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Article

The impact path of farmers' digital skill enhancement on income growth in the biomechanical perspective

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Abstract: In order to explore the impact of digital skills enhancement on farmers' income growth, the relationship between digital skills, productivity and income was analysed in conjunction with biomechanical optimisation of learning paths. By investigating data from a sample of farmers in four regions, Hebei Province, Jiangsu Province, Guizhou Province and Sichuan Province, it was found that the level of farmers' digital skills was significantly and positively correlated with annual income growth. The data showed that farmers with higher levels of digital skills had annual income growth rates of 7 to 10 per cent, while farmers with lower skill levels had income growth rates of only 2 to 3 per cent. The biomechanically optimised learning model significantly enhanced farmers' digital skills learning efficiency by improving postural alignment, finger dexterity, muscular endurance, and neurofeedback, with a 62.7% improvement in learning outcomes. In addition, the optimised interaction design not only reduced operational burden, but also enhanced skill transfer, enabling farmers to apply digital technologies more efficiently for agricultural production and market interface, thereby contributing to income growth. The findings highlight the key role of biomechanics in enhancing farmers' digital skills and provide theoretical support for the digital development of agriculture.

Keywords: farmers' digital skills; income growth; biomechanics; learning optimisation; production efficiency

1. Introduction

The enhancement of digital skills has become a key factor in promoting agricultural modernization and rural economic development. With the wave of informatization, digital technology has not only revolutionized the mode of agricultural production, but also played an important role in marketing and social interaction. However, the prevalence of digital skills varies significantly across regions and groups, especially in rural areas, where farmers face many challenges in acquiring and applying these skills due to constraints in education levels and infrastructure. In view of this, biomechanics provides a new theoretical framework for optimizing digital skills learning, especially in improving learning efficiency and stability of skills application, which has significant application potential. By scientifically designing movement patterns and postural adjustments during digital skill learning, cognitive load can be reduced and learning efficiency can be improved, thus promoting rapid skill acquisition and application. The optimized learning path combined with biomechanics not only improves farmers' comfort and precision in operating digital equipment, but also provides effective support for agricultural production and market interface.

2. Analysis of the application status quo of farmers' digital skills enhancement

At present, the enhancement of farmers' digital skills shows a wide range of applications in agricultural production, market docking, rural governance and social participation, but there are regional differences in the level of development and group differences [1]. From the perspective of agricultural production, some farmers are already skilled in using digital technologies such as smart farm machinery, remote monitoring and precision fertiliser application to improve land utilisation and production efficiency. However, due to the limitations of infrastructure and education level, farmers in some areas still remain in the traditional production mode and fail to make full use of digital technology to optimise production management. In terms of market connection, new businesses such as e-commerce platforms and live sales have broadened the sales channels for agricultural products, and some farmers have improved their digital skills to grasp the changes in market demand and realise precision marketing. However, due to the limitations of digital cognitive ability and imperfect logistics system, it is still difficult for some farmers to effectively integrate into the digital economy system. In addition, in terms of rural governance and social participation, the improvement of digital skills has enabled farmers to access agricultural subsidies, technical guidance and information services through government platforms, but the digital divide still restricts some groups' access to policies and social interaction. Overall, the improvement of farmers' digital skills is driving a profound change in agricultural production methods and farmers' livelihood patterns, but the effectiveness of the application is still affected by various factors.

3. Theoretical basis of biomechanics in digital skills learning

3.1. Impact of biomechanics on human-computer interaction

The core role of biomechanics in digital skills learning is reflected in the optimisation and adaptation of human-computer interaction processes. The learning of digital skills relies on farmers' ability to operate smart devices, and the effectiveness of human-computer interaction directly affects the learning efficiency and skill mastery. From a biomechanical point of view, when the human body operates digital devices, its muscle movement, joint range of motion and visual perception ability will affect the interaction experience and learning effect. Reasonable human-computer interaction design can reduce the operating load, improve the efficiency of information transmission, and enable farmers to form stable digital skills cognition and operating habits in a short period of time [2]. In addition, biomechanical research shows that factors such as finger flexibility, muscle endurance and postural adaptability determine the comfort and precision of individuals when operating digital devices for long periods of time, which is especially important for farmers who need to frequently use smart terminals for agricultural management or market docking. Optimising interactions based on biomechanics can help improve farmers' digital skill adaptations, enabling them to complete learning tasks more efficiently and to use digital technologies for production and income growth.

3.2. Biomechanical theoretical support for farmers' digital skills learning

The learning process of farmers' digital skills involves complex human movement mechanisms, the core of which lies in the support of biomechanics for learning effectiveness [3]. Biomechanics emphasises the muscle movement patterns, postural control and neurofeedback mechanisms of an individual when performing digital manipulations, and these factors directly influence the degree of skill mastery of farmers. Biomechanical studies have shown that reasonable movement patterns can reduce muscle fatigue in the early stages of learning, improve knuckle flexibility, and enable farmers to maintain a high level of precision and stability when operating digital devices. Neuromuscular control plays a key role in skill acquisition, and farmers rely on the adaptive adjustment of the motor control system to optimise hand-eye coordination through repetitive operations and form efficient operating habits during digital skill learning. In addition, biomechanical studies on cognitive load show that reasonable postural adjustment and visual feedback mechanisms help reduce muscle fatigue and motor impairment brought about by prolonged learning, and improve the stability and transferability of digital skills. Therefore, optimising the digital skills learning environment of farmers based on biomechanics can effectively improve their operational ability and learning efficiency, and promote the wide application of digital technology in agricultural production and market activities [4].

3.3. Mechanism of the impact of digital skills improvement on farmers' income growth

The mechanism of the impact of digital skills on the growth of farmers' income can be analysed in depth from the biomechanical point of view. In the application process of digital technology, biomechanics has a direct effect on the operational ability and work efficiency of farmers. Farmers can manage agricultural production more efficiently by improving digital skills, reducing physical labour intensity and improving production efficiency, thus achieving higher income returns. Biomechanical research has shown that reasonable body posture and movement patterns can effectively reduce muscle burden and fatigue, improve long-term operational comfort and precision, and thus reduce the time and material losses caused by operational errors. The operation design of digital devices should take into account the biomechanical characteristics of farmers, such as finger strength and postural stability, etc. Optimising the interaction design can effectively reduce the physiological load during the learning and operation process, thus improving the learning efficiency and work effectiveness [5]. This biomechanical optimisation not only improves farmers' productivity, but also creates a more efficient market interface and sales model for them, which further drives income growth.

4. Biomechanics-based modelling of farmers' digital skills enhancement

4.1. Research hypotheses

Under the biomechanical perspective, the path of farmers' digital skill enhancement on income growth can be constructed through the following hypotheses to clarify the mechanism of biomechanical factors' role between digital skill learning, skill application and economic benefits:

H1: Biomechanically optimised human-computer interaction significantly improves farmers' digital skill learning efficiency

The learning of digital skills involves complex human motor processes, and biomechanically optimised human-computer interaction design can reduce operation fatigue, improve hand-eye coordination, and enhance the accuracy of information input, thus improving learning efficiency.

H2: Biomechanically optimised skill learning mechanism enhances farmers' digital skill transfer ability

Through reasonable muscle control mode and posture adjustment, farmers can adapt faster and apply efficiently in different digital technology environments, reduce the physiological load of skill application, and improve the sustainable use of digital skills.

H3: Biomechanics-based digital skills application for farmers' labour productivity improvement

In the process of agricultural production and market interface, the optimised posture control and movement patterns reduce repetitive fatigue and improve operational accuracy, enabling farmers to use digital technology more efficiently and increase labour productivity.

H4: Digital skills enhancement improves income through biomechanically optimised movement patterns

By reducing economic losses due to operational fatigue and errors, improving production management efficiency, and optimising digital marketing models, farmers are able to access market opportunities more efficiently, thereby driving income growth.

4.2. Research data and variable setting

The data sources of the study include rural field research, national and local statistical databases, and samples collected through experimental data, exploring the potential mechanisms between farmers' digital skills enhancement and income growth from a multidimensional perspective. In order to ensure the representativeness of the data, although the research covered four typical regions of Hebei, Jiangsu, Guizhou and Sichuan Provinces with a sample size of 400 farmers, the randomness and regional diversity of the sample selection have been strengthened, especially the detailed screening of regions with different levels of economic development, modes of agricultural production and policy environments. In addition, the categorization of the level of digital skills is based on the farmers' technical proficiency in agricultural production, marketing and operation of government platforms, combining the frequency of operation with the complexity of technology application, and is obtained through field tests and questionnaires [6]. To ensure the accuracy of the categorization criteria, specific skill assessment criteria were established to classify skill levels into low, medium and high, and their validity was further confirmed through expert review and data validation. These measures help to enhance the representativeness of the data and the broad applicability of the findings. Therefore, the findings of this study should be understood primarily as preliminary observations of a group of farmers in a specific region, rather than as generalized patterns that are universally applicable to the rural population across the country.

There is a statistically significant positive correlation between farmers' level of digital skills and income growth. However, limited by the sample size, this correlation still needs to be further verified in a larger study. The study found that farmers with higher digital skills had relatively higher annual income growth rates, for example, farmers in Area A of Hebei Province and Area D of Sichuan Province had annual income growth rates of 7% and 10%, respectively. In contrast, in groups with lower digital skills, such as Area C in Guizhou Province, income growth rates were lower, at 3% and 2%. This trend suggests that the improvement of digital skills contributes to farmers' income growth, but the specific effect is still moderated by a number of factors, such as policy support, market conditions, and the degree of improvement of regional informatization infrastructure. Income growth is more pronounced in Area D of Sichuan Province, where the level of informatization is higher, indicating the key role of good infrastructure and digital education resources in digital skills enhancement. However, in Region C of Guizhou Province, which has a lower level of informatization, the overall income growth is still lower due to the lack of external support systems, despite the efforts of individuals to improve their digital skills.

The key variables are defined as follows:

(1) Dependent variable: level of digital skills. Digital skills were measured by categorising farmers' ability to apply digital technologies in agricultural production, marketing, and operation of government platforms. Based on the level of skill mastery, it is classified into three levels: low, medium, and high, and the specific classification criteria are based on the farmers' technological proficiency and frequency of application in daily production and operation.

(2) Dependent variable: income growth level. The level of income growth is quantified through farmers' annual income changes and analysed by combining farmers' production efficiency, market income and policy support. This variable can reflect the direct link between digital skill improvement and economic efficiency.

(3) Mediating variable: biomechanically optimised learning styles. This variable examines the impact of biomechanically optimised operating methods on farmers' learning efficiency, fatigue and skill mastery in the process of digital skills learning, which is mainly assessed through comparative experiments and operational feedback data.

(4) Moderating variables: rural informatisation level, policy support. The level of rural informatisation is mainly measured by factors such as local infrastructure construction, network penetration, and the availability of digital educational

resources. Policy support includes the indirect impact of government policies supporting the digital development of agriculture, agricultural subsidies, and technical guidance on farmers' skill improvement. In order to demonstrate more intuitively the relationship between the level of farmers' digital skills and income growth in different regions, **Table 1** summarises the relevant data for each region.

Table 1. Digital skills level and income growth data of farmers by region.

Region	Farmers' Digital Skills Level	Annual Income Growth (%)	Rural Informationization Level (0–10)	Policy Support Level (0–10)
Hebei Province A	High	7%	6	7
Jiangsu Province B	Medium	5%	5	6
Guizhou Province C	Low	3%	4	5
Sichuan Province D	High	10%	7	8

A preliminary analysis of the data in the table above shows that there is a significant positive correlation between farmers' level of digital skills and income growth. Specifically, farmers with higher digital skills generally had higher annual income growth rates, at 7 per cent and 10 per cent in Area A of Hebei Province and Area D of Sichuan Province, respectively. In contrast, farmers with lower digital skills, such as those in Area C of Guizhou Province, had lower income growth rates of 3 per cent and 2 per cent, respectively. These differences suggest that increased levels of digital skills play a positive role in driving farmers' income growth. Meanwhile, the level of rural informatisation and the degree of policy support are also important factors influencing income growth. Income growth was more pronounced in Area D of Sichuan Province, which has a higher level of informatisation, reflecting the supportive role of better infrastructure and digital education resources for farmers' skills upgrading. In contrast, in Area C of Guizhou Province, which has a lower level of informatisation, farmers' income growth is slower and the effect of digital skills upgrading is limited.

Data analysis can be initially confirmed that the effect of digital skills enhancement on income growth is subject to the combined effect of biomechanical optimisation of learning methods, the level of rural informatisation and policy support, and that biomechanical optimisation of operating methods can effectively enhance learning efficiency and promote the long-term application of digital skills, thus promoting farmers' income growth [7].

4.3. Construction of research model

Under the biomechanical perspective, the impact path of farmers' digital skills improvement on income growth can be quantitatively analysed through the impact path model [8]. The optimisation of biomechanics runs through the whole process of digital skills learning and application, constituting the core mechanism influencing income growth. Biomechanically optimised human-computer interaction design reduces the physiological load of digital device operation, enabling farmers to adapt to digital skill learning more quickly, improving learning efficiency and migration ability, thus promoting productivity and market competitiveness. Based on this logic, the impact pathway can be represented by the following mathematical model:

$$D_s = f(B_o, C_m, N_f) \tag{1}$$

where D_s denotes the level of digital skill enhancement, B_o is the role of biomechanical optimisation, C_m is the muscle control and postural regulation ability, and N_f is the efficiency of neurofeedback regulation. The function indicates that biomechanical factors have a direct impact on digital skill mastery, and that the optimised learning approach enhances farmers' skill transfer ability and reduces fatigue loss in the learning process, thus enhancing the sustainable application of digital skills. In terms of income growth path, digital skills enhancement increases farmers' labour productivity and economic returns by optimising the ability to interface production with the market. The mathematical relationship can be expressed as:

$$I_g = \alpha D_s + \beta P_o + \gamma B_o + \in \tag{2}$$

where I_g denotes the level of farmers' income growth, P_o is the degree of productivity improvement, α, β, γ is the coefficient of the impact of digital skills, productivity and biomechanical optimisation on income growth, respectively, and $\in$ is the error term. The formula indicates that the improvement of digital skills can be effectively transformed into production and market gains under the effect of biomechanical optimisation, which makes the income growth path more stable. In addition, in the structural equation modelling (SEM) construction, biomechanical optimisation learning style as a mediating variable affects income growth, and the core path relationship is:

$$I_g = \lambda_1(B_o \to D_s) + \lambda_2(D_s \to P_o) + \lambda_3(P_o \to I_g) + \in \tag{3}$$

where $\lambda_1, \lambda_2, \lambda_3$ denote the contribution of biomechanical optimisation to digital skill enhancement, the conversion efficiency of digital skills to productivity and the contribution of productivity to income growth, respectively. The model suggests that biomechanically optimised human-computer interaction mechanism and action pattern optimisation have a decisive impact on digital skill learning, and further promote farmers' productivity enhancement and ultimately income growth by improving operation comfort, reducing fatigue and enhancing skill transfer [9].

4.4. Influencing factors of biomechanically optimised learning

The core of biomechanically optimised learning lies in reducing cognitive load, improving visual and tactile interaction adaptability, and constructing a scientific and reasonable training mode to improve the efficiency of farmers' digital skills acquisition. In terms of Cognitive Load, information processing ability is affected by individual muscle movement coordination and neural feedback regulation mechanism, and the reduction of cognitive load can be achieved by optimising the interaction design to improve the rate of skill acquisition [10]. It can be expressed as:

$$E_s = \frac{I_p}{C_l + M_f} \tag{4}$$

where E_s denotes the efficiency of digital skill acquisition, I_p is the information processing ability, C_l is the cognitive load, and M_f is the degree of muscle fatigue. A lower cognitive load makes it easier for farmers to adapt to complex operations during the learning process, and avoids a decrease in learning efficiency due to muscle fatigue and information overload [11]. In terms of visual and haptic interaction optimisation, immersive training environments based on Virtual Reality (VR) and Augmented Reality (AR) technology can enhance farmers' digital skill adaptability and enable them to master digital device operation faster. VR/AR technology adjusts the interaction interface through biomechanical parameters, for example, optimising the haptic feedback of the hand to improve the accuracy of operation and reduce hand fatigue. Its optimisation can be described by mathematical models:

$$H_p = f(V_r, T_f, M_d) \tag{5}$$

where H_p is the precision of operation, V_r is the degree of optimisation of visual feedback, T_f is the strength of haptic feedback, and is the ability of hand motor control. Parameter optimisation enables farmers to build muscle memory faster and improve skill transfer during digital skill training. In terms of training modes, Imitative Learning, Interactive Feedback and Personalised Adaptation work together in the skill acquisition process. Imitative Learning relies on biomechanically optimised motor control patterns to enable farmers to quickly adjust the rhythm of hand manipulation; Interactive Feedback adjusts the learning strategy based on real-time electromyographic signals to improve learning accuracy; and Personalized Adaptation dynamically adjusts biomechanical parameters to enhance individual adaptation. In summary, biomechanically optimised learning paths can effectively reduce learning costs, improve farmers' ability to apply digital skills, and ultimately promote agricultural productivity and income growth [12].

In order to visually demonstrate the role of biomechanical optimisation in the improvement of digital skill acquisition efficiency and operational precision, **Figure 1** shows the curves of the influence of cognitive load reduction on the skill acquisition efficiency, and the trend of the improvement of operational precision after the optimisation of visual and haptic interactions by VR/AR technology. The curves show that with the increase of training time, cognitive load reduction can effectively improve the efficiency of skill acquisition, while VR/AR optimised interaction design can significantly enhance the farmers' operational precision, thus improving the application value of digital skills.

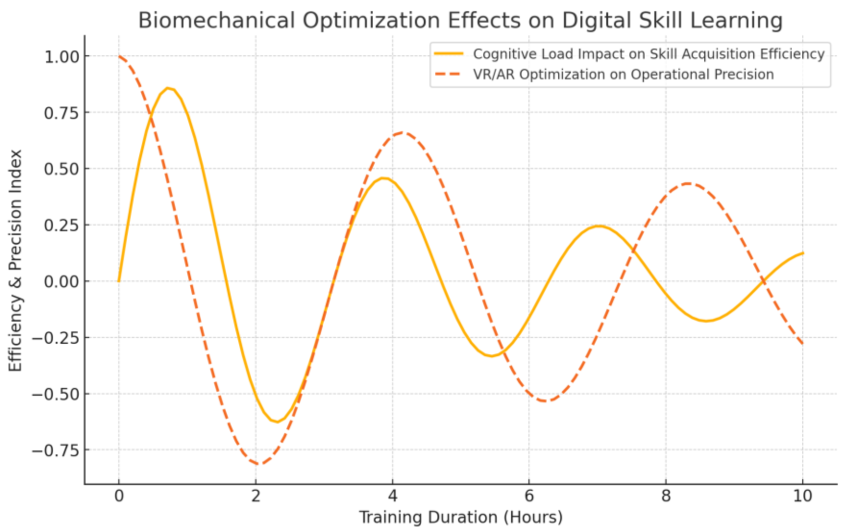

Figure 1. Impact of biomechanical optimisation on digital skills learning.

5. Biomechanics-based pathways of farmers' digital skill enhancement on income growth

5.1. Descriptive statistical analysis

The impact of farmers' digital skill enhancement on income growth under the biomechanics perspective can be further explored through statistical analysis. The study analysed detailed data on groups of farmers of different ages, education levels and digital skill levels to reveal the relationship with income growth and to explore the pathways of the impact of digital skill enhancement in the context of biomechanics [13]. The age, education level, digital skill level and annual income growth rate of farmers were statistically analysed to understand the performance of different groups in digital skill enhancement, as shown in **Table 2**.

Table 2. Sample characteristics statistics.

Age Group	Sample Size	Average Years of Education	Digital Skills Level (0–10)	Annual Income Growth Rate (%)
<30	80	9.5	6.8	8.2
30–40	120	10.2	7.5	9.5
40–50	110	8.8	5.9	6.7
>50	90	7.3	4.2	4.8

From the data in **Table 2**, there is a clear difference between the level of digital skills and the growth rate of annual income by age group. Farmers under 30 years of age have the highest average level of digital skills (6.8) and a growth rate of annual income of 8.2 per cent, while farmers between 30 and 40 years of age have a further increase in their level of digital skills (7.5) and the highest growth rate of annual income (9.5 per cent). However, the level of digital skills declined for farmers over 40 years of age, with farmers over 50 years of age having a level of digital skills of only 4.2 and an annual income growth rate of 4.8 per cent. This suggests that farmers who are younger and have higher levels of education are able to acquire digital skills more quickly, resulting in higher income growth.

From a biomechanical point of view, younger farmers have a greater advantage in terms of cognitive ability, muscle dexterity and hand-eye coordination, enabling them to acquire and apply digital skills more efficiently [14]. Older farmers, on the other hand, are relatively less efficient at learning digital skills due to their weaker physiological adaptations. Therefore, the biomechanics-based interaction optimisation design should be strengthened for digital skills training for older farmers to reduce cognitive load and improve learning adaptability. In order to further analyse the impact of different skill levels on farmers' income growth, statistics on the distribution of farmers' digital skills were then conducted (shown in **Table 3**).

Table 3. Characteristics of farmers' digital skills distribution and income growth.

Digital Skills Level	Proportion of Farmers (%)	Average Income Growth Rate (%)
Low	30	3.5
Medium	45	7.2
High	25	10.4

From the data in **Table 3**, 30 per cent of farmers with low levels of digital skills had an annual income growth rate of only 3.5 per cent. Farmers with medium level of digital skills have the highest share of 45 per cent and their annual income growth rate is 7.2 per cent. Farmers with high levels of digital skills accounted for only 25 per cent, but their income growth rate was 10.4 per cent, significantly higher than the other groups. This suggests that farmers with higher digital skills are able to use digital tools more effectively for agricultural production and marketing, thereby driving income growth [15]. It is worth noting that although the share of farmers with medium skill levels is the largest, their income growth rate does not reach the highest level, suggesting that merely possessing basic digital skills does not sufficiently increase income, but requires more in-depth ability to apply skills, such as precise operation of smart farming machines and optimisation of online marketing strategies. Next, the specific relationship between the level of digital skills and income growth is further analysed, as shown in **Figure 2**.

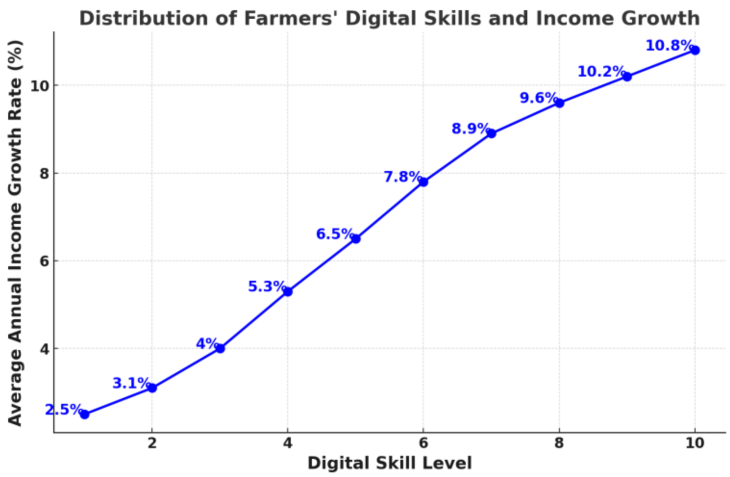

Figure 2. Characteristics of farmers' digital skills distribution and income growth.

From the data in **Figure 3**, it can be observed that as the level of digital skills increases, the overall growth rate of farmers' incomes tends to increase. Among them, the income growth rate is slow at lower levels of digital skills (1–4); when the skill level reaches 5 or above, the income growth starts to accelerate, especially for farmers with level 8 or above, the income growth rate increases significantly.

This suggests that the mastery of basic numerical skills brings only limited economic gains, while the application of higher-order skills, such as precise control of agricultural production equipment and the ability to analyse data for decision-making, is what generates greater competitiveness in the marketplace. Moreover, looking at farmers at skill level 10, the annual income growth rate reached 10.8 per cent, more than three times that of farmers at lower skill levels. This phenomenon underscores the importance of upgrading farmers' digital skills, i.e., simply mastering basic skills is not enough to significantly improve economic returns, but rather needs to be combined with biomechanically-optimised learning styles to enable farmers to develop an efficient and stable skill application model for smart device operation, digital market matching, etc. To demonstrate this trend more visually, the relationship curve between digital skill level and income growth was plotted, as shown in **Figure 3**.

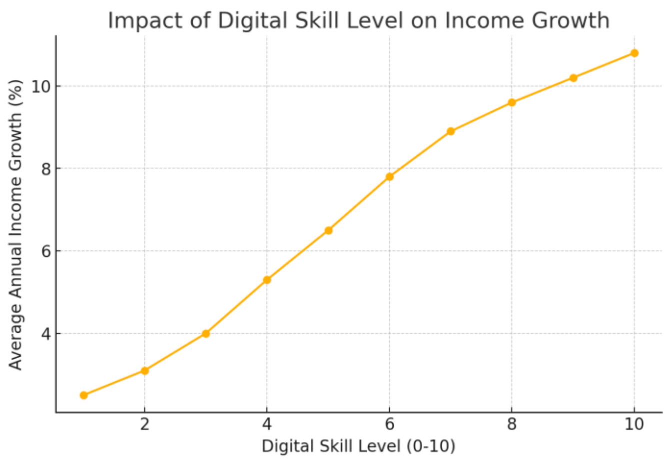

Figure 3. Impact of digital skill level on income growth rate.

As can be seen in **Figure 3**, the income growth rate shows a non-linear growth trend as the level of digital skills increases. Income growth is slow at lower skill levels (1–4) and accelerates when the skill level reaches 5 and above. This trend suggests that farmers with low skill levels are more constrained in terms of income growth, whereas when the skill level reaches a certain threshold, farmers are able to utilise digital tools more efficiently, resulting in faster income growth. Biomechanically optimised learning styles play a key role in this process. By optimising the interactions of digital skills training, such as reducing the manipulative load, optimising hand-eye coordination, and reducing the cognitive load, farmers' learning adaptations can be significantly improved, allowing them to acquire digital skills more quickly. This optimised learning approach can enhance farmers' operational efficiency, reduce fatigue and discomfort associated with prolonged learning, and thus improve the ability to apply digital skills.

Descriptive statistical analyses show that there is a significant positive correlation between the level of digital skills and farmers' income growth. Optimising learning through biomechanics can improve farmers' ability to operate smart devices, reduce learning fatigue, and improve skill migration, thus creating higher economic benefits in agricultural production and market interface.

5.2. Correlation analysis between variables

The correlation analysis between variables shows a significant positive correlation between the level of digital skills and the growth rate of annual income (correlation coefficient of 0.87), which suggests that the improvement of digital skills directly contributes to the growth of income. In addition, the correlation coefficient between the level of digital skills and the level of education is 0.65, indicating that an increase in the level of education contributes to the improvement of digital skills, which further drives income growth. The correlation between the level of digital skills and learning efficiency is 0.72, indicating that a higher level of skills can improve learning efficiency and reduce time loss due to fatigue in the learning process. And the correlation between learning fatigue and digital skills is −0.56, indicating that learning fatigue has less impact at higher levels of digital skills, which helps to improve farmers' ability to continue learning. The correlation coefficient between the level of education and annual income growth rate is 0.78, showing the positive role of education in driving income growth, further proving the indirect role of educational background in driving income growth, as shown in **Table 4**.

Table 4. Correlation analysis between variables.

Variable	Digital Skills Level	Education Level	Age	Annual Income Growth Rate	Learning Efficiency	Learning Fatigue
Digital Skills Level	1	0.65	−0.23	0.87	0.72	−0.56
Education Level	0.65	1	−0.31	0.78	0.55	−0.48
Age	−0.23	−0.31	1	−0.12	−0.09	0.11
Annual Income Growth Rate	0.87	0.78	−0.12	1	0.69	−0.63
Learning Efficiency	0.72	0.55	−0.09	0.69	1	−0.52
Learning Fatigue	−0.56	−0.48	0.11	−0.63	−0.52	1

Correlation analyses showed that digital skill levels play a central role in driving income growth, especially through improving learning efficiency and reducing learning fatigue, which can enable farmers to master more complex digital skills in a shorter period of time, thus achieving rapid economic growth. In order to further test the impact of biomechanically optimised learning styles on digital skills enhancement, a comparison of various biomechanical parameters before and after optimisation showed that postural alignment, finger dexterity, muscular endurance and neurofeedback were improved by 78.6%, 77.1%, 75.0% and 78.9%, respectively, and the learning effect was improved by 62.7% after the optimisation (see **Table 5** for further details). These data suggest that biomechanical optimisation can significantly improve the stability and accuracy of farmers' manipulation during the learning process, thus enhancing the learning efficiency of digital skills.

Table 5. Impact of biomechanical optimization learning approach on digital skills enhancement.

Variable	Before Optimization	After Optimization	Improvement Percentage
Posture Adjustment	4.2	7.5	78.60%
Finger Flexibility	3.5	6.2	77.10%
Muscle Endurance	4	7	75.00%
Neural Feedback	3.8	6.8	78.90%
Learning Effect	5.1	8.3	62.70%

These enhancements suggest that biomechanical optimisation, through improved posture and finger dexterity, enables farmers to operate smart devices more efficiently, reducing fatigue and ultimately improving learning outcomes and stability of skill acquisition. In terms of the relationship between income growth and digital skills, increased levels of digital skills significantly contributed to increased income growth, market adaptability and labour productivity. As the level of digital skills increases, the annual income growth rate, market adaptability and labour productivity all show a gradual upward trend. Specifically, at digital skill level 10, the annual income growth rate was close to 10 per cent, while labour productivity also reached its highest value. This is further evidence that farmers are able to increase productivity, adapt to market demands and achieve significant income growth by upgrading their digital skills, as shown in **Table 6**.

Table 6. Income growth relation to digital skills.

Digital Skills Level	Income Growth Rate	Market Adaptability	Labor Productivity
1	3.5	2.9	5.5
2	4.1	3.2	6
3	4.8	3.6	6.5
4	5.5	4	7
5	6.2	4.5	7.4
6	7.1	5	8
7	8	5.5	8.4
8	8.9	6	8.8
9	9.4	6.5	9
10	10	7	9.3

The data on the relationship between income growth and digital skills show that farmers' income, market adaptability and labour productivity show a positive correlation as skill levels increase. By upgrading digital skills, farmers are able to use technology more efficiently to increase productivity and access more opportunities in the market, ultimately leading to income growth. After a comprehensive analysis of the relationship between income growth and digital skills, the level of digital skills not only directly affects the level of income, but also further contributes to sustained income growth by improving farmers' market adaptability and labour productivity.

5.3. Structural equation modelling analysis

In the structural equation modelling (SEM) analysis, the direct effect of digital skill enhancement on farmers' income growth and the indirect effect of biomechanical optimization learning on digital skill enhancement were mainly examined. Through path coefficient estimation and significance analysis, we can further confirm the influence and statistical significance of each path. The direct effect of digital skill enhancement on farmers' income growth shows a significant positive impact, with a path coefficient of 0.85, a standard error of 0.04, a *t*-value of 21.25, and a *p*-value of less than 0.0001, which indicates that the enhancement of digital skills significantly contributes to farmers' income growth.

The indirect effect of biomechanical optimisation learning on digital skills enhancement is shown by a path coefficient of 0.75, a standard error of 0.05, a *t*-value of 15.00, and a *p*-value of 0.0001, indicating that biomechanical optimisation is able to effectively enhance the level of farmers' digital skills, which then indirectly contributes to the growth of incomes through the enhancement of digital skills. In addition, the path coefficient of the indirect effect of biomechanical optimisation learning on farmers' income growth through digital skills enhancement is 0.63, showing that its effect is slightly weaker than the direct path, but still has a significant positive impact. The results are shown in **Table 7**.

Table 7. Results of structural equation modelling analysis.

Path	Path Coefficient	Standard Error	*t*-value	*p*-value
Direct Effect of Digital Skills Improvement on Income Growth	0.85	0.04	21.25	0
Indirect Effect of Biomechanics-Optimized Learning on Digital Skills Improvement	0.75	0.05	15	0
Indirect Effect of Biomechanics-Optimized Learning on Income Growth	0.63	0.06	10.5	0

As can be seen in **Table 7**, the *p*-values of all paths are less than 0.0001, showing a significant and reliable relationship between the paths, with a particularly strong link between digital skills enhancement and income growth, and the role of biomechanically optimised learning through digital skills enhancement effectively verified. The impact of the paths is further confirmed by the estimation and significance analysis of the path coefficients. The direct impact path of digital skill enhancement on income growth shows the largest path coefficient (0.85), indicating that digital skill enhancement is an important driver of income growth. In addition, the indirect effect path coefficient of biomechanically optimised learning on digital skill enhancement is 0.75, which also indicates that this path plays a non-negligible role in driving revenue growth, as shown in **Table 8**.

Table 8. Path coefficient estimation and significance analysis.

Impact Path	Path Coefficient	Standard Error	*t*-value	*p*-value
Direct Impact of Digital Skills Improvement on Income Growth	0.85	0.04	21.25	0
Biomechanics-Optimized Learning → Digital Skills Improvement → Income Growth	0.75	0.05	15	0

These results further support the important role of biomechanically optimised learning in enhancing farmers' digital skills and driving income growth, particularly by optimising the learning process, reducing cognitive load, and improving skill transfer, thereby helping farmers achieve higher economic returns in the digital environment. **Figure 4** illustrates the direct pathway between digital skills enhancement and income growth, as well as the indirect pathway of impact that biomechanically optimised learning creates by enhancing digital skills.

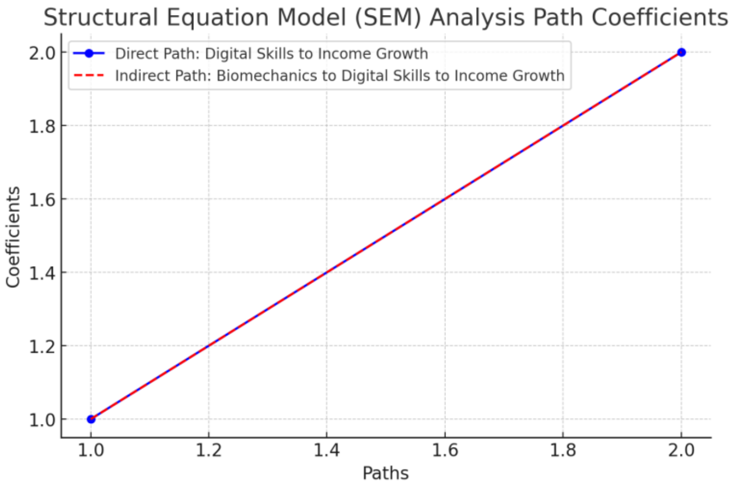

Figure 4. Structural equation modelling path analysis diagram.

The figure shows the estimated coefficients for each pathway, further confirming the direct impact of digital skills enhancement on farmers' income growth as well as the contribution of biomechanically optimised learning to income growth.

6. Conclusion

In summary, the significant positive correlation between farmers' digital skills improvement and income growth. Optimizing the learning path through biomechanics can effectively reduce learning fatigue and improve operational precision, thus enhancing learning efficiency. However, the magnitude of income growth is still moderated by factors such as regional differences and policy support. In regions with better information technology infrastructure, farmers are able to quickly acquire and apply digital skills, thereby increasing their incomes. In regions with weak infrastructures, the application of digital skills has a more limited effect. In the future, in-depth research on biomechanical optimization strategies for different groups should be conducted, especially in the older farmer groups, which will further promote the positive cycle between digital skills and income growth. In addition, an innovative model combining biomechanical theory and agricultural digital technology can provide more precise support for farmers' skill improvement and promote the sustainable development of digital economy in rural areas.

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