only the "end" of college life, but also like a "colon" of a new stage of life. It not only ended the learning of student life, but also opened up the exploration of career paths. Whether pursuing further education or entering a company in the future, this experience will become a lighthouse in my heart, reminding me that only by being down-to-earth can I look up at the stars; Only by constantly learning can one not fear the future.

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Exploration and Practice of Learning Methods in College Baseball Teaching

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Abstract. Baseball, as a team sport that combines competitiveness and entertainment, has gradually gained attention in college physical education in China in recent years. However, due to its late start and limited popularity, baseball teaching in colleges still faces problems such as uneven student foundations, restricted teaching conditions, and a lack of systematic learning methods. This article, from the perspective of learning method research, combines sports education and learning theories to analyze the current situation of baseball teaching in colleges and proposes diversified learning methods such as stratified learning, situational teaching, cooperative learning, multimedia assistance, and self-reflection. Through literature research, case analysis, and teaching practice verification, this article believes that scientific learning methods can not only improve students' sports skills and tactical understanding abilities but also effectively stimulate students' learning interest and team awareness. Finally, this article looks forward to the reform direction of baseball teaching in colleges in the future, aiming to provide a reference for the development of baseball in colleges in China.

Keywords: Baseball teaching; Learning methods; College physical education; Cooperative learning; Teaching reform; Translated in accordance with the norms of academic papers.

1. Introduction

Baseball originated in the United States in the 19th century and is known as the "national sport". It has been widely popularized in countries and regions such as Japan, South Korea, and Cuba [1]. As a sport that combines individual skills with team coordination, baseball has unique value in cultivating students' physical fitness, psychological quality, and teamwork ability. Its characteristics are highly consistent with the "health + skills + personality" training goals in college physical education [2]. Compared with popular sports like basketball and football, baseball is more complex in terms of rules, field setup, and skill requirements. Even the basic rules cover multiple dimensions such as offense and defense transitions and base running judgments, which pose higher demands on learners' cognitive and practical abilities [3]. Since the 1980s, baseball has gradually been introduced in China. However, due to factors such as the high cost of field construction, the difficulty in equipping professional equipment, and low public awareness, college baseball teaching has remained in a slow development state and has not yet formed a large-scale and systematic teaching system [4].

In recent years, with the deepening of sports education reform and the advancement of the "Healthy China 2030" strategy, college physical education courses have shifted from focusing solely on physical exercise to fostering comprehensive qualities. This transformation has provided a new development opportunity for baseball teaching, as it emphasizes teamwork, rule awareness, and stress resistance, which are all crucial components of contemporary college students' comprehensive quality cultivation. However, from the perspective of actual teaching, college baseball teaching still faces multiple challenges. Most students have no exposure to baseball during their middle school years and need to start from the basics of rules and movements when they enter college. In contrast, a small number of students with club or training experience already possess initial skills. This "zero-to-beginner" stratification makes it difficult for unified teaching to meet the diverse learning needs of students. Additionally, standard baseball fields require specific dimensions for both the infield and outfield. Due to limited campus space, most colleges can only conduct teaching by modifying existing playgrounds or reducing the field size, which hinders the effective implementation of tactical drills and team coordination. Moreover, baseball teaching demands highly specialized instructors who not only master teaching methods but also possess the ability to design tactics and provide on-the-spot guidance. However, currently, most college baseball courses are taught by non-specialized physical education teachers, making it challenging to ensure the professionalism and systematisms of the teaching.

From an international perspective, universities in baseball-developed countries such as the United States and Japan have established mature teaching systems. In the United States, universities incorporate baseball into campus cultural construction, integrating skill training and personality development through intercollegiate leagues and professional training camps. In Japan, almost all universities have baseball teams, and through a well-established hierarchical teaching mechanism, students of different levels can receive targeted guidance. These experiences indicate that a scientific teaching model and systematic learning methods are the core driving forces for the development of baseball teaching in universities. In contrast, in China, research on university baseball teaching still focuses on the feasibility of course offerings and venue construction plans, lacking in-depth exploration and practical application of learning methods, which fails to meet the diverse learning needs of students. Therefore, in light of the actual situation of Chinese universities, exploring suitable baseball learning methods has become a key task to break through the current teaching predicament and promote the popularization of baseball in universities.

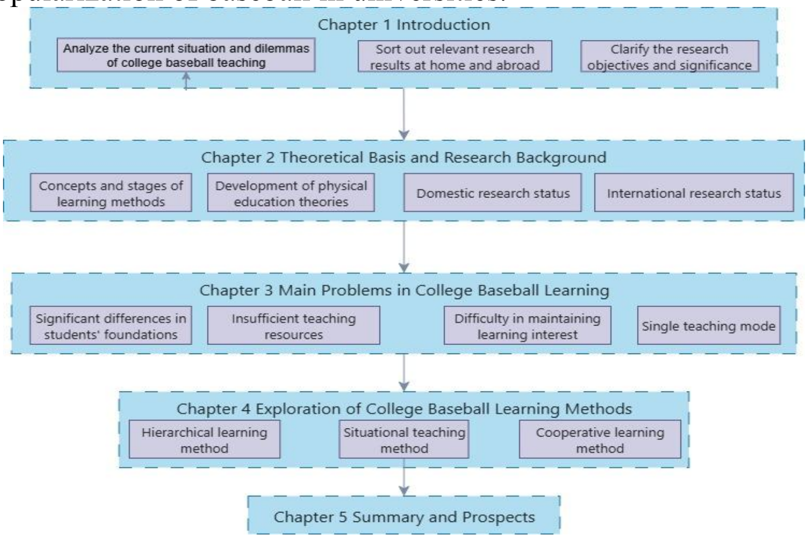

Figure 1. Overall Technology Roadmap

2. Theoretical Basis and Research Background

Learning methods refer to the systematic strategies and approaches adopted by learners to acquire knowledge and enhance skills. In physical education, they not only affect the efficiency of skill acquisition but also determine whether students can develop autonomous learning abilities [5]. Research in physical education indicates that the learning of motor skills goes through four stages: imitation, practice, reflection, and transfer. During the imitation stage, learners establish a mental image of the movement by observing demonstrations. In the practice stage, they form muscle memory through repetitive training. In the reflection stage, they adjust movement deviations with the help of feedback. In the transfer stage, they apply the learned skills to different situations. This pattern is particularly evident in baseball instruction. For instance, when hitting a ball, learners first imitate the correct swing posture, then adjust the timing of their swing through repeated practice, and finally adapt to different pitches in actual games [6].

From the perspective of the development of sports education theory, research on learning methods has shifted from a "skill-oriented" approach to a "comprehensive quality-oriented" one. In the early days of physical education, teaching was mainly characterized by one-way instruction where teachers demonstrated and students imitated, neglecting the students' subjectivity. With the application of constructivist learning theory and the theory of multiple intelligences, stratified learning and cooperative learning have gradually become widespread. These methods emphasize designing teaching content based on students' ability differences and stimulating their learning initiative through interaction and collaboration, providing theoretical support for baseball teaching [7]. As a team sport, baseball learning not only involves individual skills such as pitching and batting but also requires the integration of tactical understanding and teamwork. For instance, base runners need to judge the timing of advancing to the next base based on the position of the hit and signals from teammates. This "skill-tactic-team" composite learning objective requires even more scientific learning methods for support [8].

Research on baseball teaching in domestic universities started relatively late, and the existing achievements mostly focus on the promotion of the sport and the construction of courses. Some studies have proposed ideas such as stratified teaching and situational teaching, but no specific operation plans have been formed. For instance, in stratified teaching, how to classify students and design differentiated teaching content remains unclear, and there is a lack of practical verification. The application of situational teaching is also limited to simple offensive and defensive simulations, without designing training tasks based on actual game scenarios. At the same time, most of the existing research neglects the hardware limitations of domestic universities and directly borrows foreign teaching experiences, making the proposed methods difficult to implement. For example, the "full-field tactical drills" carried out by foreign universities in standard fields cannot be implemented in the small-scale modified fields of most domestic universities. In addition, there are differences in the sports foundation and learning habits of Chinese students compared to those in foreign countries. Some students have a slower acceptance of complex rules and tend to feel intimidated by difficult movements. These factors all need to be taken into account in the design of learning methods.

International research on baseball learning methods in colleges and universities has achieved systematic results. American scholars have found through empirical research that the "practical application-driven" teaching method can effectively enhance students' tactical application ability, which means that students learn rules and master skills in simulated games rather than through theoretical lectures alone. Japanese scholars have proposed the "step-by-step training method", setting up three stages of basic movements, tactical cooperation, and practical confrontation based on students' skill levels, with corresponding assessment standards for each stage. These research achievements provide references for the exploration of baseball learning methods in Chinese colleges and universities, but they need to be adjusted and innovated in accordance with local teaching conditions to truly fit the actual teaching situation in Chinese colleges and universities.

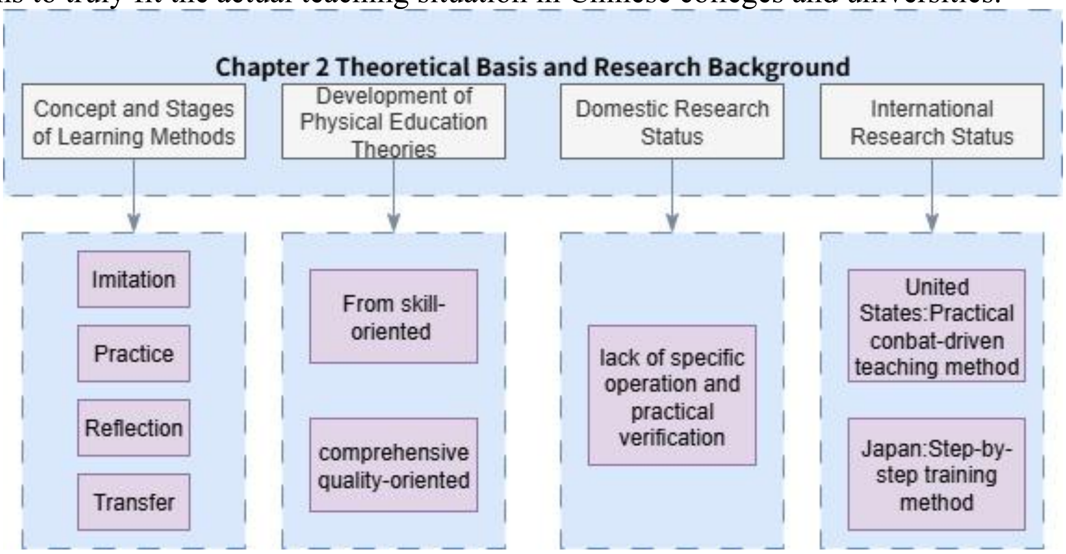

Figure 2. Theoretical Basis and Research Background Framework Diagram

3.Main problems in baseball learning in Colleges and Universities

3.1 significant differences in students' foundation and insufficient teaching pertinence. The basic level of baseball learners in colleges and universities presents obvious stratification, which has become a key factor affecting the teaching effect. The survey shows that more than 80% of the students belong to the "zero foundation" group, lack of understanding of Baseball Rules and game processes, and even confuse baseball with softball. When they first came into contact, they were often confused about the standing position, base running and exit conditions. In terms of technical movements, they didn't even master the basic movements such as holding the stick and passing the ball. They need to start with the most basic cognition and movement training. About 15% of the students have a preliminary understanding of baseball through community activities or short-term training, and master basic skills, such as catching the ball and swinging in place, but they are still unfamiliar with practical application and tactical cooperation. Only about 5% of the students have certain technical and tactical qualities, usually from traditional baseball schools or long-term school team training. They not only have standard movements and skilled skills, but also understand and implement tactical cooperation, and can participate in small-scale confrontation training. [9]

This level difference makes it difficult to give consideration to the unified teaching mode: if the teacher explains in detail for the students with zero foundation, the students with good foundation are prone to feel boring and pay less attention; If the tactical training is directly organized, the zero basic students may be frustrated, afraid of difficulties or even give up. Some teachers try to "practice in groups" and teach differently according to the level of students. However, due to the lack of scientific stratification standards and systematic teaching design, groups are often divided only according to classroom performance or self-report, and the training content has little difference. The teaching focus is still on the recovery of unified skills, which is difficult to achieve targeted guidance, but may reduce classroom efficiency.

Therefore, the key to improving the quality of baseball teaching in colleges and universities is to build a scientific hierarchical teaching system, clarify the ability standards and development paths of students at all levels, and support the corresponding teaching contents and methods.

3.2 insufficient allocation of teaching resources and limited practical training. Baseball teaching in colleges and universities is highly dependent on hardware resources, which is closely related to its sports characteristics and rule structure. Standardized baseball teaching needs to be equipped with a variety of professional equipment: in addition to bats, gloves and practice balls, different positions also need to be equipped with special equipment, such as catchers need to wear breast protection, leg protection and masks, pitchers need to use a pitching board, and batters need to wear protective devices such as helmets [10]. This equipment requirement based on functional division of labor makes the standardized training involving all staff face resource pressure. However, due to funding constraints, baseball equipment in domestic colleges and universities is generally insufficient, and the sharing mode of 3-4 people sharing gloves, using bats in groups in turn or multiple people alternately wearing protective equipment is often adopted. This "queuing practice" method significantly shortens the operation time of students, and it is difficult for technical movements to form muscle memory through repeated training, and the strength and proficiency of skill mastery are limited. At the same time, equipment with high frequency use and lack of maintenance is prone to aging and damage, further affecting the quality and safety of training.

Field conditions also restrict college baseball teaching. The standard baseball field covers an area of about 14000 square meters, including the inside and outside fields, home run areas and buffer zones. However, due to the shortage of land, most colleges and universities can only reconstruct 5000-8000 square meters of small training grounds in the playground or idle land. The lack of outfield distance, the lack of home run wall, and the nonstandard running path and pitching mound size make it difficult to carry out typical actions such as "home run hit", "outfield high-altitude catch" and "long pass blocking". Affected by this, the content of tactical teaching was forced to be reduced. Teachers mostly focused on the basic cooperation in the infield, such as passing and receiving the ball, filling positions and double play cooperation, while it was difficult to implement the whole field coordination tactics such as outfield defense, playing and running, and sacrificing the high-flying ball.

To sum up, the dual restrictions of hardware resources formed by the shortage of equipment and the nonstandard field not only hinder the improvement of students' technical level, but also restrict the cultivation of tactical literacy and practical ability, which has become the key bottleneck of baseball teaching in colleges and universities.

3.3 learning interest is difficult to maintain, and the degree of active participation is low. The "high threshold" characteristics of baseball lead to the loss of students' interest in learning in college teaching. First of all, from the perspective of rules, baseball contains more complex basic rules, such as "strike zone judgment", "forced base entry", etc. beginners often need to explain and demonstrate for many times to accurately understand and apply [11]. In contrast, the rules of basketball, football and other sports are relatively intuitive. Students can get rule feedback through practice in a short time and experience instant sense of achievement, while there is a large cognitive load in the understanding and application of baseball rules.

Secondly, from the perspective of skills, baseball hitting needs to coordinate the strength of arms, waist, legs and other parts. Beginners need 20 to 30 repeated exercises to master the basic movement rhythm and swing accuracy [11]. Passing and catching, base running and pitching also need high-frequency repetitive training to form muscle memory. Due to the complex action and obvious feedback delay, students often miss the ball or receive the ball many times in the initial learning stage, which is prone to frustration and self-denial, and their interest in learning decreases.

In addition, baseball courses in colleges and universities are mostly offered in the form of elective courses, with scattered class hours, usually only once a week and two class hours each time. Such a course arrangement limits the opportunities for students' continuous training, fails to form a stable habit of skill practice, and significantly reduces the learning effectiveness constrained by time and space. In the long run, it is difficult for students to make systematic progress in mastering skills and understanding tactics, and their learning motivation and enthusiasm for participation are further frustrated.

To sum up, the high threshold characteristics of baseball increase the difficulty of learning at both the level of rule understanding and skill mastering. In addition, due to the scattered curriculum arrangement and the lack of practice time, students are prone to frustration and interest decline at the initial learning stage. This phenomenon not only affects the improvement of students' skills, but also restricts the cultivation of tactical understanding and team cooperation ability. Therefore, it is urgent to improve students' learning enthusiasm and sustainability through scientific teaching design and incentive mechanism in college baseball teaching, so as to alleviate the negative effects brought by the high threshold.

3.4 single and fixed teaching mode, unbalanced ability training. At present, baseball teaching in colleges and universities is still based on the traditional mode of "teacher explanation demonstration student imitation". The classroom process is usually arranged as "rule teaching (about 20 minutes) - action demonstration (about 30 minutes) - repeated practice (about 40 minutes)" [12]. In this mode, students are mainly in a passive acceptance state, lacking opportunities for independent exploration, problem solving and tactical thinking. For example, in tactical teaching, teachers often directly tell students “The hitting strategy when the second base is occupied", rather than guide students to analyze the situation on the field, evaluate offensive and defensive variables and make plans independently. The result is that although students can remember the key points of tactics, it is difficult to apply them flexibly in actual competitions, and there is a significant gap between tactical understanding and implementation.

In addition, the traditional model overemphasizes skill training and ignores the cultivation of tactical understanding and team cooperation ability. Classroom training is mostly based on a single action, such as pitching, hitting or catching the ball. Students can complete basic actions under the guidance of teachers, but they lack the practice opportunity to adjust strategies according to the position of teammates and the defensive layout of opponents in team confrontation. Long term teaching in this way, some students present an embarrassing situation of "skills, but not competition", that is, the technical movement is standardized, but the practical adaptability is insufficient, and they cannot make effective decision and cooperation in the dynamic competition environment.

The limitations of this teaching model are also reflected in learning motivation and participation. Due to the lack of independent design and decision-making, it is difficult for students to form an internal driving force for learning, lack of enthusiasm for classroom participation, and prone to distraction, negative practice and other phenomena. At the same time, the unified schedule of teaching arrangement is difficult to meet the student groups with obvious differences in basic level, zero basic students are difficult to keep up with the schedule, and students with good foundation are easy to feel bored due to repeated practice.

To sum up, the traditional "explanation demonstration imitation" mode has significant limitations in college baseball teaching, which not only restricts the cultivation of students' tactical thinking and team cooperation ability, but also affects classroom participation and learning effect. Therefore, it is urgent to explore the teaching innovation mode with students' autonomous learning, task driven and collaborative training as the core, so as to realize the synchronous improvement of skill training and tactical application, personal ability and team cooperation. Translated into English according to the English standard of academic papers.

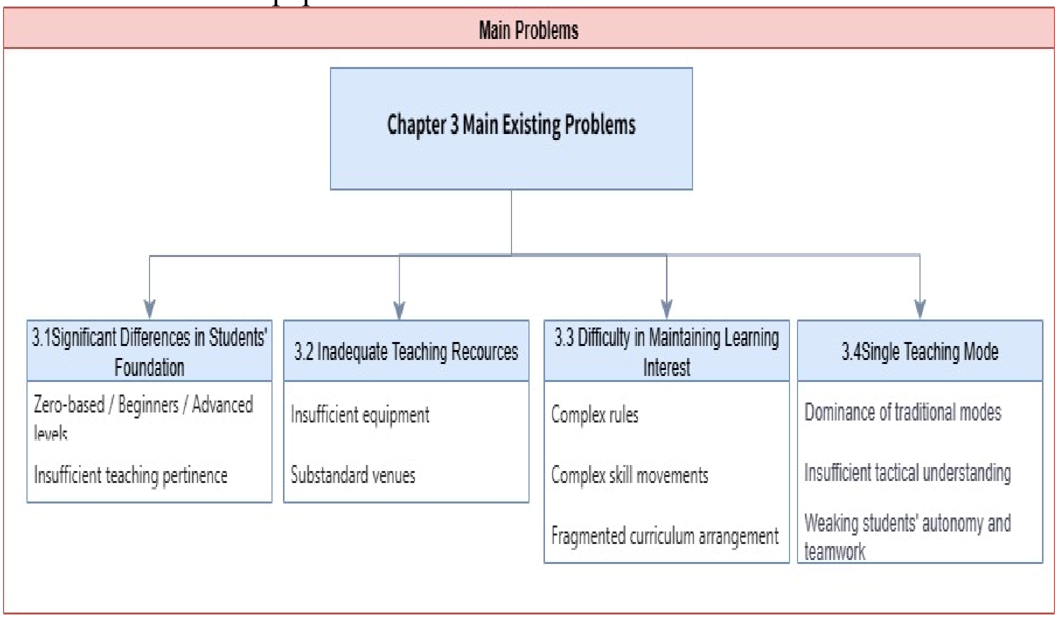

Figure 3. Framework Diagram of Major Issues in Baseball Learning

4.Exploration of baseball learning methods in Colleges and Universities

4.1 hierarchical learning method: accurately adapt to students' basic differences. Aiming at the problem of students' basic stratification, a "three-level and nine step" hierarchical learning system is constructed. According to the entrance test (rule cognition and basic action), students are divided into basic level, advanced level and promotion level, and each level is set with clear learning objectives and training content [13]. The basic level takes "interest cultivation+basic cognition" as the core, stimulates interest through the appreciation of baseball history stories and classic game clips, and simultaneously carries out basic movement training such as "holding the bat posture - standing posture adjustment - short distance passing". Each class is provided with a "movement breakthrough" link (such as completing the correct passing for three consecutive times to pass the pass), so as to help students build learning confidence; The advanced class focuses on "skill consolidation+simple tactics". On the basis of strengthening the training of pitching and hitting accuracy, simple tactics such as "batting coordination when first base is manned" and "double defensive position" are introduced to let students understand the roles and responsibilities in different scenes through "tactical cards"; With the goal of "actual combat capability+tactical innovation", the promotion level organizes 5v5 and 7v7 small-scale confrontation games, requiring students to independently design tactics (such as "sacrificial touch" and "double kill cooperation") in the game, and analyze the effect of tactics execution through video playback after the game. In order to ensure the implementation of hierarchical teaching and establish a "tutorial system" counseling mechanism, each teacher is responsible for 15-20 students, and regularly carry out one-to-one skill guidance and learning planning adjustment.

4.2 situational teaching method: crack the limitation of practical training resources. Based on the realistic conditions of limited venues and equipment in Colleges and universities, the teaching mode of "micro situation full scene" can be designed to improve students' tactical application ability with the key scene of simulated competition as the core [14]. Among them, the "micro situation" training is designed for small reconstruction sites. For example, in a 20 m × 30 m court, high-frequency game situations such as "two outs with full bases" and "no one out with second base manned" can be simulated to clarify the roles of both sides of the offense and defense, including pitcher, catcher, batter and base runner. During the training, students need to complete the attack and defense conversion within a limited time. The teacher guides the action selection, tactical implementation and cooperation strategies through immediate comments, such as "the batter should give priority to push rather than pull", "the base runner should observe the catcher's passing rhythm to adjust the starting time", so as to help students understand the tactical intention and optimize the decision-making process. Micro situational training emphasizes improving students' observation ability, decision-making ability and cooperation level in a limited space, while reducing the impact of site limitations on teaching effect.

The "full scene" training uses multimedia and virtual simulation technology to make up for the shortage of the actual site. By watching professional game videos, such as the key situation of MLB (Major League Baseball), students analyze the batting order, base running strategy and defensive arrangement, and discuss the Tactics Selection and execution in different situations; At the same time, the virtual simulation software can simulate the changes of different field sizes, weather conditions and ball speed, so that students can carry out diversified tactical exercises on the computer side, and improve their adaptability to complex situations and strategic flexibility. The whole scene training emphasizes the combination of theoretical analysis and practical experience, so that students can fully understand the key points of tactics at the visual, thinking and operational levels.

The practice results show that the situational teaching mode can significantly improve the students' tactical understanding level, the accuracy of tactical implementation can be improved by 30% -40%, and the actual combat response ability is significantly enhanced. Through the organic combination of micro situation and the whole scene, it not only overcomes the constraints brought by the limited hardware resources, but also provides a systematic, operable and effective teaching strategy for college baseball teaching, which helps to achieve the synchronous improvement of tactical literacy and practical ability.

4.3 cooperative learning method: strengthen team cooperation and autonomous learning. Relying on the team attribute of baseball, we can build a cooperative learning mode with "group cooperation task driven" as the core, divide students into 4-6 teams, set up roles such as team leader, tactician and recorder in each group, and clarify the division of labor and responsibilities [15]. Classroom training is carried out around the "group task", and students are guided to organize and collaborate independently through the task objectives. For example, in the basic training stage, the group task can be set to "complete 10 successful passes and catches within 30 minutes". Students need to reasonably allocate practice time, adjust the rhythm of cooperation within the group, and continuously optimize the quality of action completion through self-feedback. In the tactical training stage, the group task can be designed as "developing the hitting tactics for the left hander". Students need to determine the hitting order, base running strategies and defensive countermeasures through discussion, and test the effect of the scheme in the simulated game.

In order to ensure the training effect, the feedback mechanism of "group mutual evaluation teacher comments" is introduced into the model. At the end of each class, each group should show the training results, and the other groups should score according to the dimensions of "cooperation fluency", "tactical rationality" and "role participation". The teacher should make targeted summary and guidance based on the scoring situation, and point out the operation deficiencies and improvement direction. This feedback mechanism not only enhances students' cognition of training results, but also improves the interactivity and pertinence of learning.

Through this cooperative learning mode, students can gradually form a clear sense of responsibility and organizational ability in team cooperation, and cultivate the ability of independent planning, problem solving and tactical innovation. Research and practice show that some students actively organize group training after class, extend classroom learning time, and form a positive learning atmosphere. In addition, this model helps to make up for the differences in students' basic level, so that zero basic students can get the opportunity of guidance and imitation in the group. The medium-level students can improve their practical ability in cooperation, while the high-level students can strengthen their leadership and analysis ability by taking the role of tactical design and guidance, so as to achieve the unified goal of teaching students in accordance with their aptitude and full participation. On the whole, the cooperative learning mode of "group cooperation task driven" has strong practical value and promotion potential in college baseball teaching.

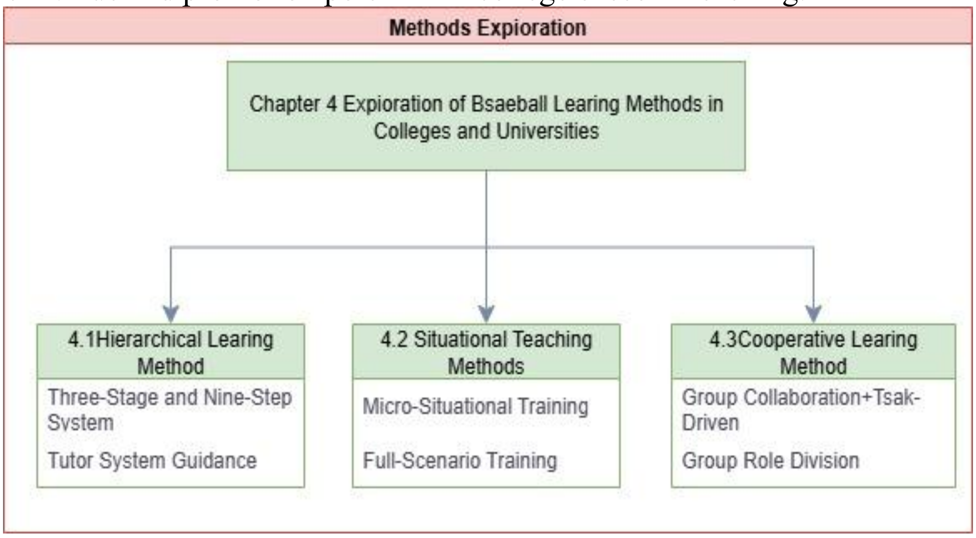

Figure 4. Baseball Learning Methodology Exploration Framework

5 conclusions and Prospects

5.1 research conclusion. Through the analysis of the current situation of baseball teaching in Colleges and universities and the exploration of learning methods, this paper draws the following conclusions: first, the current baseball teaching in Colleges and universities is faced with problems such as large differences in students' foundation, lack of teaching resources, low interest in learning, and single teaching mode. The core of these problems is the lack of appropriate learning methods, which leads to the lack of teaching pertinence and effectiveness; Second, hierarchical learning method, situational teaching method and cooperative learning method can effectively solve the above dilemma: hierarchical learning method solves the problem of "lack of teaching pertinence" by accurately matching the students' foundation; Situational teaching method relies on micro Situational Design and multimedia assistance, breaking through the limitations of venues and equipment on actual training; Through task driven and group cooperation, cooperative learning method stimulates students' learning initiative and strengthens the ability of team cooperation; Third, the three learning methods do not exist independently, but complement and cooperate with each other. Hierarchical learning is the basis, situational teaching is the carrier, and cooperative learning is the means, which together constitute a baseball learning method system suitable for the actual situation of colleges and universities in China.

5.2 future outlook. The development of baseball teaching in colleges and universities in the future should continue from the three dimensions of curriculum system, resource allocation and evaluation mechanism. In terms of curriculum system, we should build a progressive curriculum chain of "basic courses - elective courses - school team training". Basic courses should popularize baseball culture and basic skills for all students, elective courses should focus on the improvement of special skills, and school team training should carry out competitive ability training for high-level students; At the same time, baseball is integrated with health education and mental health education, and characteristic modules such as "baseball+stress training" and "baseball+team cooperation" are developed to enrich the connotation of the course. In terms of resource allocation, we explored the "inter school cooperation+social linkage" mode, and many colleges and universities jointly built and shared baseball fields to reduce construction costs; Cooperate with local Baseball Clubs and sports enterprises, introduce professional coaches and equipment resources, and improve teaching professionalism. In terms of evaluation mechanism, the "process evaluation+multi-dimensional evaluation" system is established. The process evaluation covers classroom participation, the number of training clocks, and the quality of group task completion. The multi-dimensional evaluation includes four dimensions: skill level, tactical understanding, team cooperation, and learning attitude. Through the combination of student self-evaluation, peer mutual evaluation, and teacher evaluation, it comprehensively reflects students' learning outcomes.

With the deepening of the reform of physical education and the increase of students' demand for diversified physical education courses, baseball has broad prospects for development in colleges and universities. Through continuous optimization of learning methods and improvement of teaching system, baseball teaching can not only become an important part of college physical education curriculum, but also provide strong support for the cultivation of high-quality talents with team spirit, rule awareness and pressure resistance ability.

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On the challenges and solutions of College Students' role transformation from campus to society

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Abstract. With the popularization and development of higher education, millions of college students leave the campus and enter the social stage every year. According to the statistics of the Ministry of education, the number of college graduates in 2025 is expected to reach 12.22 million, a record high. This huge group of young people is facing a major change from students' role to social professional role, which is full of opportunities and challenges. The socialization of college students refers to the process of learning, absorbing and creating social culture, mastering social behavior, gradually adapting to social life, and becoming a social person who can perform social role behavior. This process is of great significance to personal growth and social development. It is not only related to whether individuals can smoothly adapt to the society, shape personality and promote success, but also affects the benign operation of society, cultural inheritance and social division of labor. The role transformation of college students is not only an educational problem, but also a social problem. Based on the role theory and socialization theory, this paper analyzes the main challenges faced by college students in the process of role transformation, explores its deep-seated reasons, and puts forward systematic solutions from the perspective of multi-agent, in order to promote college students to better realize the smooth transition from campus to society.

Keywords: Social adaptation; Role switching; Social competition; Higher education

1. Introduction

The socialization of college students refers to the process in which individuals gradually master social norms, skills and values through systematic learning and social practice at the stage of higher education, and change from "biological man" to "social man". This process is not only crucial to personal growth and development, but also the basis of social inheritance and innovation. According to the statistics of the Ministry of education in 2023, the number of college graduates in China has reached 11.58 million, a record high, while the implementation rate of college graduates' whereabouts is only 81.5%, which reflects that there are significant obstacles in the process of College Students' transformation from campus to society [1]. The 2024 China youth development report pointed out that the extension of the role transition period has become the core incentive for the rising youth unemployment rate, and about 37% of the "slow employment" phenomenon stems from the difficulty in adapting to the transition (Chinese Academy of Social Sciences, 2024). This "slow employment" trend is not merely a delay in job-seeking, but a complex coping mechanism shaped by identity paralysis, fear of failure, and social comparison. A 2024 longitudinal study by the Chinese Academy of Social Sciences found that over 60% of graduates who remained unemployed six months after graduation reported "not knowing what kind of adult they were supposed to become". This identity diffusion is exacerbated by social media, where peer comparisons—such as classmates landing high-paying tech jobs or studying abroad—create a distorted perception of success. Rather than risk "falling behind", many graduates opt to wait, hoping for a role that aligns with their imagined future self. This waiting period, however, often leads to skill atrophy, social withdrawal, and even depression [5]. The study also noted that graduates from first-tier universities were more likely to delay employment, not less—challenging the assumption that elite education guarantees smoother transitions. The global comparative study shows that the average career adaptation cycle of graduates in China is 9.2 months, which is significantly longer than 5.1 months in Germany and 6.8 months in Japan (OECD, 2023).

The role transformation of college students refers to the transformation process of graduates from "student role" to "professional role", involving the fundamental reconstruction of cognitive structure, behavior mode and social relations. Successful role transformation is not only related to the beginning of individual career, but also affects the optimal allocation of human resources and the vitality of social and economic development [2]. However, the reality shows that many college students are facing severe challenges in this process. The research shows that about 64.2% of the surveyed graduates believe that there are difficulties in the process of moving from school to society, and the proportion of college graduates with difficulties in adaptation is higher.

Social identity theory explains the identity conflict mechanism in the transformation of group identity, and explains the lack of sense of belonging after graduates leave the "student group". According to the survey of Tencent Research Institute, 68% of new employees said they "don't know how to introduce their new identity to colleagues" (Tencent, 2023).

Career construction theory emphasizes the process of individual identity construction through career narrative, and provides a new perspective for career education in colleges and universities.

2. Theoretical basis and concept

2.1 Theoretical Basis of Role Transformation. The symbolic interaction theory proposed by the social psychologist George Herbert Mead emphasizes that individuals can understand others' attitudes and expectations through interaction with others, using language, symbols and other media, and then form self-concept and social role cognition. In the process of socialization, college students gradually understand the social expectations and requirements for professional roles through interaction with others in the society, so as to adjust their behavior and attitude [3].

The life course theory focuses on the interaction between individual development and social and historical background, and believes that college students' socialization process is phased and dynamic in different life stages, which are affected by family, school, society and other factors. The theory emphasizes that the role transformation of college students cannot be separated from the specific social and historical environment, and macro factors such as economic development stage, employment market situation and social and cultural background should be considered.

Career chaos theory puts forward that career is a dynamic, nonlinear and open complex system, which is affected by complexity, change, construction and random factors. For young people who are new to the society, accepting uncontrollability is the primary task. It is necessary to try to break the situation from the aspects of goal clarification, awareness of the current situation, and analysis of the situation.

2.2 Connotation and Characteristics of College Students' Role Transformation. The role transformation of college students from campus to society is essentially the transformation from "student role" to "professional role". This transformation has the following characteristics:

Multidimensional: it involves the adjustment of multiple dimensions such as psychology, behavior, ability and interpersonal relationship.

Procedural: it is not an event completed in an instant, but a process that requires time to adapt. Interactivity: it is the result of the interaction between individuals and the environment, which is affected by both personal factors and social environment.

Challenge: due to the huge differences between campus and society, the role transformation process is bound to face various challenges and difficulties.

Table 1 Comparison of the main differences between students' roles and professional roles

Comparison dimension	Student role	Professional role
Social responsibility	Learn cultural knowledge well and develop in an all-round way	Perform specific responsibilities and reflect responsibilities through work results

Social norms	The "code of conduct for college students" is the main violation, and the main violation is education and help	More stringent due to different occupations, violation of which requires liability or even legal liability
Social rights	Receive education and obtain financial guarantee or subsidy	Get paid through labor, no pay, no pay
Activity mode	Accept and input knowledge, require understanding	Using knowledge and ability to provide labor to the outside world requires creativity in combination with practice

3 Multidimensional challenges faced by college students' Role Transformation

3.1 Psychological and Cognitive Challenges. College students first face psychological and cognitive challenges in the process of role transformation, mainly in the following aspects:

Role attachment and identity confusion: many college students have profound experience and attachment to student roles, are used to the simplicity and tranquility of student life, and are difficult to adapt to new professional roles, resulting in identity confusion. The survey shows that about 60% of college students say it takes 6 months to 1 year to adapt to the new role [4].

The gap between ideal and reality: college students are full of vision for the future at school, but soon find that there is a huge gap between reality and expectation after entering the society. This gap not only comes from the change of working environment, but also from the reevaluation of their own ability. After his master's degree in 1995, Li Wenli became a teacher in Dongguan. After graduation, he first faced living problems such as housing and consumption. Only by solving these basic problems can he gain a firm foothold in the new city. The recruitment data of Zhilian show that the average expected salary of graduates of 2023 is 28% higher than the actual offer, and the cost-of living income ratio in first tier cities reaches 0.62 (Zhilian, 2023).

Fear and anxiety: many college students feel uncomfortable after leaving the campus and are full of fear for the future. For example, Huang, a graduate who has not fully accumulated internship experience, is trapped in an interview dilemma, tossing and turning every night and crying; Zhang was busy with his internship and was in a tense mood. He worried that he could not compare with others because he printed the wrong form. The anxiety index of junior college students (GAD-7 average score 8.2) was significantly higher than that of undergraduates (6.7) and postgraduates (5.9) (Peking University mental health report, 2023).

Self-Efficacy decline: Many students experience a sharp drop in self-efficacy—the belief in their ability to succeed in specific situations—once they leave the structured environment of university. Without syllabi, grades, or professors' feedback, they struggle to self-regulate and self-evaluate. A 2023 Tsinghua University study found that 68% of graduates reported "feeling stupid" in their first month of work, even when performing adequately. This decline is particularly pronounced among women and first-generation college students, who are less likely to have professional role models or family guidance.

3.2 Challenges at Skill and Ability Levels. College students often place excessive emphasis on theoretical knowledge at the expense of practical application skills. Many graduates discover that the knowledge and skills acquired at school do not fully align with societal needs, necessitating additional learning and training. Newcomers to the workforce frequently lack practical work experience and essential professional skills, leaving them feeling inadequate and overwhelmed in their jobs.

The intelligence levels of college graduates do not differ significantly, whereas non-intellectual skills (such as communication, teamwork, problem-solving, and stress resistance) are crucial factors influencing graduates' career choices, employment, and entrepreneurship. A deficiency in these non-intellectual skills makes it challenging for college students to effectively handle complex work scenarios in the professional environment.

The rise of generative AI has disrupted traditional entry-level roles. Tasks once assigned to juniors—such as data entry, basic translation, or report drafting—are now automated. A 2024 McKinsey report found that 31% of "graduate jobs" in China's financial and legal sectors have been restructured or eliminated due to AI integration. Graduates, trained in outdated software or theoretical frameworks, find themselves underqualified for AI-augmented roles. For instance, a finance major from Fudan University reported being rejected from 11 analyst positions for lacking Python or Prompt Engineering skills—none of which were part of her curriculum.

3.3 Interpersonal and Social Challenges. After leaving school, college students need to rebuild their interpersonal networks. Different from the simple classmate relationship on campus, the interpersonal relationship in society is more complex and subtle, and there are conflicts of interest. Graduates need to learn to deal with all kinds of people, establish and maintain good interpersonal relationships, which is a huge challenge for many college students who have just entered the society.

Many college students may only interact with a few people on campus, but they need to deal with all kinds of people after entering the society. Due to the lack of interpersonal experience and interpersonal skills, it is easy to lead to poor communication between students and their superiors and colleagues. For example, Wang felt that his colleagues and leaders insisted on cronyism at work, alienated colleagues, and had heavy psychological burden and anxiety symptoms.

3.4 Challenges at the Level of Environment and Expectation. Graduates need to pass the probation examination after taking part in the work. During the campus period, college students' learning and living conditions are relatively superior, with more free time, moderate rhythm and less pressure; After working, especially during the probationary period, graduates are often assigned to the grass-roots units with difficult conditions for exercise. They are busy with work and often need to work overtime, so their time is less and less.

The number of fresh college graduates is huge and lack of work experience. Employers' demand for talents is limited, and jobs cannot meet the demand for graduates. Former unemployed students and social unemployed also participate in the competition, making the employment environment more severe. In 2022, the number of fresh graduates reached 10.76 million, the number of college graduates' recruitment demand decreased, the number of job applications increased, and the success rate of job hunting was lower than last year.

The practical life challenges faced by graduates also make it harder for them to adapt. For instance, Gao, a graduate from a university in Nanjing, started preparing to rent an apartment after securing a job. He discovered that the online information was a mix of genuine and fake listings, with intermediaries posting false housing ads. The actual apartments he viewed did not match the descriptions, and the cost-effectiveness was poor [6].

4. Cause analysis of challenges

4.1 Personal Factors. College students, who are excessively protected by their families during their growth, often lack experience in independently handling difficulties and setbacks. Consequently, when confronted with workplace pressures and challenges, they are prone to experiencing anxiety and a tendency to withdraw. This situation affects college students' psychological maturity and resilience to setbacks [7].

Students lack clear career planning during school and rush to deal with the employment problem before graduation. They have no clear career goals and development path, which leads to blindly following the trend in the process of job hunting and choosing jobs that are not suitable for them.

Some college students have such conceptual problems as high employment expectations, strong stability seeking mentality (preference for examination editing and public examination), and unwilling to enter the grass-roots or specific industries. Some graduates do not have a comprehensive understanding of talents and think that they have received higher education and are already high-level talents, so they often look down on grass-roots work and grass-roots personnel.

4.2 University Education Factors. Currently, the employment guidance system is far from perfect, with many colleges and universities resorting to "last-minute efforts" in their employment guidance, which lacks comprehensiveness and systematic planning. Employment guidance is predominantly provided just before graduation, without offering phased and targeted guidance services from the freshman to senior year.

The integration of production and education is not deep enough, the cooperation between universities and enterprises is mostly at the superficial level, and the quality of students' practice is not high or the degree of correlation with their majors is not strong. Many internship opportunities fail to provide sufficient learning and development space, and students are often arranged to do simple and repetitive work.

The specialty setting and course content of some colleges and universities lag behind the social development and fail to reflect the latest trends and demands of the industry in time. This leads to a gap between students' knowledge and social needs, which requires additional training from employers to be competent [8].

4.3 Social and Environmental Factors. Economic fluctuations and industrial transformation affect the capacity and structure of the job market. In recent years, with the slowdown of economic growth and the adjustment of industrial structure, the growth of traditional jobs has slowed down, while talent cultivation in emerging industries needs a certain period, resulting in structural contradictions in the employment market.

Policy support and social security for flexible employment, innovation and entrepreneurship need to be further improved. The employment information of some regions and industries is asymmetric, and the effectiveness of recruitment channels needs to be improved.

Too narrow and harsh life choices bind young people, such as pursuing high income, decent jobs or stable careers. Many families have high expectations for their children's employment and hope that they will engage in decent and stable work. The gap between this expectation and reality has brought extra pressure to graduates.

5 ways and strategies to promote successful role transformation

5.1 Student Level. Psychological and cognitive adjustment: students can reduce expectations, be down-to-earth, accept from scratch, change "learning attitude" to "result oriented", and clarify goals through daily work summary. Recognize the gap between ideal and reality, adjust expectations, and accept starting from the grass-roots level. When encountering problems, we should first reflect on our own shortcomings, rather than blame it on the external environment, so as to cultivate the problem-solving consciousness of professionals. Overcome the dependence psychology, cultivate independence [9], and do our best to take care of themselves and be independent.

Enhancing Abilities and Skills: Shift from "empty talk" to "action-oriented". Upon receiving a task, first break it down into steps and then accomplish it in stages. Continuously acquire new knowledge, refine your knowledge structure, and equip yourself to be competent for work and adaptable to the environment. Develop skills in communication, collaboration, time management, and other areas, master basic office skills, pay meticulous attention to details, and demonstrate professionalism. Broaden your horizons by gaining insights into the knowledge and cultures of diverse fields, and expand your network of like-minded individuals through participation in social events and membership industry organizations.

Career planning and exploration: fully understand your personality, temperament, ability, career interest, career values and career development goals with the help of career planning and design theory and evaluation tools. Accumulate experience through internships and part-time jobs to understand social operation. Establish a rational concept of employment, reasonably adjust employment expectations, recognize the rationality of "employment first, then employment", and have the courage to explore careers at the grass-roots level, small and medium-sized enterprises, and the new economy.

5.2 University Level. Deepen education and teaching reform: establish a linkage mechanism of enrollment, training and employment, dynamically adjust specialty settings and course contents according to social needs, and strengthen the proportion of practical teaching. Closely follow the development direction of new productivity, reconstruct the teaching content and training path, add cutting-edge courses such as big data analysis, intelligent manufacturing and green technology, and organically integrate industrial cases into teaching [10]. Strengthen practical teaching, jointly build laboratories and jointly develop projects with enterprises, and promote "order type" talent training.

Construct a comprehensive employment guidance system throughout college years: from freshman to senior year, implement staged services including career enlightenment, career exploration, skill training, job-hunting counseling, and post-graduation tracking. Equip the institution with professional employment guidance instructors, offer systematic training to enhance their guidance capabilities and expertise. Conduct individual consultations and group counseling sessions to foster a healthy employment mindset among college students, improve their mental well-being, and help them maintain a positive attitude towards career selection.

Strengthen school enterprise cooperation and psychological support: build high-quality internship bases and order classes with enterprises, invite enterprise mentors to participate in teaching and employment guidance, and let students contact real projects of enterprises in advance. Strengthen mental health education, provide psychological counseling, and help students relieve pressure. Make full use of the second classroom activities to carry out various forms of "social workplace zero distance" activities, such as inviting entrepreneurs into the campus to create an atmosphere of innovation and entrepreneurship.

5.3 Social and Government Level. Policy support and guarantee: implement and improve tax relief, social security subsidies and other policies that encourage enterprises to absorb graduates. We will improve the security system to support flexible employment, innovation and entrepreneurship, and provide guaranteed loans, site support, and training guidance for entrepreneurship. Vigorously explore grassroots employment positions (such as "special post teachers" and "Western China plan"); Foster and expand emerging industries and create more high-quality jobs [11].

Create a fair and healthy employment environment: eliminate employment discrimination, standardize the recruitment market, and safeguard the legitimate rights and interests of graduates. Establish a multi-party collaborative education mechanism of "government, school, enterprise and bank", clarify the responsibilities of all parties, and build a resource sharing platform. Strengthen the guidance of public opinion, publicize the value of "leading by industry", commend outstanding youth representatives who have made achievements in different fields, and create a social atmosphere that encourages innovation and tolerates failure.

Build a multi collaborative support platform: the government takes the lead in establishing regional alliances, through resource barriers, and realize cross regional resource interconnection; Dynamically release the industrial demand map and regularly update the list of regional scarce posts. Innovate the "credit mutual recognition" mechanism, promote mutual recognition of courses and transfer of credits among colleges and universities, and provide more flexible learning paths for students.

Table 2 Multi-dimensional support strategies for college students' role transition

Subject of responsibility	Strategies	Measure
Student	Psychological cognitive adjustment	Set realistic expectations; Take responsibility; Adjust goals
	Ability and skill improvement	Boost execution；Fix soft-skill gaps；Adopt lifelong learning
	Exploration of career planning	Set Goals；Get Field Experience

Institutions of higher learning	Education and teaching reform	Establish the linkage mechanism of enrollment training employment; Strengthen practical teaching
	Employment guidance system	Whole process vocational guidance; Professional teaching staff
	School enterprise cooperation	Co construction of practice base; Enterprise mentor participation
Government	Policy support guarantee	Tax relief and social security subsidies; Flexible employment support
	Fair employment environment	Eliminate discrimination in employment; Standardize the recruitment market
	Multi-domain collaboration platform	Cooperation between government, school, enterprise and bank; Resource sharing platform; Regional coordinated development

6 conclusions and Prospects

The role transformation of college students from campus to society is a complex system engineering, which is a profound change in individual psychology, ability, behavior and interpersonal relationship. At present, college students are facing multiple challenges from subjective cognition and objective environment in this process. The causes involve multiple levels of individuals, schools, families and society. The successful role transformation needs multi-party collaborative efforts: college students themselves need to be proactive, adjust their psychology and improve their ability; Colleges and universities need to reform education, strengthen guidance and optimize services; The society and government need to optimize the environment, create opportunities and policy support [12].

Looking forward to the future, with the further development of society, new technologies and new economic forms (such as artificial intelligence and green economy) will spawn more new jobs and put forward new requirements for talents' ability. The process of College Students' role transformation will put more emphasis on lifelong learning ability, digital transformation adaptability and cross domain knowledge integration ability. This also puts forward higher requirements for the future education and teaching reform in colleges and universities and the support system of the whole society. Through joint efforts, we believe that every college student can successfully complete the role transformation from campus to society, shine brilliantly on the social stage, and realize the unity of personal value and social development.

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