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Research on Optimization and Teaching Effectiveness Evaluation of a Transformer-Based Simulation Platform for Mechanical Manufacturing Experiments

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ABSTRACT To address the limitations of traditional mechanical manufacturing simulation platforms in scene fidelity, teaching adaptability, and effectiveness evaluation, this study proposes an optimized experimental platform integrating Transformer models with a multidimensional assessment framework. Considering that intelligent simulation environments are increasingly important for complex engineering systems and digital training scenarios relevant to electromagnetic equipment and advanced manufacturing, the platform adopts a five-layer architecture incorporating Vision Transformer (ViT), Time-Series Transformer, and BERT models. A high-fidelity virtual scene module is developed to achieve cutting process simulation errors below 5%, while a behavior perception module attains 86.3% accuracy in learning behavior recognition. Personalized recommendation and multidimensional evaluation modules achieve 87.6% consistency with instructor assessments. Teaching experiments involving 236 mechanical engineering students demonstrate that the proposed platform improves participation by 35%, practical skill scores by 18.2%, and innovation design scores by 22.5% compared with conventional methods. The results verify that Transformer-based intelligent simulation effectively enhances teaching quality and adaptive learning capability, providing a practical reference for digital engineering education and simulation-based training frameworks applicable to intelligent manufacturing and electromagnetic system operation environments.

INDEX TERMS transformer model, mechanical manufacturing, simulation platform, intelligent engineering education, electromagnetic system training

I. INTRODUCTION

RESEARCH BACKGROUND AND SIGNIFICANCE

WITH the rapid advancement of technologies such as artificial intelligence, virtual reality, and digital twins, experimental teaching simulation platforms have emerged as an effective solution to address the aforementioned challenges. This technological shift is particularly vital for industrial education, providing the textile industry with essential simulation tools to safely and efficiently train technicians on complex, high-value dyeing, weaving, and advanced manufacturing equipment [1-5]. Although existing mechanical manufacturing simulation platforms have achieved digital simulation for certain experimental processes, they still exhibit significant shortcomings: insufficient dynamic interactivity in simulation scenarios, limited fidelity in reproducing the physical mechanisms of complex manufacturing processes; lack of precise perception of student learning behaviors and personalized feedback; teaching content updates lag behind industrial technological advancements, making it difficult to align with new technologies and processes in the field of intelligent manufacturing [6-9].

CURRENT RESEARCH STATUS DOMESTICALLY AND INTERNATIONALLY

In engineering education, the application of Transformer models remains in its infancy. This slow adoption represents a significant opportunity, especially within textile engineering programs, where leveraging Transformer models could revolutionize technical training by providing highly personalized, adaptive simulations essential for mastering complex, specialized manufacturing processes. Some studies have employed Transformer models for engineering drawing recognition and process parameter optimization, such as using Transformer models to achieve intelligent interpretation of mechanical part drawings and extraction of dimensional annotations [10], or optimizing CNC machining process parameters based on Transformer-based sequence prediction models [11]. However, no studies have reported the application of Transformer models to mechanical manufacturing experimental teaching simulation platforms, and systematic research on scenario optimization, behavioral perception, and effectiveness evaluation remains lacking.

II. THEORETICAL FOUNDATIONS

THEORETICAL FOUNDATIONS OF MECHANICAL MANUFACTURING EXPERIMENTAL TEACHING

The core tenet of constructivist learning theory posits that knowledge is not passively received through teacher-centered transmission but actively constructed by learners through interaction with their environment within specific contexts [12-16]. This theory emphasizes the agency, contextuality, and collaborative nature of learning, viewing learners as active knowledge constructors rather than passive recipients of information. Authentic problem scenarios and self-directed inquiry processes serve as critical vehicles for knowledge construction.

Situated Learning Theory, formally proposed by Lave and Wenger in 1991, posits that learning is fundamentally a sociocultural practice. Learners acquire professional knowledge and skills, and develop corresponding professional identities, by participating in specific communities of practice and interacting with others, tools, and environments within authentic occupational contexts [17]. Contextual learning theory emphasizes authenticity, practicality, and participation in learning. It advocates placing learning within concrete occupational scenarios, enabling learners to “learn by doing” and “learn by applying.”

Personalized teaching theory originated from American educator John Dewey’s “child-centered theory.” Through continuous development and refinement, it has evolved into a teaching theoretical system centered on individual student differences [18]. Its core principle is respecting individual differences among students—including variations in knowledge foundations, cognitive levels, learning styles, interests, and career aspirations. By precisely identifying each student’s learning needs, it enables tailored instructional objectives, content, and methods to provide personalized learning support, ultimately fostering holistic development for every learner.

DATABASE MANAGEMENT SYSTEMS

MySQL 8.0: Stores structured data (student basic information, experimental parameter configuration, final evaluation results) to leverage its transaction consistency advantage;

InfluxDB 2.7 (specialized time-series database): Newly added to store real-time sensor data (cutting process time-series data, operation behavior trajectory data), supporting high-frequency IO (1000+ writes/queries per second) to solve MySQL’s time-series data processing bottleneck.

Performance test results: Under 12,000 samples, the hybrid database architecture achieves data write latency $\leq$ 10ms and query response time $\leq$ 50ms, fully meeting the requirements of real-time simulation and model inference.

TRANSFORMER MODEL-RELATED THEORIES

The self-attention mechanism forms the core of the Transformer model. Its essence involves calculating the degree of association (attention weights) between each position in the input sequence and all other positions. Subsequently, the vector at each position is obtained by performing a weighted sum of all positions based on these attention weights, yielding a contextual vector representation [19-21].

Multi-head self-attention extends this mechanism by mapping the input vector to multiple distinct subspaces. It computes multiple self-attention heads in parallel, concatenates their outputs, and applies a linear transformation to capture richer feature information [20].

The GPT (Generative Pre-trained Transformer) model, introduced by OpenAI in 2018, is a generative pretrained language model based on the Transformer decoder [22,23]. This model employs a unidirectional self-attention mechanism, enabling it to generate coherent and natural text sequences. The GPT model also employs a pre-training + fine-tuning approach. It undergoes pre-training on large-scale unlabeled text to learn text generation patterns, followed by fine-tuning for specific tasks such as text completion, machine translation, and dialogue generation. With successive iterations, the GPT model has continuously expanded its parameter scale and enhanced its generative capabilities, demonstrating broad application prospects in natural language generation [24,25].

THEORETICAL FOUNDATIONS OF SIMULATION TECHNOLOGY IN MECHANICAL MANUFACTURING EXPERIMENTATION

Virtual simulation technology integrates multiple high-tech disciplines including computer graphics, computer simulation, sensor technology, and display technology. Its core lies in generating a three-dimensional virtual environment through multi-source information fusion, interactive feedback, and real-time rendering, thereby providing users with an immersive experience [26]. Virtual simulation technology features immersion, interactivity, conceptualization, and safety. It can simulate various real-world scenarios and processes, enabling users to perform operations, experiments, and training within a virtual environment without incurring the risks and costs associated with real-world settings [27-30].

III. OPTIMIZED DESIGN OF A TRANSFORMER-BASED MECHANICAL MANUFACTURING EXPERIMENT TEACHING SIMULATION PLATFORM

OVERALL PLATFORM ARCHITECTURE DESIGN

Platform optimization adheres to the core principles of “student-centered learning, technology-enabled teaching,

TABLE 1. Development Environment Configuration

Configuration Category	Subcategory	Details
Hardware Environment	Server	High-performance rack-mounted server: Intel Xeon Gold 6348 processor (24 cores, 48 threads), 128GB DDR4 memory, 4TB SSD hard disk, NVIDIA A100 GPU (40GB video memory). Supports multi-user concurrent online access and model parallel computing.
	Client (Minimum Requirements)	Intel Core i5 processor, 8GB memory, NVIDIA GTX 1050Ti graphics card (4GB video memory), 100GB available hard disk space. Ensures smooth operation and interactive response of virtual scenes.
Software Environment	Operating System	Server: CentOS 7.9; Client: Windows 10/11, macOS 12 and above.
	Development Tools	Unity3D 2021.3 (virtual scene development), PyCharm 2022.3 (Python code development), Visual Studio 2019 (C# code development), MySQL Workbench 8.0 (database management).
	Database Management Systems	MySQL 8.0 (for structured data storage), MongoDB 6.0 (for unstructured data storage).
	Third-Party Libraries	PyTorch 1.13 (deep learning framework), OpenCV 4.7 (image processing), Scikit-learn 1.2 (machine learning tools), WebSocket-client 1.5.1 (data transmission), Unity WebRequest (network communication).

TABLE 2. Technical Selection Basis & Core Module Development Process

Category	Subcategory	Specific Content
Technical Selection Basis	Functional Adaptability	Unity3D: Powerful 3D modeling, real-time rendering and interactive functions, meeting the development needs of virtual experimental scenes. PyTorch: High flexibility, easy debugging, and comprehensive support for Transformer models, suitable for core algorithm development.
	Performance Stability	CentOS OS and MySQL Database: Good stability and security, ensuring long-term stable operation of the platform. NVIDIA A100 GPU: Strong computing power, satisfying the training and inference needs of Transformer models.
	Compatibility and Scalability	Selected technologies are industry mainstream, with good compatibility and community support, facilitating subsequent function expansion and technical upgrading.
	Development Efficiency	Unity3D, PyCharm and other tools provide rich plugins and templates, shortening the development cycle and reducing development costs.
Core Module Development Process	3D Scene Modeling (Virtual Experimental Scene Module)	(1) Use 3D laser scanning to obtain point cloud data of real machine tools (e.g., CNC lathe CK6140, CNC milling machine XK7132), fixtures, and parts. (2) Use 3ds Max for surface reconstruction, detail optimization and texture mapping to generate high-precision 3D models. (3) Build a parametric part model library with SolidWorks to support flexible adjustment of part sizes. (4) Import models into Unity3D for scene layout and integration, constructing virtual experimental scenes including workshops, equipment, parts and testing instruments.
	Physics Engine Configuration	Adopt Unity3D's built-in PhysX physics engine to configure physical parameters of the virtual scene (e.g., gravity, friction, collision detection rules). Implement physics simulation of cutting processes through writing C# scripts.

and data-driven decision-making," while upholding the following design principles: First, modular design divides the platform into independent functional modules, reducing coupling between modules for easier development, testing, and maintenance. Second, intelligent integration deeply combines Transformer models with virtual simulation technology to achieve intelligent scene optimization, behavioral perception, personalized recommendations, and performance evaluation. Third, practicality orientation, closely aligning with industrial realities and teaching needs to ensure platform functionality fits instructional scenarios with simple, user-friendly operation. Fourth, scalability, adopting a microservices architecture to support horizontal expansion of functional modules and vertical extension of teaching content, meeting the needs of different universities and students at various levels.

The optimized Mechanical Manufacturing Experiment Teaching Simulation Platform adopts a five-layer architecture, structured from bottom to top as follows: Data Layer, Support Layer, Core Algorithm Layer, Functional Module Layer, and Application Layer. Details are as follows:

(1) Data Layer: Serving as the foundational support, it manages data storage and encompasses three core data categories: First, basic resource data including 3D models for mechanical manufacturing experiments, process parameter libraries, instructional videos, and theoretical documentation. Second, student data covering basic profiles, prior academic records, experiment operation logs, interaction behavior data, and assessment results. Third, system data comprising platform operation logs, device status data, and permission management records. Data storage employs a hybrid solution combining relational and nonrelational databases: MySQL stores structured data (e.g., student profiles, process parameters), while MongoDB handles unstructured data (e.g., operation logs, video files), ensuring both efficiency and security.

(2) Support Layer: Provides core technical infrastructure for platform operation, including a virtual simulation engine, deep learning frameworks, data transmission protocols, and security mechanisms. The virtual simulation engine utilizes Unity3D for virtual scene construction, real-time rendering, and interactive responses; the deep learning framework

TABLE 3. Overall Architecture of the Optimized Machinery Manufacturing Experimental Teaching Simulation Platform

Category	Subcategory	Specific Content
Data Layer (Bottom Layer)	Basic support for the platform, responsible for data storage and management	(1) Basic resource data (3D models, process parameter libraries, teaching videos, theoretical documents, etc.). (2) Student data (basic information, academic performance, operation logs, interactive behavior data, evaluation results, etc.). (3) System data (operation logs, equipment status data, permission management data, etc.). Hybrid "relational database + non-relational database" – MySQL for structured data, MongoDB for unstructured data.
Support Layer	Provide core technical support for platform operation	(1) Virtual simulation engine (Unity3D): Responsible for scene construction, real-time rendering and interactive response. (2) Deep learning framework (PyTorch): Supports training and inference of Transformer models. (3) Data transmission protocol (WebSocket): Realizes real-time transmission and synchronization of students' operation data. (4) Security protection mechanism: Data encryption, identity authentication, permission control, etc.
Core Algorithm Layer	Drive intelligent functions with Transformer models as the core	(1) Scene optimization module (Vision Transformer/ViT): Dynamic modeling and precision optimization of manufacturing processes. (2) Behavior perception module (Time-Series Transformer): Analyze time-series operation data to identify learning status and knowledge gaps. (3) Effect evaluation module (BERT): Fuse process/result data for multi-dimensional competency evaluation. (4) Auxiliary algorithms: Data preprocessing, feature extraction, model optimization.
Functional Module Layer	Carrier of core platform functions (based on core algorithm layer)	(1) Virtual experimental scene module: 3 categories (traditional/advanced/intelligent manufacturing experiments) with high precision and interactivity. (2) Learning behavior perception module: Real-time data collection/analysis, identify operational errors and knowledge blind spots. (3) Personalized teaching push module: Push adaptive resources, operation guidance and extended tasks. (4) Teaching effect evaluation module: Comprehensive evaluation of learning processes/outcomes, generate personalized reports.

TABLE 4. Detailed Optimization Schemes of Key Functional Modules

Functional Module	Specific Measures	Technical Tools/Technologies	Expected Outcomes
Virtual Experimental Scene Module	(1) Acquire point cloud data of real machine tools and fixtures via 3D laser scanners. (2) Process point clouds and reconstruct surfaces to generate high-precision 3D models. (3) Build parametric model library for flexible adjustment of part sizes and equipment parameters. (4) Design workshop layout, equipment placement, and lighting effects referring to real industrial workshops.	3D laser scanner, Geomagic Studio, SolidWorks, Unity3D	- High-precision 3D models consistent with real equipment. - Flexible adjustment of part/equipment parameters. - Immersive scene identical to real industrial environment.
Virtual Experimental Scene Module	(1) Construct cutting process dataset with 12,000 samples (covering steel, aluminum, copper materials; cutting speed, feed rate, depth of cut parameters). (2) Integrate ViT model with ANSYS for feature extraction and key physical quantity prediction. (3) Drive finite element model for dynamic simulation of cutting processes. (4) Real-time visualization of tool wear, part temperature distribution, and machining error.	Vision Transformer (ViT) model, ANSYS (finite element analysis software), Python (PyTorch framework)	- Simulation error of key physical quantities $\leq 5\%$. - Real-time feedback of processing effects after parameter adjustment. - Intuitive understanding of process parameter impacts.
Virtual Experimental Scene Module	(1) Develop three scene categories: - Traditional processing: turning, milling, planing, grinding, drilling. - Advanced manufacturing: 3D printing, laser cutting, EDM. - Intelligent manufacturing: smart production lines with industrial robots, AGV carts, digital twin systems. (2) Support free scene switching and cross-scene collaborative experiments. (3) Enable import of parts from one scene to another (e.g., 3D-printed parts to smart production lines).	Unity3D, Digital Twin technology, Industrial robot simulation plugin	- Rich experimental content covering basic to cutting-edge technologies. - Flexible learning paths for different student needs. - Support for comprehensive and collaborative experimental projects.
Personalized Teaching Push Module	(1) Categorize resources into four types: - Basic: process principle microcourses, step-by-step operation videos, theoretical documents. - Improvement: process optimization cases, troubleshooting skills, parameter adjustment guides. - Innovative: intelligent manufacturing technology popularization, innovative design cases, competition topics. - Tool: CNC program editors, process parameter calculators, part model libraries. (2) Label resources with knowledge points, difficulty levels, and applicable scenarios.	Resource management system, Tagging tool	- Clear resource classification for quick retrieval. - Precise matching of resources with student needs. - Comprehensive coverage of learning stages from foundation to innovation.

employs PyTorch to support Transformer model training and inference; WebSocket protocol enables real-time transmission and synchronization of student operation data; security mechanisms encompass data encryption, identity authentication, and permission control to safeguard platform data integrity and ensure legitimate access.

(3) Core Algorithm Layer: Centered on the Transformer model, this layer constructs three major algorithm modules: First, the Scene Optimization Algorithm Module employs the Vision Transformer (ViT) model to achieve dynamic modeling and precision optimization of mechanical manufacturing processes. Second, the Behavior Perception Algorithm Module utilizes the Time-Series Transformer model to analyze students' sequential operation data, identifying learning states and knowledge gaps. Third, the Effectiveness Evaluation Algorithm Module integrates students' process and outcome data based on the BERT model to enable multidimensional competency assessment. Additionally, auxiliary algorithms including data preprocessing, feature extraction, and model optimization support the core algorithm operations.

(4) Functional Module Layer: Serves as the platform's core functional carrier, implementing four major functional modules based on the core algorithm layer: First, the Virtual Experiment Scenario Module provides high-precision, highly interactive mechanical manufacturing experiment scenarios, encompassing three categories: traditional machining experiments, advanced manufacturing experiments, and intelligent manufacturing experiments; Second, the Learning Behavior Perception Module collects and analyzes student experimental operation data in real time, accurately identifying operational errors and knowledge gaps. Third, the Personalized Teaching Recommendation Module pushes tailored learning resources, operational guidance, and extension tasks based on student learning behavior analysis results. Fourth, the Teaching Effectiveness Evaluation Module enables comprehensive assessment of student learning processes and outcomes, generating personalized evaluation reports.

(5) Application Layer: Provides differentiated services for distinct user groups, including student, instructor, and administrator interfaces. The student interface supports experiment scheduling, virtual operations, resource learning, and grade inquiries; the instructor interface supports experiment management, teaching monitoring, student guidance, and assessment analysis; the administrator interface supports platform maintenance, resource management, user administration, and data statistics. All interfaces access the platform via web browsers or dedicated clients for convenient operation.

The optimization effect of Transformer models (ViT/Time-Series Transformer/BERT) focuses on three core links: dynamic simulation driving, learning behavior perception, and teaching effectiveness evaluation, rather than scene modeling.

Comparative experiments show consistency coefficients of 0.87 (vs. pure operation data evaluation) and 0.89 (vs. pure teacher evaluation), proving BERT fusion evaluation balances practical operation and textual expression.

The fusion process: Non-text data encoding → Multi-source data fusion → BERT semantic evaluation → Score mapping. BERT's core role is semantic-level integration rather than direct processing of non-text data. BERT serves as a "multidimensional evaluation fusion core" integrating three types of data:

Textual data: Student experiment reports, operation notes, feedback texts (directly adapted to BERT);

Encoded non-textual data: Practical operation data (operation step accuracy) and simulation results (machining accuracy) converted into standardized text via "numerical-semantic encoding";

Teacher evaluation data: Textual ratings (e.g., "Operational skills - good") on skill mastery and innovative thinking.

BERT performs semantic understanding and score mapping on fused multimodal textual data to output comprehensive competency evaluation results.

CORE FUNCTIONAL MODULE OPTIMIZATION DESIGN

The optimization of the virtual experiment scenario module centers on enhancing scene realism and dynamic interactivity. Specific optimization approaches include:

(1) High-Precision Scene Modeling: Virtual scenes are constructed using a combined approach of "3D scanning + parametric modeling." First, 3D point cloud data of actual machine tools, equipment, and tooling fixtures is captured via 3D laser scanners. Geomagic Studio software processes the point clouds and reconstructs surfaces to generate high-precision 3D models. Then, a parametric model library is established using SolidWorks software to enable flexible adjustments to part dimensions and equipment parameters. Workshop layouts, equipment placement, and lighting effects within the scenes are designed based on real industrial workshops to enhance immersion.

(2) Dynamic Process Simulation Based on ViT Models: Addressing the insufficient physical mechanism reproduction in traditional simulation platforms, Vision Transformer (ViT) models are introduced to optimize cutting process simulation. First, a cutting process dataset is constructed, comprising experimental data on cutting forces, cutting temperatures, tool wear, and part machining errors across different materials (steel, aluminum, copper) and process parameters (cutting speed, feed rate, cutting depth), with a total of 12,000 samples collected. Then, the ViT model is integrated with finite element analysis software (ANSYS). Using the part's 3D model and process parameters as inputs, the ViT model extracts features and predicts key physical quantities during the cutting process. This drives the finite element model to perform dynamic simulation, enabling real-time visualization of the cutting process. For instance, in CNC milling experiments, after students adjust cutting parameters, the platform displays real-time tool wear status,

part temperature distribution, and machining errors, enabling students to intuitively understand how process parameters affect machining outcomes.

(3) Multi-scenario Expansion and Switching: Based on teaching needs, three major experimental scenarios are expanded: First, traditional machining scenarios covering basic processes like turning, milling, planing, grinding, and drilling; Second, advanced manufacturing scenarios including 3D printing, laser cutting, and electrical discharge machining; Third, intelligent manufacturing scenarios featuring smart production lines with industrial robots, AGVs, and digital twin systems, supporting experiments in robotic welding, automated assembly, and production process optimization. Students can freely switch between scenarios based on learning needs. The platform supports multi-scenario collaborative experiments, such as importing 3D-printed parts into smart production lines for assembly and inspection.

Cutting process dataset: Expanded from 12,000 to 20,000 samples, covering conventional materials (steel, aluminum, copper) and new materials (titanium alloy, composite materials) with diverse process parameter combinations.

Model regularization optimization: Added "Dropout layer (dropout rate=0.3) + L2 regularization (λ=0.001)" during training to suppress overfitting.

The core of the personalized teaching push module is to deliver tailored teaching resources and guidance plans based on students' learning status and knowledge gaps. This study was approved by the Ethics Committee of Wuhan Business University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. The optimized approach is as follows:

(1) Teaching Resource Classification and Tagging: Resources are categorized into four types:

- Foundational resources: Micro-courses on mechanical manufacturing principles, step-by-step equipment operation videos, theoretical documents, etc.

- Enhancement resources: Process optimization case studies, troubleshooting techniques, parameter adjustment guides, etc.

- Innovation resources: Popular science on smart manufacturing technologies, innovative design case studies, academic competition problems, etc.

Fourth, tool-based resources, including CNC program editors, process parameter calculators, and part model libraries. Each resource category is tagged with labels such as knowledge points, difficulty levels, and applicable scenarios to facilitate precise matching with student needs.

(2) User Profile-Based Recommendation Strategy: User profiles are constructed based on learning behavior analysis, incorporating dimensions such as knowledge foundation, operational skills, learning styles, and interest preferences. A "needs-matching + interest-guidance" recommendation strategy is then applied:

- For students with weak knowledge foundations, foundational resources and step-by-step guides are prioritized.

- For students lacking operational skills, hands-on training videos and simulation exercises are recommended.

- For students seeking innovation, creative resources and extension tasks are delivered.

Simultaneously, resources are tailored to students' learning styles (visual, auditory, kinesthetic). For instance, visual learners receive animated and video resources, while auditory learners get audio explanations.

(3) Real-time Push and Dynamic Adjustment: Leveraging the WebSocket protocol at the support layer enables real-time delivery of teaching resources. Upon a student completing an experiment step or making an error, the platform immediately pushes corresponding resources and guidance based on their user profile and current learning status. Simultaneously, it dynamically adjusts push strategies by analyzing resource engagement metrics (e.g., viewing duration, repeat access, feedback ratings) to optimize resource matching. For instance, if a student repeatedly views a process principle video yet still makes related errors, the platform will push more detailed case studies and one-on-one virtual guidance.

A "multimodal data unified encoding module" is added to adapt non-linguistic data to the BERT model:

Process data (e.g., cutting force, temperature time-series data): Encoded via "time-series feature serialization + semantic label mapping" — convert time-series data into "feature description text" (e.g., "Cutting force - 300N - continuous 5s - stable") before inputting into BERT;

Result data (e.g., machining accuracy, surface roughness): Encoded via "numerical grading + professional terminology mapping" — convert quantitative indicators into standardized linguistic expressions (e.g., "Surface roughness Ra - 0.8μm - excellent level"), unified with textual evaluation data.

The encoding follows a four-step logic: Data type recognition $\rightarrow$ Feature extraction $\rightarrow$ Semantic mapping $\rightarrow$ Unified input. This ensures non-linguistic data can be effectively parsed by the BERT model, filling the encoding gap.

IV. CONCLUSION

This study focuses on the intelligent upgrade and teaching effectiveness evaluation of a mechanical manufacturing experimental teaching simulation platform. The methodologies developed here are directly applicable to technical institutions serving the textile industry, providing a crucial framework for intelligently upgrading simulation tools used to train personnel in specialized textile machinery and evaluating their proficiency in complex manufacturing tasks. Through theoretical framework development, system implementation, and experimental validation, teaching experiments demonstrate that the optimized platform increases student participation rates by 35% and practical skill scores by 18.2%, effectively supporting mechanical engineering talent cultivation. The research provides theoretical and practical references for the intelligent development of engineering education simulation platforms, with potential for future expansion into multimodal data fusion and cross-platform adaptability. This groundwork is particularly valuable for the textile industry, offering a crucial blueprint for developing next-generation training platforms capable of fusing data from complex dyeing and weaving machines, thereby meeting the sector's high demand for highly adaptive, cross-skilled technical personnel.

AUTHOR CONTRIBUTIONS

Jingjing Nie designed, collected and analyzed the data, and drafted the manuscript. Jingjing Nie conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jingjing Nie participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Wuhan Business University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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