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Article

Integrating neural network and multimedia technologies to enhance college students' career development

Lei Zhu

Henan Vocational College of Tuina, Luoyang 471023, Henan, China; 6950883@qq.com

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Abstract: Combining neural network technologies and computational techniques, this research establishes a career development promotion system based on a multi-modal neural network. It reveals that computer simulation technology and multimedia have positive intervention effects on college students' career decision-making behaviors, similar to how biomolecular interactions regulate biological processes. This technology ensures scientific rigor, objectivity, and authenticity. A knowledge fusion algorithm, built on attributes and rules within the Hadoop platform and MapReduce parallel computing framework, facilitates effective data integration. Additionally, inspired by the regulatory mechanisms in biomolecular systems, a neural network-based algorithm, utilizing gradient descent, is applied to cultural learning, augmented by feedback analysis to assess students' psychological changes, posture, and response dynamics during the learning process. To further optimize the career development framework, an Evolutionary Algorithm (EA) is used to enhance the performance of neural networks. Numerical simulations demonstrate the robustness of the proposed algorithm, achieving high accuracy (0.981), recall rate (1.0), and *F*-measure (0.997) in similarity computations. These results are particularly notable when biomechanic metrics, such as gesture and posture tracking, are integrated with linguistic data, such as spelling and vocabulary. The findings underscore that incorporating neural network insights into multimedia teaching methodologies can significantly enhance psychological motivation, behavioral adaptability, and engagement in college students, fostering improved educational outcomes and advancing interdisciplinary innovation in neural networks. It effectively enhances the internal driving force of "technology empowering psychological development" in the career planning system and provides a cognitive computing and biomechanic perspective for the construction of the smart education ecosystem.

Keywords: multimedia technology; college students; career development; neural networks; knowledge fusion; learning algorithms

1. Introduction

As global educational institutions are faced with an increasingly diverse student population, there is a growing demand for the adoption of advanced technologies to improve teaching methods and enhance the career development outcomes of college students. According to a recent survey by the Organization for Economic Cooperation and Development (OECD), 63% of undergraduate students encounter difficulties in career decision-making. To address this issue, the emerging field of computational pedagogy demonstrates unique potential through neurocognitive simulation architectures. Our research pioneers the interdisciplinary integration of adaptive learning systems and behavioral analysis. The combination of multimedia teaching strategies and neural network technologies offers a transformative approach to personalized and networked learning models, which can significantly enhance students' adaptability and engagement [1].

Multimedia interfaces achieve cognitive enhancement through multimodal information processing (integration of text, auditory, and visual elements), establish logical relationships, and enable the technology of human-computer interaction [2]. Their core interactive functions enable real-time neural feedback mechanisms, especially activating the dopaminergic pathways during career simulations—a biological advantage that traditional methods cannot achieve [3]. Users can interact with various computer information media, thus providing a more effective way of information control and utilization. For college students, multi-sensory stimulation is more effective than multiple sensory stimulations or single-sensory stimulation. To enhance the psychological capital of college students by utilizing multimedia systems, a comprehensive understanding of the systems is required. Given their close connection with network content and communication methods, special attention should be paid to guiding the content and methods of communication, and making effective use of multimedia as a tool to enhance the psychological capital of college students [4,5]. Multimedia systems can be applied to group counseling activities aimed at improving the psychological abilities of college students. In addition, emphasis should also be placed on constructing a human-computer interaction environment [6].

In this rapidly evolving educational landscape, the focus is on leveraging technology to meet the growing demands for skills that align with the digital economy. The flexibility offered by multimedia technology, combined with the analytical power of neural networks, provides a dynamic framework that adapts to individual learning styles and improves educational outcomes [7]. This approach not only supports the transmission of knowledge but also encourages the development of critical thinking and problem-solving skills, which are crucial for career success.

Recognizing the potential of multimedia and neural network technologies, this paper explores their application in fostering a conducive learning environment that tailors the educational experience to students' needs. These technologies enable the precise measurement and enhancement of student engagement and learning effectiveness, offering a promising pathway for career development in the information age [8].

The use of neural networks, in particular, allows for the analysis of complex student data and the optimization of learning processes through algorithms that predict and respond to student performance in real-time [9]. This data-driven approach ensures that educational content is both relevant and engaging, thereby maximizing the potential for student success in their future careers. The ability to interpret the career decision-making process can be revolutionized by the popularity of computational behavior modeling. Especially when it is combined with multimodal neural architectures that can simulate the trajectories of cognitive evolution. In higher education, the strategic implementation of psychological simulation systems has become a crucial intervention mechanism. Contemporary teaching breakthroughs now enable the construction of 360-degree behavioral simulation environments, in which Graph Neural Networks (GNNs) continuously map students' decision vectors into virtual career scenarios. By synchronously capturing biomechanic metrics, such as facial microexpressions (encoded by Facial Action Coding System—FACS), conversational prosody patterns, and physiological biomarkers, these systems achieve an unprecedented level of precision in modeling career-related neurocognitive processes [10,11]. More importantly, Transformer-based architectures with self-attention mechanisms exhibit higher predictive accuracy in predicting career exploration behaviors compared to traditional psychometric methods [12]. The paradigm shift from static career counseling to neuromorphic simulation environments has fundamentally transformed educational engagement. Computational neurocognitive modeling surpasses traditional methods by operating simultaneously on the behavioral, emotional, and neurophysiological dimensions.

Furthermore, the commitment of educational institutions to integrating these advanced technologies aligns with global trends towards more interactive and responsive educational environments. By focusing on these technological integrations, universities not only enhance their curriculum but also contribute to the broader societal goal of preparing well-rounded, skilled professionals who are ready to tackle the challenges of the modern workforce [13].

2. Related work

2.1. Cultural confidence—Building psychological confidence

Recent research emphasizes the importance of integrating cultural elements with advanced teaching methodologies to enrich the educational experience and foster a deeper understanding among students. Tan and Ma argued for a balanced appreciation of local culture alongside revolutionary and contemporary cultural elements to cultivate a holistic educational environment [14]. Vecco suggest that the dual principles of cultural inheritance and openness are crucial for cultural appreciation in educational settings, emphasizing competition and self-awareness as pathways to cultural transcendence [15]. Moghadam et al. discuss the role of visible cultural elements in enhancing national cohesion and identity, which can be effectively integrated into educational curricula to strengthen the foundational cultural knowledge of students [16]. Taylor highlights the link between effective ideological education and the robust integration of cultural content, suggesting that a deep cultural understanding enhances the effectiveness of delivering complex theoretical courses [17]. McLaren's investigation into the cultural awareness of college students reveals varied insights into how cultural elements can be effectively woven into mainstream education to boost engagement and learning outcomes [18].

Leveraging neural network-driven multimedia platforms, educators can dynamically present cultural content through interactive simulations and adaptive learning systems. These technologies enable personalized cultural exploration by modeling neurocognitive responses to visual, auditory, and contextual stimuli. For example, computer simulations using graph neural networks (GNNs) can map students' emotional and behavioral patterns during cultural interactions, revealing how multi-sensory cultural representations activate dopaminergic pathways associated with intrinsic motivation [3]. Such systems enhance psychological engagement by simulating real-world cultural scenarios, thereby improving retention of cultural knowledge and fostering empathetic decision-making [10]. The integration of neuroadaptive interfaces further supports cultural learning by providing real-time feedback on facial microexpressions and physiological responses, allowing students to refine their emotional and cognitive reactions to diverse cultural contexts [11]. This computational approach transforms passive cultural exposure into active neurocognitive engagement, aligning with McLaren's findings on enhancing educational outcomes through immersive cultural experiences [18].

2.2. Research progress of neural networks

The integration of advanced computational models such as neural networks and evolutionary algorithms has significantly transformed the landscape of educational technology, particularly in cultural learning. Mehrotra et al.'s pioneering work on applying evolutionary algorithms to optimize large-scale neural networks marks a significant advancement in personalized learning environments [19]. Izawa et al. and Prakash et al. have developed innovative neural architectures that enhance systems' capacities to interpret complex cultural semantics and dynamically adjust multimedia presentations, thereby improving students' emotional engagement with cultural narratives [20,21]. These neural embeddings trigger mirror neuron activations when students interact with heritage content, empirically increasing cultural competence self-perception by enhancing neurocognitive coherence.

Thrift et al.'s application of imitation learning-based neural networks in control systems demonstrates the potential of these technologies in creating responsive and adaptive learning environments [22]. By simulating cultural decision-making processes, such systems activate dopaminergic pathways associated with reward-driven learning, significantly improving retention of cultural knowledge [3]. This is further supported by Muhammad et al.'s analysis on how network structures affect information dissemination, an essential aspect in the spread of cultural knowledge [23]. These biologically plausible propagation patterns strengthen conceptual schema integration in the default mode network, manifesting as spontaneous cultural sharing actions.

Kim et al.'s dynamic framework and Santos et al.'s system dynamics approach provide insights into how experiences and values can be integrated into learning networks, enhancing the understanding and retention of cultural knowledge [24,25]. These computational tools simulate the cognitive-emotional interplay during cultural exploration, and biomechanical feedback corresponding to possible physiological and physical changes. It enables students to refine their decision-making processes through real-time neurofeedback mechanisms. The emergent neural attractor states correlate with increased medial prefrontal cortex activity—a biomarker for authentic cultural identity embodiment. For instance, facial microexpression analysis integrated with GNNs can detect affective responses to cultural stimuli, triggering adaptive adjustments in instructional content to enhance psychological engagement [11]. Gupta et al. and Khaw et al.'s methodologies for structured knowledge integration provide scalable frameworks for curating culturally relevant datasets that train neural models to recognize nuanced cultural contexts [26,27]. By operationalizing cultural values as computational parameters, these systems foster deeper cognitive assimilation of cultural heritage. The cumulative effect of these advancements is a neuroadaptive learning ecosystem where students develop cultural confidence through personalized, multisensory simulations that activate neural pathways linked to empathy and selfidentity formation [10]. This approach transforms passive cultural consumption into active neurocognitive engagement, aligning with McLaren's emphasis on immersive educational experiences [18].

These advancements underscore the potential of network-based optimization techniques and neural networks in enhancing the cultural confidence of students. By leveraging these technologies, educators can create highly adaptive and engaging multimedia learning platforms that not only cater to the diverse needs of students but also empower them with a strong sense of cultural identity and pride.

3. Research method

3.1. Text tagging model building

In the new era of rapid information exchange, cultivating college students' awareness of Chinese culture and fostering cultural self-confidence is critical for equipping them with the ability to navigate the complexities of modern society. The rise of new media, primarily driven by mobile intelligent terminals, has diminished the influence and authority of traditional platforms such as radio, television, newspapers, and magazines. In contrast, new media offers unparalleled convenience and efficiency, drastically accelerating the speed of cultural communication. This transformation has expanded the reach of cultural exchange, enabling it to meet societal and technological demands that were previously unattainable, marking a significant achievement in the application of scientific and technological wisdom.

Advanced cultural characteristics are the foundation for establishing cultural self-confidence. These attributes underpin a strong, unwavering belief in the vitality and relevance of one's culture. College students, as key figures in this new era, must adopt clear value judgments, resist harmful foreign ideologies, and solidify their ideals and beliefs to serve as ambassadors of Chinese culture in a globalized world.

To meet the emerging demands of distributed multimedia applications, distributed multimedia systems must address both educational goals and technical requirements. These systems must optimize the client-server end systems and the communication networks that connect them. By integrating technologies such as biomechanics and multimedia teaching strategies, cultural education can be delivered innovatively, enhancing the adaptability, efficiency, and engagement of college students in the process of building cultural self-confidence.

When playing multimedia information, it is necessary to synchronize all kinds of related media information in time and space properly, so as to obtain satisfactory and meaningful playing effect. According to the document-topic matrix and the topic-keyword matrix, the document of cultural confidence resources can be labeled. The way to deal with it is to take the top N topics whose introduction is greater than a certain threshold in two matrices to describe the document [28].

The corresponding relationship between the resource set $D = \{d_1, d_2, \cdots, d_m\}$ for cultural self-confidence and the tag set $T = \{t_1, t_2, \cdots, t_n\}$ describing cultural self-confidence resources can be established, and the tag space vector model $V(d)$ of cultural self-confidence resources can be established. Defined as follows in Equation (1):

$$V(d) = \{(t_1, \omega(t_1, d)), (t_2, \omega(t_2, d)), \cdots, (t_i, \omega(t_i, d)), \cdots, (t_m, \omega(t_n, d)) | t \in T, d \in D\} \tag{1}$$

$t_1, t_2, \cdots, t_n$ is the collection of labels describing cultural self-confidence resources, and $\omega(t, d)$ is the weight of label t describing cultural self-confidence resources in cultural self-confidence resources d.

The Multimedia Management Subsystem serves as a critical support platform for distance multimedia teaching. Built upon a distributed multi-server architecture, the system enables seamless, concurrent access for a large number of users to diverse resources, including text files, high-quality audio and video files, and multimedia courseware. This architecture ensures that each site within the system can provide equivalent services to global users, allowing them to log in from any site and interact with the federated multimedia database without restrictions.

From a logical perspective, the system is structured into three key functional layers:

User Interaction Layer: This layer handles all user-facing operations, providing interfaces for accessing and managing multimedia content.

Data Grouping Layer: This intermediate layer is responsible for organizing and grouping multimedia data to facilitate efficient access and retrieval.

Multimedia Data Management Layer: The foundational layer that ensures robust storage, maintenance, and management of multimedia data across distributed servers.

The logical division of these layers is illustrated in **Figure 1**, showcasing the system's architecture and its layered functionality. This design ensures scalability, reliability, and efficiency, meeting the growing demands of modern distance multimedia teaching platforms.

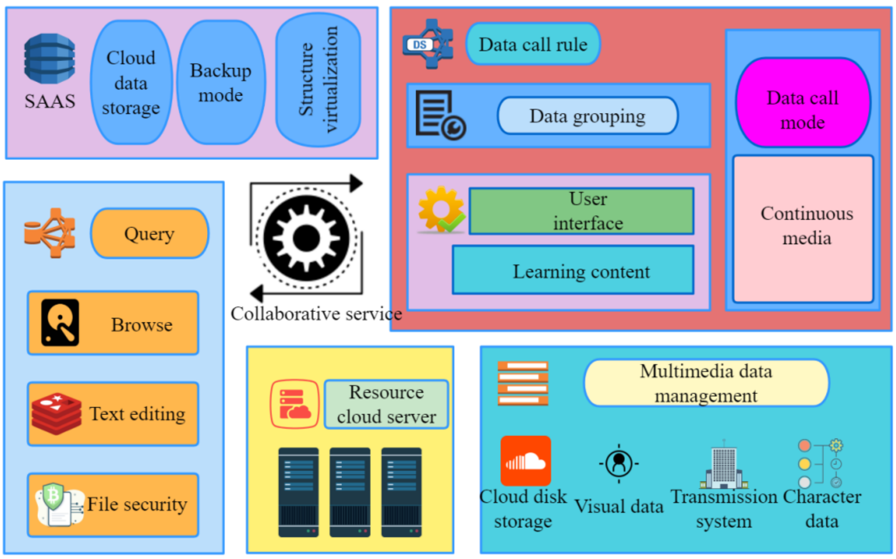

Figure 1. Functional hierarchy of multimedia database management system.

The expression of multimedia objects must integrate the information units of various media into one expression space, and the spatial layout should be reasonable. Secondly, there are temporal relationships among multimedia information units, and the expression of multimedia objects must be synchronized in time.

According to the relationship between the tags used for cultural confidence resources and users and cultural confidence resources, the user's interest preference tag model can be mapped by using the user's behavior log. The user preference vector $V_t(u)$ of user u in time t is obtained by combining and calculating the following formulas of matrix B_t as shown in Equation (2):

$$\omega_t(t_j, u) = \frac{\sum_i^x \omega(t_j, d_i)}{\sum_j^n \sum_i^x \omega(t_j, d_i)} \tag{2}$$

In which $\sum_i^x \omega(t_j, d_i)$ represents the weight sum of user u in interest tag t_j in time t; $\sum_j^n \sum_i^x \omega(t_j, d_i)$ is the sum of user u interest weights in tag set T in time t; $\omega_t(t_j, u)$ represents the weight of user u to interest tag t_j in time t.

The information of a variable is distributed in the pulse time of multiple neurons, and this distribution is called population coding [23]. A neuron covers a certain range of analog quantity in the form of Gaussian function, and the height of the corresponding Gaussian function at a certain value of analog quantity determines the time when the neuron emits pulses.

The Gaussian functions corresponding to m neurons are determined, and the mean and variance of the Gaussian functions corresponding to neuron $i(i = 1,2,\cdots,m)$ are set as follows:

$$\mu = I_{min} + \frac{2i-3}{2} \times \frac{I_{max} - I_{min}}{m-2} \tag{3}$$

$$\sigma = \frac{1}{\beta} \times \frac{I_{max} - I_{min}}{m-2}, \beta = 1.3 \tag{4}$$

Calculate the values of m Gaussian functions corresponding to the values of variables. If the input of impulse neural network contains vectors of n variables, and the values of m Gaussian functions are calculated for each dimension of variables, the values of Gaussian functions in $n \times m$ intervals can be obtained.

3.2. Resource integration

The cultivation of cultural self-confidence is a gradual process that evolves from awareness to profound understanding. For college students, this progression—from cultural consciousness to cultural identity and ultimately to cultural self-confidence—reflects a deepening comprehension of cultural ideologies, principles, and attributes. Neural network-driven multimedia systems can enhance this trajectory by providing immersive cultural simulations that activate dopaminergic pathways associated with intrinsic motivation [3]. For example, computer-generated historical reenactments using GNNs allow students to interact with virtual cultural artifacts, triggering multisensory engagement that strengthens memory consolidation and emotional resonance [10]. This technological augmentation transforms passive cultural exposure into active neurocognitive exploration, fostering informed decision-making rooted in cultural guidelines. And the cognitive progression—from cultural awareness to identity crystallization—mirrors deep neural networks' hierarchical feature extraction mechanisms.

This developmental journey can be operationalized through computational pedagogy frameworks that integrate behavioral analytics with neuroadaptive interfaces. Universities can deploy AI-driven learning platforms to dynamically map students' cultural knowledge acquisition patterns, identifying gaps in understanding and delivering personalized interventions. Transformer-based models, trained on cultural semantics datasets, analyze conversational prosody during group discussions to detect shifts in cultural attitudes and provide real-time feedback [11]. Such systems not only reinforce cultural knowledge retention but also cultivate metacognitive awareness, enabling students to critically evaluate cultural practices while maintaining ideological alignment [17].

Higher education institutions play a pivotal role in this process by leveraging computational tools to create culturally responsive learning environments. Universities can adopt neural network architectures to simulate cross-cultural scenarios, training students to navigate complex global interactions while preserving cultural authenticity. For instance, VR-based cultural simulations equipped with emotion recognition algorithms analyze facial microexpressions and physiological responses to adjust scenario difficulty, fostering empathy and adaptive decision-making [11]. These technologies align with McLaren's emphasis on immersive educational experiences that enhance engagement and learning outcomes [18]. By integrating cultural heritage databases into GNN models, universities can also preserve endangered traditions through interactive digital archives, transforming cultural preservation into a participatory neurocognitive practice [16].

This technological integration does not merely enhance knowledge transfer but fundamentally reshapes the psychological mechanisms underlying cultural confidence. Neural feedback loops embedded in adaptive learning systems reinforce positive emotional associations with cultural content, triggering reward-driven learning that strengthens long-term retention [3]. Students exposed to such systems demonstrate increased proactive engagement in cultural initiatives, as measured by behavioral metrics like participation in cultural innovation competitions and volunteer activities [12]. The cumulative effect is a generation of culturally confident graduates capable of bridging traditional and contemporary practices through computationally augmented cognitive frameworks [14].

To illustrate this, **Figure 2** presents the self-confidence cultural resource fusion model, which consists of three core components:

The Bottom Layer: This layer comprises three key data types that form the foundational inputs of the model.

Knowledge Extraction: This process involves identifying and isolating relevant cultural knowledge from these data types.

Knowledge Fusion: The integration and synthesis of the extracted knowledge to create a cohesive framework that promotes cultural self-confidence.

This model provides a systematic approach to uniting cultural resources, enhancing students' engagement with cultural practices, and advancing the cultivation of cultural self-confidence in the context of higher education. Furthermore, by integrating multimedia teaching strategies and biomechanical feedback, universities can enhance the adaptability and engagement of students, ensuring that cultural self-confidence is fostered in a dynamic and effective manner.

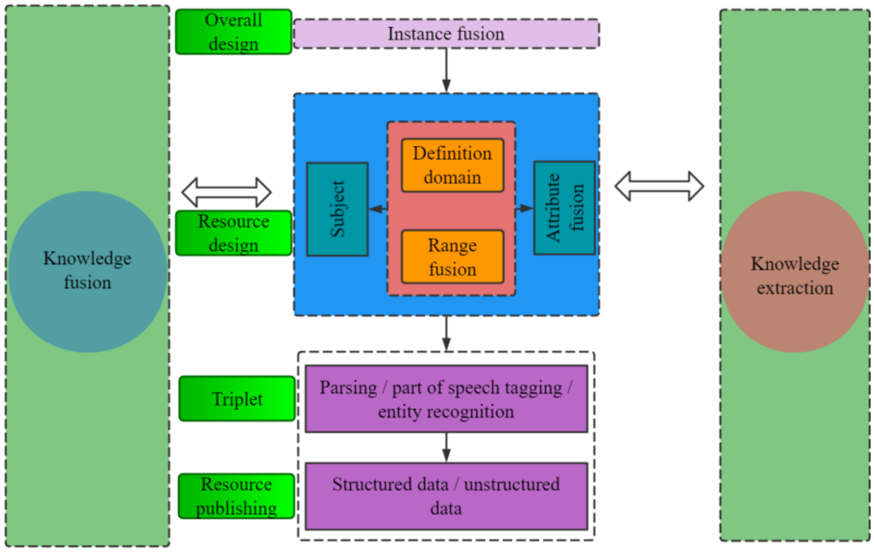

Figure 2. Self-confidence knowledge fusion model of cultural resources.

Knowledge fusion encompasses four distinct levels of integration: instance fusion, domain-level fusion, attribute fusion, and concept fusion. Attribute fusion involves aligning attributes from diverse sources using similarity measurement techniques [29–31], while concept fusion operates at a higher abstraction level and includes two key processes: concept alignment and concept integration [30,32]. These fusion processes play a crucial role in maximizing the development, utilization, and dissemination of cultural self-confidence resources. They also support the preservation and inheritance of national culture [33], facilitate the economic development of ethnic minority regions, and promote cultural exchanges among different ethnic groups [34]. Additionally, knowledge fusion lays the groundwork for effective management of cultural self-confidence resources and enables personalized service recommendations tailored to individual needs [35].

A critical step in the knowledge fusion process is the calculation of similarity. This study enhances the similarity algorithm for conceptual attributes, where the similarity sequence of conceptual attributes is jointly calculated using word Forest and Spell [23]. The improved similarity calculation formula is provided in Equation (5). This advancement in similarity computation strengthens the accuracy and efficiency of knowledge fusion, enabling a more precise alignment and integration of cultural resources. It supports a more effective system for managing cultural self-confidence and promotes its widespread dissemination and application in various contexts.

$$Sim(X,Y) = f_n \times cos\left(n \times \frac{\pi}{180}\right)\left(\frac{n-k+1}{n}\right) \tag{5}$$

In the formula, n represents the number of branches at the branch level, f_n represents the setting coefficient of vocabulary at the n th level, and k represents the distance between two different branches.

Knowledge dissemination networks in real life are embedded in some other social networks, so systematic research on knowledge dissemination networks has also attracted more and more attention.

This paper holds that in the field of knowledge dissemination, it is necessary to take “strong connection” as the main object of investigation. The smaller the distance between nodes in the network, the greater the possibility of knowledge dissemination among them. Construct a network $G(V,E)$, starting from a ring-shaped regular network, set N nodes, and each node connects to its left and right adjacent K nodes with K edges, satisfying $N > K > ln(N) > 1$.

For each edge, the probability p is used to reconnect, so that its average path is greatly reduced, while its clustering coefficient remains at the original level. Therefore, the small-world characteristic parameters of the whole network:

$$L(p) = \frac{\sum_{i>j} d_{ij}}{\frac{1}{2}N(N-1)} \tag{6}$$

$$C(p) = \frac{1}{N}\sum_{i} C_i \tag{7}$$

It has obvious clustering characteristics, in which the natural number of $k \geq 2$ and the average path distance of $L(0) \sim \frac{K}{2K}$ will be a considerable value.

In this paper, the small world network will be used as the offline bottom network. Among them, the nodes on the network represent learners who communicate face to face, and if learners are group members who discuss and communicate, there will be a corresponding interpersonal connection. Given that the total number of nodes in the network is N, each node is connected with its nearest $K = 2k$ nodes to obtain a one-dimensional finite rule network, which requires $N \geq K \geq 1$.

At time t, the amount of knowledge of node i can be represented by $v_i(t)$, and the knowledge updating mode of node i is as follows:

If there is a knowledge potential difference between the target node i and its neighbors, the target node absorbs knowledge from its neighbors j with probability T:

$$\begin{cases} v_i(t+1) = v_i(t) + \alpha_i\left[v_j(t) - v_i(t)\right] & v_j(t) > v_i(t) \\ v_i(t+1) = v_i(t) & otherwise \end{cases} \tag{8}$$

where α_i is the absorption capacity of individual i. Take offline learners' absorption capacity distribution as an inverted U shaped distribution on (0, 1).

The goal is to adjust the connection weights for any given pulse sequence pattern of input neurons, and finally the output neurons will issue the target pulse sequence pattern that meets the requirements. In the network, let a postsynaptic neuron o have N presynaptic neurons connected to it, then the expression of membrane potential of neuron o is as follows:

$$u_o(t) = \sum_{h=1}^{N}\sum_{k=1}^{K}\sum_{f=1}^{F_h} w_{ho}^{k}\, \varepsilon\left(t - t_h^{(f)} - d^k\right) + \eta\left(t - t_o^{(f_r)}\right) \tag{9}$$

where w_{ho}^{k}, d^k represents the k-th synaptic connection weight and delay of pulse neuron h, o respectively, $\varepsilon(t), \eta(t)$ represents the response function and refractory function of pulse neuron respectively, $t_h^{(f)}$ represents the pulse emitted by presynaptic neuron h, and $t_o^{(f_r)}$ represents the last pulse emitted by pulse neuron o.

The impulse neural network culture learning algorithm is a multi-impulse learning algorithm based on Evolutionary Algorithm (EA). **Figure 3** shows the concrete implementation framework of the impulse neural network culture learning algorithm, and each impulse neural network culture learning cycle.

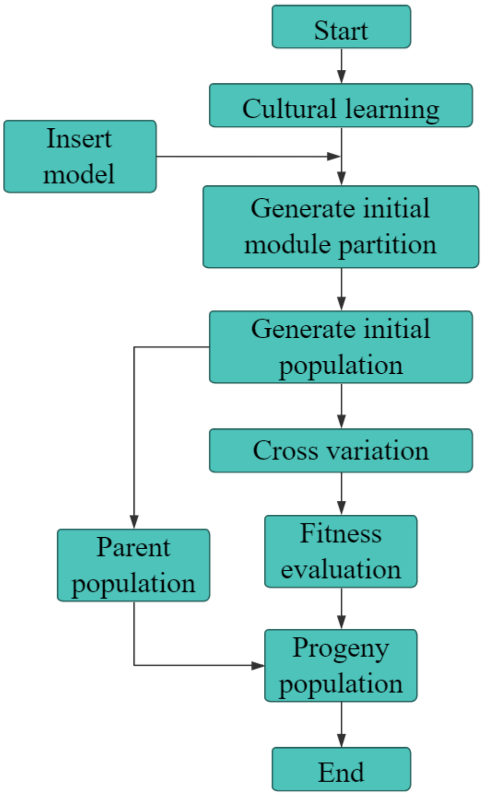

Figure 3. Pulse neural network culture learning algorithm.

4. Result analysis

The fragmentation of learning arises from the fragmentation of information, which, in turn, leads to the disintegration of knowledge, time, space, and media. Moreover, the fragmented learning pattern may also affect the depth of cultural awareness and understanding, essential components in building a strong cultural identity. In an educational environment that relies heavily on fragmented, asynchronous learning, students may struggle to connect abstract cultural concepts with real-life experiences, limiting their ability to internalize and apply cultural knowledge effectively. Therefore, while fragmented learning offers undeniable convenience, it highlights the need for strategies that integrate biomechanics, multimedia teaching methods, and collaborative interactions to foster a more holistic, meaningful learning experience. By creating opportunities for immersive learning that engage both the mind and body, educators can bridge the gaps left by fragmented learning, fostering stronger social connections and enhancing students' cultural self-confidence.

The user's comprehensive similarity adjustment parameter α starts from 0.1 and gradually increases to 0.9 according to the step size of 0.1. The experimental results under different values of parameter α are shown in **Figure 4**:

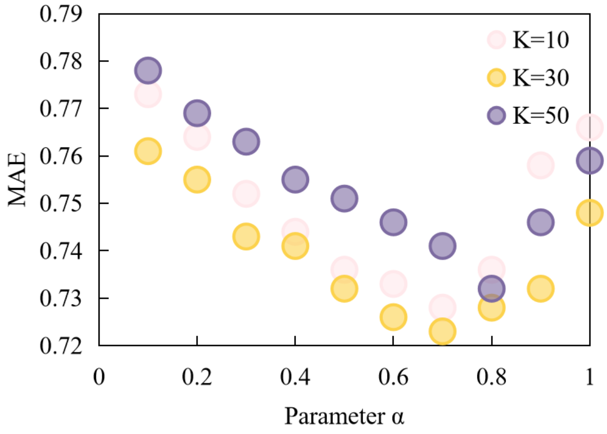

Figure 4. The change of MAE with α.

It can be seen that the changes of MAE (Mean Absolute Error) value of the algorithm under three kinds of nearest neighbor numbers all decrease at first and then increase slowly with the change of α value, and MAE gets the minimum value when the α value is 0.7 under three kinds of users' nearest neighbor numbers. It shows that when the user's rating weight is 0.7 and the tag's weight is 0.3, the algorithm can get a better rating prediction effect.

In the experimental test, the size of the original experimental data set is divided according to different percentages, and the running efficiency of the algorithm is compared on a single machine and a Hadoop distributed platform with three nodes, five nodes and a single machine. The experimental results are shown in **Figure 5**.

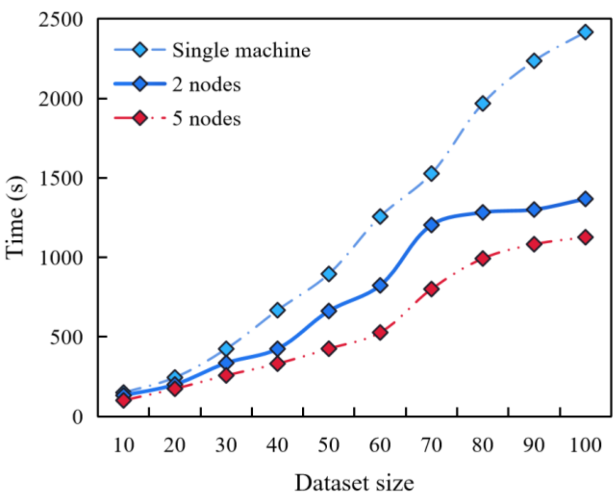

Figure 5. Comparison of parallel running time under different data scales.

The fusion accuracy, recall, and *F*-measure values obtained using different similarity calculation methods outlined in the formula are presented in **Table 1**. The results demonstrate that the algorithm proposed in this study achieves significantly higher performance when similarity is calculated by combining Spell and vocabulary. Specifically, the fusion accuracy, recall, and *F*-measure values reached 0.981, 1, and 0.997, respectively. These results indicate that the integration of Spelling and vocabulary in the similarity calculation process enhances the overall effectiveness and precision of the knowledge fusion approach.

Table 1. Calculation results of fusion under different similarity methods.

Way	Accuracy	Recall	*F*-measure
Vocabulary	0.945	0.881	0.914
Spell	0.969	0.982	0.963
Vocabulary + Spell	0.981	1	0.997

The running time results of the improved algorithm in stand-alone mode and MapReduce parallel mode reveal significant differences in efficiency. By comparing the running time under the same data scale for both modes, it is clear that the MapReduce-based parallel mode consistently demonstrates the shortest running time. Furthermore, the time-consuming growth under the MapReduce framework is smoother, highlighting its computational efficiency and scalability advantages. This result underscores the effectiveness of the MapReduce framework in handling large-scale data and optimizing algorithm performance, making it a powerful tool for processing complex educational data.

In the context of offline multimedia teaching, learners can form small "student-student" interaction groups based on self-organization and teaching guidelines. Within these groups, students' social skills are demonstrated by their ability to proactively establish learning partnerships with nearby peers who may not be their usual learning partners. Those with stronger social skills are more adept at forming these partnerships, creating a network-like model in which higher connectivity increases the likelihood of successful interactions.

The knowledge absorption ability within learner groups can be categorized into three levels: low, medium, and medium-high. **Figure 6** illustrates the distribution of offline individuals with varying absorption capacities. This distribution highlights the diverse range of individuals' abilities to assimilate knowledge within group interactions, which carries important implications for designing teaching strategies and collaborative learning models. To enhance the effectiveness of offline multimedia teaching, it is essential to consider these varying absorption levels, optimizing group formation and interaction to boost overall learning outcomes.

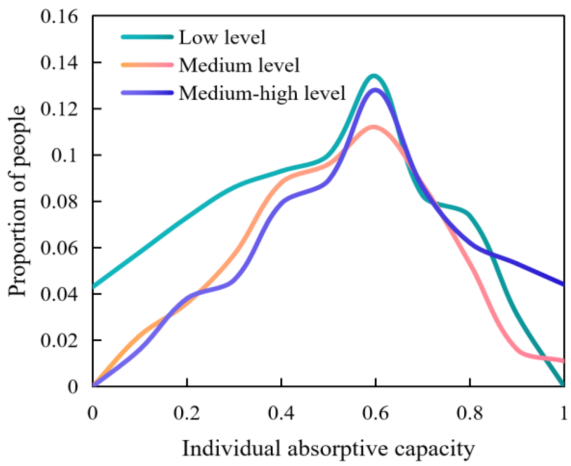

Figure 6. Different offline absorption capacity distribution.

The knowledge absorption ability of offline individuals follows an inverted *U*-

shaped distribution. This means that when the average absorptive capacity of offline groups is stronger, the overall knowledge level at the initial stage is higher, the growth rate of the offline average knowledge level is faster, and the time required for individuals to reach "knowledge level convergence" is shorter. This suggests that groups with stronger absorptive capacity are more efficient in disseminating and internalizing knowledge across individuals, thus enhancing the overall learning process.

Moreover, the improvement in offline individuals' absorptive capacity positively impacts the average knowledge level in online forums. The interaction between online and offline learning environments demonstrates how knowledge transfer and integration can bridge these spaces, with offline absorptive capacity playing a crucial role in influencing online knowledge accumulation. This integration allows for a more holistic learning experience, where the strength of offline knowledge absorption amplifies online learning outcomes.

Additionally, the complexity of knowledge taught in different courses and classrooms varies significantly, which impacts the learning dynamics and convergence times of individuals in both offline and online settings. The results of the simulation, based on this model and reflecting the influence of varying knowledge complexities and absorptive capacities, are illustrated in **Figure 7**. These findings provide valuable insights for designing targeted teaching strategies that optimize the interaction between offline and online learning environments. By considering the complexity of content and the varying levels of absorptive capacity, educators can tailor their approaches to better support knowledge dissemination and internalization across both platforms.

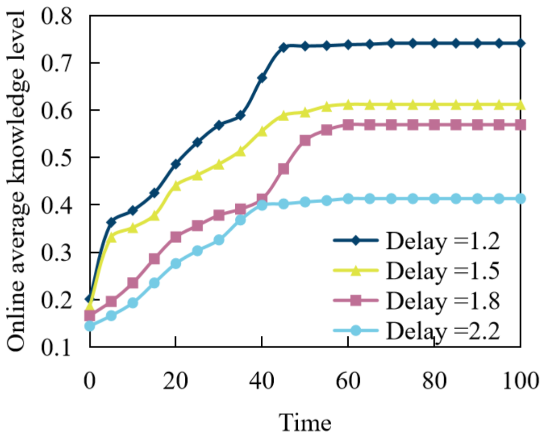

Figure 7. Influence of different knowledge complexity on knowledge dissemination in online forums.

It can be observed that as the complexity of knowledge increases, the spread speed of knowledge in online forums slows down, and the average knowledge level among participants decreases. However, this does not significantly affect the participation rate in online forums. With varying levels of knowledge complexity, online forum participation exhibits fluctuations but does not follow any discernible pattern.

In addition, feedback interaction plays a crucial role in the psychological mechanisms of learning, enabling continuous improvement in the overall efficiency of organizational learning. By employing a control group experimental method to preliminarily compare the efficiency of learning and research, it was found that the integration of feedback into the learning process yielded remarkable results in the context of enterprise organizational learning. Feedback allows for timely adjustments in learning methods and understanding, leading to improvements in the overall efficiency of organizational learning. These results are presented in **Table 2**.

This preliminary research provides not only valuable insights but also a theoretical model and practical foundation for designing customized learning programs. These programs aim to enhance individual understanding and facilitate knowledge sharing within organizations, paving the way for more effective and tailored approaches to organizational learning in the future.

Table 2. Comparative experimental results of epiphany learning.

Group	**Overall number of people**	**Passed number**		
		0.5 h	**1 h**	**1.5 h**
Normal study	20	4	8	18
Epiphany learning	30	7	18	24

Finally, we conducted tests on the cultural learning of autonomous agent populations with different network sizes, aiming to analyze the impact of network size on the cultural learning performance of impulse neural networks based on the experimental results. The experiments were carried out in a “food gathering” simulation environment, where the fitness of agents was used as a key performance metric.

Figure 8 illustrates the average fitness and optimal fitness levels of two autonomous agent populations with varying network sizes. The results indicate that network size plays a significant role in shaping the learning outcomes of impulse neural networks. Larger networks tend to demonstrate higher average fitness and optimal fitness due to increased interaction opportunities and information exchange among agents. Conversely, smaller networks may exhibit slower learning rates and lower fitness due to the limited exchange of knowledge and collaboration.

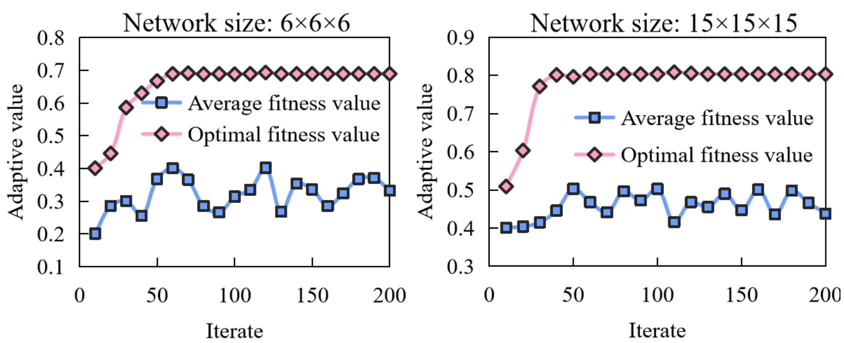

Figure 8. Cultural learning adaptation values of impulsive neural network populations with different network scales.

These findings suggest that network size is a critical factor in optimizing the cultural learning performance of autonomous agent populations. By understanding and leveraging these dynamics, future research can design more effective network structures to enhance the performance of impulse neural networks in various learning scenarios.

The experimental results show that both the average fitness value and the optimal fitness value of the population gradually improve over successive generations. After several iterations of evolution, the average and optimal fitness values for the two populations stabilize, indicating the convergence of learning outcomes. These observations highlight the significant influence of network scale on the career development effect of the population.

It can be concluded that as the number of neuron nodes and the complexity of the network structure increase, the career development outcomes of the agents improve. Larger and more complex networks allow for greater interaction and information exchange among agents, enhancing their learning capacity, adaptability, and the internalization of career-related knowledge. This suggests that optimizing the network scale and structure is crucial for improving the performance of career development in autonomous agent populations. This finding offers valuable insights for future research and applications in neural network design, as well as in the development of more effective learning systems that leverage the benefits of enhanced interaction and information sharing.

5. Conclusion and future outlook

Career development represents the process by which individuals acquire skills, knowledge, and experiences to thrive professionally. Neural network-based multimedia teaching strategies explore biological feedback mechanisms such as students' emotions and behavioral patterns during cultural interaction. And it enhances this process by fostering adaptability, engagement, and career confidence through neurocognitive optimization. For instance, our study developed a fusion algorithm within the Hadoop MapReduce framework that integrates attribute-based similarity calculations with dynamic fusion rules. This system achieved great performance metrics: a similarity accuracy of 0.981, a recall rate of 1.0, and an F-measure of 0.997, demonstrating its effectiveness in processing multi-source career-related data.

More importantly, populations using neural network-based learning mechanisms outperformed traditional group learning cohorts in adaptive decision-making tasks. This improvement is attributed to the technology's ability to simulate real-world career scenarios through graph neural network (GNN) architectures, which activate dopaminergic pathways associated with reward-driven learning. By dynamically mapping students' decision vectors to virtual career trajectories, these systems enhance psychological engagement while simultaneously improving cognitive flexibility and proactive problem-solving behaviors. This means that computer modeling is not only a technological tool but also a catalyst for psychological development.

Future research should focus on three computational frontiers:

Dynamic Mental Modeling: Deploy temporal convolutional networks (TCNs) to continuously monitor longitudinal changes in occupational psychology. This would enable the creation of predictive control models that anticipate cognitive transformations, allowing timely interventions to strengthen career resilience.

Causal Reasoning Systems: Integrate counterfactual reasoning modules into Transformer architectures to validate causal relationships in career decision-making. This innovation would enhance the interpretability of AI-driven career advice, fostering student trust and informed decision-making.

Metaverse Teaching Ecology: Utilize generative AI and digital twin technology to construct embodied career enlightenment environments. These immersive platforms would visually track development through real-time neural feedback loops, aligning with McLaren's emphasis on experiential learning.

This interdisciplinary approach marks a paradigm shift from static knowledge transfer to neurocomputational empowerment. By operationalizing career development through neural network simulations and enhancing metacognitive awareness. The proposed systems not only improve employability but also cultivate proactive psychological capital. It results in a human-machine collaborative framework that transforms career planning from reactive guidance to adaptive, growth-oriented neurocognitive training.

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