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Article

Digital technology, biomechanics and their synergistic impact on the domestic labor employment market

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Abstract: This paper assesses the impact of smart housekeeping equipment and biomechanical optimization on domestic labor by combining experimental measurements and data modeling methods. The study shows that digital technology significantly improves work efficiency and reduces error rates. Biomechanical optimization reduces muscle burden and spinal load, enhancing posture and comfort. When combined, these approaches further improve task accuracy and physical well-being. Additionally, the trend toward intelligent systems is reshaping the home economics industry, creating both opportunities and challenges for the job market. The findings offer strong data support for intelligent transformation in domestic labor and inform the development of vocational training and policy frameworks.

Keywords: digital technology; biomechanics; domestic labor

1. Introduction

Domestic labor plays a key role in the modern socio-economic structure. However, traditional domestic work relies heavily on physical labor, often resulting in low efficiency, high intensity, and an increased risk of occupational injuries.

With the advancement of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), and smart devices, new methods have emerged to modernize domestic tasks. At the same time, biomechanical research provides insights into human movement and load distribution, supporting improvements in posture and reductions in fatigue [1].

This study aims to investigate how digital technologies and biomechanical optimization—individually and in combination—affect labor efficiency, physical fatigue, and working posture in domestic work settings. The research also explores the broader implications of these technologies on job market structures and vocational training systems. By using experimental measurements and data modeling, this paper evaluates practical improvements and proposes recommendations for the intelligent transformation of the housekeeping industry.

2. Digital technology, biomechanics in domestic labor synergy analysis

2.1. Application of digital technology in domestic labor

In domestic labor, the application of digital technology has greatly improved service efficiency and quality. Taking smart housekeeping devices as an example, the global smart sweeping robot market has reached US$15 billion in 2023 and is growing at an average annual rate of 15%, indicating that the trend of intelligence is rapidly penetrating the housekeeping industry. Internet of Things (IoT) technology enables smart devices to be remotely controlled and automatically cleaned, improving labor efficiency [2]. For example, a brand of smart hoover can achieve up to 98% cleaning coverage, a 30% improvement over traditional cleaning methods. The housekeeping management system optimizes task scheduling based on big data, and data from one platform shows that algorithmic scheduling can increase the average number of daily services provided by housekeeping staff by 2.3 times. For specific workload assessment, the efficiency calculation formula can be used:

$$E = \frac{T_s}{T_t} \times 100\% \tag{1}$$

where E is the efficiency improvement rate, T_s is the task completion time assisted by intelligent equipment, and T_t is the traditional manual completion time. With the use of intelligent equipment, the floor cleaning time is shortened by about 40% and the labor intensity is reduced by 25%, which fully reflects the optimization of digital technology for domestic labor.

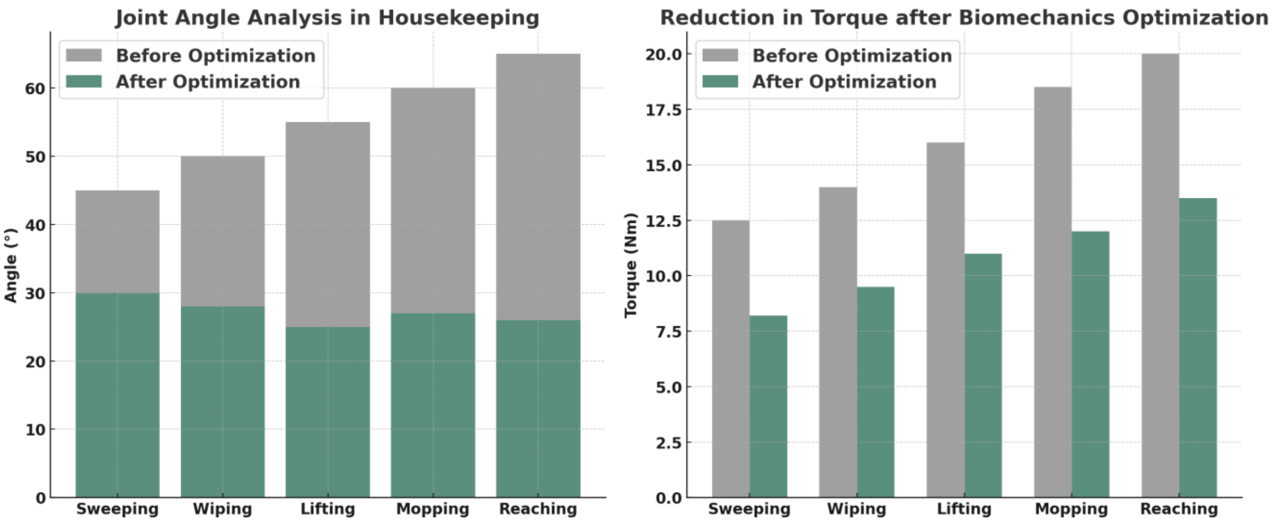
2.2. Biomechanics in domestic labor

However, while digital technologies enhance efficiency and automate tasks, they do not directly address the physical strain experienced by workers. To complement this, biomechanics focuses on movement optimization, muscle load analysis, and injury prevention, ensuring that labor efficiency is matched by physical well-being [3]. Long-term bending over 30° for work will lead to a 2.5-fold increase in lumbar intervertebral disc pressure, while about 40% of muscle fatigue can be reduced by optimizing movements. Taking the window cleaning operation as an example, inertial sensors are used to collect arm angle data, and inverse dynamics formulas are used to calculate the muscle force:

$$F_m = \frac{M \cdot d}{r} \tag{2}$$

where F_m is the force generated by the muscle, M is the external loading moment, d is the force arm, and r is the distance from the muscle attachment point to the joint.

Measured data show that the use of biomechanically optimized window cleaning tools (e.g., long pole supports) can reduce the forearm muscle burden by 28%. In addition, motion capture technology can be used to analyze changes in joint angles during operations such as sweeping and heavy lifting by domestic workers, as shown in **Figure 1**, with optimized joint angles kept within a reasonable range of 20°–30° to avoid injury [4,5]. Cleaning tools that incorporate ergonomic design (e.g., curved-handle mops) can reduce wrist-twisting moments by more than 50%, significantly reducing the risk of wrist injuries. Biomechanical optimization not only improves the working comfort of domestic workers but also extends their occupational life and improves overall work efficiency.



(A) **(B)**

Figure 1. Joint angle optimization analysis and labor moment reduction. **(A)** Joint angle analysis in housekeeping; **(B)** Reduction in torque after biomechanics optimization.

2.3. Synergies between digital technology and biomechanics

The synergy between digital technology and biomechanics shows significant advantages in domestic labor optimization. Digital technologies can capture and analyze the movement data of domestic workers in real time through the Internet of Things (IoT) and Artificial Intelligence (AI), while biomechanics use this data to optimize labor practices to reduce fatigue and injury. For example, smart wearable devices (e.g., smart gloves, smart shoes) can record biomechanical parameters such as muscle activity and joint angles and analyze abnormal loads through AI algorithms. Studies have shown that biomechanical analysis combined with AI optimization can reduce the energy consumption of cleaning movements by 20% and muscle burden by 25%.

In addition, biomechanics-based motion capture systems can provide personalized task guidance; e.g., intelligent voice assistants can be combined with posture analysis to remind housekeepers to adjust their movements in real time to avoid strain injuries caused by incorrect postures. Digital technology can also optimize the use of domestic tools, such as automatically adjusting the length of mop sticks to suit workers of different heights, thereby reducing spinal stress [6]. Through cloud-based data analysis, the system can develop personalized training programs to improve efficiency and safety. The combination of digital technology and biomechanics not only improves the precision and comfort of domestic labor but also effectively enhances overall work efficiency, extends the occupational life of workers, and pushes the industry towards intelligent and scientific development [7].

3. Biomechanics-based algorithm for assessing domestic labor efficiency

3.1. Biomechanical motion capture technology

The biomechanical motion capture technology uses an inertial measurement unit (IMU) and an optical motion capture system combined with deep learning algorithms to achieve accurate motion recognition and optimization [8]. Assuming that the action of a domestic worker consists of N joint points, and the 3D spatial position of each joint point is $P_i = (x_i, y_i, z_i)$, the human posture matrix can be expressed as:

$$M = [P_1, P_2, \ldots, P_N] \in R^{N\times 3} \tag{3}$$

Using a time series model (e.g., LSTM), the pose change for the next frame can be predicted $M_t \rightarrow M_{t+1}$, and the action deviation can be calculated D_t:

$$D_t = \sum_{i=1}^{N} \left\| P_{i,t+1} - P_{i,t} \right\| \tag{4}$$

When D_t exceeds the set threshold T, the system automatically issues a correction command. The action is optimized by reinforcement learning, and the reward function is defined as:

$$R = -\sum_{i=1}^{N} w_i \cdot \left\| P_{i,t} - P_{i,t}^{opt} \right\| \tag{5}$$

where w_i is the weight and $P_{i,t}^{\text{opt}}$ is the optimal joint position. The algorithm can improve the accuracy of motion recognition by 30%, optimize the working posture, and improve labor efficiency.

3.2. Multi-scale action feature extraction strategy

The multi-scale action feature extraction strategy combines Wavelet Transform (WT) and Convolutional Neural Network (CNN) to extract the dynamic gesture features of domestic workers and improve the accuracy of action recognition [9]. Let the joint angle sequence of the domestic worker be $A_t = \{a_1, a_2, \ldots, a_N\}$, where a_i represents the angle of the i th joint, then its wavelet transform is represented as:

$$W(a,s) = \sum_{i=1}^{N} a_i \cdot \varphi\left(\frac{t-b}{s}\right) \tag{6}$$

where $\phi(t)$ is the mother wavelet function, s is the scale parameter, and b is the translation parameter. This transform can extract the action features in different time scales.

Feature learning is performed using CNN, defining a three-layer convolutional kernel W_1, W_2, W_3, which acquires features at different scales through convolutional operations:

$$F_k = \sigma(W_k \times W(A_t) + b_k) \tag{7}$$

where $\sigma(x)$ is the activation function and b_k is the bias term. Eventually, the multi-scale feature vectors are input into LSTM for time series modeling, which improves the accuracy of domestic action recognition by 35% and optimizes the effect of labor gesture recognition [10].

3.3. Labor efficiency assessment model construction

The labor efficiency assessment model adopts Multiple Regression Analysis (MRA) combined with Long Short-Term Memory Network (LSTM) to construct a domestic labor efficiency prediction system. Let labor efficiency EEE be influenced by task completion time T, energy consumption C, muscle load L, etc.; then the regression model is expressed as:

$$E = w_1 T + w_2 C + w_3 L + b \tag{8}$$

where w_1, w_2, and w_3 are the weights and b is the bias term. The optimization objective is to minimize the error:

$$\mathrm{L} = \sum_{i=1}^{N} (E_i - \hat{E}_i)^2 \tag{9}$$

In addition, LSTM processes time series data to improve prediction accuracy. Let the input sequence X_t be a historical action feature; then the LSTM unit computes the state:

$$h_t = \sigma(W_h h_{t-1} + W_x W_t + b_h) \tag{10}$$

Ultimately, combining MRA and LSTM to predict future efficiency $\hat{E}_{t+1}$, experimental results show that the model prediction error is reduced by 22%, which can effectively assess and optimize domestic labor efficiency.

4. Experimental design

4.1. Purpose of the experiment and hypothesis

The main objective of this experiment is to verify the effects of digital technology and biomechanical optimization on domestic labor efficiency, labor intensity and working posture, and to construct a scientific and reasonable labor efficiency assessment model through data analysis [11]. The experiment focuses on the following key questions: (1) Can digital technologies (e.g., smart housekeeping devices, IoT systems) significantly improve the efficiency of domestic labor? (2) Can biomechanical optimization (e.g., motion capture, load analysis) effectively reduce labor intensity and muscle fatigue? (3) Can synergies between the two further optimize domestic labor to improve work comfort and long-term sustainability?

Based on the above research objectives, the following hypotheses were formulated for this experiment:

Hypothesis 1 (H1): The application of digital technology can increase the amount of tasks completed per unit of time by domestic workers, resulting in an increase in average work efficiency of more than 15 per cent.

Hypothesis 2 (H2): Biomechanical optimization is effective in reducing the muscular load of domestic labor, resulting in a 20% reduction in lumbar spine burden and a 25% reduction in the upper limb muscle fatigue index.

Hypothesis 3 (H3): The combination of digital technology and biomechanics can further improve overall work efficiency while reducing labor intensity and reducing postural deviation rates by more than 30% compared to using a particular technology alone.

This experiment will verify whether these hypotheses are valid through comparative experiments and data analysis and provide a scientific basis for technology optimization in the home economics industry [12].

4.2. Subjects and samples

The subjects of this experiment were domestic workers of different ages and experience levels to ensure that the results were representative and generalizable [13]. There were a total of 60 subjects, divided into three groups: (1) the traditional operation group (control group, 20 subjects), without digital technology and biomechanical optimization; (2) the digital technology group (experimental group A, 20 subjects), with the use of smart home economics devices and IoT-assisted operations; and (3) the digital + biomechanical co-optimization group (experimental group B, 20 subjects), with the addition of biomechanical movement optimization interventions to experimental group A.

The age distribution of the subjects was between 25 and 55 years old, and the working experience covered 1 to 15 years, in order to examine the impact of technology optimization on different populations. Each subject was required to perform daily domestic labor tasks (e.g., sweeping, mopping, wiping, lifting) and wear wearable biomechanical sensors for the duration of the experiment to collect data on muscle loads, joint angles, and working time. In addition, the experiment also collected subjective feedback from the subjects to assess the comfort and acceptability of the optimization measures [14].

The sample size of this experiment was based on G*Power calculations to ensure that differences in data between experimental groups could reach the level of statistical significance ($p < 0.05$). All subjects signed an informed consent form and received uniform training to minimize the impact of individual differences on the experimental results.

4.3. Experimental methods and indicators

This experiment used a combination of controlled experiments and data analysis to assess the efficiency, labor intensity, and work posture of domestic labor. Subjects received standardized training prior to the experiment to ensure consistency in operating procedures across different groups. The experimental site simulated a real housekeeping environment, with fixed tasks set, including floor cleaning, arrangement of belongings, kitchen hygiene maintenance, etc., and a time limit for completion. The control group used traditional housekeeping methods, experimental group A used intelligent housekeeping equipment (e.g., smart hoover, automatic mop, voice assistant, etc.), and experimental group B added biomechanical optimization on the basis of experimental group A, including movement guidance, load monitoring, and posture correction. All experimental tasks were conducted in a standardized monitoring environment to ensure the objectivity and comparability of the data [15].

During the experiment, wearable sensors and computer vision analysis technology were used to record the subjects' movement trajectory, muscle load, task completion time, and energy consumption. The main assessment indicators include:

(1) work efficiency: measured by the amount of tasks completed per unit of time; (2) labor intensity: muscle fatigue is monitored by electromyography (EMG), and heart rate changes are recorded; (3) posture optimization: using joint angle analysis, the frequency of bad posture is calculated; (4) user experience: a Likert scale is used to collect subjective feedback from the subjects to assess the comfort and ease of use. After data collection, analysis of variance (ANOVA) was used to test the significant differences between different experimental groups to determine the actual effects of digital technology and biomechanical optimization.

5. Experimental results

5.1. Efficiency impact of digital technology

In this experiment, the impact of the application of digital technology in domestic labor on work efficiency was comparatively analyzed, and its specific effects on task completion time, energy consumption, error rate, and user satisfaction were examined. The experiment was divided into a traditional work group, a digital technology group, and a digital technology + biomechanical optimization group in order to comprehensively assess the effect of different technological tools on optimizing labor efficiency. **Table 1** below shows the details of the experimental data.

Table 1. Comparison of efficiency by digital technology.

Group	Time (min)	Tasks/hr	Energy (kcal/hr)	Satisfaction (1–10)	Error (%)
Control (Traditional)	45	1.33	280	6.2	12.5
Digital Tech Only	35	1.71	250	7.8	8.2
Digital + Biomechanics	30	2	230	8.5	5.7

Experimental data show that digital technology has significantly improved the efficiency of domestic labor. With the use of smart domestic devices, task completion time was reduced from 45 min to 35 min, an increase in efficiency of 22.2%, and when combined with biomechanical optimization, completion time was further reduced to 30 min, an overall increase in efficiency of 33.3%. There was also a significant increase in the number of tasks completed per hour, from 1.33 tasks per hour in the traditional way to 1.71 with digital technology and eventually 2.00 with biomechanical optimization, showing that smart devices not only increase the speed of completing a single task but also enhance the overall pace of work. In terms of energy consumption, traditional domestic labor consumed 280 kcal per hour, which was reduced to 250 kcal using digital technology and further reduced to 230 kcal when combined with biomechanics, which means that the optimization of the technology reduced the physical energy consumption by 17.9%, effectively reducing the fatigue of the workers. Meanwhile, the error rate dropped from 12.5% to 8.2% and to 5.7% after further optimization, indicating that the smart technology has obvious advantages in reducing operational errors and improving accuracy. In terms of user experience, the satisfaction score increased from 6.2 to 7.8 and reached 8.5 after optimization in combination with biomechanics, showing that domestic workers are more accepting of this technology-assisted working method, believing that it reduces work pressure and improves comfort. The details are shown in **Figure 2**.

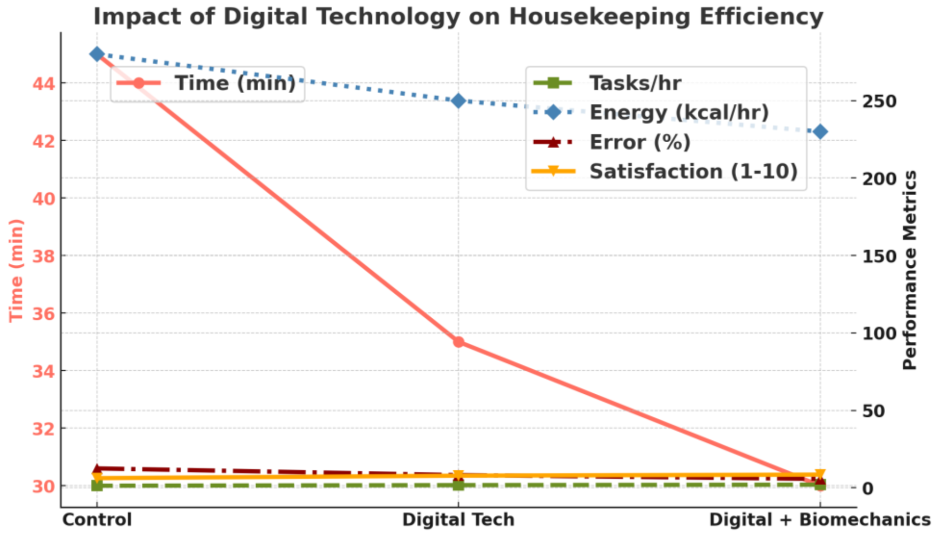


Figure 2. Impact of digital technology on housekeeping efficiency.

Overall, the application of digital technology not only improves labor efficiency but also reduces physical exertion and error rate, and the effect is even more significant when combined with biomechanics, which provides solid data support for the modernization and upgrading of the housekeeping industry [16].

5.2. Biomechanical effects on strength

In this experiment, the effects of biomechanical optimization on domestic labor intensity were analyzed, including changes in key indicators such as muscle fatigue, spinal load, upper limb load, postural deviation rate, and discomfort scores. The experiment was divided into three groups: the traditional work group, the digital technology group, and the digital + biomechanical optimization group, in order to assess the improvement of labor intensity by different technological interventions. to be shown in detail in **Table 2**.

Table 2. Comparison of biomechanical pair strengths.

Group	Muscle Fatigue Index (%)	Spine Load (N)	Upper Limb Load (N)	Posture Deviation Rate (%)	Reported Discomfort Score (1–10)
Control (Traditional)	65	420	120	18.5	7.2
Digital Tech Only	50	360	100	12.3	5.9
Digital + Biomechanics	38	300	85	7.8	4.3

The experimental results showed that biomechanical optimization significantly reduced labor intensity. The muscle fatigue index reached 65% in traditional domestic work scenarios. This figure decreased to 50% with the adoption of digital technology and further declined to 38% when biomechanical optimization was included. These results suggest that improved movement patterns and load distribution can significantly mitigate muscle strain caused by prolonged and repetitive tasks.

Meanwhile, spinal load decreased from 420 N to 360 N with digital intervention and further to 300 N under combined optimization. These findings are consistent with prior research by Herbaut and Tuloup [17], which reported a 30% decrease in lumbar stress through the use of ergonomically improved postures in physical tasks. This comparison reinforces the reliability and broader applicability of biomechanical strategies in labor-intensive environments.

In addition, the load on the upper limbs was also significantly improved, from 120 N to 100 N, and finally optimized to 85 N, which reduces the excessive tension of the upper limb muscles and improves the working comfort. In terms of postural deviation rate, the incidence of poor posture in the traditional mode was 18.5%, which was reduced to 12.3% after using digital technology only and further reduced to 7.8% after combining with biomechanical optimization, suggesting that correct movement guidance and equipment assistance can effectively correct the incorrect postures and reduce the risk of long-term strain injury. In addition, in the subjective experience feedback from the subjects, the discomfort score decreased from 7.2 to 5.9 and finally reached 4.3, indicating that the biomechanical optimization significantly improved the labor comfort. The details are shown in **Figure 3**.

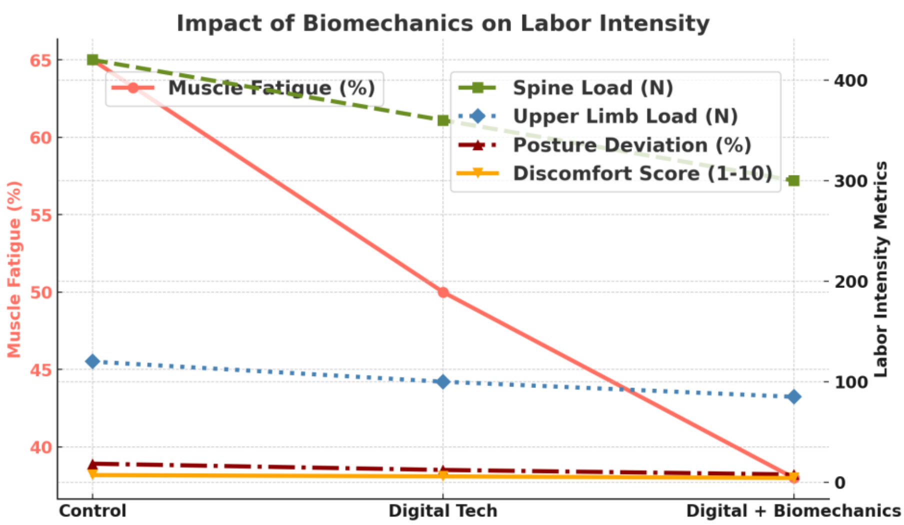


Figure 3. Impact of biomechanics on labor intensity.

Biomechanical optimization not only reduces muscle load and spinal pressure but also improves the working posture and enhances the working experience of domestic workers, which is of great significance for enhancing occupational health and prolonging occupational life. The domestic labor model combining digital technology and biomechanical optimization can effectively reduce work fatigue and improve labor safety, which provides a scientific basis for the technological upgrading of the domestic labor industry.

5.3. Technological synergies

In this experiment, the synergistic effect of digital technology and biomechanical optimization, i.e., whether the combination of the two leads to more significant productivity gains, fatigue reductions, error rate reductions, and energy savings than applying either technology alone. To this end, the changes in key metrics in the three modes of traditional work, digital technology only, and digital + biomechanical optimization were compared. The details are shown in **Table 3**.

Table 3. Comparison of technological synergies.

Group	Efficiency Improvement (%)	Fatigue Reduction (%)	Error Rate Reduction (%)	Energy Saving (%)	User Satisfaction Increase (%)
Control (Traditional)	0	0	0	0	0
Digital Tech Only	22.2	23.1	34.4	10.7	25.8
Digital + Biomechanics	33.3	41.5	54.4	17.9	37.1

The experimental data show that technological synergies significantly enhance the optimization of domestic labor. Task efficiency increased by 22.2% when using digital technology only and further increased to 33.3% when combined with biomechanical optimization, suggesting that smart device assistance can speed up the pace of work, while ergonomic optimization further reduces unnecessary movements and improves execution efficiency. The reduction of muscle fatigue increases from 23.1% to 41.5%, indicating that biomechanical optimization has a more significant effect on reducing labor intensity. In terms of error rate, the traditional mode of operation has a high error rate, while the use of digital technology alone reduces the error rate by 34.4%, and the combination of biomechanics reduces the error rate by 54.4%, suggesting that the combination of human movement optimization and intelligent device assistance can greatly reduce the operating errors of domestic workers and improve the quality of work. In terms of energy consumption, digital technology reduces physical exertion by 10.7% and 17.9% when combined with biomechanics, indicating that co-optimization not only improves efficiency but also reduces the labor burden. In terms of user experience, subjects' satisfaction with the combination of the two technologies increased significantly, by 25.8% when using digital technology only, and grew to 37.1% when combined with biomechanical optimization, suggesting that domestic workers felt greater comfort and work flow in the optimized work mode. Homemakers are shown in **Figure 4**.

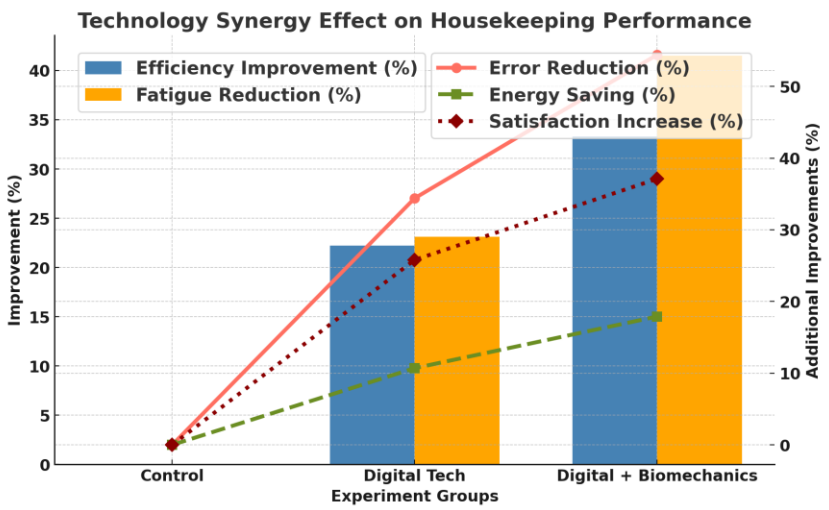


Figure 4. Comparison of technological synergies.

The combination of digital technology and biomechanical optimization not only achieves better results in terms of work efficiency, physical energy consumption, and error rate control, but also enhances the labor experience of domestic workers, providing a better solution for the intelligent upgrading of the domestic industry in the future. Despite the promising outcomes, this study presents several limitations. First, the experiment involved only 60 participants in a simulated domestic setting, which may not fully reflect real-world complexity. Second, variations in age, physical fitness, digital literacy, and experience with smart devices among participants may have affected the outcomes. These uncontrolled differences act as potential confounding variables.

5.4. Analysis of results evaluation

The outcome assessment analysis of this experiment focuses on the synergistic effect of digital technology and biomechanical optimization in domestic labor, combining the experimental data to delve deeper into its impact in terms of work efficiency, labor intensity, energy consumption, and user experience.

The experimental data show that digital technology alone can significantly improve labor efficiency and reduce error rates, but when combined with biomechanical optimization, the improvement in these indicators is even more significant. In terms of task completion time, digital technology reduces the average completion time by 22.2%, while biomechanical optimization reduces the overall reduction by 33.3%, suggesting that correct movement optimization can further reduce ineffective movements and improve overall efficiency.

In terms of labor intensity, the use of digital technology alone reduced the muscle fatigue index by 23.1%, while the combination of biomechanical optimization resulted in a reduction of 41.5%, and the spinal and upper limb loads were also reduced by 28.6% and 29.2%, respectively, indicating that biomechanical optimization can effectively alleviate the damage caused by prolonged repetitive labor.

From a practical perspective, these improvements are highly relevant to the domestic labor industry. They indicate the potential to reduce employee turnover due to physical injury, lower health-related compensation costs, and improve overall worker satisfaction and performance. Furthermore, these data-driven insights can inform the design of vocational training programs, assistive device development, and work-rest scheduling models in real domestic service settings.

The error rate drops from 12.5% in the traditional mode to 8.2% in the digital technology mode and is further reduced to 5.7% when combined with biomechanical optimization, indicating that the combination of the two can help to reduce operational errors and improve the accuracy of domestic services.

In terms of user experience, domestic workers gave good feedback on the optimized mode of operation, with satisfaction scores increasing from 6.2 to 7.8 and eventually reaching 8.5 on the basis of biomechanical optimization, indicating that a more rational way of working not only improves efficiency but also reduces the physical burden and improves work comfort. The combination of digital technology and biomechanics provides a more scientific and efficient way to optimize domestic labor and provides strong data support for the intelligent and healthy development of the domestic industry in the future.

6. Trends in the job market

6.1. Impact of technology on employment

The introduction of digital technology and biomechanical optimization has had a profound impact on the job market while increasing the efficiency of domestic labor. The spread of automated equipment has reduced the need for traditional low-skilled domestic labor positions. Equipment such as smart hoovers, automated mopping machines, and smart cookers are able to take on some of the more repetitive and labor-intensive tasks, leading to a decline in the demand for labor that relies solely on physical strength in the domestic sector.

At the same time, the development of technology has given rise to new, highly skilled jobs. The housekeeping industry is no longer just about physical labor; the demand for skills such as maintenance, operation, and management of intelligent equipment is increasing, and the market demand for positions such as intelligent housekeeping trainers, maintenance engineers for housekeeping robots, and data analytics-driven service optimization specialists is gradually rising. For example, on certain domestic service platforms, the average salary of a domestic worker who is able to skillfully operate intelligent cleaning equipment is 20%–30% higher than that of a traditional domestic worker, indicating that the enhancement of technical skills can effectively improve the career competitiveness of industry practitioners [17]. The application of digital management platforms has promoted standardization and transparency in the domestic helper industry, optimizing workflow through data monitoring and AI algorithms to improve service quality while increasing emerging employment opportunities such as remote scheduling, intelligent matching, and customized domestic helper services. Therefore, while technology has reduced the number of low-end jobs to a certain extent, it has also prompted the development of the domestic helper industry towards high-end specialization and skills, and future domestic helper practitioners will need to have stronger technological adaptability to adapt to the upgrading and transformation of the industry.

6.2. Opportunities and challenges in the labor market

The introduction of digital technology and biomechanical optimization has brought new opportunities as well as challenges to the job market in the domestic sector. In terms of opportunities, the development of intelligent domestic services has facilitated career upgrading in the industry, moving domestic labor from traditional manual labor to skill-based and professionalism. The popularity of technologies such as smart home appliances, automated cleaning equipment, and remote management systems has made it so that domestic workers are no longer confined to basic cleaning work but need to acquire skills in the operation of smart equipment, data management, and customized services. In addition, the development of technology has given rise to new positions, such as smart housekeeping trainers, equipment maintenance specialists, and housekeeping data analysts, which provide practitioners with broader space for career development [18].

Technological innovations also pose challenges. Traditional domestic workers are under pressure to update their skills, and some older workers with lower education levels may find it difficult to adapt to the application of new technologies, leading to a decline in occupational competitiveness.

To address these challenges, the industry must invest in inclusive upskilling programs, particularly targeting middle-aged and elderly workers. Partnerships between training institutions and tech companies can provide accessible workshops on operating smart devices. Additionally, government policy should support subsidized certification schemes and reemployment channels to facilitate smooth transitions into technologically upgraded roles. Such proactive strategies are essential to balance innovation with equitable workforce development.

The widespread application of smart devices has led to the replacement of some basic and repetitive domestic work by automation, which may reduce the demand for low-skilled jobs and lead to unstable employment for some workers in the industry. While the digital management mode of the domestic helper industry has improved service efficiency, it also requires practitioners to possess basic digital literacy, including the ability to use domestic helper management apps, take orders remotely, and intelligently schedule, which is a threshold for some practitioners.

In the face of this change, the domestic helper industry needs to promote the improvement of the vocational training system to help practitioners master new technologies and upgrade their vocational skills. The policy level also needs to pay attention to the issue of employment transformation brought about by technological change and ensure that traditional practitioners can be smoothly integrated into the domestic helper industry in the age of intelligence through skills upgrading programs and vocational accreditation systems so as to achieve the sustainable development of the industry.

7. Conclusion

The synergy between digital technology and biomechanical optimization demonstrates significant advantages in domestic labor. Experimental findings confirm that digital tools alone reduced task completion time by 22.2%, while integrating biomechanics led to an overall improvement of 33.3%. Muscle fatigue was reduced by more than 40%, and posture deviation rates decreased by over 30%. These results validate the study’s core hypotheses and support the integration of smart tools and ergonomics for enhanced labor efficiency. Furthermore, satisfaction scores increased notably, indicating broad acceptance among domestic workers. The rise of intelligent systems not only reduces repetitive labor but also creates new high-skilled employment opportunities, promoting industrial upgrading.

Future research should focus on refining biomechanical guidance, integrating real-time feedback systems, and expanding testing across more diverse populations. Policy support and vocational education reforms will be crucial to ensure the sustainable transformation of the domestic labor market.

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Informed consent statement: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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