Exploring AI-Interactive Teaching Models in the Context of Art-Science Integration: A Case Study on the "Design Thinking" Course

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Abstract. The convergence of art and technology catalyzes innovation in design education. This study aims to empower design students to intertwine innovative thinking with intelligent technologies, thereby enhancing their capabilities in systemic design and diversified problem-solving. It examines the roles and significance of generative artificial intelligence within educational settings and proposes a human-computer interactive teaching model. Through interdisciplinary dialogues, interactive learning, and integrating technological skills, the model encourages students to transcend traditional academic boundaries and foster creative thinking. Utilizing cutting-edge AIGC technology, it facilitates exploration, innovation, and production. Furthermore, the model's emphasis on interdisciplinary collaboration and evaluation promotes knowledge exchange and personal growth, enabling students to critically reflect on their design journey and outcomes. Addressing the needs of design education in an art-science integration backdrop, the course leverages artificial intelligence to establish an interactive teaching paradigm, providing valuable insights and guidelines for developing similar curricula.

Keywords: Art-Science Integration; Artificial Intelligence; AIGC Technology; Multifaceted Communication Platforms; Interactive Teaching

1 Introduction

In the "New Liberal Arts Construction Declaration" issued by the Ministry of Education in 2020, it is stated that "the new era and mission require that liberal arts education must accelerate its innovative development." As a traditional discipline within the liberal arts, Art and Design's integration with science and technology represents a detailed expansion of the "New Liberal Arts" construction concept. General Secretary Xi Jinping emphasized during the fifth collective study session of the Political Bureau of the CPC Central Committee that "the digitization of education is an important breakthrough for China to open up new tracks for educational development and shape new advantages." The development of digitization has entered an era dominated by large models, artificial intelligence, and spatial algorithms. However, seeking innovation in

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disciplinary understanding in the face of complex realities is also characterized by uncertainty.[1]This demands that the training of art and design talent break down professional barriers and disciplinary obstacles. Based on a diverse disciplinary perspective, broad problem awareness, and profound professional accumulation, it necessitates providing students with comprehensive quality training that aligns with the needs of the times. [2]In other words, under the demands of new era policies, tailoring artificial intelligence courses for students, enhancing the foundational training in utilizing technological means for design conception, and improving the "Artificial Intelligence + Design" thinking capability have become key in course design. [3]

2 Current Teaching Status and Challenges

2.1 Outdated Curriculum System, Difficulty in Interdisciplinary Integration

Currently, the curriculum system for design courses in Chinese universities is outdated. It lacked cutting-edge courses on design integration and technology fusion. Moreover, most design courses still adopt the traditional "teacher-led" mode of delivery and content, failing to fully integrate avant-garde technologies like AIGC to facilitate multidimensional interaction among teachers, AI, and students, forming multicentric discussion groups comprising tutors, AI, and students. [4]Traditional design thinking education emphasizes the cultivation of artistic theory and professional skills, with limited exploration into integrating artificial intelligence and other disciplinary perspectives throughout the design process, particularly lacking multidisciplinary participation, and corresponding interdisciplinary practice during the design discussion phase.[5]

2.2 Homogenized Outcomes, Minimal Technological Integration

The outcomes of art and design courses in Chinese universities often tend towards homogeneity. Student projects usually focus on traditional visual art expressions, such as painting and display boards, leading to a trend of uniformity in style, material, and expression, lacking innovation and diversity. There is a lack of professional interpretation and in-depth integration of technologies like AIGC in teaching, resulting in fewer opportunities for students to create new media and interactive works driven by AIGC or other technologies. This limits the deep exploration and utilization of the creative potential of AIGC in systemic and divergent thinking, failing to integrate deeply with the educational goals of the "new liberal arts." [6]

2.3 Closed Evaluation System, Barriers to Innovation

The current evaluation system focuses more on specific problem-solving and final visual outcomes, with less consideration for the divergent process of design thinking, interdisciplinary integration, and technological innovation. An singular evaluation system often overlooks the encouragement and reward for students to innovate with new technologies, leading students to avoid new technologies and methods with certain learning costs in pursuit of high grades. This suppresses the desire for innovation, limiting the fusion and development of innovative thinking and technological application capabilities among students. [7]Additionally, the outdated evaluation system impacts the effectiveness of interdisciplinary teaching. When the evaluation criteria do not reflect the value of integrating interdisciplinary knowledge and skills, students may not be motivated to explore cross-disciplinary collaborations proactively, significantly limiting the breadth of innovative thinking across disciplines.

3 Exploring AI-Interactive Teaching Models

In 2005, the D.School team at Stanford University proposed the five stages of design thinking training—empathize, define, ideate, prototype, test—to cultivate students' systematic thinking abilities. [8]In today's intelligent era, there is a need for interdisciplinary design talents with cutting-edge technological proficiency, flexibility, and adaptability. By examining the teaching needs of design disciplines in Chinese universities for the new era and using the ChatGPT large language model as a basis, combined with the similarity index algorithm, an "AI Persona" communication and collaboration platform is created for students. This platform enriches the divergency of students' design thinking, optimizes the design outcome evaluation system, enhances students' innovative abilities in design, and constructs a teaching model framework based on cutting-edge technological theories to meet the actual needs of future society for innovative talents in design disciplines.[9]

3.1 Phase One: Constructing the Platform and Framework

This phase's teaching content is tailored to the characteristics of design studies, helping students understand the basic theories and applications of artificial intelligence and constructing a diverse communication platform that integrates reality and virtuality. It places students in a brainstorming scenario of "multi-person" discussions, co-creating with AI playing the roles of virtual tutors from different disciplines, interdisciplinary peers, and non-academic participants. Compared to the traditional classroom's singularity and the limited "one-on-one" interaction with AI, the multi-role communication platform better facilitates the exchange of collective design thinking, examining design plans from different perspectives to generate innovative ideas.

The development platform for the communication platform's web interface is Visual Studio Code. Architecturally, it adopts a B/S (Browser/Server) structure, divided into data layer, logic layer, service layer, and application layer, as shown in Figure 1:

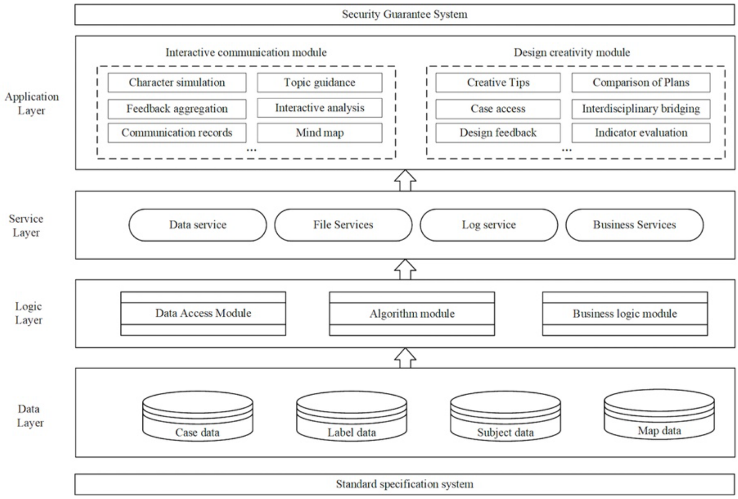

Fig. 1. System Architecture

The construction of the multi-role communication platform's frontend utilizes Vue.js as the frontend framework. Its support for reactive programming and component-based development simplifies and streamlines the construction of user interfaces. In developing the chat interface, Vue components are employed to separate different interface elements, such as the chat message window, message input box, and send button. To enhance user-friendliness, CSS is utilized for further beautification, and Flexbox layout is employed to ensure adaptability across various devices and screen sizes. Vue's data binding feature dynamically displays user inputs and robot responses in the chat window in real time.

For the backend, the Python Flask framework is chosen, establishing a RESTful API to handle chat functionalities. An API endpoint, /api/message, is created to manage POST requests from the frontend, containing user input messages. Upon receiving a request, the user's message is extracted from the request body and passed to a defined language model processing function. The language model generates a response by calling the model and returns it to the frontend in JSON format. Moreover, to improve response speed, a caching mechanism is introduced, optimizing the processing of responses to frequently asked questions.

3.2 Phase Two: Interactive Teaching and Implementation

The innovative educational model encourages students to cross the boundaries of art, design, technology, and humanities, absorbing knowledge, and skills from different domains. Teaching is based on the real-time interactivity of the multi-role communication platform, constructing an interdisciplinary learning environment. This fosters collaboration between students and virtual "tutors" and "students" from diverse backgrounds and specialties, achieving an integration of knowledge and skills across disciplines.

During interactions between students and the model, the communication platform presents solutions from different roles, relying on the language model implemented on the backend. The platform utilizes the Transformer model architecture, particularly the pre-trained BERT model, which is finely tuned for specific chat tasks. The use of its self-attention mechanism allows the model to effectively process complex dialogue contexts, enhancing the model's understanding of language. The specific process flow is illustrated in Figure 2:

Fig. 2. Implementation flowchart

Before model training, the collected dialogue data undergo a thorough preprocessing, which includes text cleaning (removing irrelevant characters, correcting punctuation, etc.), tokenization (breaking sentences into words or lexical units), and word embedding (transforming words into a numerical form that the model can process), using toolkits like NLTK and spaCy. This step ensures the high quality of the training data, laying the foundation for model training. During the model training process, a transfer learning strategy is employed. This involves initially pre-training on a large-scale general corpus to capture the general features of the language, followed by fine-tuning on specific chat data to adapt to application scenarios. The pseudo-code for the specific algorithmic process is illustrated in Figure 3.

Table 1. Algorithm for Deep Learning Model Training Process

Algorithm 1: Deep Learning Model Training Process

```
Initialize model parameters θ
for each training epoch do:
    Shuffle training data
    for each batch in training data do:
        X, Y = Load current batch input and labels
        Y_pred = Forward pass(X, θ) // Predict with model
        Loss = CrossEntropyLoss(Y_pred, Y) // Compute loss
        Gradient = Compute gradient(Loss, θ) // Backpropagation
        θ = AdamOptimizerUpdate(θ, Gradient) // Update parameters
    end for
    Validate model on validation set
    Compute validation loss and accuracy
    if validation loss has not improved for N epochs:
        Trigger early stopping
        break
```

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        end if
        Optionally adjust learning rate // Learning rate scheduling
    end for
    Save final model parameters
    Initialize model parameters θ
    for each training epoch do:
```

During this process, to optimize the model's performance and accelerate the training process, Cross-Entropy Loss function and Adam optimizer are introduced. The Cross-Entropy Loss function is utilized to calculate the difference between the model's output and the true labels. Optimizing this loss function helps in enhancing the model's classification accuracy. The formula for the Cross-Entropy Loss is as follows:

$$L = -\frac{1}{N}\sum_{i-1}^{N} y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot \log(1-\hat{y}_i) \tag{1}$$

Where N is the number of samples, y_i represents the true label, and $\hat{y}_i$ denotes the predicted probability.The Adam optimizer, by dynamically adjusting the learning rate combined with bias correction from estimates of first and second-order moments, effectively balances training speed and convergence quality. This ensures the model's training efficiency and stability at different stages. The formula for the Adam optimizer is as follows:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \varepsilon}} \tag{2}$$

In the formula, θ denotes the model parameters, η is the learning rate, $\hat{m}_t$ and $\hat{v}_t$ correspond to bias corrections for the estimates of the first and second moments, respectively, and ε is a very small number used to prevent division by zero.

Through a communication platform built on large language models, design students can efficiently engage in brainstorming sessions with AI serving as virtual tutors from various disciplines, alongside interdisciplinary peers, and individuals from non-academic backgrounds. This setup enables a vibrant exchange of ideas, fostering creativity and collaborative problem-solving across diverse fields of knowledge.

3.3 Phase Three: Prototype Testing and Refinement

The multi-role communication platform utilizes a MySQL database to store user information and chat records. In the process of training a custom deep learning language model, a series of optimization measures were taken to enhance the model's accuracy and efficiency. Initially, thorough preprocessing of chat data was conducted, including cleaning of invalid characters and standardization of expressions, as well as employing data augmentation techniques to increase the diversity of the training set, ensuring the dataset's high quality and balance. Moreover, fine-tuning was based on pre-trained Transformer models, adjusting the size of the hidden layers and parameter settings, and applying regularization techniques such as Dropout and L2 regularization to reduce overfitting.

This project successfully integrates technology with art, offering a new interactive mode for teaching and learning. Future considerations include introducing more personalized and interactive features, such as intelligent recommendations for learning resources and personalized learning pathway planning, to further enhance user experience and learning efficiency. Coupled with the multi-role communication platform, the teaching of the design thinking course through practical projects allows students to solve real-world design problems and continuously refine the communication platform and design solutions through practice. Both the design solutions and the prototype testing of the communication platform aim to encourage students to freely explore and experiment with new design concepts and interaction technologies, autonomously learning how to apply new technologies and creative thinking to diverse design scenarios through continuous improvement.

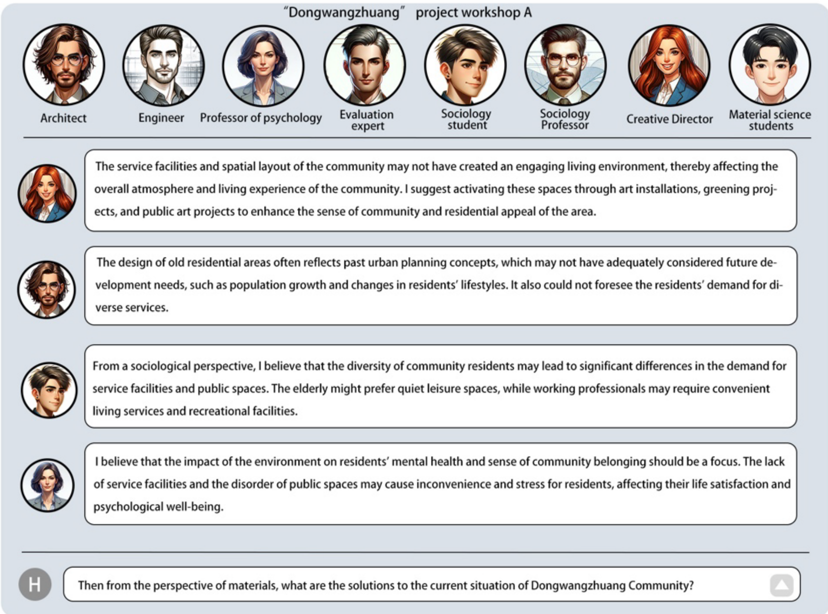

Fig. 3. Multi Role Interaction Interface

3.4 Phase Four: Evaluation System Innovation

Transforming the traditional design outcome evaluation system into a more process-oriented and interactive approach allows for a comprehensive and dynamic assessment of students' learning outcomes and the development of their design capabilities. This approach requires educators to track and document every step of the student's journey from problem definition, research, prototype creation, to the final solution. Evaluation criteria include the student's interdisciplinary engagement, innovation capability, and the logic, systematic approach, and adaptability demonstrated in the problem-solving process. Process-oriented evaluation enables teachers to provide immediate feedback and guidance, helping students adjust their learning strategies and thus fostering continuous skill development.

Interactive evaluation focuses on the interaction among participants during the evaluation process. It encourages open communication and the exchange of critical thinking, making the evaluation process an opportunity for joint learning and growth. In the design thinking course, interactive evaluation can be implemented through peer assessment, group evaluations, and public presentations. By assessing their peers' projects, students learning different design thinking methods and skills, also enhance their ability to critique and self-critique.

4 Analysis of Teaching Outcomes

The AI-interactive learning environment not only fosters multi-perspective divergence in students' design thinking, enhancing their adaptability and flexibility in a rapidly changing world. Throughout various stages such as design conception, discussion, research, and outcome, students have produced a series of works incorporating human-computer interaction concepts. An analysis is provided below, taking the project design "Optimization of the Clutter Issue Behind the Dongwangzhuang Residential Building in Beijing" as an example.

4.1 Multi-role Group Discussion and Research

Focusing on practical design issues, discussions among design students, AI-simulated interdisciplinary students and tutors were conducted in a multi-role format. Initially, students majoring in design propose potential design ideas. AI-simulated roles of interdisciplinary students and tutors, emulating experts from various disciplinary backgrounds like environmental psychology and sociology, introduced new perspectives and solutions. During the discussions, group members first conducted detailed research and analysis on the cluttered condition of the communal spaces, identifying the root causes of the issue. Subsequently, through brainstorming, the team proposed a series of improvement measures, such as spatial reorganization, functional optimization, and environmental beautification. Cooperation within multi-role groups guides students to conduct field research from an interdisciplinary perspective. Specific methods included time-lapse photography, semi-structured interviews, scenario enactment, measurements, and documentation, enhancing the students' ability to solve problems diversely and providing innovative directions for subsequent design proposals.

4.2 Multidisciplinary Conception and Definition

Group members engaged in thorough discussions with the "AI entities" playing multiple roles, identifying six major design directions: "social significance," "economic benefits," "academic value," "aesthetic orientation," "functional positioning," and "technical support." After summarizing the design points, they eventually narrowed down from over a hundred to 60 selected points. The students divided the coordinate system into four axes: "psychological," "physical," "order," and "clutter." They then "pinned" the 60 design points onto the coordinate system using pushpins, sticky notes, etc., and linked them with lines to form a systematic creative map. This process not only facilitated a comprehensive understanding and definition of the project's scope but also encouraged innovative thinking by visually organizing and connecting diverse concepts and solutions across multiple disciplines.

4.3 Multiform Outputs and Evaluation

The arrangement of work groups was based on professional background and gender, ensuring 2-3 people in each group could collaborate and conduct peer evaluations. For example, comic interpretation tasks were cooperated on by students from animation and visual communication, video interpretations were done by digital media and visual communication students, and facility design was completed through collaboration between product design and environmental design students. As a result, within the context of the Dongwangzhuang community issue, a variety of outcomes were produced, including site facility modules, narrative comic posters, and outdoor transformable seating. This multi-form output approach not only diversified the solutions to the community problems but also facilitated a comprehensive evaluation of the project's effectiveness from multiple perspectives.

Throughout this course, students engaged with an artificial intelligence interaction platform, experiencing a learning process that spanned "multi-role discussions and research—multidisciplinary conception and definition—multiform output and evaluation." This approach effectively fulfilled the design thinking educational objectives oriented around complex problem-solving.[10]

5 Conclusion

Big data and artificial intelligence, among other emerging technologies, are transforming the educational landscape, paving new pathways for a global educational revolution.[11] In the era of "Art-Science Integration," the fusion of technology with design education, represented by AIGC technology, has become a significant direction for teaching innovation. Higher education is necessary to update the curriculum, integrating artificial intelligence knowledge and skills as compulsory or elective courses within design education. Interactive, project-based learning allows students to apply AI technology in real design projects, while also highlighting design ethics in the AI era, fostering a comprehensive design literacy among students. [12]It is hoped that the AI-interactive teaching model explored in this paper can offer some insights to design disciplines nationwide, sparking further innovation and refinement.

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