From “Add-on” to “Integration”: Ecological Pathways for Aesthetic Education Embedded in Vocational Skills Training

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ABSTRACT New technological avenues for the coordinated development of vocational skills and aesthetic literacy in vocational education are emerging thanks to the advent of artificial intelligence, knowledge graph and multimodal learning analytics. A digital ecosystem model for skill-oriented aesthetic education was built to solve the problems of add-on aesthetic education content, coarse-grained resource matching and delayed evaluation feedback of traditional aesthetic education skills training. There are four components in the model: professional skill–aesthetic element knowledge graph, multimodal feature fusion of students' works, profiling of aesthetic competence and dynamic optimization mechanism of learning path. Based on this, a collaborative teaching platform for multi-stakeholders was designed, which could be used for resource management, work assessment, individualized recommendation and virtual simulation experience. Experimental results demonstrate that the proposed method obtained 91.4% task completion rate, 92.1% operational accuracy, 88.3 work quality score and 0.801 NDCG@5, which is better than the traditional teaching methods and single-recommendation methods. In the experimental group the aesthetic literacy, and vocational competence scores were 82.7 and 84.9. These results prove that, based on data, the ecological construction can facilitate the coordinated development of vocational skills, aesthetic literacy and professional competence, which is a practical way to turn the “add-on” of aesthetic education from skills into an “integrated” one.

INDEX TERMS skills-based aesthetic education; vocational education; knowledge graph; multimodal learning; personalised recommendations

I. INTRODUCTION

With the rapid development of artificial intelligence, knowledge graph, multimodal analysis and data mining technology, it provides new technological support for the deep integration of skills training and aesthetic literacy in vocational education. In the practice of traditional skills-oriented aesthetic education, aesthetic is still not fully integrated into professional skills training, practical training process and vocational assessment, and aesthetic is still an independent component, which is the form of supplementary teaching and learning. Traditional aesthetic education based on skills has mostly appeared in the form of art teaching and learning outside the professional work, it can be seen that in the traditional aesthetic education there is a separation between aesthetic development and skills development. In the era of digital transformation, Zhang notes that aesthetic education curricula in vocational colleges must incorporate intangible cultural heritage and the spirit of craftsmanship to rebuild the content system of aesthetic education curricula [1], while Chen and Keat have summarized the current situation of aesthetic education and its importance in developing students' comprehensive qualities in higher vocational education in China [2]. Tao and Tao identified the intrinsic relations between aesthetic education, sustainable development and quality-oriented education through the bibliometric analysis [3] and Lanu and Mäenpää developed the value dimensions of skills education by introducing sustainable thinking to the field of arts and crafts education [4]. Zhao et al. built the aesthetic literacy model of vocational education teachers, and pointed out that the competence of teachers is an important condition for the implementation of aesthetic education [5]; Li and Hu used fuzzy comprehensive evaluation method in the aesthetic education in higher vocational education to analyse the integration effects, providing a reference for the aesthetic education quantification evaluation [6]. Conversely, Obrecht et al. [7] and Christou et al. [8] and

Chinedu et al. [9] have advocated for the need to build a connected educational model from the perspectives of systems thinking, whole-institution collaboration and curricular model respectively. Current studies are mainly centred around curricular philosophy and teacher competencies and macro-level integration mechanisms, and research on the connection between skills and aesthetic elements, the evaluation of multimodal works, students aesthetic profiling and dynamic learning pathways are still scarce.

This study therefore proposes to build a digital ecosystem for aesthetic education based on skills, with the aid of data. This work extends the skills-based aesthetic education from being 'add-on' to 'integrated' through synergistic interaction among resources, tasks, participants and assessment with the help of knowledge graph, and validates the promoting effects of the transition through teaching platforms and comparative experiments, thus paves a path for skills-based aesthetic education to be computable, implementable and evaluable.

II. MODELLING THE DIGITAL ECOSYSTEM FOR SKILLS-BASED AESTHETIC EDUCATION IN VOCATIONAL EDUCATION

A. THE ESSENCE OF SKILLS-BASED AESTHETIC EDUCATION AND THE CHALLENGES OF 'ADD-ON' IMPLEMENTATION

Aesthetic education based on skills: Aesthetic perception, craftsmanship, innovative thinking and work professionalism permeate the entire process of skills training. It is the synergistic transformation of the operational behaviour, works' form and the professional context that makes it possible to enhance the technical competence and aesthetic literacy of works simultaneously [10]. In traditional 'add-on' implementation, art courses are often used as an extra activity, with thematic lectures or work exhibitions as an add-on to it, and not tightly coupled with professional tasks, practical training processes and assessment criteria. This leads to disconnection of teaching content, poor resource allocation, difficulties in finding student differences and poor use of corporate aesthetic standards, and it is difficult to establish a closed-loop teaching system, that is, continuous feedback and dynamic optimisation.

B. ANALYSIS OF THE NEED FOR INTEGRATION BETWEEN SKILLS TRAINING AND AESTHETIC LITERACY

Skills training and aesthetic literacy integration needs to be job-specific, meaning that the technical standards, precision in operation, aesthetics of form and innovative expression have to be integrated in the process of practical training, and the differentiated training should be carried out according to the students' skill base and aesthetic lacunae and the conditions of the available resources [11]. The level of integration needed can be stated as:

$$D_i = \alpha S_i + \beta A_i + \gamma P_i + \delta C_i \tag{1}$$

where D_i represents the comprehensive integration requirement for student i ; S_i denotes the skills capability gap; A_i denotes the aesthetic literacy gap; P_i denotes the job standard alignment requirement; C_i denotes the learning context adaptation requirement; and $\alpha, \beta, \gamma, \delta$ denotes the weights, the sum of which is 1. By dynamically calculating the integration requirement, a basis can be provided for the allocation of teaching resources, task design and the adjustment of learning pathways, thereby achieving the synergistic advancement of skills enhancement and aesthetic development [12].

C. KEY ACTORS AND CONSTITUENT ELEMENTS OF THE SKILLS-BASED AESTHETIC EDUCATION ECOSYSTEM

Aesthetic education skills are not only formed by the aesthetic education in-school teachers and students, but also by the industrial teachers and students, who are the main body of skills training; it consists of various industry teachers, students, in-school aesthetic education teachers, and students, with aesthetic aspects, job standards, evaluation feedback, and practical training tasks serving as the primary elements [13]. There are several actors who have multi-directional interactions including task design, provision of resources, learning and practice, evaluation of work and standardised feedback, and interconnection and dynamic synergy between the elements is realised through data flows. Specific relations between the stakeholders and elements are presented in Figure 1; this is a model that attains an ecologic structure of skills training, aesthetic cultivation and professional contexts, related to one another.

D. REPRESENTATION OF SKILLS AND AESTHETIC EDUCATION ELEMENTS BASED ON MULTI-SOURCE DATA

Characterisation of elements in skills-based aesthetic education is done by multi-source data, namely learning behaviors, training process in practice, images of students' products, teacher's evaluations, and corporate feedback. A unified data space is created by cleansing, normalising and aligning (historically) the data. The semantic, visual, temporal and behavioural features of the text, image, video and operation logs respectively are extracted and through feature fusion, mapped to vectors representing skill level, aesthetic perception, craftsmanship quality and innovative expression, which can be used to provide data support for student profiling, resource matching and optimisation of integration pathways [14].

E. OVERALL ARCHITECTURAL DESIGN OF THE DIGITAL ECOSYSTEM FOR SKILLS-BASED AESTHETIC EDUCATION

The whole design of the digital system for aesthetic education based on skills follows a layered structure: a data collection layer, a data processing layer, a model service layer, a business application layer and an interactive display

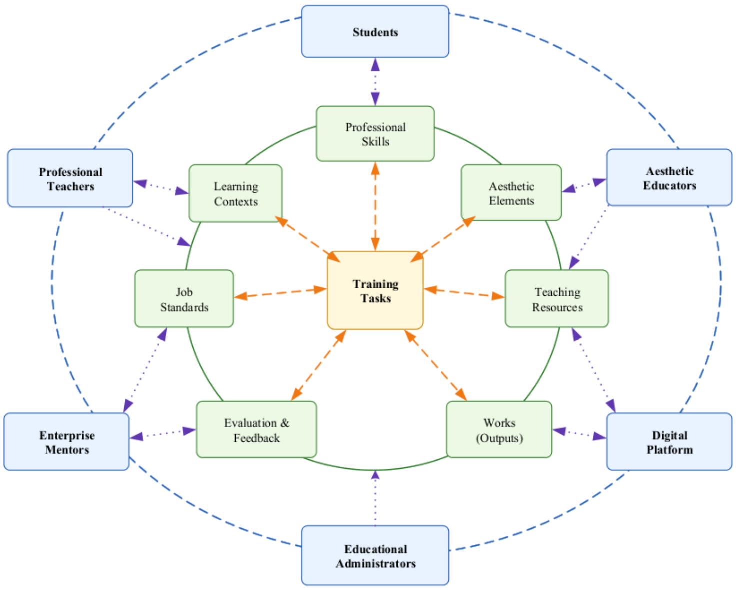

Fig. 1. Model of the Relationships between Actors and Elements in the Skills and Aesthetic Education Ecosystem

layer [15]. The lower layer collects information about the learning behaviour of students, practical training procedures, the quality of the students' work and the standards of the companies; this data is cleaned, fused and encoded in features and is then used for the operation of knowledge graphs, aesthetic profiling, intelligent recommendation and pathway optimisation. The upper layer is responsible for teacher and student and enterprise resource management, work evaluation, collaborative teaching and decision-support. The general structure is illustrated as in Figure 2.

III. DATA-DRIVEN MECHANISM FOR THE INTEGRATION OF SKILLS AND AESTHETIC EDUCATION

A. DATA COLLECTION AND PRE-PROCESSING OF SKILL-LEARNING BEHAVIOUR

Data on skills learning behaviour is primarily collected from information such as resource browsing, task execution, project submission, error correction and evaluation feedback, and multi-source records are aligned based on student ID numbers and timestamps [16]. To eliminate differences in units of measurement, the raw features undergo normalisation:

$$x'_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{2}$$

where x_{ij} represents the j th behavioural feature of student i [17]. For anomalous records, a standard deviation threshold is applied for identification:

$$|x_{ij} - \mu_j| > 3\sigma_j \tag{3}$$

where μ_j and σ_j represent the mean and standard deviation of the features, respectively [18]. To further account for the temporal nature of behaviour, a time-decay-adjusted composite behavioural representation is constructed:

$$B_i = \sum_{t=1}^{T} e^{-\lambda(T-t)} x_i^t \tag{4}$$

where λ is the decay coefficient, and x_i^t is the behavioural vector at time t [19]. The data collection sources, pre-processing methods and generated features for each data type are shown in

B. KNOWLEDGE GRAPH-BASED MODELLING OF THE RELATIONSHIP BETWEEN PROFESSIONAL SKILLS AND AESTHETIC ELEMENTS

The professional skills—aesthetic elements knowledge graph is based on curriculum standards, practical training tasks, job specifications and teaching resources. It defines disciplines, courses, skill points, process steps, aesthetic elements, work characteristics and assessment criteria as entities, and constructs semantic relationships such as 'belonging, prerequisite, manifestation, association and evaluation' [20]. The graph is represented as follows:

$$G = (V, E, R) \tag{5}$$

where V denotes the set of entity nodes, E denotes the set of relationship edges, and R denotes the set of relationship types [21].

To quantify the strength of the association between the skill nodes v_i and the aesthetic element nodes v_j , edge weights are calculated by combining expert ratings, textual semantic similarity and co-occurrence frequency in teaching data:

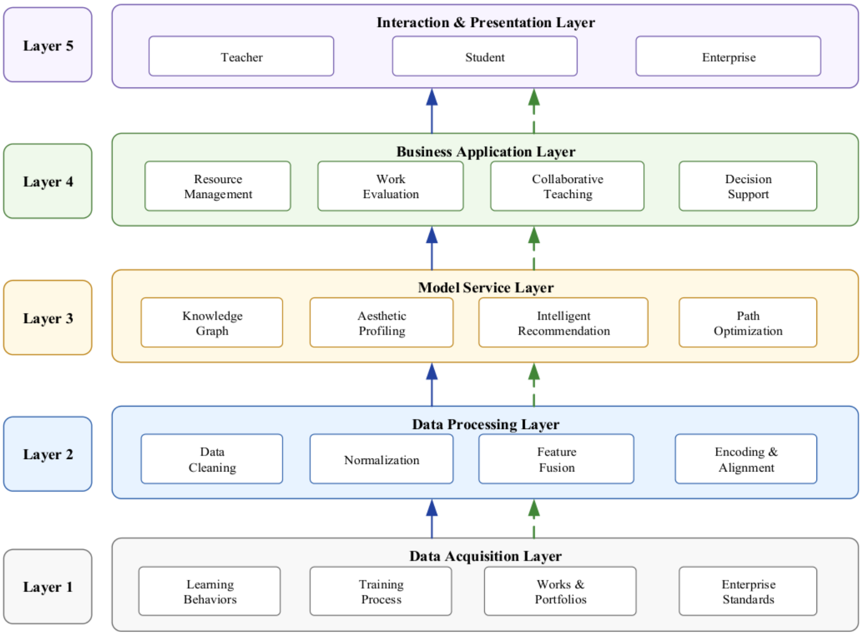

Fig. 2. Overall Architectural Design

TABLE I. Data collection and pre-processing methods for learning behaviour

Data Type	Collection Source	Preprocessing Method	Output Feature
Resource learning	Platform logs	Deduplication and normalization	Browsing frequency and duration
Training operation	Training system	Time alignment and outlier removal	Operation accuracy and completion time
Task performance	Task records	Missing-value filling	Task completion rate
Work submission	Portfolio database	Format conversion and feature extraction	Submission and revision frequency
Evaluation feedback	Teacher and enterprise scores	Score normalization	Comprehensive evaluation score

$$w_{ij} = \alpha e_{ij} + \beta s_{ij} + \gamma c_{ij} \tag{6}$$

where e_{ij} represents the expert association score, s_{ij} represents semantic similarity, c_{ij} represents co-occurrence strength, and $\alpha+\beta+\gamma = 1$. Furthermore, graph embedding methods are employed to learn node vectors, and potential associations are identified using cosine similarity:

$$\mathrm{sim}(i, j) = \frac{h_i^\top h_j}{\|h_i\|_2 \|h_j\|_2} \tag{7}$$

This ultimately forms a structured association network between skills, aesthetic elements, tasks and resources, providing a knowledge foundation for content retrieval, aesthetic evaluation and personalised recommendations. The specific model is shown in Figure 3.

C. FEATURE EXTRACTION AND AESTHETIC REPRESENTATION OF MULTIMODAL SKILL-BASED WORKS

Multimodal skill works consist of images, videos, 3D models and textual descriptions. The image branch extracts features such as colour, texture, structure and symmetry; the video branch characterises the rhythm of operations and procedural standards; and the text branch extracts design intent and cultural semantics. The encoding for the mth modality is:

$$h_i^m = f_m(x_i^m) \tag{8}$$

where x_i^m represents the modal input for the work i , and f_m denotes the corresponding feature extraction network [22].

An attention mechanism is employed to perform feature fusion:

$$z_i = \sum_{m=1}^{M} \alpha_i^m h_i^m \tag{9}$$

$$\alpha_i^m = \frac{\exp(q_i^m)}{\sum_{k=1}^{M} \exp(q_i^k)} \tag{10}$$

The fused vector is further mapped onto aesthetic dimensions such as proportional harmony, formal beauty, craftsmanship, innovative expression and cultural significance, thereby achieving a unified representation of the skill-based work that bridges perceptual features and aesthetic semantics, whilst providing a feature foundation for intelligent evaluation and the construction of student profiles.

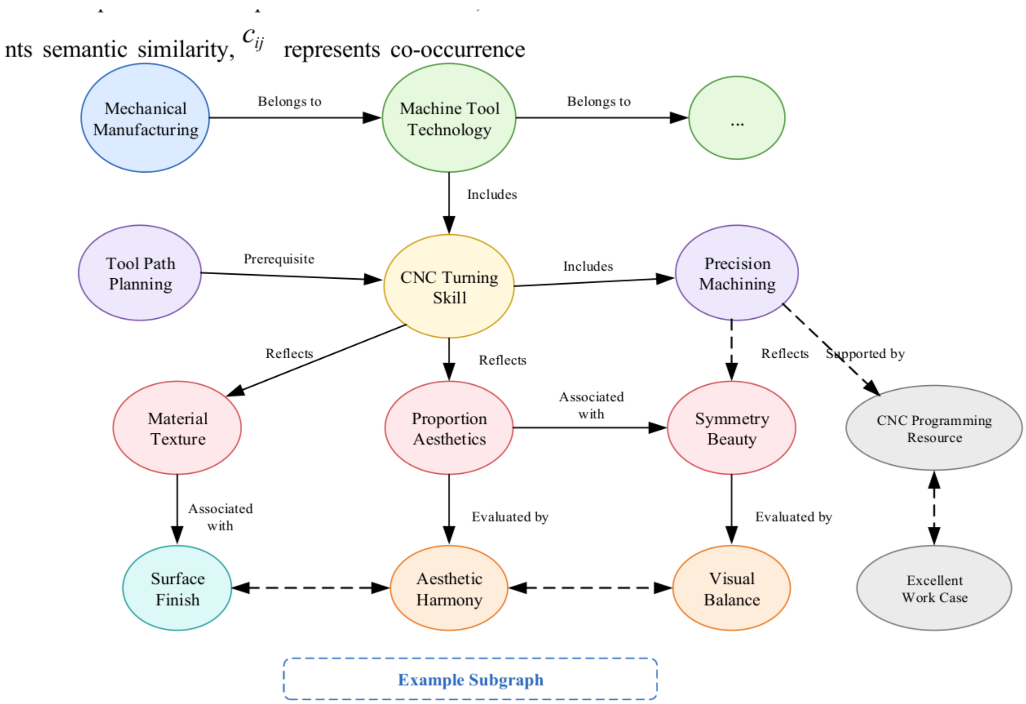

Fig. 3. Knowledge graph model of professional skills and aesthetic elements

D. CONSTRUCTION OF STUDENT AESTHETIC COMPETENCE PROFILES BASED ON LEARNING ANALYTICS

Student aesthetic competence profiles are constructed based on learning behaviour, skill-based works, assessment results and teacher evaluations. Dimensions include formal perception, structural understanding, craftsmanship aesthetics, innovative expression and cultural cognition. The profile of student i at time t is represented as:

$$p_i^t = \alpha b_i^t + \beta w_i^t + \gamma q_i^t + \delta e_i^t \tag{11}$$

where b_i^t, w_i^t, q_i^t and e_i^t represent behavioural, work-related, assessment and evaluation features, respectively, and the sum of their weights is 1. To reflect changes in competence, a time-updating mechanism is adopted:

$$p_i^{t+1} = \lambda p_i^t + (1-\lambda)\Delta p_i^t \tag{12}$$

where λ is the historical information retention coefficient, and Δp_i^t is the current learning increment [23]. The dynamic profile identifies students' aesthetic strengths and areas for improvement, providing a basis for resource recommendations and pathway adjustments.

E. INTELLIGENT MATCHING MECHANISM FOR SKILLS AND AESTHETIC EDUCATION CONTENT

With the student's skill level, aesthetic profile, current task and job standards as inputs, the system retrieves related resources through a knowledge graph, and evaluates and sorts the candidates by a comprehensive analysis of the skill compatibility, aesthetic compensation, resource difficulty and learning context [24]. The system is based on the prioritisation of case studies, videos and virtual simulation resources that are highly relevant to the tasks of practical training, that can be used to address aesthetic weaknesses and that have moderate difficulty, but that do not allow too much diversity and repetition as this can lead to monotonous content. Finally, based on students' learning time, learning performance, and variations of work and evaluation feedback, matching weights are dynamically adjusted after learning, so that the amount of resource provisioning continuously changes according to the students' ability development, thus forming a closed-loop mechanism of 'diagnosis—matching—learning—feedback—rematching'.

F. ALGORITHM FOR INTEGRATED PATH GENERATION AND DYNAMIC OPTIMISATION

A fusion path consists of skill tasks, aesthetic resources, practical activities and assessment nodes arranged in sequential order, with candidate sequences generated based on the student's current profile. The comprehensive utility of a path P is defined as:

$$J(P) = \alpha G_s(P) + \beta G_a(P) + \gamma G_o(P) - \delta C_t(P) - \varepsilon C_l(P) \tag{13}$$

In this context, G_s, G_a and G_o represent skill gains, aesthetic gains and job suitability, respectively, whilst C_t and C_l denote time cost and cognitive load [25].

The system determines the optimal path subject to constraints on resource difficulty, prerequisite skills and learning duration:

$$P^* = \underset{P \in \Omega}{\arg\max}\, J(P) \tag{14}$$

During the learning process, path weights are updated based on task performance, work evaluations and behavioural feedback:

$$w_{t+1} = w_t + \eta(r_t - \hat{r}_t) \tag{15}$$

where η represents the update rate, r_t represents the actual learning gain, and $\hat{r}_t$ represents the expected gain [26]. This algorithm is capable of dynamically replacing inefficient nodes and adjusting task sequences, thereby achieving continuous optimisation of the pathways for skills training and aesthetic cultivation.

IV. DESIGN OF AN ECOLOGICAL TEACHING PLATFORM FOR SKILLS AND AESTHETIC EDUCATION

A. PLATFORM FUNCTIONAL REQUIREMENTS AND MODULE DIVISION

The functional design of the platform focuses on skills training, aesthetic cultivation, provision of resources and multi-stakeholder collaboration, and covers aspects like learning behaviour data collection, analysis of works based on skills, diagnosis of aesthetic abilities, personalisation of recommendations and feedback for teaching. Data governance, knowledge graphs, resource management, work evaluation, student profiling, pathway recommendations, and virtual simulation and collaborative management are all modules of the system, and each module provides an interface for data sharing and model invoking. The technical architecture of the platform is a layered one, which links the student end, teacher end and enterprise end, as illustrated in Figure 4.

B. MULTIMODAL SKILLS TEACHING RESOURCE MANAGEMENT MODULE

The Multimodal Skills Teaching Resource Management Module supports text, images, video, 3D models and virtual simulation teaching resources, allowing for unified access, categorisation and storage, tag generation, and versioning. The system builds a metadata index based on specialisation, course, skill points and aesthetic elements and resource difficulty and implements a knowledge graph for resource association, semantic search and on-demand retrieval. Review, update and access control mechanisms are in place to ensure the quality of the resources, standardised sourcing and efficient multi-party sharing.

C. INTELLIGENT ANALYSIS AND AESTHETIC EVALUATION OF SKILLS PROJECTS MODULE

Intelligent Analysis and Aesthetic Evaluation of Skills Projects module is able to capture features of a piece (colour, structure, proportion, texture and operational processes) from images, videos and 3D works, to facilitate a technical-compliance and aesthetic-expression analysis. Evaluation results combine both the model scores and feedback from the tutor and industry standards to provide metrics like craftsmanship quality, formal aesthetics, innovative expression and occupational suitability and to provide feedback on specific areas requiring improvement.

D. PERSONALISED LEARNING RESOURCE RECOMMENDATION MODULE

The personalised learning resource recommendation module selects case studies, videos, 3D models and virtual simulation resources from the knowledge graph based on the students' skill level, aesthetic profile, ongoing practical learning task and learning history. The system is able to rank these resources based on their relevance, in terms of their difficulty, aesthetic compensation and content variety, and to create phased learning sequences [27]. After students finish a task, the module's recommendation weights are dynamically adjusted according to students' browsing behaviors, task completion results, and the evaluation results and feedback from their work, to maintain a good match between the provision of resources and skill training.

E. VIRTUAL SIMULATION-DRIVEN SKILLS AND AESTHETIC EXPERIENCE MODULE

The interactive virtual simulation skills and aesthetic experience module creates vocational scenarios, which include the processes involved in crafts, proportions of the structure, colour schemes and material textures. The system can compare, adjust and review different parameters and design proposals as well; meanwhile, the operational trajectory, design options and evaluating results are recorded in a way that will be used in the student profiling and resource recommending modules. The platform brings teachers, students and industry mentors together for co-construction of tasks, for guiding the process and evaluating output, and forms a multi-stakeholder collaborative teaching mechanism as illustrated in Figure 5.

F. MULTI-STAKEHOLDER COLLABORATIVE MECHANISM INVOLVING TEACHERS, STUDENTS AND INDUSTRY PARTNERS

Multi-stakeholder collaborative mechanism is based on the data sharing and task collaboration performed in the platform, and it has a closed loop of 'instructional design – learning practice – workplace feedback – dynamic improvement' among teachers, students and industry. Teachers create and grade skill-based tasks, add aesthetic elements, and direct students in the process; students conduct resource-based learning, virtual operations, and create works; industry mentors offer job standards, typical case studies, and professional assessments. Evaluation discrepancies are used to re-allocate resources and redirect learning pathway and the platform is a hub for centralizing the behaviour record, work outcomes and feedback, while the learning content is continuously aligned with the demand of the industry and

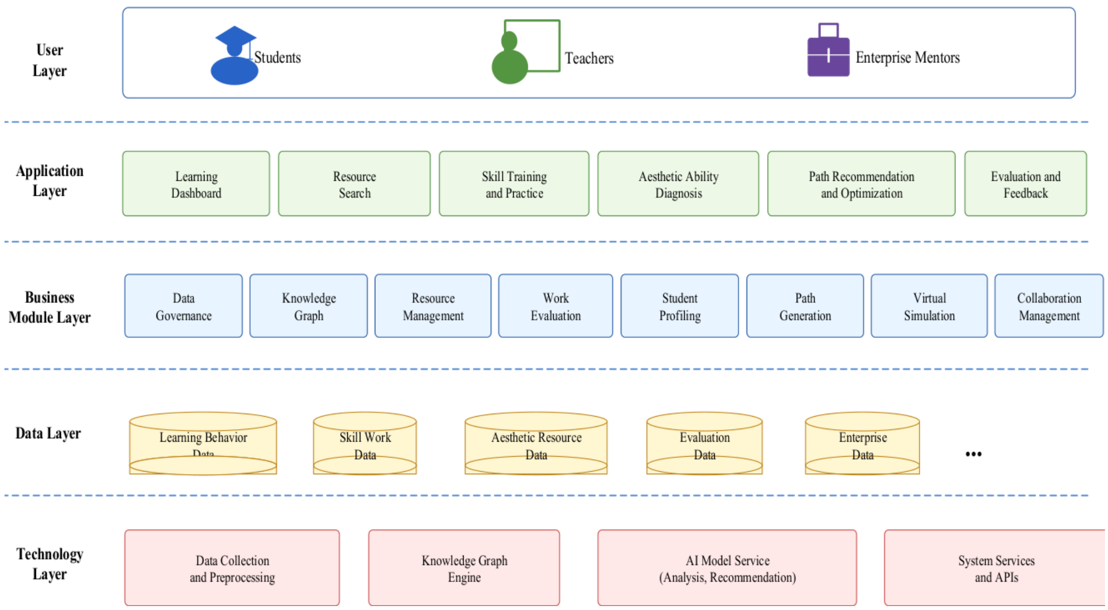

Fig. 4. Platform Technical Architecture Diagram

TABLE II. Indicators for Intelligent Aesthetic Evaluation of Skills Projects

Evaluation Dimension	Main Indicator	Data Source	Weight
Craft Quality	Accuracy, completeness and surface quality	Image and task data	0.25
Formal Aesthetics	Proportion, symmetry and structural coordination	Image or 3D model	0.20
Color and Texture	Color harmony, material and texture expression	Image data	0.15
Creative Expression	Originality and design differentiation	Work and text data	0.20
Occupational Adaptability	Compliance with process and enterprise standards	Process and evaluation data	0.20

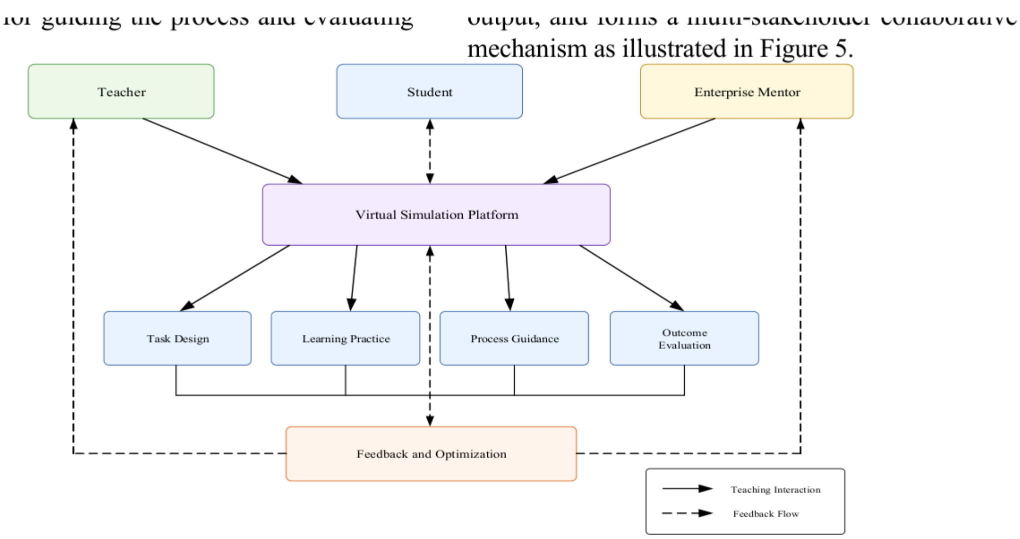

Fig. 5. Virtual Simulation and Multi-Stakeholder Collaborative Teaching Mechanism

enhance the synergy of skills training, aesthetic literacy and developing professional competencies.

V. EXPERIMENTAL DESIGN AND ANALYSIS OF RESULTS

A. EXPERIMENTAL ENVIRONMENT AND DATASET CONSTRUCTION

The operating system used in the experimental platform is Ubuntu 22.04 with an Intel Xeon processor, 64 GB of RAM, and an NVIDIA RTX 4090 GPU and the model is implemented through Python and PyTorch. The data collected were from practical skills training courses in 240 students in 3 vocational education courses, 36 practical training tasks, 4250 project activities in learning skills, and 18600 records of learning behavior and 1280 teaching resources. After anonymisation, deduplication and outlier handling, the data was split into 10, 3 and 2 sets, respectively, for training, validation, and testing.

B. COMPARISON OF METHODS AND EVALUATION METRICS

There are four groups: traditional supplementary teaching, rule based recommendation, collaborative filtering and knowledge graph based recommendation and the proposed hybrid method, and the course content, teaching time and teaching staff are all the same. We evaluated skill learning outcomes by the task completion rate, operational accuracy, work quality, and work completion time, while aesthetic literacy was evaluated by the aesthetic perception score, craftsmanship score, innovative expression score, with significance testing to determine differences between groups, and the recommendation performance was measured by Precision@5, Recall@5, F1@5, and NDCG@5.

C. COMPARATIVE ANALYSIS OF SKILL LEARNING OUTCOMES

The impact of different integration methods on skill training outcomes was compared across four dimensions: task completion rate, operational accuracy, quality of work and average completion time. The results are shown in

As can be seen from Table 4, the completion rate of the task and the accuracy of the operation of the fusion method were 91.4 per cent and 92.1 per cent respectively, which were 12.8 per cent and 10.2 per cent higher than those of the traditional supplementary teaching method. The average completion time was decreased by 10.7 minutes and the quality score of the work increased to 88.3 points, suggesting that knowledge association, competency profiling and dynamic path adjustment can help to reduce ineffective operations and enable the skills and knowledge to be transferred to practical outcomes.

D. ANALYSIS OF IMPROVEMENTS IN AESTHETIC LITERACY AND VOCATIONAL COMPETENCE

Pre- and post-tests were used to assess changes in the experimental and control groups regarding aesthetic perception, craftsmanship aesthetics, innovative expression and vocational competence; the results are shown in

Prior to the experiment, there were minimal differences in the various indicators between the two groups, indicating good homogeneity. Following the implementation of the teaching programme, the experimental group's scores for aesthetic perception, craftsmanship aesthetics and vocational competence increased by 14.3, 14.4 and 13.8 points respectively, with all increases exceeding those of the control group. The improvement in craftsmanship aesthetics was most pronounced, suggesting that embedding job standards, work evaluation and aesthetic elements into practical training tasks helps to strengthen students' comprehensive judgement of craftsmanship quality and formal expression.

E. PERFORMANCE ANALYSIS OF PERSONALISED RESOURCE RECOMMENDATIONS

To evaluate the effectiveness of resource matching, Precision@5, Recall@5, F1@5, NDCG@5 and Coverage were selected as metrics to compare different recommendation methods; the results are shown in

The fusion method achieved the best performance across all evaluation metrics, with NDCG@5 reaching 0.801, representing an improvement of 0.100 over collaborative filtering. The knowledge graph strengthened the semantic associations between skill-based tasks and aesthetic resources, while student profiling improved the accuracy of resource adaptation. In addition, the diversity constraint increased Coverage to 0.724, thereby reducing the risk of recommendation results being concentrated on a small number of popular resources.

F. ABLATION EXPERIMENTS AND SYSTEM PERFORMANCE ANALYSIS

To analyse the actual contributions of the core modules, the knowledge graph, multimodal representation, aesthetic profiling and dynamic path optimisation modules were removed individually; the results are shown in

After removing the aesthetic competence profile, Precision@5 decreased to 0.711, indicating that individual differences in competence constitute an important basis for resource matching. Without multimodal representation, the aesthetic literacy score declined by 3.8 points, demonstrating that the visual, textual, and process-related features of student works directly contribute to aesthetic recognition. The complete model maintained a favorable synergistic advantage between recommendation performance and teaching effectiveness.

Platform performance testing simulated resource access, graph queries, work analysis and recommendation generation processes using different scales of concurrent users; the results are shown in

As the number of concurrent users increased from 20 to 200, the average response time rose from 184 ms to 476 ms, whilst the P95 response time remained within 1 s. Under conditions of 200 users, throughput reached 365.2 requests/s with an error rate of 0.46 per cent, indicating that the platform is capable of supporting resource-based learning, assignment submission and assessment analysis for both standard classes and multiple classes running simultaneously.

G. EFFECTIVENESS OF THE TEACHING APPLICATION AND DISCUSSION

A sample of 240 students was selected and divided equally into an experimental group and a control group, with the

TABLE III. Experimental Environment and Dataset Statistics

Category	Item	Configuration / Quantity
Hardware	Processor	Intel Xeon
	Memory	64 GB
	GPU	NVIDIA RTX 4090
Software	Operating system	Ubuntu 22.04
	Development environment	Python, PyTorch
Dataset	Students	240
	Training tasks	36
	Skill works	4,250
	Learning behavior records	18,600
	Teaching resources	1,280
	Data split	Training/validation/test = 7:2:1

TABLE IV. Comparison of skill learning outcomes across different methods

Method	Task Completion Rate (%)	Operation Accuracy (%)	Work Quality Score	Completion Time (min)
Traditional Add-on Teaching	78.6	81.9	76.8 ± 5.7	52.4
Rule-based Recommendation	82.3	84.1	79.5 ± 5.2	49.8
Collaborative Filtering	84.7	86	81.2 ± 4.9	47.6
Knowledge Graph Recommendation	87.9	88.7	84.6 ± 4.5	45.1
Proposed Fusion Method	91.4	92.1	88.3 ± 4.1	41.7

TABLE V. Results on Improvements in Aesthetic Literacy and Vocational Competence

Evaluation Dimension	Experimental Pre-test	Experimental Post-test	Control Pre-test	Control Post-test
Aesthetic Perception	68.4 ± 6.1	82.7 ± 5.3	68.9 ± 6.0	75.4 ± 5.8
Formal and Structural Understanding	67.8 ± 6.4	81.9 ± 5.5	68.1 ± 6.2	74.8 ± 5.9
Craft Aesthetic Awareness	70.2 ± 5.8	84.6 ± 4.9	69.7 ± 6.1	76.5 ± 5.6
Creative Expression	66.9 ± 6.7	80.8 ± 5.8	67.3 ± 6.5	73.2 ± 6.1
Vocational Competence	71.1 ± 5.9	84.9 ± 5.0	70.8 ± 6.0	78.1 ± 5.7

TABLE VI. Comparison of Personalised Resource Recommendation Performance

Method	Precision@5	Recall@5	F1@5	NDCG@5	Coverage
Rule-based Recommendation	0.641	0.598	0.619	0.662	0.584
Collaborative Filtering	0.684	0.647	0.665	0.701	0.621
Knowledge Graph Recommendation	0.731	0.692	0.711	0.754	0.676
Proposed Fusion Method	0.772	0.741	0.756	0.801	0.724

TABLE VII. Results of Ablation Experiments

Model Variant	Precision@5	Recall@5	Work Quality Score	Aesthetic Literacy Score
Full Model	0.772	0.741	88.3 ± 4.1	82.7 ± 5.3
Without Knowledge Graph	0.724	0.688	85.1 ± 4.6	79.8 ± 5.7
Without Multimodal Representation	0.746	0.713	84.7 ± 4.8	78.9 ± 5.9
Without Aesthetic Profile	0.711	0.674	85.8 ± 4.5	79.3 ± 5.8
Without Dynamic Path Optimization	0.738	0.701	86.2 ± 4.4	80.4 ± 5.6

TABLE VIII. Platform System Performance Testing

Concurrent Users	Average Response Time (ms)	P95 Response Time (ms)	Throughput (requests/s)	Error Rate (%)
20	184	276	101.7	0
50	231	358	198.4	0.1
100	318	492	287.6	0.18
200	476	731	365.2	0.46

teaching cycle, course content and teaching staff remaining consistent across both groups. An independent samples t-test was used to analyse differences in post-test results; the results are shown in

All post-test indicators reached the level of statistical significance, with effect sizes ranging between 0.99 and 1.59. The effect size for work quality was the largest,

TABLE IX. Effectiveness of the Teaching Application and Significance Tests

Evaluation Indicator	Experimental Group	Control Group	t-value	p-value	Cohen's d
Skill Mastery	86.9 ± 5.8	80.4 ± 6.2	8.39	< 0.001	1.08
Work Quality	88.3 ± 4.1	81.0 ± 5.0	12.36	< 0.001	1.59
Aesthetic Literacy	82.7 ± 5.3	75.4 ± 5.8	10.18	< 0.001	1.31
Vocational Competence	84.9 ± 5.0	78.1 ± 5.7	9.82	< 0.001	1.27
Learning Engagement	4.31 ± 0.42	3.86 ± 0.48	7.7	< 0.001	0.99

indicating that intelligent analysis and multi-stakeholder feedback can directly improve the quality of outcomes; the increase in learning engagement was relatively modest, which may be related to familiarity with virtual simulation operations and resource usage habits. This model achieves a continuous alignment between skills training, aesthetic evaluation and job standards; however, the effectiveness of cross-disciplinary transfer is still influenced by the quality of resource annotation and differences in professional aesthetic standards.

VI. CONCLUSIONS

The ecological construction of aesthetic education in vocational skills training has helped to transform the attitude of "dressing up" aesthetic education in the training content to "stitching" aesthetic education in the training process. Using multi-source learning data representation, the knowledge graph between professional skills and aesthetic elements, multi-modal work analysis, dynamic competency profiling and the optimisation of integration pathways, a closed-loop teaching system in which resource organisation, precise recommendations, work evaluation and multi-stakeholder collaboration are closely interconnected has been created. The experimental findings show that it can not only enhance the mastery of skills and improve the quality of work, but also enhance aesthetic literacy, vocational skills and the effectiveness of resource recommendation, and it shows that the use of digital technology is of great value in changing the structure of aesthetic education and innovating aesthetic education mechanism of skill. The innovation is that it makes abstract aesthetic requirements into interlinked and calculable, feedback-enabled teaching elements, but the data sources, the disciplinary coverage and the long-term application cycle are still relatively limited, and differences in disciplines and annotation experience might play a role in the aesthetic evaluation. Future tasks may include: Extending data source in different institutions and different fields, optimizing the evaluation interpretation mechanism, dynamically incorporating industry standards, and further verifying the transferability, lasting impact and scope of application of the ecological model.

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