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The Integrated Development of the Manufacturing and Service Industries Facing Human-Computer Interaction Based on Deep Learning

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ABSTRACT

With the rapid development of modern technology and the economy, the global value chain is also constantly evolving, and the links between various industries are becoming closer. With the continuous optimization of the international situation and the support of Chinese policies, the integrated development of manufacturing and service industries is the general trend. This study proposes to use human-computer interaction to conduct in-depth research and analysis of the development relationship, influencing factors, and evolution direction between manufacturing and service industries in the perspective of deep learning. Firstly, based on the current development status of the two industries, the influencing factors of mutual evolution are summarized, including environment, market, technology, and management. Secondly, the computer is used to construct the evolution models of the two major industries. The simulation verification and evolution feature extraction are carried out.

KEYWORDS

deep learning, evolution model, human-computer interaction, manufacturing, service industry

1 INTRODUCTION

1.1 Research Background and Motivations

The two major manufacturing and service industries have made a sub-quality leap from their initial establishment to today's development. With the encouragement of national policies, the two major industries have merged and are well connected, resulting in huge wealth and interests (Mohsen, Attaran, Sharmin, & Attaran, 2018). Since the reform and opening, the Party Central Committee and the State Council have formulated important reform policies, and the government has vigorously promoted the integration of the two major industries (Moss, Henshall, Arya, Shire, Eames, & Hyde, 2018). The country attaches great importance to the development of manufacturing and service industries.

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Under such a premise, the relationship between the two industries has been deeply analyzed, and a reasonable and efficient convergence evolution path has been explored.

Human-computer interaction (HCI) technology uses multimodal information such as voice, image, text, eye movement, and touch to exchange information between humans and computers. With the development of the Internet of Things, HCI devices have been widely used in people's daily life. In recent years, computer vision, gesture recognition, and artificial intelligence have flourished, and hardware technologies such as headsets, displays, and sensors have significantly progressed. HCI is no longer limited to the input and output modalities of a single perceptual channel (vision, touch, hearing, smell, and taste). The big data visualization interaction shares the resource information of the service industry and the manufacturing industry. It uses the computer simulation technology to study the development status and trends of the integration of the two industries (Liu, Zhao, & Zhu, 2022) (Chen et al., 2022).

From the perspective of deep learning, this study firstly uses HCI to conduct in-depth research and analyze the developing relationship, influencing factors, and evolution direction between manufacturing and service industries. The literature review summarizes the development status of the two major industries and studies the factors affecting the mutual evolution of industrial integration, including environment, market, technology, and management. Secondly, the simulation software is used to construct the evolution models of the two major industries, and the simulation verification and evolution feature extraction are carried out. This study aims to obtain a benign development strategy for integrating manufacturing and service industries based on the above methods, promote industrial upgrading, and realize the integrated development of producer services and manufacturing.

1.2 Research Objectives

This study aims to clarify the thinking and suggest the integrated development of the manufacturing and service industries. Additionally, the introduction of HCI technology in industrial integration is the innovation point. The existing theoretical results are few, so the research is needed to confirm that the technology can be used for industrial integration and will play a role in promoting it. From the perspective of deep learning, this study uses computer simulation technology to conduct an in-depth analysis of the integrated development of the two industries and explore opportunities for HCI. According to the analysis results of influencing factors, based on HCI, computers are used to construct two major industrial evolution models and carry out simulation verification and evolution feature extraction. The experiment shows a new idea of the integrated development strategy of the manufacturing and service industry based on HCI (Deng et al., 2021).

2 LITERATURE REVIEW

The historical status of the integrated development of manufacturing and service industries mainly includes:

Fernandes and Paunov studied the progress made in innovation in the service industry. They believed that foreign direct investment had played a significant role in narrowing the gap in the industry (Di Berardino & Onesti, 2020). Leiponen conducted an empirical analysis of the integration factors of Finnish manufacturing and service industries, focusing on the core factors in the research and development process. The results show that the efficiency of the service industry is greater than that of the manufacturing industry. The two industries should interact more in the research and development (R&D) module to promote the integrated development of the two industries (Leiponen, Koutroumpis, & Bohlin, 2020). Olausson et al. studied the integration process of the two industries. There is a relatively significant relationship between manufacturing and service industries at the design level, but it is difficult to achieve complete matching of communication at the technical level. They proposed that information management strategies can be used to remedy this deficiency (Olausson & Timsjö, 2018). Fernández et al. studied manufacturing and services separately in a sample of Spanish firms. They pointed out that in manufacturing, the firm effect is greater than the industry effect, while in the service sector, the opposite is true over the ten years. However, when the time horizon is divided into two five-year sub-periods, this behavior is retained only in the second five-year period, which is moderate economic growth (Fernández, 2022). Yu et al. found that the opening of China's financial services industry has promoted domestic value-added exports of manufacturing. Under the liberalization of the policy area, the opening and cross-border measures of the financial services industry have produced differences. The intensity of external financial services imports impacts domestic value-added exports of manufacturing. Their research provides a path for accurately expanding the opening of the financial service industry, promoting the improvement of the overall competitiveness of the manufacturing industry and the transformation and development of manufacturing enterprises (Yu, Tang, Tenkorang, & Bethel, 2021) (Feng & Chen, 2022)(Chen & Du, 2022A)(Chen & Du, 2022B).

Scholars in this field have conducted in-depth research on the manufacturing and service industries. They confirmed that the integration of the service industry and the manufacturing industry is the general trend, which can promote the common development of both parties and provide insights for future integration and development. However, scholars have not put forward a clear theoretical discussion on the detailed integration process and development trend of the two major industries. It is difficult to confirm the credibility of the conclusion. From the perspective of exploring the development status of the two major industries in detail, this study deeply analyzes the current specific integration process between the service industry and the manufacturing industry, extracts the characteristics of the trends at each stage, and provides new insights for future industrial development (Lu et al., 2022)(Ng et al., 2021)(Liu et al., 2021).

3 RESEARCH MODEL

(1) The field of view of deep learning

In *Seven Powerful Strategies for Deep Learning* by Eric Jensen and LeAnn Nickelsen, some strategies are included in the deep learning process to help implement and promote deep learning. They proposed a process model of the "Deeper Learning Cycle" (Lee, Hwang, Son, & Shin, 2022), as shown in Figure 1. This model starts from the perspective of teachers' teaching and helps learners to carry out deep learning. "Deep processing knowledge" is the key to the deep learning route. At this stage, teachers should guide students to understand, analyze, apply, and transfer the new knowledge finely and effectively (Ching, Himmelstein, Beaulieu-Jones, Kalinin, & Way, 2018).

In Figure 1, deep learning refers to multi-layer artificial neural networks and methods for training neural networks. It is a specific type of machine learning with powerful automatic learning capabilities and flexibility. At present, deep learning models are widely used in computer vision, speech recognition and natural language processing, and other fields and have achieved excellent results in these fields. Commonly used deep learning models are the convolutional neural network, Recurrent Neural Network (RNN), and Residual Neural Network (ResNet) (Zhao, Liu, Hu, & Yan, 2018).

Kunihiko Fukushima first proposed Convolution Neural Network (CNN). The computer performance at that time could not meet the needs of network training, so CNN was not widely used. After that, the researchers made improvements and optimizations, adding a gradient-based learning algorithm to the structure so that the pooling layer of CNN can better change the shape of the data. Additionally, CNN has the property of weight sharing, which makes it have fewer parameters than fully connected neural networks that are similar in size. Gradient-based learning algorithms can reduce gradient problems. Gradient-based algorithm training allows the entire network to minimize the standard error directly. CNN can make the weights highly optimized (Kattenborn, Leitloff, Schiefer, & Hinz, 2021) (Chen & Zhang, 2022). The general structure of CNN is shown in Figure 2:

In Figure 2, the convolutional layer mainly performs the convolution operation on the input data of the previous layer through the convolution kernel. The data output after the convolution operation passes through a linear or nonlinear activation function to output the feature map. The feature map of each output can be combined with the feature maps of multiple inputs. The calculation of the convolutional neural network is shown in Eq. (1):

Figure 1. The route of deep learning

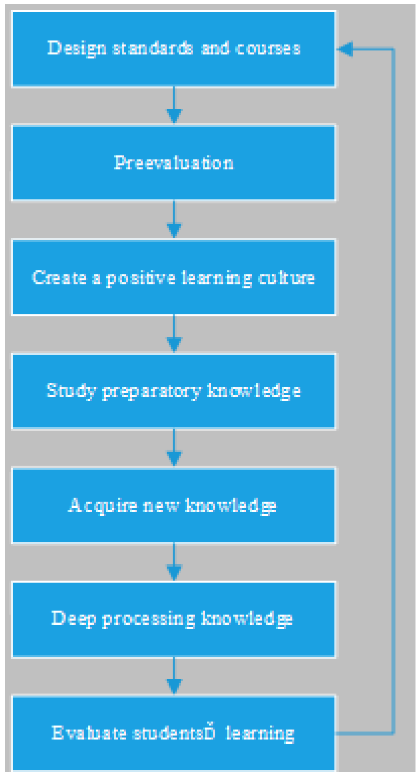
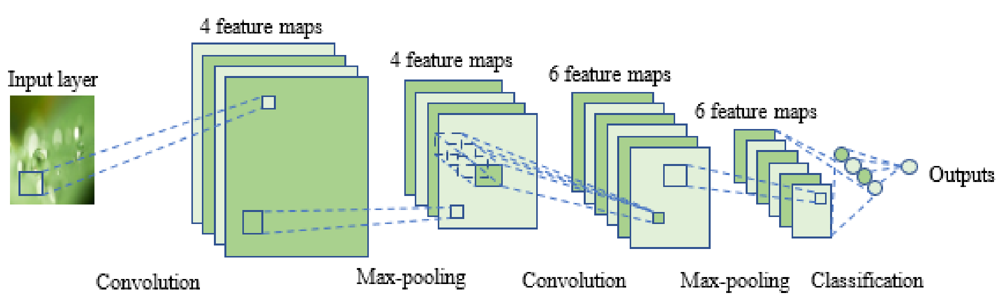


Figure 2. The structure of the convolutional neural network



$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^{l-1} + b_j^l\right) \quad (1)$$

In Eq. (1), x_j^l represents the output of the current layer; x_i^{l-1} represents the output of the previous layer; k_{ij}^l represents the convolution kernel used by the current layer; b_j^l represents the bias of the current layer; Mj represents the selected input mapping. The bias term b is added to each output feature map. The input features operate on different convolution kernels to generate new output features. The new feature map is selectively output through an activation function.

RNN allows operating on a sequence of vectors over time. It can transmit information in sequence. RNN is regarded as the superposition of multiple network copies in time series, and the information of the previous moment will be passed to the next moment. The structure of RNN expanded over time is shown in Figure 3:

ResNet is designed to construct an ultra-deep network architecture, which is no longer restricted by the gradient vanishing problem like existing neural network architectures. ResNet changes the normal deep network to increase the depth of the network by simply stacking layers. It introduces the residual learning framework into the neural network architecture. The increase in the number of network layers no longer fits the desired base map by simply stacking layers but lets these layers fit the residual map. In ResNet, vanishing gradients and exploding gradients are well suppressed. The model mainly includes an input layer, a residual module, and an output layer. The number of residual modules can be set according to the actual problem. The structure of the residual network is shown in Figure 4:

In the ResNet, the skip connection structure breaks the original structure of the network model. The output of any layer can span multiple network layers and serve as the input of the lower network. Cross-layer connections provide a new direction to address reducing the error rate of models in overlay networks. The construction of neural networks is no longer constrained by the depth of the network, providing feasibility for advanced semantic feature extraction and classification (Ahn & Sura, 2020)(Feng et al., 2021).

(2) Analysis of factors influencing the evolution of interactive integration

The interaction and evolution of the manufacturing and service industries is an inevitable trend in developing the two industries. The interaction, integration, and evolution of the two industries should not only analyze the environment of the two industries, but also pay attention to their own

Figure 3. Unfolded structure of RNN

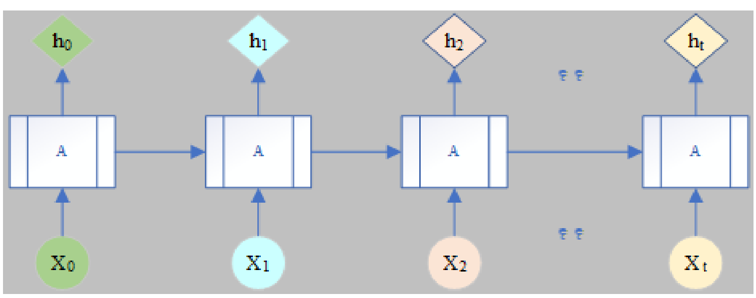
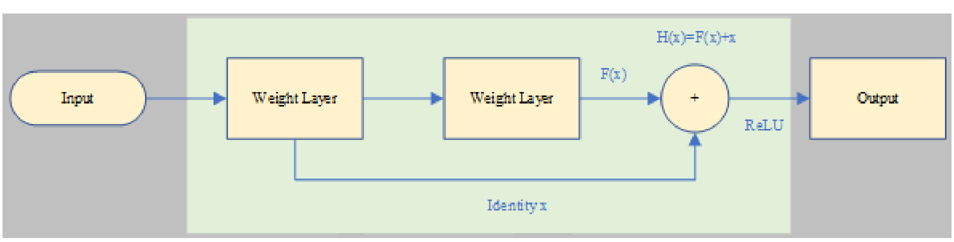


Figure 4. Basic structure of residual network



conditions (Mohsen, Attaran, Sharmin, & Attaran, 2018). This work takes the environmental, market, technology, and management factors as the research perspective. It analyzes the influencing factors of the interaction and integration of the two industries from four aspects (Grant & Yeo, 2018). The influencing factors of evolution are shown in Figure 5.

Environmental factor. In the process of interaction and integration of the two major industries, the support of government policies and related systems is the key point. The process of industrial development requires a certain degree of support and guidance from the government regarding taxation and capital. If the government strongly supports integrated development, it will accelerate the evolution of the two industries (Asadi, 2019). The main policies mainly include industrial policy, security system, and economic environment. The market factor is a leading factor determining the interaction and integration of the two industries and is the basic condition for the evolution of the two industries. It is gradually matured and improved in harmony with elements such as government policies and systems and promotes the interaction, integration, and evolution of the two (Dong, 2021). Factors mainly include market demand, market specialization, and scientific research and intermediary. Technology is a major factor influencing the decision-making of individuals, companies, or industries to adopt innovations. The advancement and support of technology will effectively promote the interaction, integration, and evolution of the two industries (Kang, Kim, & Seol, 2019). The technological stock brought by the technological innovation of the two major industries is the basis for technological synergy and diffusion. Technological factors are the decisive factors in the evolution of interactive integration, mainly including technological innovation capability, stock, and diffusion capability(Chong, Ramayah, & Cheah, 2019).Management factors. The interaction, integration, and evolution of the manufacturing and service industries have continued to deepen, and a long-term and stable interactive relationship has been established between industries. Enterprises form a close industrial and value chain with each other. The improvement of the internal management level of enterprises and the exchange of information reduces transaction and communication costs (Hang, Wang, Zhou, & Zhang, 2019) (Zhang et al., 2022). Management factors mainly include research and development atmosphere, knowledge and information sharing, and production and human resource allocation. The elements contained within the four factors are shown in Figure 6:

(3) Interactive fusion evolution model

With the changes in internal and external exchanges in different periods, the interactive integration and evolution process of the two major industries presents different evolution states at different stages. The evolution process corresponds to different evolution models, namely, the evolution model

Figure 5. Factors influencing the integrated development of manufacturing and service industries

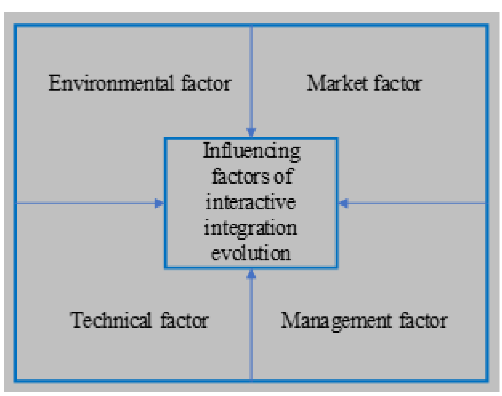
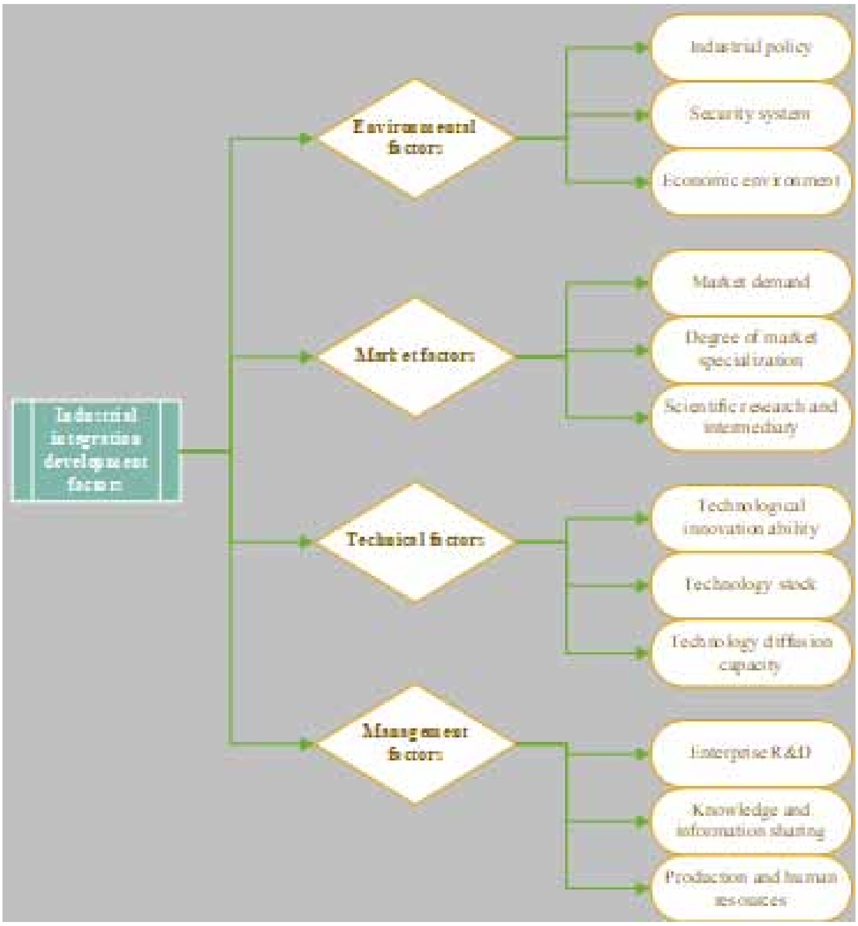


Figure 6. The structure of factors affecting the integration of the two major industries



in the differentiation stage, the evolution model in the association stage, the evolution model in the interaction stage, and the evolution model in the fusion stage. In the initial period of the interaction and evolution of the two industries, the service industry was differentiated from the manufacturing industry and became an independent industry. At this stage, the role between the two industries is very small. With the refinement of the division of labor in the service industry, the demand for the service industry in the manufacturing industry has deepened. There is a certain impact on each other, affecting the output level of both parties (Sreedharan V, Nair, Chakrabort, & Antony, 2018)(Wu et al., 2021).

In the early stage of the interactive development of the two industries, the service industry developed rapidly, and the interaction between the two industries was promoted. After a certain stage, an industry level with similar strength was formed. Therefore, this study conducts model construction from two stages. The first stage is the evolution model of the rapid development stage of the service industry. The previous output level can no longer meet the development needs of the manufacturing industry. The service industry needs to change its industrial strategy promptly, speed up the pace of development, and promote the interaction between the two industries. The industry grew rapidly during this period. Since the industry's strength is smaller than that of the manufacturing industry, its development still needs to depend on the manufacturing industry. The second stage is the evolution model of the industrial cluster stage. Driven by the rapid development of science, technology, and the economy, the two major industries have gradually emerged as industrial clusters. Industrial clusters can improve the competitiveness of industries, form a mutually beneficial symbiotic relationship with similar strengths, and improve the output level of the two major industries (Ye & Chen, 2021).

Based on the analysis scales of the two major industrial evolution influencing factors, a structural equation model is constructed. AMOS 17.0 software is used to solve the structural equation model to verify the correctness of the assumptions. The evolution structure model of the interaction and integration of the two industries is shown in Figure 7:

Manufacturing and service industries have changed over time in interaction and integration. The evolution process of the two major industries is autonomous and random, showing a self-organizing feature. Therefore, this work cites the self-organization theory to study its complex evolution. Usually, the mathematical model of nonlinear differential equations is adopted (Yu, 2021), as shown in Eq. (1):

$$\frac{dX}{dt} = rX\left(1 - \frac{X}{M}\right) \tag{2}$$

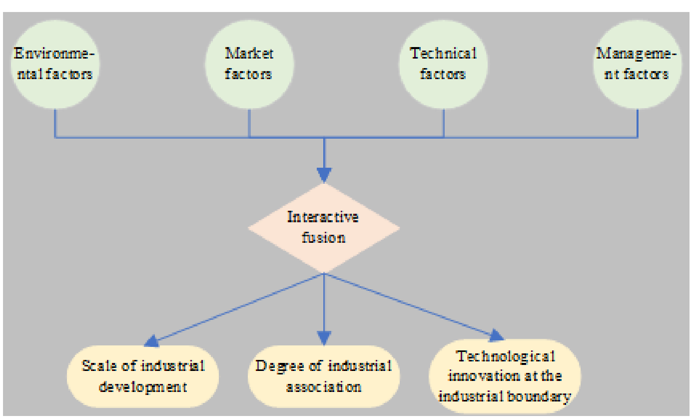
In Eq. (1), t represents time; r represents the natural growth rate of the main body of the industry under normal circumstances; M represents the maximum value that the industry can reach within the range of a certain carrying capacity and capacity of the market. Eq. (1) is further explained, as shown in Eq. (2):

$$X = 0, X = M \tag{3}$$

Eq. (2) indicates that the modified model reaches a steady state. When r<0 changes to r>0, the value of X moves from 0 to M; when r>0, the change in the value of M will cause the evolution of the two major industries to change, forming different evolution trends.

With the change of internal and external exchange in different periods, the evolution process of interaction and integration of the two industries presents different evolution states in different stages, corresponding to different evolution models. Based on the assumptions and the proposed mathematical model of evolution, when the two industries are in the stage of differentiation, the two industries interact and merge in the initial period of evolution. The state of the two industries in the initial state is shown in Eq. (3):

Figure 7. Structural model of industrial integration and evolution



$$\begin{cases} \dfrac{dL_A}{dt} = r_A L_A \left(1 - \dfrac{L_A}{E_A}\right) \\ \dfrac{dL_B}{dt} = r_B L_B \left(1 - \dfrac{L_B}{E_B}\right) \end{cases} \tag{4}$$

In Eq. (3), L_A represents the output level of the service industry; L_B represents the output level of the manufacturing industry; E_A represents the maximum output value of the service industry when it reaches the best state (natural state) within the known environmental carrying capacity, and E_B is maximum output value of manufacturing in the natural state. r_A and r_B represent the natural growth rate of the service and manufacturing industries, respectively.

The business homogeneity of the two industries will affect the degree of competition between the two industries. The existence of business heterogeneity is an important prerequisite for the trend of interaction and integration between the two industries (Zhang, Ming & Yin, 2020). In the initial period of the evolution of the two major industries, the manufacturing industry lacked complete market information. The external transaction cost is high, and the service industry is completed within the industry as an auxiliary activity, resulting in a lack of effective demand for it and restricting the development of the industry (Sony, Antony, Dermott & Garza-Reyes, 2021). Therefore, only in the differentiated stage of the interaction and integration of the two industries can expand the manufacturing demand and provide market opportunities for service enterprises. This situation reduces competitive pressure, frees up market demand, and facilitates evolution and development (Gusmerotti, Corsini, Testa, Rizzi & Frey, 2019).

Based on the assumption of evolutionary development and the proposed mathematical model, when the two major industries are in the associated stage, with the continuous expansion of the overall scale of the industry, the refinement, and modularization of supporting production. The value chain division of labor at this stage is refined and deepened. The relationship between the two industries is getting closer (Yadegaridehkordi, Hourmand, Nilashi, Shuib, Ahani, & Ibrahim, 2018). The manufacturing industry outsources the links that it is not good at, focusing on and enhancing its core competitiveness. This way of production and manufacturing can gain an advantage over the competition and improve their own profits. Additionally, the outsourcing business provides opportunities and platforms for the service industry, enabling the service industry to develop tremendously. The gradual formation of a cooperative and mutually beneficial relationship between the two industries can promote the benefits of the two industries (Wang, Li, Liu, Yang, & Gao, 2019). At this time, the output growth level of the two major industries is described, as shown in Eq. (4):

$$\begin{cases} \dfrac{dL_A}{dt} = r_A L_A \left(1 - \dfrac{L_A}{E_A} - \alpha_{AB}\dfrac{L_B}{E_A} + \beta_{AB}\dfrac{L_B}{E_B}\right) \\ \dfrac{dL_B}{dt} = r_B L_B \left(1 - \dfrac{L_B}{E_B} - \alpha_{AB}\dfrac{L_A}{E_B} + \beta_{BA}\dfrac{L_A}{E_A}\right) \end{cases} \tag{5}$$

In Eq. (4), α represents the impact on the other's industry during the evolution of the two major industries, which is called the competition coefficient. α_{AB} represents the impact of the service industry on the manufacturing industry, α_{BA} represents the impact of the manufacturing industry on the service industry; β_{AB} represents the contribution coefficient of the manufacturing industry to the service industry; β_{BA} represents the contribution coefficient of the service industry to the manufacturing industry, which reflects the two major industries' evolution effect.

Based on these assumptions and the proposed mathematical model of evolution, when the two industries are in the interactive stage, the evolution model can be further subdivided into two stages. The state of the stage is shown in Eq. (5):

$$\begin{cases} \dfrac{dL_A}{dt} = r_A L_A \left(1 - \dfrac{L_A}{E_A} + \beta_{AB}\dfrac{L_B}{E_B}\right) \\ \dfrac{dL_B}{dt} = r_B L_B \left(1 - \dfrac{L_B}{E_B} + \beta_{BA}\dfrac{L_A}{E_A}\right) \end{cases} \tag{6}$$

Based on the assumptions and the proposed mathematical model of evolution, when the two industries are in the integration stage, the established interactive integration evolution model is shown in Eq. (6):

$$\begin{cases} \dfrac{dL_A}{dt} = r_A L_A \left(1 - \dfrac{L_A}{E_A + \beta_{AB} L_B}\right) \\ \dfrac{dL_B}{dt} = r_B L_B \left(1 - \dfrac{L_B}{E_B + \beta_{BA} L_A}\right) \end{cases} \tag{7}$$

In Eq. (6), the two major industries expand market capacity through technological innovation. Under the promotion of positive effects, the two major industries gradually reach a balanced state, and the two sides can promote each other and further integrate. Obviously, the coordination of organization and management, the penetration of technology, the interactive sharing of integrated product information, the improvement of research and development capabilities, and the continuous innovation capabilities will improve the efficiency of technological innovation in the two industries. The improvement of technological innovation level will play a decisive role in the co-evolution of the two industries.

4 EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

4.1 Experimental Materials

Based on HCI, this experiment uses computer simulation technology to simulate and predict the trend of each stage of the integration of manufacturing and service industries and analyzes and summarizes the simulation results. The equipment and versions used in this experiment are:

The PC model is Intel(R) Core (TM) i5-9300H CPU @ 2.40GHz, 2.40 GHz, 64-bit operating system;

The Windows specification is Windows 11 Home Chinese Edition, version 21H2;

The SPSS version is the SPSS22.0 Chinese version, which is used to determine the feasibility of the experiment;

The software is MATLAB 7.0;

Based on these experimental tools and software, the current development status and influencing factors of the two major industries are analyzed. The development trends corresponding to the four stages of development are integrated to analyze and summarize the development characteristics of the trends.

In order to more accurately use the structural equation model to solve practical problems, the estimated parameter data statistics of the calculated structural equation model are shown in Table 1. The C.R. value is a statistic constructed as the ratio of the parameter estimate (unstandardized Estimate) to its standard deviation.

4.2 Experimental Environment

Based on HCI, this experiment uses computer simulation technology to simulate and predict the trend of each stage of the integration of manufacturing and service industries and conduct interviews and research on the influencing factors of the two industries in the process of interaction and integration (Tuomas, 2019). The survey has a total of 15 questions, using a 5-level scale method, one means strongly disagree, and five means strongly agree. KMO and Bartlett tested the interviewed results. The KMO test is generally used to check the correlation and partial correlation between variables, with a value between 0 and 1. The closer the KMO statistic is to 1, the stronger the correlation between variables. This method is used to test the validity of survey results (Mo & Wu, 2018). The test results are shown in Table 2.

In Table 2, the KMO value of the research environment constructed by this model is 0.967, which is greater than 0.8 and has good validity. The significance level of the chi-square value of the Bartlett test of sphericity is 0.000, and the significance level is high.

4.3 Parameters Setting

L_A is the output level of the service industry;

L_B is manufacturing output level;

E_A is the maximum output value of the service industry when it reaches the best state (natural state) within the known environmental carrying capacity;

E_B is the maximum output value of the manufacturing industry in the natural state;

r_A and r_B are the natural growth rate of service and manufacturing;

Table 1. Fitted data for the model

Factors	Estimate	C.R.
Environmental	0.35	7.31
Market	0.34	6.28
Technical	0.31	6.82
Management	0.20	4.60

Table 2. KMO and Bartlett tests

Bartlett's test of sphericity			
KMO metric for sampling adequacy	approximate chi-square	Df	Sig.
.967	2507.987	105	.000

T represents time;
r represents the natural growth rate of the main body of the industry under normal circumstances;
M represents the maximum value that the industry can reach within the range of a certain carrying capacity and capacity of the market;
α refers to the influence of the two industries on each other in the evolution process, which is called the competition coefficient;
α_{AB} is the impact of the service industry on the manufacturing industry;
α_{BA} is the impact of manufacturing on the service industry;
β_{AB} is the contribution coefficient of the manufacturing industry to the service industry;
β_{BA} is the contribution coefficient of the service industry to the manufacturing industry;

4.4 Performance Evaluation

In order to deeply analyze the evolution law of the interaction and integration of manufacturing and service industries, this study uses MATLAB 7.0 to draw a dynamic evolution trend graph. Among them, the assignment of each parameter is $L_A(0)=1, L_B(0)=5, E_A=5, E_B=7, r_{AB}=r_{BA}=0.05$. The simulation period is 160months. After compiling and running, Figures 8, 9, 10, and 11 are derived:

In Figure 8, when $\alpha_{AB}=\alpha_{BA}=0.5$, the service industry curve grows slowly. In this case, the two industries compete in business, but the manufacturing industry cannot provide sufficient demand. Therefore, the integration of industries hinders the development of the service industry to varying degrees.

In Figure 9, when $\beta_{AB}>\alpha_{AB}, \beta_{BA}=\alpha_{BA}$, the service industry's demand for manufacturing increases, and the manufacturing industry's demand for the service industry also increases. The closeness between the two industries is stronger, and the dependence is stronger. Additionally, the two major industries have formed a certain scale, and the manufacturing industry has significantly enhanced the promotion of the development of the service industry, which has played a role in promoting the rapid development of the service industry.

Figure 8. Evolution trend of differentiation stage

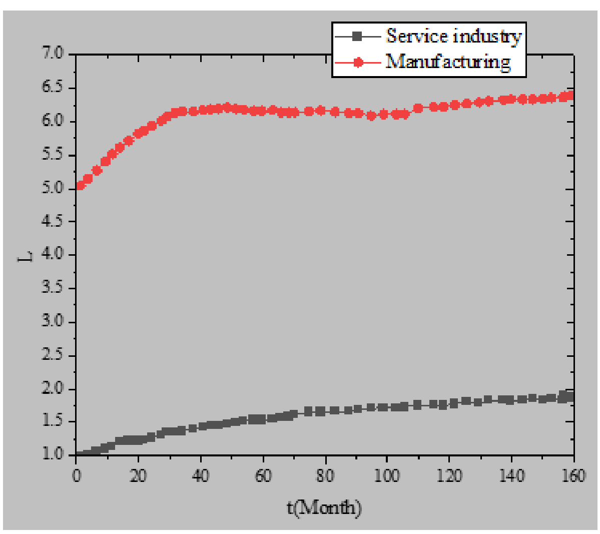
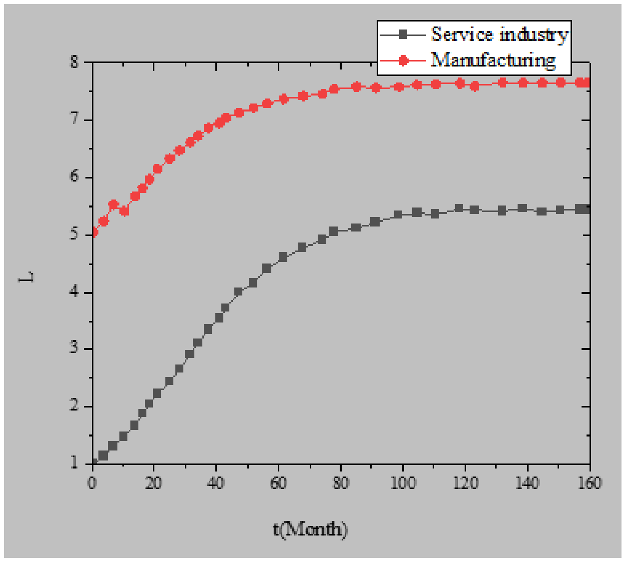


Figure 9. Evolution trend of the association stage



In Figure 10, when $\alpha_{AB} = \alpha_{BA} = 0$, $\beta_{AB} = \beta_{BA} = 0.7$, the period of rapid growth is shortened, the two industries are in a state of interactive development, and the two industries interact, gradually showing a trend of interactive evolution. The interactive evolution stage of the two industries promotes each other, and the evolution trend is accelerated.

In Figure 11, when $\alpha_{AB} = \alpha_{BA} = 0$, $\beta_{AB} = \beta_{BA} = 0.7$, the two major industries have made certain progress in technological innovation, the level of technological innovation has been improved, and the research and development capabilities have become stronger. Advanced technology promotes

Figure 10. Evolution trend of the interactive stage

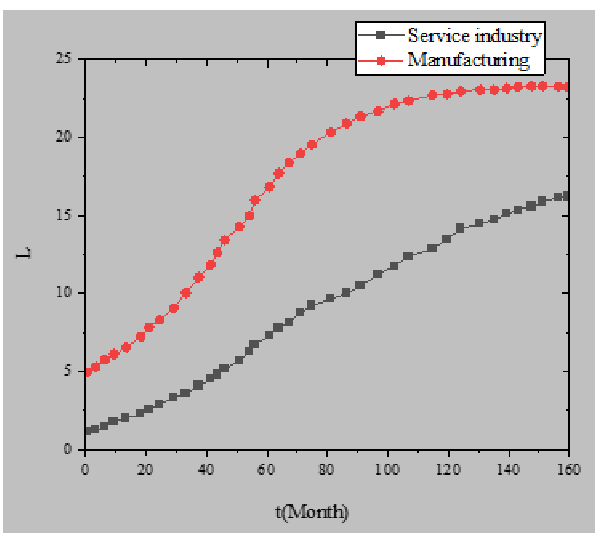
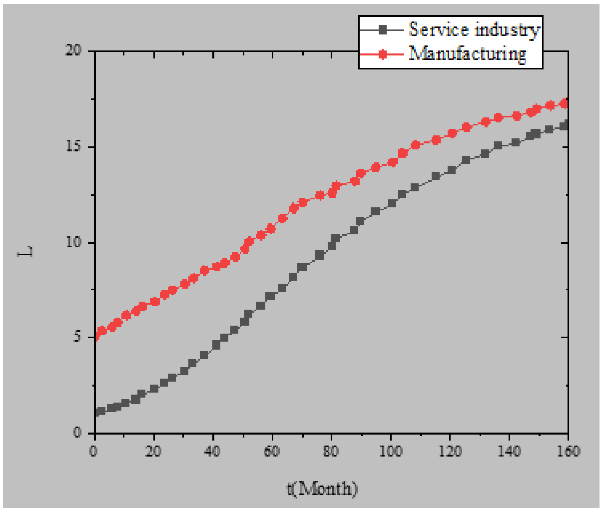


Figure 11. Evolution trend of the fusion stage



the integration and evolution of both the service industry and the manufacturing industry and positively impacts each other.

From the above experiments, the evolution trends of interactive fusion can be obtained as follows:

(1) Servitization of the industrial chain

In the process of interactive integration and evolution of the manufacturing industry and the service industry, the industrial structure center has a regularity of gradually deducing to the service industry. The servitization of the industrial chain has become a development trend in the interactive integration and evolution of the two industries (Song & Liu, 2020). Among the products provided by the manufacturing industry, the proportion of service products is increasing, which is mainly reflected in the improvement of the level of after-sales service (Yan, Dong, Li, Yang & Amin, 2022). This service-oriented transformation meets the different needs of customers, prompts the transformation of the manufacturing industry from a single manufacturer to a diversified service provider, improves the profitability of the manufacturing industry, and promotes the evolution and development of the two major industries.

(2) Premiumization of the value chain

Technological innovation and market demand have promoted the penetration and extension of the service industry into the manufacturing value chain, making the relevant nodes in the process of value creation of the two industries penetrate each other and recombine to form a new industrial value chain (Tang, PEI-Jie, Lan, Zhao-Hua & Wang, 2019). In the formation process of the new industrial value chain, the service industry combines the characteristics of each link in the creation process of the manufacturing industry to increase its industrial added value and improve the value creation level of the overall value chain. The value center shifts to a high-profit service link to meet high-end market demand, expand market share, and promote the high-end development of the industrial value chain (Min & Luo, 2020).

(3) Market dominance

The interaction, integration, and evolution of the two major industries require the integration of business and management, promoting the formation of new integrated industries and products, and forming new markets and new competitiveness (Li, Marik, Gao & Shen, 2021). The market-led interactive integration evolution process requires the support of technology, business, and management. The integration of technology, business, and management is a necessary means for the interaction and evolution of the two industries. Market integration is the inevitable result of the evolution of the interaction and integration of industry (Gang & Chenglin, 2021).

4.5 Discussion

Interconnecting information and communication technologies with production facilities, Sarbu et al. studied the impact of the new industrialization of Industry 4.0 on manufacturing and service companies. Using representative firm-level data from 4,121 German firms, they analyzed how adopting Industry 4.0 changed innovation performance. The results show that Industry 4.0 increases the propensity to create product innovation compared to manufacturing firms and positively impacts the intensity of product innovation in the service sector. This study depicted the trends of the two major industries at various stages of integration (Sarbu, 2022). Sharma et al. examined the impact of corporate social responsibility on the financial performance of selected manufacturing and service companies in India. The experiment considered financial data from India's manufacturing and services sectors from 2008 to 2017. Experiments show no significant association between corporate social responsibility (CSR) scores and the financial performance of manufacturing companies (Sharma & Dadhich, 2021). This study not only expounds on the influencing factors of the integration of the two major industries but also conducts an in-depth analysis of the relationship between the influencing factors. This work summarizes the evolution characteristics of the integration and evolution of the service industry and the manufacturing industry through experiments and simulations. It provides new ideas for the future integration strategies of the two industries: environmental adaptability, subject synergy, nonlinearity, and gradualness.

5 CONCLUSION

5.1 Research Contribution

The manufacturing and service industries play an important role in China's economic development. The integration and development of the two industries is an inevitable requirement for economic development. Combining deep learning and HCI, the historical development status and evolution trend of the two major industries have been comprehensively and carefully analyzed. Firstly, based on the development status of the two major industries, the influencing factors of mutual evolution are summarized, including environment, market, technology, and management. Secondly, according to the analysis results, computers are used to construct the evolution models of the two major industries and carry out simulation verification and evolution feature extraction. The characteristics of interactive fusion evolution include environmental adaptability, subject coordination, nonlinearity, and gradualness. The service-oriented industrial chain, the high-end value chain, and the market-leading trend are the two major industries' interactive integration and evolution trends. This study expounds on the deep principles and influencing factors of the interaction and integration of the two industries. It provides a theoretical basis for further research on the evolution and development of the manufacturing and service industries.

5.2 Future Works and Research Limitations

The integration of manufacturing and service industries will not stop anytime soon. China's economic and technological development is also inseparable from the optimization and integration of these two major industries. Scholars should continue to explore the operating principles between the manufacturing and service industries and find a reasonable and efficient way of industrial integration and development that is suitable for national conditions. This new development path should enable the two major industries to develop and evolve rapidly on the right path, providing a solid force for China's overall development.

This experiment is not comprehensive enough to analyze the influencing factors of the integrated development of the two industries. The successful operation of the manufacturing and service industries includes many factors. This study only investigated and analyzed the four major factors. In the future, more and more detailed factual data should be collected, and more detailed experiments and trend forecasts should be carried out.

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