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*Molecular & Cellular Biomechanics* 2025, 22(3), 1089.
https://doi.org/10.62617/mcb1089

Article

# Biological analogy analysis of digital economy on the transformation and upgrading of manufacturing industry: Research based on D-S model

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**CITATION**

Shi X, Yu Y. Biological analogy analysis of digital economy on the transformation and upgrading of manufacturing industry: Research based on D-S model. Molecular & Cellular Biomechanics. 2025; 22(3): 1089. https://doi.org/10.62617/mcb1089

**ARTICLE INFO**

Received: 12 December 2024
Accepted: 14 February 2025
Available online: 20 February 2025

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**Abstract:** This study aims to explore the dynamic relationship between biomechanical modeling and manufacturing productivity in the context of the digital economy, with a particular focus on the interaction between worker movement patterns and production efficiency. By combining biomechanical analysis with VAR (Vector Autoregressive) models, this study reveals the dynamic effects of worker movement patterns on productivity. The VAR model, as a multivariate time series analysis tool, can effectively examine the causal relationship between factors such as production efficiency, labor input, technological level and worker movement patterns. In the study, kinematic and dynamic analysis were combined, with a focus on analyzing biomechanical variables such as the movement trajectory, velocity, acceleration, and applied forces of workers' arms and joints during the execution of production tasks, in order to evaluate the impact of these factors on production efficiency. Biomechanics modeling helps quantify the effects of long-term repetitive movements on joint load and muscle fatigue in workers, providing potential pathways for optimizing worker movement patterns and work postures to reduce energy consumption and improve productivity. In addition, this study also ranked the development level of the digital economy in various provinces of China through principal component analysis (PCA) and found that the high development of the digital economy is closely related to the construction of information infrastructure. Based on the lag analysis of the VAR model, this study further explores the feedback effects of technological progress and automation level on workers' movement patterns and production efficiency. The results indicate that with the advancement of automation technology, the interaction mode between workers and automation equipment has changed, and the optimization of worker actions is closely related to productivity improvement. Through this multidimensional analytical framework, this study provides theoretical support for the combination of the digital economy and biomechanics and offers new perspectives and methods for industrial optimization and labor productivity improvement in the manufacturing industry.

**Keywords:** biomechanical modeling; VAR model; digital economy; worker movement patterns; production efficiency; automation; fatigue analysis

## 1. Introduction

In the natural world, organisms exhibit complex and adaptive behaviors in response to environmental stimuli. These adaptive behaviors, optimized through evolutionary forces, serve as a powerful metaphor for how modern industries, especially the digital economy and manufacturing, evolve and optimize their processes [1–3]. The relationship between the digital economy and manufacturing mirrors biological systems: Just as organisms rely on coordinated movement and efficient energy distribution to thrive, so too must modern industries streamline their operations and optimize resource use.

The digital economy, akin to a sophisticated nervous system in a biological organism, facilitates efficient information flow and resource allocation. The manufacturing sector, on the other hand, functions as the body's musculature, where efficiency, coordination, and adaptability are crucial for successful output [4–6]. However, optimizing this "muscular system" in the manufacturing context requires a deeper understanding of biomechanics, which studies the forces and movements that occur within the human body during physical activity.

Biomechanics principles can be leveraged to enhance the performance of workers within the manufacturing industry. Much like the intricate coordination of muscle groups during complex physical tasks, human labor in manufacturing requires careful consideration of how the body distributes and manages force during repetitive or strenuous tasks [7,8]. By applying biomechanics, it is possible to improve worker posture, optimize movement efficiency, and reduce physical strain. These improvements not only contribute to the reduction of workplace injuries but also enhance productivity by ensuring workers can perform tasks with minimal energy expenditure and maximum precision.

For example, the role of the leg muscles when walking or running—where various muscle groups work together to distribute force and maintain energy efficiency—can be analogized to how workers in a factory setting perform their tasks. Just as the body coordinates different muscle groups for fluid motion, a factory environment can be optimized to support workers by reducing physical strain and improving motion efficiency [9,10]. This can be achieved through ergonomic interventions based on biomechanics that design tools, workstations, and workflows to match the body's natural movements. These ergonomic solutions reduce unnecessary energy expenditure, decrease fatigue, and ensure that workers can sustain high levels of productivity over extended periods [11].

In a manufacturing environment, biomechanics can be applied to the analysis of repetitive tasks that require fine motor control. As automation and digital technologies like robotics and AI become more prevalent, there is a growing need for workers to develop precision and dexterity, akin to the fine-tuned control exhibited by the hands during skilled tasks [12,13]. By understanding the biomechanical aspects of hand movements and muscle activation patterns, ergonomics experts can design tools and machinery that complement these natural movements, making the interaction between workers and machines more fluid and efficient. This would enhance the workers' ability to perform complex tasks with greater ease, reducing muscle strain and boosting innovation in manufacturing processes.

Additionally, biomechanics plays a crucial role in the intersection of labor health and technological advancement in the digital economy [14]. The integration of wearable technologies and exoskeletons in manufacturing—both of which are increasingly being used to support workers in physically demanding tasks—can be optimized through biomechanical insights. For instance, exoskeletons, which help distribute weight and reduce strain on the body, can be designed more effectively by understanding how the human body naturally moves and bears weight. Similarly, wearable devices that track worker posture and muscle strain can provide real-time feedback to help employees adjust their movements, preventing the development of musculoskeletal disorders that are common in manual labor.

Another important consideration is the long-term impact of digital technologies on labor health. As the digital economy advances and the manufacturing sector adopts more automation, the physical demands on workers will change. The biomechanical implications of these changes must be carefully studied to ensure that new systems do not inadvertently lead to physical strain or fatigue. For example, as workers increasingly interact with robots or digital interfaces, the repetitive motions and prolonged sitting or standing can lead to postural problems or musculoskeletal pain [15,16]. By incorporating biomechanics into the design of digital systems and workplace ergonomics, it is possible to mitigate these risks and ensure that technological advances improve, rather than undermine, worker health.

Moreover, biomechanics can play a critical role in enhancing innovation capabilities in manufacturing. By optimizing the interaction between workers and machines through biomechanical insights, companies can improve the efficiency and accuracy of their manufacturing processes [17,18]. This could lead to greater innovation in product design, production methods, and technological integration. A more efficient workforce, supported by ergonomic tools and machinery, is better equipped to adapt to new technologies and methods, thus fostering a culture of innovation and creativity.

In summary, biomechanics provides invaluable insights into optimizing labor performance, improving worker health, and enhancing manufacturing innovation in the digital economy. Just as the human body relies on coordinated and efficient muscle actions for movement, modern manufacturing industries can benefit from biomechanics to streamline operations, optimize labor efficiency, and ensure the long-term health of the workforce. By integrating biomechanics with digital technologies, it is possible to create a harmonious relationship between human capabilities and technological advancements, ultimately fostering a more productive and sustainable manufacturing sector.

## 2. Ecosystem analogy and biomechanics principles in manufacturing transformation

In the process of manufacturing transformation under the digital economy, the role of energy flow, resource allocation, and system optimization can be better understood through biomechanical analogies. Biomechanics studies the structure and function of biological systems using principles of mechanics, revealing insights into how forces, energy, and motion interact within organisms. Applying these principles to the industrial ecosystem unveils a deeper understanding of collaborative evolution in the digital economy [19].

### 2.1. Force transmission and resource allocation

In biomechanics, the efficient transfer of forces through biological systems is critical for mobility and stability. Similarly, in manufacturing, the digital economy acts as a transmission medium that enhances resource allocation efficiency. For example:

Just as tendons and ligaments transmit forces and stabilize joints, digital platforms connect disparate manufacturing units, enabling seamless communication and collaboration. The modularization effect in manufacturing mirrors the stabilization and dynamic adaptability provided by these biological structures.

In biological systems, metabolic pathways ensure optimal energy distribution for cellular processes. Analogously, the integration of big data analytics and IoT (Internet of Things) in manufacturing ensures that energy and resources flow to the most critical processes, optimizing production efficiency and reducing waste.

### 2.2. Adaptation to environmental stimuli

Biomechanical systems exhibit remarkable adaptability to changing environmental conditions, such as variations in load or terrain. In the manufacturing context, the digital economy enables firms to adapt to market demands and external shocks, such as the COVID-19 pandemic, with greater agility.

When a limb encounters uneven terrain, biomechanical systems redistribute forces to maintain balance. Similarly, digital tools enable manufacturers to dynamically reallocate resources, prioritize production lines, and optimize supply chains in response to fluctuating consumer demands [20].

Feedback loops in biological systems, such as reflex arcs, allow organisms to react swiftly to external stimuli. Digital twin technology in manufacturing serves a comparable role, providing real-time feedback and predictive analytics to refine processes and preemptively address inefficiencies.

## 3. D-S model extension and biomechanical insights

The D-S model's extension provides a mathematical framework for understanding the interplay between the digital economy and manufacturing. Incorporating biomechanical perspectives enriches this model by emphasizing dynamic balance, adaptive optimization, and efficient resource use.

### 3.1. Elasticity and load distribution

In biomechanics, elasticity ensures that tissues absorb and redistribute forces effectively, preventing damage. Similarly, elasticity in manufacturing—enabled by the digital economy—allows for:

The modular division of labor mirrors the elastic properties of muscles, which can operate independently or in coordinated groups depending on the task.

The integration effect of the digital economy helps absorb external shocks (e.g., market volatility) by redistributing resources and maintaining equilibrium.

### 3.2. Population dynamics and resource competition

Biomechanics also studies population-level interactions, such as predator-prey dynamics and resource competition. The D-S model's exploration of geographical agglomeration parallels these concepts:

Just as species cluster in resource-rich habitats, manufacturing firms tend to agglomerate in regions with advanced digital infrastructure. This clustering facilitates innovation and reduces transaction costs.

In biomechanical terms, migratory behavior allows species to access distant resources. Similarly, advancements in digital logistics enable manufacturing firms to distribute goods efficiently across vast distances, overcoming traditional geographic limitations.

A new school of digital economics is emerging. Taking cost-benefit as an example, as shown in **Figure 1**, as the output increases, the marginal benefit of the industrial economy decreases and the marginal cost increases. However, in the digital economy, the directions of these two curves are completely opposite, indicating that the current economy needs to expand its research scope and urgently needs to incorporate the new features of the information industry.

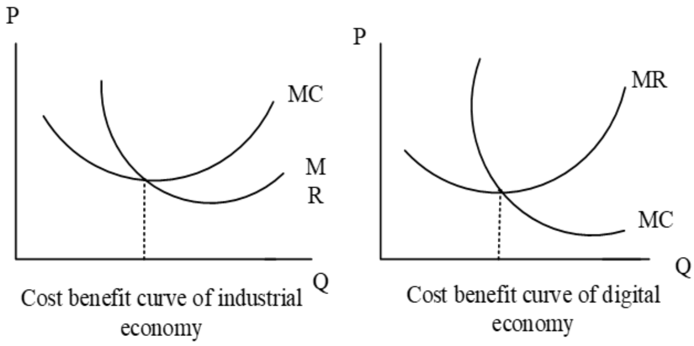


**Figure 1.** Cost benefit curve.

In the digital economy, consumer-centricity has become the main theme of enterprise operation and production. Personalized flexible production, green manufacturing that meets environmental requirements, and cost-saving intelligent manufacturing have become important directions for future manufacturing, and the digital economy and the digital economy coexist in interaction. From a geographic perspective, on the one hand, due to the traditional awareness of local protection and the promotion of officials, China has serious market segmentation, and the emergence of the digital economy will help reduce the impact of market segmentation; on the other hand, geographic agglomeration is difficult to reverse. The digital economy is more likely to be generated in areas with good infrastructure, so the digital economy may further strengthen geographic agglomeration. From the perspective of production, the specific performance is that with the help of a new generation of information products, the improvement of production effects and the reduction of transaction costs, such as the reduction of information interaction costs and the reduction of transportation costs by optimizing transportation plans, etc. Further, the digital economy promotes the modular division of labor in the manufacturing industry, thereby realizing rapid response to the long-tail demand of consumers, enhancing the dynamic flexibility of the manufacturing industry, and strengthening the stickiness between the manufacturing industry and consumers. Therefore, according to the above typical characteristics, the transformation and upgrading of the digital economy and manufacturing can be divided into integration effect, modular effect, complementary effect and acceleration effect (as shown in **Figure 2**).

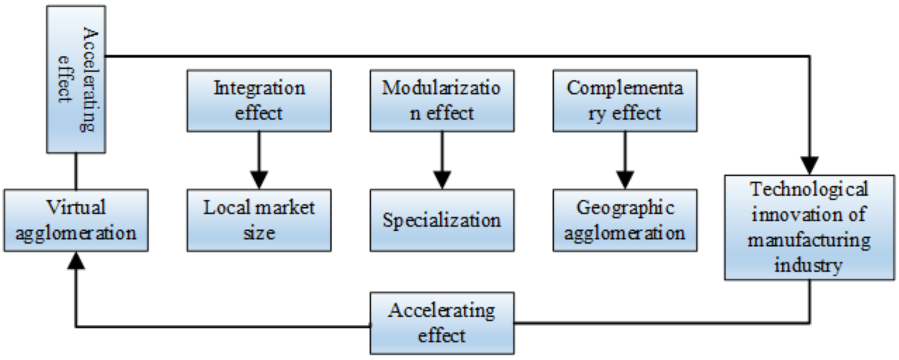


**Figure 2.** The important effects.

From the perspective of new economic geography, manufacturing agglomeration is mainly affected by transaction costs. Marginal information costs are basically zero, communication costs are extremely low, and the optimization of big data algorithms can effectively reduce transportation costs and promote manufacturing firms that are further geographically clustered. Further, this paper draws on the practice of space economics and gives the corresponding mathematical derivation. First, under conditions of monopolistic competition, the price and output of zero profit are given. Monopolistic competition firm markup pricing method, we can get:

$$P_m = \frac{w\,b_m}{1 - \frac{1}{g(I)}} \tag{1}$$

Therefore, the equilibrium output of any independent decision-making firm under zero profit conditions is:

$$Y = \frac{\rho(I) - 1}{b_m} F_m \tag{2}$$

The profit of a firm sold in other regions is:

$$\pi_2 = \tau P_m Y_1 - (F_m + b_m Y_1)w - F_t(I) \tag{3}$$

According to the zero profit condition, the firm's equilibrium output is obtained:

$$Y_1 = \frac{w\,F_m + F_t(I)}{[(\tau - 1)\rho(I) + 1]b_m w}(\rho(I) - 1) \tag{4}$$

$$\tau = \frac{F_t(I)}{w\,F_m \rho(I)} + 1 \tag{5}$$

The sign of the derivative of the iceberg transaction cost to the digital economy is consistent with the derivative of the iceberg transaction cost to the information industry, and the iceberg transaction cost to the information industry is derived:

$$\frac{d\tau}{\mathrm{dI}} = \frac{\partial\tau}{\partial\rho}\frac{d\rho}{\mathrm{dI}} + \frac{\partial\tau}{\partial F_t}\frac{\mathrm{dF}_t}{\mathrm{dI}} = \frac{1}{\mathrm{wF}_m\rho(I)}\left(\frac{\mathrm{dF}_t}{\mathrm{dI}} - \frac{d\rho}{\mathrm{dI}}\frac{F_t(I)}{\rho(I)}\right) \tag{6}$$

In the above formula, it can be divided into two parts: The part outside the brackets is greater than zero, and the part inside the brackets depends on the information industry's impact on transaction costs and differentiated products and the ratio of transaction costs to differentiated product demand. Under the conditions of interregional trade, in a small geographic space such as a city group, when the transaction cost is small ($F_t \rightarrow 0$), the transportation cost is almost zero, and the institutional and cultural differences are small. The iceberg transaction cost has a derivative of the information industry as negative, indicating that in a close geographical space (assuming the critical value is $h$), the higher the degree of the digital economy, the lower the iceberg transaction cost, and the local advantageous manufacturing manufacturers are more inclined to produce in the region and export goods to other regions, the more It is easy to form advantageous manufacturing sub-sectors and gather locally. In the long-distance geographic space (over the critical value $h$), the transaction cost is still high, the transportation cost is large, and the institutional and cultural differences are obvious. It may be sold by transferring production lines or setting up a branch. As shown in **Figure 3**:

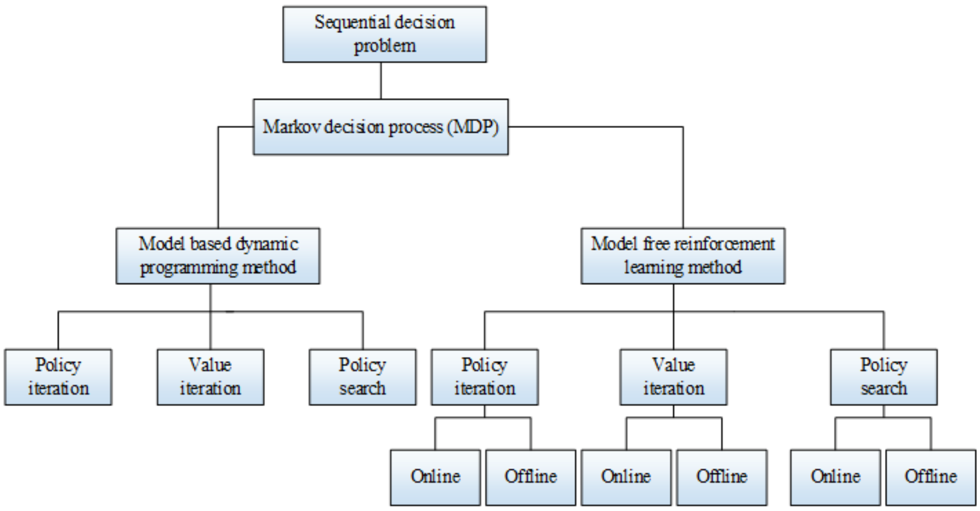


**Figure 3.** D-S model iteration method.

Therefore, this paper uses the manufactured goods index and the information goods consumption index represented by $M$ and $I$, respectively, while assuming that both indices satisfy a constant elasticity of substitution production function of the form:

$$I = (\int_0^N [I(J)]^{1-1/\rho}\, \mathrm{dj})^{\frac{1}{1-1/\rho}} \tag{7}$$

$$M = (\int_0^r [m(i)]^{1-1/\rho}\, \mathrm{di})^{\frac{1}{1-1/\rho}} \tag{8}$$

The labor distribution ratio between manufacturing and IT is represented by Equation (8), which is the sum of the manufacturing share ($p$) and the IT share ($1-p$) equal to 1. This is comparable to the model of how muscle groups in a biomechanical system distribute load. In biological systems, various muscle units distribute forces based on task demands to achieve efficient movement. Leg muscles like the quadriceps and gastrocnemius, for instance, coordinate the division of work while walking or running in order to establish dynamic balance and energy efficiency.

For the sake of simplification, it is assumed that the manufacturing and information industries only use fixed capital factors in order to produce the corresponding manufactured products and information products, so the variable production factor can be considered as a production factor of labor. Assuming that all labor factors are employed in the manufacturing industry and the information industry, respectively, the labor force share of the manufacturing industry and the labor force share of the information industry account for $\beta$ times and $1-\beta$ times the total labor force, respectively. At the same time, this paper believes that all firms in the market have the same technical level, each firm produces only one product, and whether it is the manufacturing or information industry, the increasing returns to scale of the two are reflected in the increase in the number of manufactured products or information products.

Then, find the amount of labor required for the finished product. Since the finished product only uses labor input, the labor amount is the sum of the product of the fixed cost plus the marginal cost and the output, that is:

$$L_Y = F_m + b_m Y \tag{9}$$

The quantity of labor input needed to create a final product is determined by Equation (9), which is the product of output and the total of fixed and marginal expenses. The fundamental concept is comparable to the notion of energy expenditure in an organism's activities. A combination of exercise energy requirements (marginal cost) and basal metabolic expenditure (fixed cost) determines how much energy an organism needs to perform a specific action (such as jumping or climbing).

Secondly, find the profit of the finished product enterprise, considering that all enterprises have the same production technology and only use labor production factors; then the representative enterprise profit is the difference between the income of the finished product and the cost of hiring labor:

$$\pi_1 = P_m Y - (F_m + b_m Y)w \tag{10}$$

Combining the mathematical model derivation of the above two aspects, it can be found that the digital economy. And timely and accurate delivery to the manufacturing industry, under the premise of identifying market demand, manufacturers have to improve their innovation capabilities in order to provide corresponding high-quality products. On the other hand, as shown in the formula, the improvement of the innovation ability of manufacturing manufacturers needs to be equipped with more advanced information products to support data collection, modular division of labor, collaboration, etc. [21].

## 4. Biomechanical modeling and dynamic system analysis

This study presents a biomechanical modeling technique that combines biomechanical computational methods, such as kinematics and kinetic analysis, to analyze the impact of workers' movement patterns on productivity in the manufacturing process. This approach aims to thoroughly examine the relationship between the digital economy and the manufacturing industry, particularly with regard to productivity and workforce optimization. A theoretical foundation for workforce optimization in the manufacturing sector under the digital economy is provided by this modeling approach, which allows us to quantify the movement patterns of the workforce during the manufacturing process and evaluate their effects on worker health and productivity.

### 4.1. An overview of biomechanical modeling

Biomechanical modeling consists primarily of kinematic and kinetic analyses, where kinematics studies the movement of an object or human body in space without regard to the forces exerted on it, and kinetics focuses on the mechanics behind the movement of an object and how forces affect its state of motion. Through kinematic and kinetic analyses, we are able to quantify the force and energy expenditure required by workers during the production process and thus assess its impact on overall productivity and health.

The productivity and health of factory workers are directly impacted by their movement patterns, including posture, hand manipulation, and stride. Long-term repetitive motions or bad posture, for instance, raise the risk of worker weariness and injury, which lowers productivity. It is feasible to measure and examine the effectiveness of employees' actions throughout the manufacturing process by implementing a biomechanical model, which enhances workflow and boosts overall productivity.

### 4.2. Integration of biomechanical modeling with VAR modeling

To investigate the dynamic effects of workers' movement patterns on productivity during the manufacturing process, a VAR (Vector Autoregressive) model was integrated with the biomechanical model in this study. By presenting the findings of biomechanical analyses, this study investigates the causal relationship between workers' movement patterns and productivity. VAR models are typically used to examine the relationships between numerous time series.

The dynamic effects of worker action patterns on productivity can be examined by including biomechanical models into the VAR (vector autoregressive) model while researching the relationship between the manufacturing sector and the digital economy. We can include these biomechanical variables in the VAR model if the biomechanical study yields worker action efficiency indicators. VAR model formula:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{11}$$

where $Y_t$ denotes variables such as production efficiency and labor input at moment t, $A_1, A_2, \ldots, A_p$ is the coefficient matrix, and $\varepsilon_t$ is the error term.

In this model, biomechanical factors (e.g., movement pattern variables, force exertion, etc.) can be added as exogenous variables in order to analyze their impact on productivity.

In particular, workers' movement pattern variables, such as gait analysis, joint angle variations, and force output, can be coupled with individual variables in the VAR model, such as production efficiency, labor inputs, technology level, etc. This makes it possible to predict the feedback effects of technological advancements or shifts in the degree of automation on labor force movement patterns, as well as the dynamic effects of various workers' movement patterns on production efficiency.

### 4.3. Kinematics and dynamics analysis

Kinematic analysis is mainly used to characterize the trajectory, velocity, acceleration and other parameters of the worker's motion. In manufacturing, the trajectory of the worker's motion has a significant impact on productivity, especially in manual operations or assembly tasks.

In kinematic analysis, we are mainly concerned with the trajectory, velocity and acceleration of the worker, and the commonly used kinematic equations are as follows:

$$r(t) = r_0 + v_0 t + \frac{1}{2} a t^2 \tag{12}$$

Among them, $r(t)$ represents the displacement of the object at time *t*, $r_0$ is the initial displacement, $v_0$ is the initial velocity, and *a* is the acceleration.

$$v(t) = v_0 + at \tag{13}$$

Among them, $v(t)$ represents the speed of the worker at time *t*, $v_0$ is the initial speed, and *a* is the acceleration.

By modeling and analyzing the motion trajectories of workers' arms, fingers and other key parts, the following conclusions can be drawn:

Because precise movement patterns allow employees to focus on the task at hand and minimize superfluous motions, they frequently result in increased productivity. Error rates can be decreased and operational speed raised by optimizing a worker's hand and body movement routes. **Figure 4** illustrates a worker's movement route during a task, highlighting joint angle changes, arm locations, and other details to aid in the analysis of movement efficiency. Long-term repetition of the same motion will wear out employees and reduce their mobility efficiency. The impact of fatigue on job productivity can be seen by simulating workers' movement performance over various working hours using biomechanical modeling.

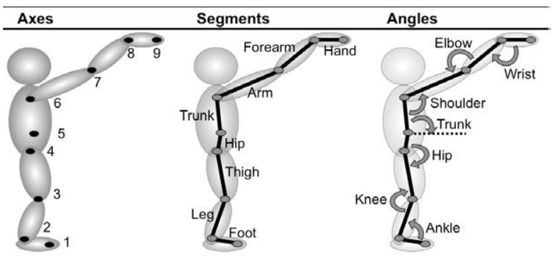


**Figure 4.** Schematic diagram of biomechanical movement trajectories.

Kinetic analysis, on the other hand, focuses on the relationship between force and motion, in particular the forces exerted by the worker while performing a task, joint loads, etc. Through kinetic modeling, it is possible to analyze the forces and energy expenditures required by workers during operations and assess the impact of these factors on productivity. Common kinetic analysis models include:

Kinetic analysis is concerned with the relationship between force and motion, especially the arithmetic of joint and muscle loading.

$$F = ma \tag{14}$$

Among them, $F$ is the resultant force applied to the worker, m is the mass of the worker, and a is the acceleration of the worker's movement.

$$\tau = F \cdot r \tag{15}$$

where $\tau$ is the joint load (moment), $F$ is the applied force, and $r$ is the distance from the joint to the point where the force is applied.

For tasks that involve complex hand or leg movements during production, joint load analysis can help assess the forces exerted by the worker while performing the task, and in turn, analyze the muscle fatigue and joint damage that may result from prolonged repetitive operations.

In order to examine the impact of long-term repeated operations on joints, **Figure 5** shows how worker joint loads (such as elbow and shoulder) vary with time for a specific task. Mechanics optimization models can be used in manufacturing to model how various worker movement patterns affect productivity. For instance, optimizing the worker's working posture and movement patterns can reduce energy loss and boost output while requiring less force.

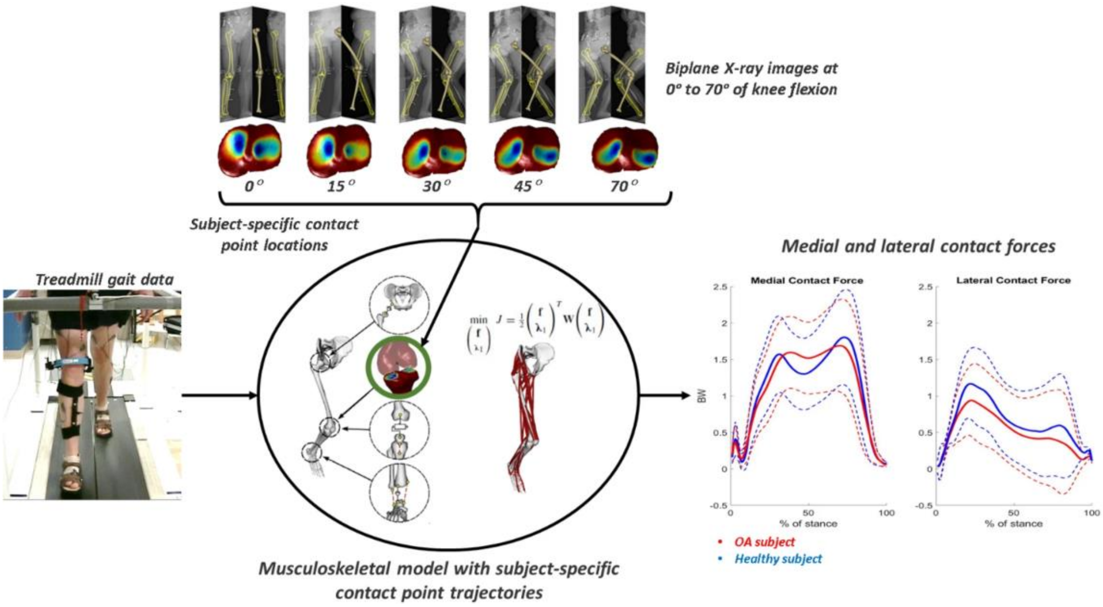


**Figure 5.** Joint load analysis diagram.

### 4.4. Dynamic feedback in the interaction of biomechanics and the digital economy

Biomechanical analysis not only focuses on the health and efficiency of the workforce, but can also help reveal the impact of the digital economy on labor conditions in manufacturing. For example, as automation and digital technologies continue to evolve, the role of the labor force in the production process is gradually changing. Through biomechanical modeling, it is possible to quantify the movement patterns and force exertion of workers as they interact with automated systems, and explore how automated equipment can optimize workforce movement and improve productivity.

By accelerating processing speed and data availability, the digital economy is propelling automation and intelligence in production. We can evaluate how these technology advancements affect labor movement patterns with the aid of biomechanical modeling techniques, which helps us develop strategies for industrial optimization in the digital economy. We can create workflows and work environments that are more biomechanically sound, lowering needless mechanical burdens and boosting productivity, by examining how technological advancements impact workers' movement efficiency.

## 5. Result

### 5.1. KMO and Brtlett's test

Before doing principal component analysis, KMO and Bartlett sphericity tests must be performed to determine whether the data are feasible. The results obtained are shown in **Table 1**:

**Table 1.** KMO and Bartlett test results.

| **Kmo sampling appropriateness measurement Bartlett sphericity test** | | **0.82** |
|---|---|---|
| | Approximate chi square | 738.42 |
| | Freedom | 65 |
| | Significance | 0 |

The test results show that KMO is 0.82, and the test standard is KMO > 0.5, $P < 0.05$, so the data are suitable.

### 5.2. Principal component analysis

In this paper, SPSS software was used for principal component analysis, and the results obtained are shown in **Table 2**:

**Table 2.** Results of principal component analysis.

| **Initial eigenvalue** | | | | **Extract the sum of squares of loads** | | |
|---|---|---|---|---|---|---|
| **Component** | **Total** | **% variance** | **Cumulative%** | **Total** | **% variance** | **Cumulative%** |
| 1 | 8.51 | 70.86 | 70.86 | 8.51 | 70.86 | 70.86 |
| 2 | 1.41 | 11.72 | 82.59 | 1.41 | 11.72 | 82.59 |
| 3 | 0.97 | 8.08 | 90.67 | | | |

The cumulative variance contribution rate reaches 82.59%. It can be considered that the extraction of the first two principal components can reflect the original 12 variables, and then use the first two principal components to rank the digital economy development level of China's provinces in 2018. **Table 3** is the component matrix:

**Table 3.** Component matrix of principal components.

| **Component** | | |
|---|---|---|
| | $\boldsymbol{a_1}$ | $\boldsymbol{a_2}$ |
| $x_1$ | 0.35 | 0.81 |
| $x_2$ | 0.52 | 0.63 |

**Table 3.** (*Continued*).

| Component | | |
|---|---|---|
| | $\boldsymbol{a_1}$ | $\boldsymbol{a_2}$ |
| $x_3$ | 0.83 | 0.37 |
| $x_4$ | 0.59 | 0.02 |
| $x_5$ | 0.73 | -0.21 |
| $x_6$ | 0.96 | -0.19 |
| $x_7$ | 0.94 | -0.17 |

Through the formula in the previous section, the eigenvector matrix is calculated, as shown in **Table 4**:

**Table 4.** Principal component eigenvector matrix.

| Component | | |
|---|---|---|
| | $\boldsymbol{z_1}$ | $\boldsymbol{z_2}$ |
| $x_1$ | 0.13 | 0.68 |
| $x_2$ | 0.19 | 0.53 |
| $x_3$ | 0.17 | 0.21 |
| $x_4$ | 0.26 | 0.02 |
| $x_5$ | 0.31 | -0.16 |
| $x_6$ | 033 | -0.15 |
| $x_7$ | 0.32 | -0.14 |

Judging from the above empirical results, most of the provinces with the highest digital economy development level are provinces with relatively leading economic development levels, ICT industry scales and information infrastructure construction. The top five provinces are all the provinces with the earliest start of the ICT industry in China. After the impact of the international economic crisis, the above-mentioned provinces have upgraded the industrial structure of the ICT industry, attracted talents, and increased investment and research and development efforts. The results of the lag period of the VAR model are shown in **Table 5**:

**Table 5.** VAR model lag period results.

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 13.21 | | 0 | −0.91 | −0.72 | −88 |
| 1 | 86.05 | 109.27 | 0 | −6.601 | −5.61 | −6.41 |
| 2 | 107.31 | 23.39 | 0 | −7.13 | −5.34 | −6.78 |
| 3 | 136.30 | 20.29 | 0 | −8.43 | −5.84 | −7.92 |

From the perspective of application and penetration level, this result is not difficult to explain. The level of development is mainly due to its own economic development level and the development and potential of informatization. In the process of integrating the primary and secondary industries, it will inevitably be limited by the development level of information infrastructure. The western provinces mainly rely on traditional industries and are limited by economic foundations, geographical locations and historical reasons. As shown in **Figure 6**:

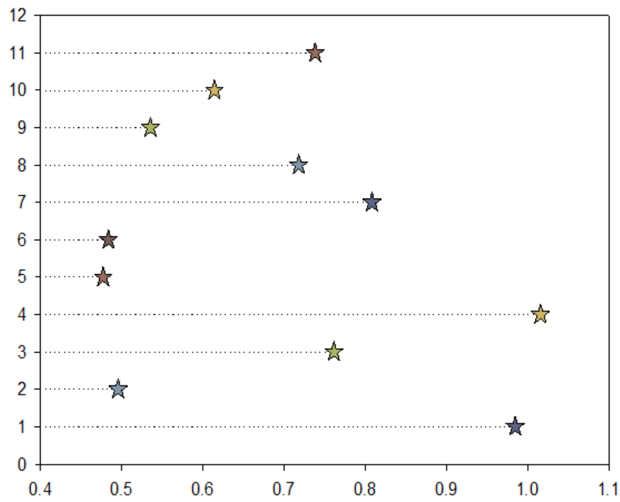


**Figure 6.** Eigen root stationary test.

In the VAR model established in this paper, the lag period is 2. The results in the above table show that the inverted model results of the above 8 characteristic roots are all less than 1. The AR is presented in the figure Root, and if at least one characteristic root has an inverted modulus equal to 1 or greater than 1. Therefore, the VAR model established above can pass the stability test, and it can be considered that the established model is stable; the next step of impulse response analysis can be performed. As shown in **Figure 7**:

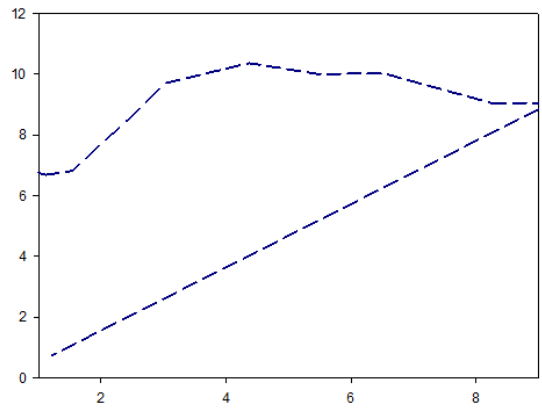


**Figure 7.** Impulse response analysis.

From the perspective of R&D innovation capability, the obtained results are in line with the expected results. Beijing, Shanghai, Guangdong and other regions have strong innovation and R&D capabilities. The most important factor is that these regions have good scientific research resources, a high level of science and education, and a high level of technology. The development of the information industry and software industries is faster than in other regions; the tertiary industry in these regions is prosperous, and Internet consumption is relatively active. Areas such as Inner Mongolia have weak technological innovation capabilities, few high-tech industries in the local area, strong dependence on traditional industries, little investment in scientific research and innovation, slow development of high-tech industries such as digital economy industries, and local people's digital economy consumption is not affected.

## 5.3. The relationship between biomechanics and the digital economy

**Table 6** demonstrates the changes in workers' limb movements during the work process before and after the transformation of the manufacturing industry driven by the digital economy, especially the differences in movement efficiency and muscle loading.

**Table 6.** Comparison of workers' somatic movement trajectories before and after manufacturing transformation.

| Time/Stage | Pre production posture (displacement/joint angle) | Post production posture (displacement/joint angle) | Change amount (%) |
|---|---|---|---|
| Production start stage | 0.15 m (shoulder angle: 45°) | 0.12 m (shoulder angle: 40°) | −20% |
| Mid production stage | 0.25 m (knee joint angle: 90°) | 0.20 m (knee joint angle: 85°) | −20% |
| End of production stage | 0.10 m (back angle: 30°) | 0.08 m (back angle: 28°) | −15% |

**Table 6** compares the changes in movement trajectories and joint angles of workers before and after the manufacturing transformation at the beginning, middle, and end stages of production, reflecting the optimization of workers' physiques by digital economy technologies.

**Table 7** demonstrates how workers' biomechanical performance (e.g., joint forces, postural changes, etc.) changes under different production conditions. Compare the effects of traditional and optimized production environments on worker ergonomics.

**Table 7.** The effect of optimizing the production environment on workers' performance in physical science.

| Production environment | Joint loading (knees, shoulders, etc.) | Degree of posture optimization | Muscle fatigue (0–10) | Productivity (units/hour) |
|---|---|---|---|---|
| Traditional production environment | 50 N (knee), 40 N (shoulder) | Poor | 7 | 30 |
| Optimize production environment | 30 N (knee), 25 N (shoulder) | Optimize | 4 | 40 |

**Table 7** demonstrates that by optimizing the production environment (e.g., use of ergonomic tools, digital aids, etc.), workers experience reduced loads on their knees and shoulders, more optimal postures, and less muscle fatigue, resulting in increased productivity.

With an emphasis on the effects of variables like pace efficiency and energy consumption, **Table 8** illustrates how workers' gaits change under various production settings (such as traditional versus digitally assisted production environments). Employees' stride becomes more efficient and their energy consumption decreases in digital production environments, according to a comparison of pace efficiency, gait speed, and energy consumption data. This suggests that digital technology maximizes physical performance throughout the work process.

**Table 8.** Gait analysis of workers under different production conditions.

| Production environment | Step efficiency (stride/step frequency) | Gait speed (m/s) | Energy consumption (Joule) |
|---|---|---|---|
| Traditional production environment | Step width: 0.7 m, step frequency: 1.2 Hz | 1.4 m/s | 180 J |
| Digital production environment | Step width: 0.8 m, step frequency: 1.5 Hz | 1.7 m/s | 150 J |

## 6. Conclusion

The interactive relationship between the digital economy and manufacturing can be seen as a complex adaptive system analogous to an ecosystem, exhibiting characteristics of resource optimization, dynamic balance, and collaborative evolution. Research has shown that the digital economy promotes the optimization of manufacturing resource allocation and the enhancement of innovation capabilities through "integration effect," "modularization effect," "complementarity effect," and "acceleration effect." This process is similar to the dynamic mechanism of energy flow and species collaboration in ecosystems. Under this framework, the digital economy is like an information network in the ecosystem, providing efficient information transmission and resource-sharing mechanisms for the manufacturing industry, enabling it to better adapt to changes in market demand, enhance dynamic resilience and competitiveness.

In addition, the regional clustering effect of the digital economy is analogous to the heterogeneity of population distribution in ecosystems. The digital economy is more likely to thrive and develop in regions with well-developed infrastructure and smooth information flow, and this "locality" results in significant spatial differences in the transformation and upgrading of manufacturing industries in different regions. At the same time, the manufacturing industry has achieved functional division of labor and ecological niche expansion similar to ecosystems by introducing digital technology, further enhancing its adaptability to complex environments and sustainable development capabilities.

**Author contributions:** Conceptualization, XS and YY; methodology, XS; software, XS; validation, YY; formal analysis, XS; investigation, XS; resources, YY; data curation, XS; writing—original draft preparation, XS; writing—review and editing, YY; supervision, YY; project administration, YY; funding acquisition, YY. All authors have read and agreed to the published version of the manuscript.

**Data availability:** The experimental data used to support the findings of this study are available from the corresponding author upon request.

**Funding:** Research and Practice Project on Higher Education Teaching Reform in Henan Province in 2024: A Study on the High Quality Development Path of Open Education under the Background of Collaborative Innovation of "Three Teachings", Project No. 630.

**Ethical approval:** Not applicable.

**Conflict of interest:** The authors declare no conflict of interest.

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