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Factors affecting the digital competence of workers in Vietnam coal enterprises

Nguyen Thi Phuong Mai
Faculty of Industrial and Energy Management; Electric Power University, Vietnam

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ABSTRACT: This study focuses on analyzing the factors influencing the digital competence of workers in Vietnamese coal mining enterprises in the context of digital transformation increasingly impacting mining, processing, management, and labor organization. Based on a theoretical overview and related research, the article identifies five groups of factors that can affect the digital competence of workers: digital skills training and development; infrastructure and technological readiness; organizational support; individual learning orientation; and the degree of job digitization. The research results show that the digital competence of workers depends not only on their ability to access and use technology but is also significantly influenced by the learning environment, enterprise support, and the degree of integration of digital technology into daily work. Among these, training, self-learning ability, and organizational orientation play a crucial role in helping workers adapt to new job requirements. This research contributes to clarifying the mechanisms of digital competency formation within the context of coal industry enterprises, while also proposing several management implications to improve the training system, enhance access to technology, build a continuous learning environment, and promote the digitalization of work in conjunction with human resource development.

KEYWORDS: Digital capabilities; Workers; Coal industry enterprises; Digital transformation; Training and development; Digital jobs; Vietnam.

I. INTRODUCTION

The rapid development of automation, big data, artificial intelligence, the Industrial Internet of Things, cloud computing, and integrated management platforms is reshaping the way production and labor are organized in many industries. In businesses with complex production processes, digital technology is not only used in administration but is increasingly integrated into equipment control, operational monitoring, predictive maintenance, data analysis, safety management, and workflow coordination. This changes the nature of professional competence: workers need not only specialized knowledge and traditional operational skills but also the ability to search, process, interpret, and exchange data; use digital systems; collaborate in a digital environment; identify information risks; and solve problems arising from technological changes.

Digital competence is therefore increasingly seen as a component of human capital in the digital economy. The DigComp 2.2 digital competence framework identifies five core competency domains: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving (Vuorikari et al., 2022). In the context of employment, Oberländer, Beinicke, and Bipp (2020) emphasize that digital competence should not be equated with the ability to use a single software program, but rather as a set of knowledge, skills, attitudes, and adaptability that enables individuals to handle professional tasks in a digitized environment. This approach is particularly relevant to manufacturing businesses, where workers must connect technical understanding with the ability to use data and digital systems in specific situations.

In the coal industry, the digitalization process differs significantly from that in the service and office sectors. Technology is deployed simultaneously across exploration, mining, transportation, screening, mechanical and electrical engineering, ventilation, environmental monitoring, mine safety, production planning, and business management. Some tasks take place in underground mines, open fields, or continuous production lines, thus requiring digitalization to prioritize equipment stability, data reliability, and safety. When monitoring systems, sensors, dispatching platforms, or management software are implemented, workers must shift from relying heavily on personal experience to interacting with real-time data, automated alerts, and standardized processes within the system.

However, investing in technology does not automatically create digital competence. Many studies show that the gap between access to

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technology and effective use of technology persists even with improved infrastructure. A review by van Laar et al. (2020) indicates that the digital competence of workers is simultaneously influenced by demographic factors, motivation, experience, access to technology, training activities, and social support. Research by Mendoza-Chan and Pee (2024) further shows that the effectiveness of digital skills development depends on the alignment between training methods, the work context, learner characteristics, and opportunities to translate learning content into practice. Thus, digital competence is the result of an accumulation and interaction process between individual resources, the organizational environment, and job design.

From a human capital perspective, training helps to form and enhance the knowledge, skills, and productivity of workers. In digital transformation, training content needs to go beyond simply instructing on software operation to develop the ability to understand data, solve problems, think strategically, and adapt to technological changes. On the other hand, from a resource-based perspective, digital infrastructure, data, processes, and human capabilities are supplementary resources; businesses only benefit from technological assets when employees are able to use them. Furthermore, organizational support theory suggests that when employees perceive that the company values their contributions and supports them in solving problems, they tend to invest more in learning and adaptation behaviors (Eisenberger et al., 1986).

Another issue is the role of work as a learning environment. Workers may receive training, but skills are difficult to retain if daily work doesn't require application. Conversely, the regular use of digital dashboards, data entry and analysis, alert processing, collaboration on platforms, or interaction with smart devices creates a "learning by doing" mechanism, helping to consolidate and expand skills. This is why the level of job digitalization needs to be viewed as an independent factor, not just an indicator of digital competence.

For Vietnamese coal industry enterprises, research on digital transformation currently focuses primarily on technology, governance, and operational efficiency, while quantitative evidence on digital capabilities at the worker level remains limited. This gap is significant because the coal industry workforce is highly diverse in terms of age, education level, position, experience, and exposure to technology. A digital transformation program may yield different results across units or worker groups if training, support, opportunities for use, and learning motivation are not uniform. Therefore, identifying the influencing factors and the relative impact of each factor is directly relevant to the design of human resource development policies.

Based on this, the study analyzes the impact of five factors—digital training and development, infrastructure and technological readiness, organizational support, individual learning orientation, and the level of job digitalization—on the digital competence of workers in Vietnamese coal industry enterprises. The study aims at three objectives: (i) developing a scale suitable for the industrial labor context; (ii) testing the impact of each factor on digital competence; and (iii) identifying differences in digital competence among several groups of workers to propose group-based management implications.

From a theoretical perspective, the research connects approaches to human capital, enterprise resources, organizational support, and workplace learning within a unified model. From a practical perspective, the results provide a basis for businesses to shift from a "invest in technology first, train later" approach to a synchronized approach between technology, work, and people. This also forms the basis for building digital competency maps, designing job-specific training programs, and facilitating continuous digital learning throughout operations.

II. THEORETICAL FOUNDATION

Digital skills of the workforce

The digital competence of workers is understood as the ability to integrate knowledge, skills, and attitudes to use digital technology effectively, safely, and responsibly in performing their professional tasks. This structure reflects not only technical manipulation abilities but also includes data comprehension, tool selection, digital communication and coordination, information security, problem-solving, and self-updating as technology changes (Vuorikari et al., 2022).

In the workplace, Oberländer et al. (2020) propose a broader view of digital competence, whereby competence is expressed through the ability to complete work in a digitized environment rather than through possessing a separate list of skills. This is relevant to coal industry workers because the same technology can require different competencies among operators, technicians, electromechanical officers, dispatchers, safety officers, and managers. This study therefore measures digital competence through the ability to use digital systems for work, process data and information, coordinate on digital platforms, solve

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technological problems, and maintain digital security.

Digital training and development

Human capital theory posits that education and training are investments that increase an individual's productive capacity. In the context of digitalization, training also helps workers reduce uncertainty when facing new technologies, form correct cognitive models of the system, and increase the ability to translate knowledge into practical use. A systems overview by Mendoza-Chan and Pee (2024) shows that developing digital skills in adults is more effective when there is a combination of formal instruction, social learning, active learning, and opportunities for application in the workplace.

For the coal industry, digital training programs need to be linked to specific operational scenarios: reading equipment data, responding to alerts, accessing electronic logs, using maintenance software, updating production information, or coordinating with other departments through the system. When training content is closely related to tasks, involves practical exercises, and is repeated according to the technological cycle, workers are more likely to develop sustainable competencies. Therefore, research expects digital training and development to have a positive impact on digital competence.

H1: Digital training and development has a positive impact on the digital capabilities of workers in Vietnamese coal industry enterprises.

Infrastructure and technological readiness

Infrastructure and technological readiness reflect the adequacy, stability, accessibility, and suitability of equipment, software, connectivity, data, and technical support. From a resource-based perspective, technological assets only create value when combined with user capabilities. If systems are frequently disrupted, access is restricted, interfaces are difficult to use, or data is incomplete, workers have fewer opportunities for training and tend to revert to manual methods.

Conversely, a stable infrastructure facilitates regular use, habit formation, and increased digital confidence. In a mining environment, this is even more crucial because many processes depend on specialized equipment, transmission networks, and monitoring systems with high safety requirements. Therefore, technological readiness is expected to provide the physical foundation for the formation and strengthening of digital capabilities.

H2: Infrastructure and technological readiness have a positive impact on the digital capabilities of workers in Vietnamese coal industry enterprises.

Organizational support

Organizational support theory emphasizes employees' perception that the organization values their contributions and cares about their working conditions (Eisenberger et al., 1986). In digital transformation, organizational support manifests itself through guidance from superiors, technical support, time spent on learning, feedback on errors, and mechanisms to encourage technology experimentation.

Support is particularly important when workers have to change habits formed over many years. The presence of a mentor or experienced colleague helps reduce the psychological cost of experimentation, while also limiting the avoidance of mistakes. A review by van Laar et al. (2020) also shows that social support is a notable antecedent to digital competence. Therefore, a supportive environment is expected to increase digital competence levels.

H3: Organizational support has a positive impact on the digital capabilities of workers in Vietnamese coal industry enterprises.

Personalized learning orientation

A learning orientation reflects a proactive approach to learning, a willingness to experiment, and a long-term focus on developing competencies. This characteristic is particularly important for digital skills because technology changes rapidly, making formally taught knowledge quickly become outdated. Individuals with a strong learning orientation often proactively seek guidance, ask colleagues, practice independently, and transfer experience from one system to another.

Studies on digital skills in workers indicate that motivation, confidence, and experience are closely linked to proficiency levels (van Laar et al., 2020). In the coal industry, where digitalization is uneven across positions, a learning orientation can help workers compensate for limitations in formal training opportunities. Therefore, this is expected to be one of the factors with a strong impact.

H4: Personalized learning orientation has a positive impact on the digital capabilities of workers in Vietnamese coal industry enterprises.

Level of job digitization

The degree of job digitization reflects the frequency and depth with which daily tasks require workers to use digital systems, data, smart devices, or integrated platforms. The workplace learning approach posits that repeated practice is a crucial

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mechanism for knowledge to become competence. An individual may attend training, but competence will be difficult to maintain if it is rarely used afterward.

In the coal industry, job digitization can manifest in the use of control panels, updating production data, receiving dispatch orders on the system, monitoring equipment parameters, extracting reports, using maintenance software, or working with electronic records. When these activities become a regular part of the job, workers have more opportunities to practice and solve real-world problems. Therefore, the level of job digitization is expected to have a positive impact on digital competence.

H5: The level of job digitization has a positive impact on the digital capabilities of workers in Vietnamese coal industry enterprises.

III. RESEARCH METHODOLOGY

Research approach and design

This study uses a quantitative method to test the model of factors influencing digital competence. The subjects of analysis are workers employed in businesses operating in mining, screening, mechanical engineering, transportation, and related production support sectors of the coal industry. Respondents were selected to cover both direct and indirect labor groups, with priority given to positions that have used or are currently using digital equipment, software, data, or platforms in their work.

The questionnaire was designed using a 5-point Likert scale, from 1 - strongly disagree to 5 - strongly agree. The scales were derived from research on digital competence, digital skills development, and organizational support, then adapted to suit the context of the coal industry. Before official use, the statements need to be reviewed for clarity, professional relevance, and to avoid duplication of content.

Research model and hypothesis system

The research model identifies the digital skills of workers (NLS) as the dependent variable. The five independent variables are digital training and development (DTS), infrastructure and technological readiness (HTC), organizational support (HTO), personal learning orientation (DHT), and job digitalization level (SHC). The relationship can be expressed as:

$$NLS = \beta_0 + \beta_1 DTS + \beta_2 HTC + \beta_3 HTO + \beta_4 DHT + \beta_5 SHC + \varepsilon$$

The model does not assume that the factors are interchangeable. Training provides knowledge and guided practice; infrastructure creates accessibility; organizational support reduces obstacles to use; learning orientation promotes self-development behavior; and job digitization creates opportunities for regular practice. Digital competence is seen as the result of a combination of these conditions.

H1: Digital training and development positively impacts digital competence.

H2: Infrastructure and technological readiness positively impact digital capabilities.

H3: Organizational support positively impacts digital competence.

H4: Personalized learning orientation positively impacts digital competence.

H5: The level of job digitization positively impacts digital competence.

Table 1. Scales for the research variables

Code	Content of observed variables
DTS1	Digital training content is linked to real-world job requirements.
DTS2	I had the opportunity to practice firsthand when learning new technologies.
DTS3	Digital training is conducted relatively frequently as the system changes.
DTS4	After the training, I received support to apply the knowledge to my work.
HTC1	The equipment and digital systems needed for the job are relatively complete.
HTC2	The digital system is stable and accessible when needed.
HTC3	Data and digital information for work purposes are available at an appropriate level.
HTC4	I received technical support when the digital system experienced problems.
HTO1	Management encourages employees to learn and use new technologies.
HTO2	I have ample time and resources to learn how to use the numbering system.
HTO3	My colleagues are always ready to help when I encounter technological difficulties.
HTO4	The company acknowledges the efforts to improve the digital skills of its employees.
DHT1	I proactively seek out new technologies relevant to my work.
DHT2	I'm willing to try a new approach using digital tools.
DHT3	I often find resources on my own or ask others for help to improve my digital skills.

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DHT4	I consider updating my digital skills to be an essential part of career development.
SHC1	My job frequently requires the use of digital systems or devices.
SHC2	I need to work with numerical data to complete the task.
SHC3	Many of my workflows are performed or recorded on digital platforms.
SHC4	The frequency of interaction with digital technology in the workplace is increasing.
NLS1	I can use the necessary number systems to complete the job.
NLS2	I can search, examine, and use digital data to serve my tasks.
NLS3	I can coordinate and communicate effectively through digital tools.
NLS4	I can handle common problems that arise when using technology.
NLS5	I understand and comply with basic information security requirements in my work.

Source: Results of research data processing.

The sample size used for the analysis consisted of 312 valid observations. With 25 observed variables, this size exceeded the minimum threshold typically used for PLS-SEM models and ensured an appropriate ratio of observations to measured variables. The sample was distributed by gender, age group, education level, and job position to increase data diversity. The technical-operational group accounted for the largest proportion, as they are the workforce directly interacting with equipment and digital systems in production operations.

Data analysis methods

The analysis was conducted in four main areas. First, descriptive statistics were used to identify the sample structure and variable distribution. Second, the measurement model was evaluated through external loading coefficients, Cronbach's Alpha, rho_A, composite reliability, and mean extracted variance; discriminant validity was tested using the HTMT criterion. Third, the structural model was evaluated through VIF, path coefficient, p-value, bootstrap confidence interval, coefficient of determination R^2, impact size f^2, and predictive power Q^2. Fourth, the study performed additional analysis by age group, job position, and frequency of technology use to clarify the training implications for the subgroups.

PLS-SEM was chosen because it is suitable for the objective of predicting and evaluating multiple relationships simultaneously within the model, while not requiring strict assumptions of multivariate normal distribution. A bootstrap of 5,000 replicates was used to assess the statistical significance of the path coefficients. The evaluation thresholds used included a preferred outload coefficient above 0.70; Cronbach's Alpha and composite reliability above 0.70; mean extracted variance above 0.50; HTMT below 0.85 or 0.90 depending on the degree of tightness; VIF below 3.3 and $p < 0.05$ for hypothesis testing.

IV. RESEARCH RESULTS AND DISCUSSION

Sample characteristics and descriptive statistics

Table 2. Characteristics of the study sample (n = 312)

Criteria	Group	Quantity	Percentage (%)
Gender	Male	221	70.8
	Female	91	29.2
Age	Under 30	66	21.2
	30-39	109	34.9
	40-49	88	28.2
	50 and above	49	15.7
Level	High school/vocational school	92	29.5
	College	78	25.0
	University	124	39.7
	Postgraduate	18	5.8
Location	Engineering - Operations	142	45.5
	Electromechanical - Maintenance	58	18.6
	Moderation/Safety/Monitoring	47	15.1
	Administration - Services	39	12.5
	Manage	26	8.3
Seniority	Under 5 years	73	23.4

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	5-10 years	101	32.4
	11-20 years	91	29.2
	Over 20 years	47	15.1

Source: Results of research data processing.

The study sample consists of 70.8% male and 29.2% female, reflecting the characteristics of the heavy industry workforce. The 30-39 age group accounts for the highest proportion at 34.9%, followed by the 40-49 age group at 28.2%. In terms of education level, 39.7% of respondents have a university degree; those with a high school or vocational school degree account for 29.5%. The job structure shows that 45.5% of respondents belong to the technical-operations group, 18.6% to the electromechanical-maintenance group, and 15.1% to the scheduling, safety, or supervisory group. This diversity facilitates the assessment of digital capabilities in both direct production and support/management positions.

Reliability and convergent validity of the scale

Table 3. Reliability and convergent validity of the scale

Scale	External download	Cronbach α	rho_A	CR	AVE
DTS	0.742-0.861	0.842	0.846	0.895	0.681
HTC	0.728-0.846	0.811	0.817	0.875	0.636
HTO	0.711-0.832	0.784	0,791	0.859	0.604
DHT	0.754-0.884	0.855	0.861	0.902	0.697
SHC	0.736-0.858	0.823	0.829	0.883	0.654
NLS	0.751-0.873	0.872	0.876	0.907	0.661

Source: Results of research data processing.

The results show that all external loading coefficients range from 0.711 to 0.884 and exceed the threshold of 0.70. Cronbach's Alpha ranges from 0.784 to 0.872, while composite reliability ranges from 0.859 to 0.907. The mean extracted variance of all scales is greater than 0.60. Thus, the scales achieve good intrinsic reliability and convergent validity. Notably, personal learning orientation and numerical competence show a high degree of intrinsic consistency, indicating that the observed variables relatively closely reflect the concepts being measured.

Discriminant validity of the scale

Table 4. HTMT Matrix

Variable	DTS	HTC	HTO	DHT	SHC	NLS
DTS	But	0.546	0.493	0.584	0.521	0.689
HTC		But	0.561	0.472	0.603	0.624
HTO			But	0.514	0.477	0.576
DHT				But	0.544	0.711
SHC					But	0.643
NLS						But

Source: Results of research data processing.

The highest HTMT value was 0.711 between learning orientation and numerical competence, lower than the threshold of 0.85. The remaining pairs ranged from 0.472 to 0.689. The results show that the six concepts in the model have appropriate levels of differentiation and there is no indication that two scales reflect the same conceptual content. This allows for further evaluation of the structural model without removing or merging variables.

Testing the structural model

Table 5. VIF coefficients of explanatory variables

Variable	VIF
DTS	1.86

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HTC	1.72
HTO	1.59
DHT	1.91
SHC	1.78

Source: Results of research data processing.

The VIF of the independent variables is in the range of 1.59-1.91, significantly lower than the threshold of 3.3. Therefore, multicollinearity is not a problem in the model. The coefficient of determination R^2 of numerical ability is 0.648, meaning that the five factors explain 64.8% of the variation in numerical ability. The adjusted R^2 value is 0.642. The Q^2 is 0.421 and greater than 0, indicating that the model has adequate out-of-sample predictive power for the dependent variable.

Hypothesis testing

Table 6. Hypothesis testing results

CT	Relationship	β	SE	t	p	CI 2.5%	CI 97.5%	f^2	Conclude
H1	DTS → NLS	0.286	0.052	5.50	<0.001	0.184	0.386	0.112	Accept
H2	HTC → NLS	0.193	0.049	3.94	<0.001	0.097	0.289	0.058	Accept
H3	HTO → NLS	0.121	0.047	2.57	0.010	0.029	0.211	0.027	Accept
H4	DHT → NLS	0.251	0.051	4.92	<0.001	0.151	0.350	0.091	Accept
H5	SHC → NLS	0.168	0.048	3.50	<0.001	0.073	0.261	0.046	Accept

Source: Results of research data processing.

Digital training and development had the largest impact coefficient ($\beta = 0.286$; $p < 0.001$; $f^2 = 0.112$). This result shows that in the context of the coal industry, digital competence is still mainly formed through organized capacity-building activities. When training programs are task-oriented, practical, and continue to be supported after the course, workers are able to translate knowledge into practical skills. This finding is consistent with Mendoza-Chan and Pee (2024), according to which the effectiveness of "digital skilling" strongly depends on the fit between learning methods and the work context.

Personal learning orientation was the second strongest influencing factor ($\beta = 0.251$; $p < 0.001$; $f^2 = 0.091$). This suggests that digital competence is not solely a result of training programs provided by the company. In a constantly changing technological environment, employees who proactively learn, experiment, and update their skills are better able to maintain their competence. This result adds evidence to the overview of van Laar et al. (2020), where motivation and experience were identified as important antecedents of digital skills.

Infrastructure and technological readiness have a positive impact with $\beta = 0.193$ ($p < 0.001$). The results show that investment in equipment and software is significant for digital competence, but its impact is lower than that of training and learning orientation. This implies that technology mainly creates a "practice space"; to develop competence, workers still need appropriate training content and motivation to use it. In the coal industry, where many devices are specialized, system access, connection quality, stability, and data availability can determine whether workers maintain regular digital operations.

The degree of job digitization had a β-value of 0.168 ($p < 0.001$). This result reinforces the learning-through-doing argument: skills are retained when employees regularly process data, operate systems, or collaborate through digital platforms. Therefore, businesses should not only measure the number of courses or the percentage of employees who have been trained. A more important indicator is the proportion of actual tasks requiring the use of digital technology and the extent to which employees are given opportunities to solve problems during the process.

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Organizational support has a β coefficient of 0.121 and is statistically significant at the 5% level (p = 0.010). This is the smallest impact among the five factors but still has practical significance. Unlike training or job digitalization, organizational support does not directly create skills but reduces barriers for employees to learn and use technology. With technical support, superiors encourage and colleagues share experiences, making employees less likely to avoid technology when errors occur. The results are consistent with the logic of organizational support theory (Eisenberger et al., 1986).

In high-safety manufacturing environments, this role is even more crucial because workers may be hesitant to experiment if they fear incorrect operation will disrupt the system. Therefore, support should be designed as a rapid feedback mechanism, on-site guidance, "digital core" teams, and controlled error learning processes, rather than just general encouraging messages.

Analyzing the differences between labor groups

Table 7. Comparison of digital skills among different worker groups.

Criteria	Group	Medium	Standard deviation	Inspection
Age	Under 30	4.01	0.48	F = 4.86; p = 0.003
	30-39	3.94	0.51	
	40-49	3.78	0.55	
	50 and above	3.69	0.58	
Location	Engineering - Operations	3.91	0.52	F = 3.72; p = 0.006
	Electromechanical - Maintenance	3.96	0.49	
	Moderation/Safety/Monitoring	4.02	0.47	
	Administration - services	3.72	0.59	
	Manage	3.88	0.50	
Frequency of using the digital system	Daily	4.08	0.44	F = 16.31; p < 0.001
	3-5 days/week	3.88	0.49	
	1-2 days/week	3.63	0.56	
	Less than 1 day/week	3.42	0.61	

Source: Results of research data processing.

The comparative results showed that digital competency scores decreased progressively with age group, and the difference was statistically significant (p = 0.003). However, the differences between age groups should not be interpreted as age determining competency. Age can simultaneously reflect differences in experience using technology, type of work, and frequency of exposure to technology. Therefore, the appropriate implication is to design training programs based on starting levels and tasks rather than using a uniform program for all ages.

Differences by position were also significant (p = 0.006), with the scheduling, safety, and monitoring groups having the highest average scores. These are positions that frequently interact with data systems, alerts, and coordination processes. In particular, the intensity of technology use showed the most significant difference: the group using digital systems daily had an average score of 4.08, significantly higher than the group using them less than one day per week (3.42). This finding reinforces the role of job digitalization as a mechanism for developing capabilities through continuous practice.

Overall, the order of impact from strongest to weakest is: digital training and development, individual learning orientation, infrastructure and technological readiness, level of job digitization, and organizational support. This order does not mean that businesses only need to focus on the top two factors. The supporting factors are: training provides initial knowledge; learning orientation promotes self-development; infrastructure provides accessibility; job digitization creates opportunities for practice; and organizational support helps maintain usage behavior when difficulties arise.

The results also highlight a crucial point for the digital transformation of the coal industry: digital competence should not be managed as a standalone training program by the human resources department. It needs to be integrated into job design, position standards, technology investment, and

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workplace support mechanisms. If technology is deployed but workers do not have frequent opportunities to use it, or if training is not linked to operational situations, the gap between digital investment and actual performance may persist.

V. CONCLUSION AND MANAGEMENT IMPLICATIONS

This study analyzes five groups of factors influencing the digital competence of workers in Vietnamese coal industry enterprises: digital training and development, infrastructure and technological readiness, organizational support, individual learning orientation, and the level of job digitization. The model results show that all five factors have a positive and statistically significant impact, explaining 64.8% of the variation in digital competence. Digital training and development is the factor with the strongest impact, followed by individual learning orientation. This confirms the central role of human capital development in digital transformation and demonstrates that training effectiveness depends on the individual's level of proactive learning and the work conditions that allow for the practice of those skills.

First, businesses need to build digital competency maps based on job positions. Instead of applying a single training program, each job group needs to define a minimum and advanced set of digital competencies, for example, the ability to use digital dashboards for operations; data mining of equipment and maintenance software for mechanical and electrical engineering; using warning data and risk analysis for safety; or report analysis and platform collaboration for management. Assessing input helps to group learners and reduce the problem of training being too easy or too difficult.

Secondly, training programs should shift from simply conveying software features to learning based on tasks and scenarios. Content should utilize data, interfaces, and typical errors from the company's own operating systems. This could involve short, modular training sessions, on-site instruction, hands-on videos, case libraries, and peer mentoring mechanisms. Following training, a supervised practice phase is necessary to enhance the transfer of skills into the workplace.

Third, businesses need to manage their digital infrastructure from a user experience perspective. A modern system that is difficult to access, lacks data, or has slow support will reduce learning opportunities. Therefore, technology deployment needs to be accompanied by data standardization, appropriate access rights, user-friendly documentation, and clear technical support channels. Metrics for evaluation should include actual usage, error rate, request processing time, and the percentage of tasks performed entirely within the system.

Fourth, a continuous digital learning environment needs to be developed. Direct managers can play a role in encouraging controlled experimentation, recognizing initiatives, and organizing experience sharing among shifts, teams, or workshops. Highly learning-oriented workers should be developed into "digital cores," supporting colleagues and participating in testing new systems. This mechanism both creates internal resources and reduces reliance on centralized training.

Fifth, job digitization should be considered a capacity-building tool. When redesigning processes, businesses should create tasks that require workers to use data and systems at an appropriate level, rather than maintaining a prolonged parallel of paper and digital processes. Increased usage frequency should be accompanied by safety control mechanisms, especially for systems related to production equipment and underground mining environments.

The study also has some limitations. The current model focuses on five groups of factors and does not consider variables such as technological confidence, digital safety culture, digital leadership quality, or technological complexity. Further research could examine the mediating role of digital self-efficacy, the moderating role of age or professional experience, and use a longitudinal design to observe changes in competence after training programs and the deployment of new technologies.

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