Available at https://journalenrichment.com/index.php/jr/

Enrichment: Journal of Multidisciplinary Research and Development

The Influence of Technology Orientation, Human Resources Readiness, and Management Support on Digital Competence and its Implications for Mining Operational Team Performance (Case Study at PT Petrosea TBK)

Yoppi Adhi Praeditia[1]*, Mohammad Riza Sutjipto[2]
Universitas Telkom, Indonesia[1,2]
Email: ypraeditia@gmail.com*

ABSTRACT

This study examines the impact of technology orientation, human resource readiness, and management support on digital competency and its implications for operational team performance at PT Petrosea Tbk, a mining services company undergoing digital transformation via the Minerva platform since 2018. Despite ongoing efforts, team performance in productivity, efficiency, and quality remains inconsistent. Using a quantitative approach, data were collected from 72 operational team leaders through proportionate stratified random sampling and analyzed using PLS-SEM via SmartPLS 4. The results show that management support (β = 0.406; $p < 0.01$), technology orientation (β = 0.319; p = 0.02), and HR readiness (β = 0.235; p = 0.017) significantly influence digital competency. In turn, digital competence (β = 0.374; p = 0.01) significantly enhances operational team performance and mediates the relationship between all independent variables and performance outcomes. The R^2 values of 0.551 for digital competency and 0.715 for team performance indicate a moderately strong model. This study contributes to the digital transformation literature in the mining sector by empirically validating how internal organizational resources and capabilities drive performance through digital competence. Practical recommendations include enhancing training for data analysis and platform usage, strengthening management's digital support role, and improving technological accessibility and innovation.

***Keywords:** digital transformation; digital competence; mining operational team performance*

INTRODUCTION

The mining sector in Indonesia makes a significant contribution to the country's economy. Based on data from the *Badan Pusat Statistik* (BPS) or Indonesian Central Statistics Agency (2023), the percentage of Gross Domestic Product (GDP) from the mining and quarrying sector increased from 6.43% in 2020 to 8.97% in 2021. In 2022, there was a substantial rise in contribution to 12.22%, with the largest contribution to GDP coming from coal mining, accounting for 6.62%. Indonesia's coal mining industry is supported by a total resource of 90 billion tons and proven reserves of 30 billion tons as of December 2023 (Ministry of Energy and Mineral Resources, 2023). According to the *Sekretariat Jenderal Dewan Energi Nasional* (2023), final energy consumption in 2022 was dominated by coal at 26%. Electricity production over the next ten years is expected to continue relying heavily on fossil fuels, especially coal. These vast reserves and continued demand for coal indicate that Indonesia's mining sector holds strong potential for continued growth.

Digitalization has become a key factor in increasing efficiency and competitiveness across various sectors, including mining. In this context, digitalization refers to the use of computerized and digital tools, systems, and information with the aim of reducing costs, increasing productivity and operational efficiency, and transforming how mining activities are carried out (Barnewold, 2019; Barnewold & Lottermoser, 2020). According to the 2021 Digital Acceleration Index (DAI) released by the Boston Consulting Group (BCG), the metals and mining sectors show lower digital maturity—between 30% and 40%—compared to other industries such as the chemical or automotive sectors. Several challenges hinder the digital transformation of mining companies, including a lack of skilled personnel to understand digital solutions, remote locations with limited network access, and cultural resistance to integrating digital systems into traditional workflows (Ganeriwalla et al., 2021; Manyuchi & Sukdeo, 2021; Whitman Cobb, 2020).

Digital transformation is essential and unavoidable for companies aiming to remain competitive in the era of globalization. Although technology can enhance the effectiveness of the supply chain, it requires significant investment, which means businesses must weigh the value of these investments carefully (Fadaki et al., 2020; Hendayani & Febrianta, 2020; Mora-Monge et al., 2023). With the rapid development of technologies such as the Internet of Things (IoT), big data analytics, cloud computing, automation, and artificial intelligence (AI), the mining industry is compelled to adapt and adopt these innovations. Research on digital transformation in the mining sector highlights its goals of optimizing production costs, increasing output, achieving economic efficiency, and enhancing safety across mining operations (Fang et al., 2024; Hushko et al., 2021; Kaniappan Chinnathai & Alkan, 2023; Shinkevich et al., 2020).

PT Petrosea Tbk, a service-based company operating in the mining sector, began its digital transformation journey in 2018. This transformation represents a strategic initiative to improve operational performance and position PT Petrosea Tbk as a leading technology adopter in the industry. The company has differentiated its mining services through the Minerva (*Mining Engineering and Construction Advanced Analytics*) project, an integrated digital mining system. This project serves as a catalyst for implementing digital transformation across all mining operation stages. The services, tailored to project needs, are facilitated through the Minerva Digital Platform, which leverages cutting-edge technology to boost productivity and efficiency.

In 2019, PT Petrosea Tbk was selected to join the Global Lighthouse Network by the World Economic Forum, recognizing its successful implementation of Industry 4.0 technologies in mining operations (www.petrosea.com). Since 2022, the company has utilized real-time data through a centralized Remote Operations Center (ROC) located at its headquarters, enabling oversight and control of operations across its mining sites. The ROC aims to maintain operational quality and profitability.

The Minerva Digital Platform at PT Petrosea Tbk integrates several digital products that support mining operations (Company Profile of PT Petrosea Tbk, 2024). Long-term mining planning is facilitated by digital tools such as the *Mine Operation Planning Dashboard* (MOPAD). For short-term planning, the company utilizes the *Mine Operation Control Dashboard* (MOCOM), along with *Augmented Reality* (AR) and *Virtual Reality* applications. Core mining operations are managed through integrated digital tools such as *Real-time Crew Management*, *Dynamic Dispatch*, *Fuel & Road Analyzer*, *Control Tower* (*Mine Dash*), *PdM & ARMS* predictive maintenance systems, and *SHEPRO*, which is designed to ensure safety compliance. Drilling and blasting activities, which demand precise positional accuracy, are supported by the *High Precision System* (HPS). Meanwhile, dewatering and geotechnical support functions are managed and monitored through the *Integrated Dewatering System* and *Geotech Monitoring* technologies. These interconnected systems work cohesively to enhance the effectiveness and precision of PT Petrosea Tbk's mining operations.

The Minerva Digital Platform has positively impacted PT Petrosea Tbk's mining operational performance, particularly in achieving productivity and efficiency targets. Productivity refers to the working capacity of production equipment measured in hours, while utilization or efficiency is defined as the ratio between time spent working and total available time. The performance quality of PT Petrosea Tbk's operational team is assessed based on the alignment between mine planning and actual results achieved.

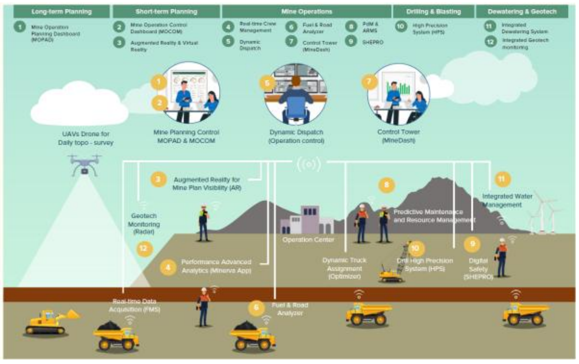

Figure 1. Digital Integrated Products of PT Petrosea Tbk
Source: www.petrosea.com (2024)

However, the performance condition of the mining operational team at PT Petrosea Tbk remains suboptimal, with achievements falling short of expectations due to fluctuating operational performance. Based on the company's internal data from PT Petrosea's projects that have implemented the *Minerva Digital Platform* between 2019 and 2024, the operational team's performance—measured in terms of productivity, efficiency, and quality—has yet to consistently reach 100%. The suboptimal performance of the mining operational team is reflected in the actual percentage of productivity, efficiency, and work quality achieved compared to the targets set by PT Petrosea Tbk, which still shows instability in meeting these targets, as illustrated in Figure 2, Figure 3, and Figure 4 below.

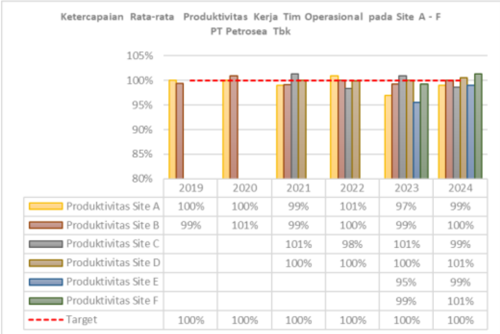

Figure 2. Achievement of Work Productivity of PT Petrosea Tbk Operational Team
Source: PT Petrosea Tbk internal data (2024)

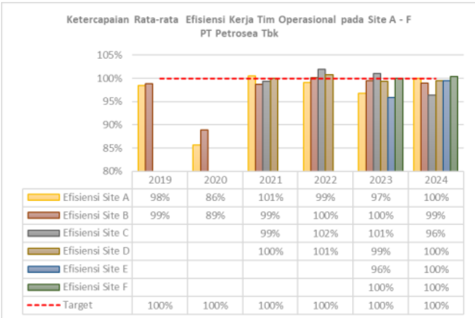

Figure 3. Achievement of Work Efficiency of PT Petrosea Tbk Operational Team
Source: PT Petrosea Tbk internal data (2024)

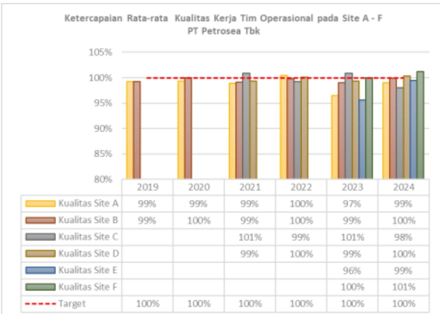

Figure 4. Achievement of Work Quality of PT Petrosea Tbk Operational Team
Source: PT Petrosea Tbk internal data (2024)

As an effort to explore the causes of the suboptimal mining operational performance at PT Petrosea Tbk—a company that has implemented digitalization—a preliminary study was conducted through a review of previous research journals, books, and data from mining consultant studies. This problem analysis was further strengthened by interviews with five heads of the *Operation Excellence* department at PT Petrosea Tbk, who possess a strong understanding of mining operations and digitalization in 2024.

Ferdiansyah & Tricahyono (2023), in their research on the implementation of digital transformation in *UMKM* (*Usaha Mikro, Kecil, dan Menengah*), identified several factors that hinder the digital transformation process, including issues related to human resources, technological utilization, the integration of information technology with business processes, and digital leadership. Digital transformation is structured around three main pillars, which present significant challenges for regional innovation systems and require critical intervention across multiple dimensions (Brunetti et al., 2020). The first pillar is culture and skills, encompassing digital learning, talent development, and fostering a digital culture. The second pillar involves infrastructure and technology, relating to the demands for data, interaction, and artificial intelligence as core strategic components. The third pillar is the ecosystem, which includes investment implementation guided by medium- and long-term visions, strategic partnerships, and quality of life considerations.

The author conducted interviews with five heads of the *Operation Excellence* department at PT Petrosea Tbk, which yielded several insights into the factors contributing to the suboptimal performance of the mining operations team. These include: minor disruptions in the digital systems used—such as bugs and errors—especially in high-volume production projects; inadequate IT infrastructure, resulting in data delays that impact real-time decision-making; inconsistent usage of digital platforms by operational supervisors; inconsistency in reward and reprimand systems related to digital platform engagement by management; and the limited ability of operational supervisors to utilize digital platforms for analyzing and resolving operational issues.

From the entirety of the preliminary study, it is indicated that the root causes of the suboptimal performance of the mining operational team are related to team resources—namely technology orientation, human resource readiness, and managerial support—as well as the team's capabilities in terms of digital competence. An organization's performance is closely linked to its resources, competencies, and systems that contribute to competitive advantage (Malhotra et al., 2024).

The *Minerva Digital Platform* has not yet been fully implemented across all PT Petrosea Tbk mining sites, particularly in projects that commenced in 2024. In these new mining projects, operational processes are still carried out manually due to the absence of an integrated digital platform for planning, automation, real-time monitoring, and advanced analytics. One of the contributing factors is the limited technological infrastructure at remote new mine sites. Projects that have already implemented the *Minerva Digital Platform* are used as benchmarks for newer projects undergoing the digital transformation process, helping them meet digitalization targets and accelerate the development of digital competencies and operational performance. Organizations that aim to accelerate digital transformation must learn from digitally mature entities, particularly in applying effective strategies to improve productivity and operational efficiency.

Based on the explanation above, this study will address the influence of technology orientation, human resource readiness, and management support on digital competence and their implications for the performance of mining operational teams at PT Petrosea Tbk. From the aforementioned background, the research questions are formulated as follows: How do technology orientation, human resource readiness, and management support influence digital competence? How do these three factors affect the performance of mining operational teams? How does digital competence impact operational team performance? And how do technology orientation, human resource readiness, and management support affect team performance through the mediation of digital competence?

The objectives of this research, in line with the issues raised, are: (1) to determine the influence of technology orientation, human resource readiness, and management support on digital competence; (2) to examine the effect of these three factors on the performance of mining operational teams; (3) to assess the influence of digital competence on operational performance; and (4) to analyze the mediating role of digital competence in the relationship between technology orientation, human resource readiness, management support, and team performance.

This study is expected to offer both theoretical and practical contributions. Academically, it will enrich the literature related to the influence of technology orientation, human resource readiness, and management support on digital competence and its implications for operational team performance in the mining sector. It can also serve as a reference for future studies exploring digital transformation strategies in the mining and broader energy industries to yield more comprehensive findings. Practically, the study is anticipated to provide insight into PT Petrosea Tbk's current digital competence status and how it can be optimized to improve operational performance. The findings may also benefit *Telkom University* and other academic institutions with a specific interest in the mining industry. Given the limited existing literature on digital transformation and competencies in Indonesia's mining sector, this research may also serve as a valuable reference for other mining companies undergoing digital transformation, enabling them to better adapt to digital developments and enhance both their digital competencies and operational outcomes.

METHOD

Research is the activity of generating knowledge derived from arguments and evidence to identify existing gaps, provide perspectives and supporting data, offer new insights, and examine arguments from various viewpoints in order to validate or refute them. Research methodology is a systematic approach used to achieve research objectives through investigative stages, consisting of various methods that serve as a reference for researchers throughout the research process.

This research falls under the category of explanatory causal research, as its primary objective is to explain the causal relationships between independent variables—namely, technology orientation, human resource readiness, and management support—with the mediating variable of digital competence and the dependent variable of operational performance. The aim of explanatory causal research is to determine the relationships and influence among variables. Additionally, this study has a descriptive component, as it seeks to understand and explain the characteristics of each variable's condition in order to identify priority issues that need to be addressed.

The methodology employed is quantitative, with data collected through an online questionnaire survey. Data analysis was conducted using *Structural Equation Modeling* (SEM). Quantitative research is scientific research that is specifically, clearly, and thoroughly designed to analyze relationships among variables, test theories, and employ predictive instruments that have undergone validity and reliability testing. It is analyzed using deductive reasoning and statistical methods to test hypotheses (Sugiyono, 2022). The decision to use a quantitative method is based on the study's aim to test relationships among variables through statistically measurable data, using a theory-based deductive approach in line with prior studies on the influence of resources and organizational capabilities on performance outcomes.

Surveys are a method used to collect data and information about individual preferences on specific topics. The survey method was chosen because it is suitable for collecting data from respondents located in various regions. This strategy involves data collection from respondents who represent the unit of analysis—namely, the excavation equipment work team at PT Petrosea Tbk, drawn from employees within the mining operations division.

This research adopts a *positivist paradigm*, focusing on measuring phenomena using quantitative methods and a deductive approach based on existing theories and previous studies, tested through empirical data. The *positivist paradigm* considers phenomena as observable, measurable, and governed by scientific principles and causal relationships. The deductive approach begins with established theories, concepts, and references to identify relationships between variables, which are then measured through data collection and field information.

The study was conducted in a real-world work environment at PT Petrosea Tbk and is therefore *non-contrived* (not artificially manipulated). Data were collected in the respondents' natural work context without any researcher intervention. The researcher's involvement was moderate, limited to designing the questionnaire instruments without influencing respondents' answers. In terms of timeframe, this research is categorized as *cross-sectional*, as data were collected within a specific period to explain the phenomena occurring at that time. *Cross-sectional* studies collect data at a single point in time, momentarily or once (Creswell & Creswell, 2017).

Population refers to a research domain comprising objects or subjects with specific characteristics and qualities that are studied, analyzed, and concluded upon by the researcher. The population encompasses all entities from which data are drawn and whose conditions are statistically assessed. *Samples* are portions of the population that are representative and used to draw conclusions. The sample represents a smaller subset of the population that shares its characteristics, allowing for accurate and unbiased statistical analysis without favoring any particular attribute.

The sampling method used is *probability sampling* through *proportionate stratified random sampling*, as the selected elements possess non-homogeneous characteristics and are distributed across proportional strata—specifically, the excavation equipment work teams in PT Petrosea Tbk's mining operations.

The population of this study includes 72 operational leaders from 36 work teams at PT Petrosea Tbk who use the *Minerva Digital Platform*. Each operational work team comprises a fleet of one excavator unit, several transport units (*dump trucks*), and a set of supporting tools (*dozers* and *graders*), all overseen by a supervisor acting as the team's operational leader. The total sample consisted of 72 individuals, in accordance with the sample size determination method. According to Sugiyono (2022), this study uses the *census method*, or *saturated sampling*, where the sample includes all members of a relatively small population.

RESULTS AND DISCUSSION

Research Results

1. **Measurement Model Test Results (Outer Model)**

In this study, the measurement model test (outer model) was carried out using SmartPLS 4 software. According to Hair et al. (2021), outer model testing is used to show the existence of a relationship between variables and variable indicators, which is used to assess reliability and validity. This measurement model (outer model) can show the observed variables in representing the latent variables to be measured. In this study, the measurement model to be tested includes convergent validity, discriminant validity, and reliability.

1) Validity Convergence

According to Ghozali & Kusumadewi (2023), convergent validity testing is used to show that measurements from a construct should have a high correlation. Convergent validity is the relationship between the value of the indicator and the value of the construct. The convergent validity of the measurement model in this study was calculated through the Loading Factor and Average Variance Extracted (AVE) values.

A. Loading Factor

The Loading Factor can be declared valid if the test result value > 0.70 so that the existing indicator is valid to measure the constructed formed. The following are the values of all the indicators in this study, as shown in Table 1 below.

Table 1. Loading Factor Test Results Value

Variable	Item Code	*Loading Factor*	Result
Technology Orientation	TAK1	0,781	valid
	TAK2	0,877	valid
	TIK1	0,807	valid
	TIK2	0,847	valid
	TIT1	0,816	valid
	TIT2	0,862	valid
Human Resource Readiness	SKK1	0,811	valid
	SKK2	0,777	valid
	SPP1	0,794	valid
	SPP2	0,797	valid
	SSM1	0,837	valid
	SSM2	0,797	valid
Management Support	DMK1	0,891	valid
	DMK2	0,878	valid
	DMP1	0,860	valid
	DMP2	0,789	valid
	DMP3	0,860	valid
Digital Competence	KDI1	0,895	valid
	KDI2	0,873	valid
	KDK1	0,848	valid
	KDK2	0,841	valid
	KDP1	0,788	valid
	KDP2	0,821	valid
Mining Operational Team Performance	KOE1	0,814	valid
	KOE2	0,837	valid
	KOK1	0,738	valid
	KOP1	0,718	valid
	KOP2	0,817	valid

Source: Researcher's processed data (2025)

It can be seen in Table 1 above that all indicators in this study can be declared valid because the loading factor value produced by each indicator > 0.7. The largest loading factor value is owned by the KDI1 indicator, which is related to the ability of the work team to understand how to access the Minerva digital platform to obtain data and information related to operations with a loading factor value of 0.895. The lowest loading factor value is owned by the KOP1 indicator, which is related to the productivity of equipment in the work team that has increased and achieved the target through the use of digital technology with a loading factor value of 0.718. The following is Figure 4 which shows the results of the loading factor test using SmartPLS 4.0 software.

Figure 4. Results of Outer Model Analysis Source: Author's processed data, 2025

B. Average Variance Extracted (AVE)

Another measuring tool in measuring convergent validity is AVE (Average Variance Extracted), which measures the level of items used in the measurement of a variable can be correlated when compared to other variable measurement items in the model. According to Hair et al. (2021), the AVE value must be >0.5 in order to be declared valid. It can be seen in Table 2 below that all variables have an AVE value of >0.5 so that all constructs are valid and have passed the convergent validity test. The Management Support variable had the highest AVE value of 0.733. Meanwhile, the one with the lowest AVE value is the Mining Operational Team Performance Variable with an AVE value of 0.618.

Table 2. Average Variance Extracted (AVE) Test Results Value

Variable	Average variance extracted (AVE)
Technology Orientation	0,693
Human Resource Readiness	0,644
Management Support	0,733
Digital Competence	0,714
Mining Operational Team Performance	0,618

Source: Researcher's processed data (2025)

2) Discriminant Validity

Discriminant validity has the principle that a variable is able to capture phenomena that cannot be represented by other variables in the model. According to Indrawati (2015), the model that meets the criteria of discriminant validity is a model that if the test results of the dimensions are constructively not significantly correlated. The discriminant validity of the measurement model was assessed based on the Cross Loading values, Fornell-Larcker Criterion, and Heterotait-monotrait Ratio.

a. Cross Loading

The cross loading value can be declared valid if the value in the intended construct is greater when compared to the cross loading value in other constructs. Based on the results of the cross loading test in Table 3 below, it can be seen that each indicator has met the criteria. Each indicator in each dimension in the variables of management support, digital competence, performance of the mining operational team, readiness of human resources, and technology has a higher correlation coefficient in each construct that will be measured when compared to the correlation coefficient in other constructs.

Table 3. Value of Cross Loading Test Results

	Management Support	Digital Competence	Mining Operational Team Performance	Human Resource Readiness	Technology
DMK1	**0,891**	0,601	0,581	0,478	0,258
DMK2	**0,878**	0,553	0,576	0,312	0,269
DMP1	**0,860**	0,543	0,583	0,427	0,406
DMP2	**0,789**	0,462	0,585	0,275	0,441
DMP3	**0,860**	0,518	0,520	0,374	0,217
KDI1	0,616	**0,895**	0,667	0,535	0,399
KDI2	0,551	**0,873**	0,719	0,449	0,407
KDK1	0,489	**0,788**	0,543	0,397	0,614
KDK2	0,520	**0,821**	0,637	0,448	0,404
KDP1	0,587	**0,848**	0,669	0,448	0,448
KDP2	0,399	**0,841**	0,632	0,334	0,522
KOE1	0,491	0,488	**0,814**	0,538	0,326
KOE2	0,530	0,641	**0,837**	0,478	0,479
KOK1	0,412	0,682	**0,738**	0,442	0,581
KOP1	0,651	0,541	**0,718**	0,338	0,452
KOP2	0,531	0,629	**0,817**	0,608	0,392
SKK1	0,403	0,465	0,508	**0,811**	0,252
SKK2	0,271	0,328	0,468	**0,777**	0,323
SPP1	0,258	0,465	0,493	**0,794**	0,341
SPP2	0,355	0,376	0,496	**0,797**	0,189
SSM1	0,384	0,442	0,440	**0,837**	0,271
SSM2	0,431	0,400	0,544	**0,797**	0,207
TAK1	0,294	0,463	0,557	0,461	**0,781**
TAK2	0,314	0,464	0,495	0,210	**0,877**
TIK1	0,238	0,455	0,428	0,262	**0,807**
TIK2	0,323	0,444	0,442	0,219	**0,847**
TIT1	0,250	0,438	0,439	0,243	**0,816**
TIT2	0,423	0,460	0,476	0,221	**0,862**

Source: Researcher's processed data (2025)

b. Fornell-Larcker Criterion

According to Hair et al. (2021), the Fornell-Larcker Criterion test can be declared passed if the square root value of AVE exceeds the correlation between latent constructs. In this study, the characteristic validity test through the Fornell-Larcker Criterion table has a greater value of the first variable in the construct of each variable, as seen in Table 4 below. Management support has a value of 0.856 greater than other variable constructs, the human resource readiness variable has a value of 0.802 greater than other variable constructs, the mining operational team performance variable has a value of 0.786 greater than other variable constructs, digital competence has a value of 0.845 greater than other variable constructs, and the technology orientation variable has a value of 0.832 greater than other variable constructs. It can therefore be concluded that the construct of all variables has met the requirements of the discriminant validity test based on the Fornell-Larcker Criterion.

Table 4. Fornell-Larcker Criterion Test Results

Variable	Management Support	Human Resource Readiness	Mining Operational Team Performance	Digital Competence	Technology Orientation
Management Support	**0.856**				

Human Resource Readiness	0.438	**0.802**			
Performance of the Mining Operational Team	0.665	0.614	**0.786**		
Digital Competence	0.627	0.518	0.765	**0.845**	
Technology Orientation	0.37	0.328	0.572	0.547	**0.832**

Source: Researcher's processed data (2025)

c. Heterotrait-Single Trait Ratio

According to Hair et al. (2021), Heterotrait-monotrait (HTMT) is a ratio that describes the average of all correlations of construct indicators that measure different constructs, so that the validity of the discriminant is well expressed if the HTMT value is less than 0.90. The following is Table 5 results from HTMT measurements.

Table 5. Heterotrait-monotrait Ratio Test Results

Variable	Management Support	Human Resource Readiness	Mining Operational Team Performance	Digital Competence
Human Resource Readiness	0.483			
Mining Operational Team Performance	0.761	0.705		
Digital Competence	0.681	0.566	0.860	
Technology Orientation	0.407	0.361	0.644	0.601

Source: Researcher's processed data (2025)

Based on Table 5, the results of the Heterotrait-monotrait Ratio test show that all construct values are less than 0.90. The HTMT ratio required in the study has been met so that it can be said that the discriminatory validity test of all constructs in the study is good and acceptable (valid).

3) Reliability Test

Reliability testing in the study was used to measure how accurate and consistent variable indicators are if latent variables increase. The reliability of the measurement model can be assessed based on Cronbach's Alpha and Composite Reliability values.

A. Cronbach's Alpha

Cronbach's Alpha (CA) in confirmatory research is acceptable if the value is greater than 0.70. The following is Table 6 of the results of Cronbach's Alpha measurements.

Table 6. Cronbach's Alpha Test Results Value

Variable	*Cronbach's Alpha*
Management Support	0,909
Mining Operational Team Performance	0,844
Digital Competence	0,920
Human Resource Readiness	0,889
Technology Orientation	0,911

Source: Researcher's processed data (2025)

From Table 6. above, it can be seen that all indicators in each variable have met the requirements for the reliability test, namely Cronbach's alpha > value of 0.7. The highest Cronbach's alpha value is digital competence, which is 0.920. Meanwhile, the lowest Cronbach's alpha value was the performance of the mining operational team, which was 0.844.

B. Composite Reliability

Composite reliability is used to test the reliability value of the indicators in the variable. If it has a value of composite reliability >0.70, then a variable is declared acceptable. The following is Table 7. results from composite reliability measurements.

Table 7. Composite Reliability Test Results Value

Variable	*Composite reliability*
Management Support	0,911
Mining Operational Team Performance	0,846
Digital Competence	0,922
Human Resource Readiness	0,891
Technology Orientation	0,912

Source: Researcher's processed data (2025)

From Table 7. above, it can be seen that all variables have a composite reliability value > 0.70. The highest composite reliability value is digital competence, which is 0.922. Meanwhile, the lowest composite reliability value was the performance of the mining operational team, which was 0.846. Based on this data, it can be concluded that all variables in this study are declared to meet the requirements so that they can be continued at the internal model testing stage.

2. Structural Model Test Results (Inner Model)

Structural model testing aims to estimate the influence of relationships between latent variables in the study, which is done by examining the R-Square of each endogenous latent variable as a predictive ability in the research model, F^2 to determine the effect size, as well as Q^2 to determine the possession of predictive relevance. The structural model test in this study was carried out through a bootstrapping procedure using SmartPLS 4. The following is Figure 5 which shows the results of internal model testing using SmartPLS 4.0 software.

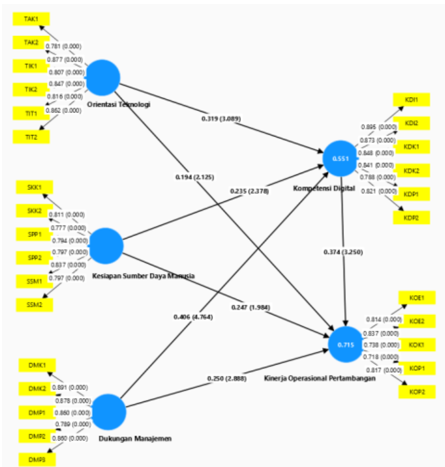

Figure 5. Results of Internal Analysis Model Source: Author's processed data, 2025

1) R-Square

R-Square is a determination coefficient in endogenous coefficients that shows the ability of exogenous constructs to explain variations in endogenous constructs. The R-Square value ≥ 0.75 means a strong model, 0.50 – 0.74 means a moderate model, and 0.25 – 0.49 means a weak model. The following is Table 8 of the results of the R-Square measurement.

Table 8. R-Square Test Results Scores

Variable	R-square	R-square adjusted

Mining Operational Team Performance	0,715	0,698
Digital Competence	0,551	0,531

Source: Researcher's processed data (2025)

Based on Table 8 above, it can be seen that the R-Square value in the performance variable of the mining operational team is 0.715 which means a moderate model. This shows that the technology orientation variable, the human resource readiness variable, the management support variable and the digital competency variable had an effect on the performance variable of the mining operational team by 71.5%. While the remaining 28.5% was influenced by other variables that were not included in this study. Furthermore, the R-Square value of the digital competency variable is 0.551 which means a moderate model. This shows that the technology orientation variable, the human resource readiness variable, and the management support variable have an effect on the digital competency variable by 55.1%. While the remaining 44.9% was influenced by other variables that were not included in this study.

2) F Square or Effect Size

F Square or effect size is a structural model test that is carried out to determine the change in value in endogenous constructs caused by the substantial influence of exogenous constructs. The interpretation of the F-Square value is 0.02 – 0.14 a weak influence, then a value of 0.15 – 0.34 is a moderate influence, and if the value is ≥ 0.35, then the influence is strong. The following is Table 9 of the results of the F-Square measurement.

Table 9. F-Square Test Results Scores

Variable	Mining Operational Team Performance	Digital Competence
Digital Competence	0,220	
Management Support	0,129	0,275
Human Resource Readiness	0,152	0,095
Technology Orientation	0,092	0,188

Source: Researcher's processed data (2025)

Based on Table 9 above, the digital competency variable affects the performance variable of the mining operational team of 0.220 (moderate). The management support variable affects the performance variable of the mining operational team of 0.129 (weak) and the digital competency variable of 0.275 (moderate). Then the variable of human resource readiness had an influence on the performance variable of the mining operational team of 0.152 (moderate) and the variable of digital competence of 0.095 (weak). Next, the technology orientation variable affects the performance variable of the mining operational team of 0.092 (weak) and the digital competency variable of 0.188 (moderate).

3) Q^2 Predictive Relevance

Q^2 Predictive Relevance is a structural model test to validate the predictive ability of the model in endogenous constructs that have reflective indicators. A value of $Q^2 > 0$ indicates that the model has predictive relevance, while $Q^2 < 0$ indicates that the model lacks predictive relevance. Based on the value of Q^2, if the value is 0.02, then the model is weak, the value is 0.15, the model is moderate, and if the value is 0.35, then the model is strong. In this study, predictive relevance was obtained through the blindfolding menu in the SmartPLS 4 software. The following is Table 10 of the results of the Q^2 Predictive Relevance measurement.

Table 10. Predictive Relevance Test Results Value

Variable	SSO	SSE	Q^2 (=1-SSE/SSO)
Management Support	360	360	
Human Resource Readiness	432	432	
Mining Operational Team Performance	360	209,328	**0,419**
Digital Competence	432	265,361	**0,386**
Technology Orientation	432	432	

Source: Researcher's processed data (2025)

Based on Table 10 above, it can be seen that the Q^2 Predictive Relevance value in the performance variable of the mining operational team is 0.419 which means that the model has predictive relevance and is strong. Meanwhile, the digital competency variable has a Q^2 Predictive Relevance value of 0.386 which means that the model has predictive relevance and is strong.

3. Hypothesis Test

According to Sugiyono (2022), data analysis in quantitative research is carried out through testing hypotheses which are the initial answers to the formulation of research problems. The value of the original sample is useful for determining the direction of hypothesis testing. If the original sample value is positive, then the direction is positive, and vice versa if the original value is negative, then the direction is negative.

Hypothesis testing is carried out through a t-statistics test so that it will produce p values. The value of t-statistics is useful for evaluating the significant influence between research variables. P values show statistical significance to determine whether or not a statement is accepted in the research hypothesis. In this study, the significance level used was 0.05 or 5%, so the t-value of the table was 1.96. Therefore, the conditions for accepting the hypothesis in this study are the t-statistics value of the table > and the p-value value < 0.05, then Ha is accepted and Ho is rejected, and vice versa. The following is Table 11 of the results of the research hypothesis test.

Table 11. Hypothesis Test Results

Variable	Original sample	Sample mean	Standard deviation	T statistics	P values
Technology Orientation -> Digital Competence	0,319	0,326	0,103	3,089	0,002
Human Resource Readiness -> Digital Competence	0,235	0,240	0,099	2,378	0,017
Management Support -> Digital Competence	0,406	0,400	0,085	4,764	0,000
Technology Orientation -> Mining Operational Team Performance	0,194	0,193	0,091	2,125	0,034
Human Resource Readiness -> Mining Operational Team Performance	0,247	0,270	0,125	1,984	0,047
Management Support -> Mining Operational Team Performance	0,250	0,255	0,087	2,888	0,004
Digital Competence -> Mining Operational Team Performance	0,374	0,346	0,115	3,250	0,001
Management Support -> Digital Competencies -> Mining Operational Team Performance	0,152	0,139	0,057	2,677	0,007
Human Resource Readiness -> Digital Competencies -> Mining Operational Team Performance	0,088	0,082	0,044	2,013	0,044
Technology Orientation -> Digital Competencies -> Mining Operational Team Performance	0,119	0,113	0,053	2,234	0,026

Source: Researcher's processed data (2025)

Based on Table 11 of the results of the hypothesis test above, it can be explained that the hypothesis in this study is as follows:

1) First Hypothesis Test

H1a-c : Technology orientation, human resource readiness, and management support have a positive influence on digital competence.

a. H1a: The results of the testing of the technology orientation variable on the digital competency variable can be seen that the regression coefficient value is 0.319. The result of the statistical T-value is 3.089, greater than the T-table value of 1.96 with a P-value of 0.002, smaller than 0.05. Therefore, H0 is rejected and H1a is accepted, so that the technology orientation variable has a positive and significant effect on the digital competency variable.

b. H1b: The results of the testing of the human resource readiness variable against the digital competency variable showed that the regression coefficient value was 0.235. The result of the statistical T-value was 2.378, greater than the T-table value of 1.96 with a P-value of 0.017, smaller than 0.05. Therefore, H0 is rejected and H1b is accepted, so that the variable of human resource readiness has a positive and significant effect on the variable of digital competence.

c. H1c: The results of the test of the management support variable on the digital competency variable showed that the regression coefficient value was 0.406. The result of the statistical T-value was 4.764, greater than the T-table value of 1.96 with a P-value of 0.000, smaller than 0.05. Therefore, H0 is rejected and H1c is accepted, so that the management support variable has a positive and significant effect on the digital competency variable.

2) Second Hypothesis Test

H2a-c : Technology orientation, human resource readiness, and management support have a positive influence on mining operational team performance.

a. H2a: The results of the testing of the technology orientation variable on the mining operational team performance variable showed that the regression coefficient value was 0.194. The result of the T-statistical value is 2.125, greater than the T-table value of 1.96 with a P-value of 0.034, smaller than 0.05. Therefore, H0 is rejected and H2a is accepted, so that the technology orientation variable has a positive and significant effect on the performance variable of the mining operational team.
b. H2b: The results of the testing of the human resource readiness variable against the mining operational team performance variable showed that the regression coefficient value was 0.247. The result of the statistical T-value is 1.984, greater than the T-table value of 1.96 with a P-value of 0.047, smaller than 0.05. Therefore, H0 is rejected and H2b is accepted, so that the variable of human resource readiness has a positive and significant effect on the performance variable of the mining operational team.
c. H2c: The results of the testing of the management support variable on the mining operational team performance variable showed that the regression coefficient value was 0.250. The result of the T-statistical value was 2.888, greater than the T-table value of 1.96 with a P-value of 0.004, smaller than 0.05. Therefore, H0 is rejected and H2c is accepted, so that the management support variable has a positive and significant effect on the performance variable of the mining operational team.

3) Third Hypothesis Test

H3 : Digital competence has a positive influence on the mining operational team performance.

The results of the test of the digital competency variable on the performance variable of the mining operational team can be seen that the regression coefficient value is 0.374. The result of the T-statistical value is 3.250, greater than the T-table value of 1.96 with a P-value of 0.001, smaller than 0.05. Therefore, H0 is rejected and H3 is accepted, so that the digital competency variable has a positive and significant effect on the performance variables of the mining operational team.

4) Fourth Hypothesis Test

H4a-c : Technology orientation, human resource readiness, and management support have a positive effect on the mining operational team performance through digital competence.

a. H4a: The results of the testing of the technology orientation variable on the mining operational team performance variable through the digital competency variable as the mediation variable showed that the regression coefficient value was 0.119. The result of the statistical T-value is 2.234, greater than the T-table value of 1.96 with a P-value of 0.026, smaller than 0.05. Therefore, H0 is rejected and H4a is accepted, so that the technology orientation variable has a positive and significant effect on the performance variables of the mining operational team through the digital competency variable as a mediation variable.
b. H4b: The results of the testing of the human resource readiness variable against the mining operational team performance variable through the digital competency variable as a mediation variable showed that the regression coefficient value was 0.088. The result of the T-statistical value is 2.013, greater than the T-table value of 1.96 with a P-value of 0.044, smaller than 0.05. Therefore, H0 is rejected and H4b is accepted, so that the human resource readiness variable has a positive and significant effect on the performance variables of the mining operational team through the digital competency variable as a mediation variable.
c. H4c: The results of the testing of the management support variable on the mining operational team performance variable through the digital competency variable as a mediation variable showed that the regression coefficient value was 0.152. The result of the statistical T-value is 2.677, greater than the T-table value of 1.96 with a P-value of 0.007, smaller than 0.05. Therefore, H0 is rejected and H4b is accepted, so that the management support variable has a positive and significant effect on the performance variables of the mining operational team through the digital competency variable as a mediation variable.

Discussion of Research Results

1. The Influence of Technology Orientation on Digital Competence

Based on the results obtained from the study, the relationship between the technology orientation variable and the digital competency variable resulted in a path coefficient value of 0.319, a statistical T-value of 3.089

(greater than T-table 1.96), and a P-value of 0.002 (smaller than 0.05). From the above results, it can be concluded that digital competence has a positive and significant influence on digital competence. This shows that the higher the level of technology orientation in the work team, the higher the digital competence possessed by the work team. Technology orientation in operational activities illustrates the extent of the company's openness to the latest digital technology, as well as its readiness to integrate technology into the work process to develop the company.

The results of this study are similar to the research conducted by Yu and Moon (2021), which stated that technology orientation significantly affects the formation of organizational digital competencies (path coefficient of 0.370, T-statistic of 6.286, and P-value of 0.001). Organizations with a high level of technology orientation will be more proactive in building digital infrastructure, providing access to the latest technology, and designing digital-based work systems so that they will create an ecosystem that supports work teams to develop and improve their digital competencies.

Çebi et al. (2022) through the DigComp framework, concluded that the formation of digital competencies is highly dependent on the extent to which technology has been integrated into the work and learning process. Technology orientation plays a role in encouraging the active use of digital technology so that it will increase data literacy, digital communication, digital content creation, and digital problem solving. Androniceanu et al. (2023) in their research stated that technology factors are one of the main drivers for the formation of digital competence, especially in facing the dynamics of digital transformation. Updating technology infrastructure is very important to ensure cybersecurity and technical needs in supporting digital competence.

2. The Influence of Human Resource Readiness on Digital Competence

Based on the results obtained from the study, the relationship between the human resource readiness variable and the digital competency variable resulted in a path coefficient value of 0.235, a statistical T-value of 2.378 (greater than the T-table of 1.96), and a P-value of 0.017 (less than 0.05). From the above results, it can be concluded that the readiness of human resources has a positive and significant influence on digital competence. These results show that the readiness of human resources is an important factor in forming digital competencies in the work team, especially in the mining industry that is increasingly digitalized.

The results of this study are in line with the research conducted by Androniceanu et al. (2023), which concluded that the digital competence of human resources is influenced by the readiness factor of human resources. In the study, the factors of human resource readiness include aspects of intrinsic motivation, readiness to learn, access to training, and openness to the adoption of new technologies.

Cattaneo et al. (2022) through research on teachers in Switzerland concluded that human resource factors such as attitudes towards technology and frequency of use of digital tools have a strong influence on the formation of digital competence, due to the readiness and willingness to actively learn digitally. Without the readiness of human resources, it will be difficult for the work team to achieve a good level of digital competence.

3. The Effect of Management Support on Digital Competence

Based on the results obtained from the study, the relationship between the management support variable and the digital competency variable resulted in a path coefficient value of 0.406, a statistical T-value of 4.764 (greater than the T-table of 1.96), and a P-value of 0.000 (less than 0.05). From the above results, it can be concluded that management support has a positive and significant influence on digital competence. This shows that management's active role in developing plans, providing technology resources, encouraging the use of technology, providing training, and providing rewards greatly determines the success of the work team's digital competency development.

The results of this study are in line with research conducted by Afrianty et al. (2022), which showed that management support such as IT training, provision of digital infrastructure, and managerial support greatly affect individual digital competencies. This is similar to the findings in Alqudah's (2023) research which concluded that management support plays an important role in shaping digital competence through the provision of training, technology resources, and strategic direction planning. Cattaneo et al. (2022) in their research found that there is a positive influence of management support on digital competencies related to empowerment and facilities. Management support is one of the important factors in the digital transformation process within the work team, especially in encouraging the development of digital competencies that will have an impact on operational performance. Management support refers to the level of commitment and support provided by management so that it affects the success of the organization in implementing its digital transformation.

The results of this study show that management support is the biggest factor in influencing digital competence compared to other variables, showing the need for active involvement of company management in directing, facilitating, and monitoring the implementation of digital transformation. The management of PT Petrosea Tbk needs to develop digital plans and strategies, provide technology resources, and strengthen internal policies that encourage the work team to use digital platforms consistently, including through a reward and punishment system based on the use of Minerva.

4. The Influence of Technology Orientation on the Mining Operational Team Performance

Based on the results obtained from the study, the relationship between the technology orientation variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.194, a statistical T-value of 2.125, and a P-value of 0.034. From the above results, it can be concluded that technology orientation has a positive and significant influence on the performance of the mining operational team. These results show that the higher the level of technology orientation in the mining work team, the more the efficiency, productivity, and operational quality of the work team will increase.

The results of this study were strengthened by Nakabuye et al. (2023) who in their research found that technology orientation has a positive and significant influence on organizational performance (path coefficient value of 0.727 and P-value < 0.05). In this study, it is concluded that technology orientation is the basis for increasing operational efficiency and productivity, especially in facing the challenges of sustainable digital transformation. Nakabuye et al. (2023), also mentioned that the technology used strategically will be VRIN resources (valuable, rare, inimitable, non-substitutable) in RBV, so that it can provide a sustainable competitive advantage for companies that are able to manage it effectively.

The results of this study are in line with the research of Buer et al. (2021) which shows that technology orientation through the digitalization of factories based on Industry 4.0, significantly improves operational performance. In another study, Ilangakoon et al. (2022) found that the implementation of technologies such as big data and IoT directly contributes to improved operational performance through process optimization, efficient use of resources, and real-time data access for strategic decision-making.

In mining operations that rely on real-time data, technology orientation will support flexibility, automation, and data-driven decision-making that will improve the performance of operational teams. Minerva's digital platform has integrated systems such as mine planning dashboards, real-time crew management, dynamic dispatch, predictive maintenance, and Control Tower (Mine Dash). With the use of this system, the work team can optimize the productivity and efficiency of the work unit, minimize tool downtime, increase work accuracy and speed of reactivity to changes in field conditions.

5. The Influence of Human Resource Readiness on the Mining Operational Team Performance

Based on the results obtained from the study, the relationship between the human resource readiness variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.247, T-statistics of 1.984, and a P-value of 0.047. From the above results, it can be concluded that the readiness of human resources has a positive and significant influence on the performance of the mining operational team. These results show that a higher level of human resource readiness is able to increase productivity, efficiency, and operational quality in mining work teams.

The results of this study are similar to the research of Tjahjadi et al. (2022) which states that the readiness of human resources has a positive effect on business performance in the context of micro, small, and medium enterprises (MSMEs) in Indonesia. Human resources who are ready and able to implement organizational strategies effectively can improve the achievement of operational performance. Li et al. (2021) concluded that the practice of improving human resource readiness through training, motivation, and empowerment has a significant impact on operational performance. Furthermore, Uraon and Gupta (2020) in their research found that human resource development practices will improve performance through training, career development, and reward systems. Based on the Resource-Based View (RBV) theory, the readiness of human resources is a valuable asset that will be a source of competitive advantage in achieving the performance of the mining operational team.

6. The Influence of Management Support on the Mining Operational Team Performance

Based on the results obtained from the study, the relationship between the management support variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.250, T-statistic of 1.984, and P-value of 0.047. From the above results, it can be concluded that management support has a positive and significant influence on the performance of the mining operational team. These results show that the stronger the support from management in developing plans, providing technology resources, encouraging the use of technology, and providing training used in operations, the better the performance achievement of the mining operational team.

The results of this study are strengthened by the research of Kabede Adem & Virdi (2021) which concluded that direct management support will improve the company's operational performance. Management support in encouraging the implementation of management processes, continuous improvement, and employee empowerment will contribute significantly to increased productivity, efficiency, and operational quality. Putra et al. (2024) in their research proved that management support has a significant influence on organizational performance. This support is not only in the provision of resources, but also includes the active involvement of management in the development of digital strategies, training, and data-based decision-making so that management has a high commitment to digitalization, efficiency, and productivity of work teams.

7. The Influence of Digital Competence on the Mining Operational Team Performance

Based on the results obtained from the study, the relationship between the digital competency variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.374, a T-statistic of 3.250, and a P-value of 0.001. From the above results, it can be concluded that digital competence has a positive and significant influence on the performance of the mining operational team. These results show that work teams with high digital competence can have more productive, efficient and quality operational performance. Digital competence is the ability to solve complex and dynamic problems by organizing and using digital resources in the form of technology, information, knowledge, culture, and attitudes.

The results of this study are strengthened by the research of Yu and Moon (2021) which states that digital competencies have a significant effect on organizational performance, resulting in increased operational speed, data-based decision-making, and work productivity. Putra et al. (2024) in their research also found that digital competence in operating digital tracking systems, fleet management devices, and logistics information systems has a significant influence on the success of digital transformation and organizational operational performance. This condition is similar to the characteristics of the mining industry which also relies on digital technology in field operations and heavy equipment management, including real-time digital systems such as dispatch systems, monitoring fleets and equipment, and data dashboards.

Based on the Resource-Based View (RBV) theory, digital competence is a capability, which is an element of a company's resources or assets that can provide opportunities for companies to utilize other resources to be able to carry out strategies to achieve sustainable operational excellence. In the mining sector, the ability of work teams to improve digital competencies to improve efficiency, productivity, and quality is a strategic asset that will strengthen the company's competitive position.

Because the results of this study show that digital competence has a positive and significant influence on the performance of the mining operational team, PT Petrosea Tbk needs to design a technical training program that is in accordance with the actual operational needs. This training includes the use of Minerva's digital platform for real-time monitoring and data analysis for quick decision-making in the field in resolving technical problems.

8. The Influence of Technology Orientation on the Mining Operational Team Performance Through Digital Competence

Based on the results obtained from the study, the relationship between the technology orientation variable and the performance variable of the mining operational team through the mediation of digital competency variables resulted in a path coefficient value of 0.119, T-statistic of 2.234, and a P-value of 0.026. From the above results, it can be concluded that technology orientation has a positive and significant influence on the performance of the mining operational team through digital competency mediation. These results show that the influence of technology orientation on the performance of mining operational teams will be stronger when the work team has good digital competence.

The results of this study are strengthened by the research of Yu and Moon (2021) which shows that technology orientation has a positive and significant influence on the performance of mining operational teams through digital competency mediation (path coefficient = 0.203; t = 4.495; p < 0.001). Yu and Moon (2021) conclude that digital competence is an important component to utilize technology orientation to good organizational performance. Technology orientation will only be effective if it is supported by internal capabilities in the form of organizational digital competencies. This supports the theory of digital maturity by Vial (2020), which states that the positive impact of technology on organizational performance will be maximized if it is supported by the individual's ability to utilize the technology optimally. Technological capabilities enable individuals or organizations to use and develop various technologies consisting of technological infrastructure, technical and managerial skills of human resources, and knowledge to support and improve business strategies and processes by taking advantage of opportunities and responding to market changes and identifying new opportunities. The results of the study from Zheng (2024), also show that the implementation of digital equipment has a positive relationship with the effectiveness of system performance through digital competency mediation. Some of the studies above confirm that technology orientation will encourage the formation of digital competencies of work teams through technology innovation and readiness, technology accessibility and availability, and technology integration, so that it will ultimately be able to optimize performance. Technological innovation occurs through 3 (three) processes, namely the initiation stage which includes initial preparation and idea generation, the development stage which includes activities to carry out the technological and business aspects of innovation, and the diffusion stage which includes feedback and follow-up to improve production.

In a mining industry that demands productivity, accuracy between plan and actual, and high efficiency, the ability of work teams to effectively use technology-based tools and systems will be key to optimizing performance. Therefore, work teams that have a high technology orientation but do not have good digital competence will face difficulties in utilizing technology to improve their performance.

However, in this study, the value of the path coefficient of indirect influence through the mediation path obtained from the research was smaller than the direct influence. The indirect path coefficient value of the relationship between the technology orientation variable and the performance variable of the mining operational team through the mediation of the digital competency variable was 0.119, while the relationship between the technology orientation variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.194. Based on these results, digital competence does not fully mediate the relationship between technology orientation and the performance of the mining operational team, so the mediation function is partially (complementary mediation). This can happen because R-Square in the performance variable of the mining operational team (0.715) and the digital competency variable (0.551) has a moderate value. This R-Square value shows that there is an influence of other variables that were not studied in this study.

The technology orientation variable does not rely entirely on digital competencies to influence team performance, but digital competencies still play a role in strengthening that influence. This result is in line with the Resource-Based View approach which states that digital competence is a capability that strengthens the competitive advantage of work team resources in the form of technology orientation.

9. The Influence of Human Resource Readiness on the Mining Operational Team Performance Through Digital Competence

Based on the results obtained from the study, the relationship between the human resource readiness variable and the performance variable of the mining operational team through the mediation of digital competency variables resulted in a path coefficient value of 0.088, T-statistic of 2.013, and P-value of 0.044. From the above results, it can be concluded that the readiness of human resources has a positive and significant influence on the performance of the mining operational team through digital competency mediation. These results show that the influence of human resource readiness on the performance of the mining operational team will be stronger when the work team has good digital competence.

The results of this study are strengthened by research by Androniceanu et al. (2023) who stated that the development of digital competencies is greatly influenced by individual readiness. The readiness of human resources must be accompanied by good digital competency development so that it can have an impact on the performance of the operational team. A work team that is ready in terms of skills and abilities, training and learning, as well as attitude and motivation will contribute to improving their digital competencies so that they will increase the productivity, efficiency, and quality of the work team.

However, in this study, the value of the path coefficient of indirect influence through the mediation path obtained from the research was smaller than the direct influence. The indirect path coefficient value of the relationship between the human resource readiness variable and the performance variable of the mining operational team through the mediation of the digital competency variable was 0.088, while the relationship between the human resource readiness variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.247. Based on these results, digital competence does not fully mediate the relationship between human resource readiness and the performance of the mining operational team, so the mediation function is complementary mediation. This can happen because R-Square in the performance variable of the mining operational team (0.715) and the digital competency variable (0.551) has a moderate value. This R-Square value shows that there is an influence of other variables that were not studied in this study.

The variable of human resource readiness does not fully depend on digital competence to influence team performance, but digital competence still plays a role in strengthening this influence. This result is in line with the Resource-Based View approach which states that digital competence is a capability that strengthens the competitive advantage of work team resources in the form of human resource readiness.

10. The Effect of Management Support on the Mining Operational Team Performance Through Digital Competence

Based on the results obtained from the study, the relationship between the management support variable and the performance variable of the mining operational team through the mediation of digital competency variables resulted in a path coefficient value of 0.152, T-statistic of 2.677, and P-value of 0.007. From the above results, it can be concluded that management support has a positive and significant influence on the performance of the mining operational team through digital competency mediation. These results show that the influence of management support on the performance of the mining operational team will be stronger when the work team has good digital competence.

The results of this study are similar to the research of Afrianty et al. (2022) which concluded that management support is one of the main organizational factors that affect individual digital competence, so that it will ultimately have an impact on work productivity. The role of management not only directly improves operational performance, but can also be through improving employees' digital competencies as mediation.

In the mining world, effective management support such as developing plans, providing technology resources, encouraging the use of technology, and providing training and rewards will contribute to shaping the digital competence of work teams. When digital competencies are formed, the productivity, efficiency, and quality of the operational work team will increase.

However, in this study, the value of the path coefficient of indirect influence through the mediation path obtained from the research was smaller than the direct influence. The indirect path coefficient value of the relationship between the management support variable and the performance variable of the mining operational team through the mediation of the digital competency variable was 0.152, while the relationship between the management support variable and the performance variable of the mining operational team resulted in a path coefficient value of 0.250. Based on these results, digital competence does not fully mediate the relationship between management support and the performance of the mining operational team, so the mediation function is partial (complementary mediation). This can happen because R-Square in the performance variable of the mining operational team (0.715) and the digital competency variable (0.551) has a moderate value. This R-Square value shows that there is an influence of other variables that were not studied in this study.

The management support variable does not rely entirely on digital competencies to influence team performance, but digital competencies still play a role in strengthening that influence. This result is in line with the Resource-Based View approach which states that digital competence is a capability that strengthens the competitive advantage of work team resources in the form of management support.

CONCLUSION

This study concludes that technology orientation, human resource readiness, and management support all have a positive and significant effect on digital competence at PT Petrosea Tbk. Among these factors, management support is the most influential ($\beta = 0.406$; $p < 0.01$), followed by technology orientation ($\beta = 0.319$; $p = 0.034$), and human resource readiness ($\beta = 0.235$; $p = 0.017$). These findings underscore the strategic importance of managerial involvement in accelerating digital adoption and capability development within mining operation teams. Furthermore, the three independent variables also positively affect the performance of the mining operational team, with management support again emerging as the most dominant factor ($\beta = 0.374$; $p = 0.004$), followed by human resource readiness ($\beta = 0.247$; $p = 0.047$), and technology orientation ($\beta = 0.194$; $p = 0.034$). Digital competence itself significantly enhances team performance ($\beta = 0.374$; $p = 0.001$), confirming that supervisors with higher digital proficiency are better equipped to lead teams with improved productivity, efficiency, and quality.

Digital competence also functions as a mediating variable in the relationship between the independent variables and team performance. However, its mediating effect is weaker than the direct effects, indicating that while digital competence is important, other factors not examined in this study also contribute to performance outcomes. The R^2 values support this conclusion, showing that 55.1% of the variance in digital competence and 71.5% of the variance in team performance are explained by the model. The *Importance–Performance Analysis* (IPA) identified five priority areas for improvement: team capability in accessing and analyzing operational data (KDI1, KDI2), the use of digital tools to identify and resolve operational issues (KDP1, KDP2), and managerial support for digital tool utilization (DMK1). These are high-impact yet currently underperforming areas, and should be prioritized for training and strategic enhancement to optimize digital transformation outcomes.

REFERENCES

Afrianty, T. W., Artatanaya, I. G. L. S., & Burgess, J. (2022). Working from home effectiveness during Covid-19: Evidence from university staff in Indonesia. *Asia Pacific Management Review*, *27*(1). https://doi.org/10.1016/j.apmrv.2021.05.002

Androniceanu, A., Sabie, O. M., Georgescu, I., & Drugău-Constantin, A. L. (2023). Main factors and causes that are influencing the digital competences of human resources. *Administratie Si Management Public*, *41*. https://doi.org/10.24818/AMP/2023.41-02

Barnewold, L. (2019). Digital technology trends and their implementation in the mining industry. *Mining Goes Digital - Proceedings of the 39th International Symposium on Application of Computers and Operations Research in the Mineral Industry, APCOM 2019*. https://doi.org/10.1201/9780429320774-2

Barnewold, L., & Lottermoser, B. G. (2020). Identification of digital technologies and digitalisation trends in the mining industry. *International Journal of Mining Science and Technology*, *30*(6). https://doi.org/10.1016/j.ijmst.2020.07.003

Brunetti, F., Matt, D. T., Bonfanti, A., De Longhi, A., Pedrini, G., & Orzes, G. (2020). Digital transformation challenges: strategies emerging from a multi-stakeholder approach. *TQM Journal*, *32*(4). https://doi.org/10.1108/TQM-12-2019-0309

Buer, S. V., Semini, M., Strandhagen, J. O., & Sgarbossa, F. (2021). The complementary effect of lean manufacturing and digitalisation on operational performance. *International Journal of Production Research*, *59*(7). https://doi.org/10.1080/00207543.2020.1790684

Cattaneo, A. A. P., Antonietti, C., & Rauseo, M. (2022). How digitalised are vocational teachers? Assessing digital competence in vocational education and looking at its underlying factors. *Computers and Education*, *176*. https://doi.org/10.1016/j.compedu.2021.104358

Çebi, A., Bahçekapılı Özdemir, T., Reisoğlu, İ., & Çolak, C. (2022). From digital competences to technology integration: Re-formation of pre-service teachers' knowledge and understanding. *International Journal of Educational Research*, *113*. https://doi.org/10.1016/j.ijer.2022.101965

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Fadaki, M., Rahman, S., & Chan, C. (2020). Leagile supply chain: design drivers and business performance implications. *International Journal of Production Research*, *58*(18). https://doi.org/10.1080/00207543.2019.1693660

Fang, C., Yuan, Y., Chen, J., Gao, D., & Peng, J. (2024). Examination of Green Productivity in China's Mining Industry: An In-Depth Exploration of the Role and Impact of Digital Economy. *Sustainability (Switzerland)*, *16*(1). https://doi.org/10.3390/su16010463

Ferdiansyah, M. R., & Tricahyono, D. (2023). Identifikasi Faktor-Faktor Penghambat Implementasi Transformasi Digital Pada UMKM. *Jurnal Ilmiah Manajemen, Ekonomi, & Akuntansi (MEA)*, *7*(2). https://doi.org/10.31955/mea.v7i2.3194

Ganeriwalla, A., Harnathka, S., Costa, A., Volkov, M., & Voigt, N. (2021). Racing Toward a Digital Future in Metals and Mining. *Boston Consulting Gruop*.

Ghozali, H. I., & Kusumadewi, K. A. (2023). PARTIAL LEAST SQUARES KONSEP, TEKNIK DAN APLIKASI Menggunakan Program SmartPLS 4.0 Untuk Penelitian Empiris. In *SmartPLS GmbH, http://www.smartpls.com*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.

Hendayani, R., & Febrianta, M. Y. (2020). Technology as a driver to achieve the performance of family businesses supply chain. *Journal of Family Business Management*, *10*(4). https://doi.org/10.1108/JFBM-10-2019-0070

Hushko, S., Botelho, J. M., Maksymova, I., Slusarenko, K., & Kulishov, V. (2021). Sustainable development of global mineral resources market in Industry 4.0 context. *IOP Conference Series: Earth and Environmental Science*, *628*(1). https://doi.org/10.1088/1755-1315/628/1/012025

Ilangakoon, T. S., Weerabahu, S. K., Samaranayake, P., & Wickramarachchi, R. (2022). Adoption of Industry 4.0 and lean concepts in hospitals for healthcare operational performance improvement. *International Journal of Productivity and Performance Management*, *71*(6). https://doi.org/10.1108/IJPPM-12-2020-0654

Kaniappan Chinnathai, M., & Alkan, B. (2023). A digital life-cycle management framework for sustainable smart manufacturing in energy intensive industries. *Journal of Cleaner Production*, *419*. https://doi.org/10.1016/j.jclepro.2023.138259

Li, Y., Wang, Q., Wang, Z., & Chen, L. (2021). Improving business processes or human resources? The performance implications and contingencies. *Industrial Management and Data Systems*, 121(7), 1577–1598. https://doi.org/10.1108/IMDS-08-2020-0476.

Malhotra, G., Dandotiya, G., Shaiwalini, S., Khan, A., & Homechaudhuri, S. (2024). Benchmarking for organisational competitiveness: a resource-based view perspective. *Benchmarking*. https://doi.org/10.1108/BIJ-09-2023-0668

Manyuchi, M. M., & Sukdeo, N. (2021). Disruptive Innovation in Digital Mining-The Future of Mining. *Proceedings of the International Conference on Industrial Engineering and Operations Management*. https://doi.org/10.46254/in01.20210020

Mora-Monge, C. A., Fatoki, J., Arslan, F., & Rauniar, R. (2023). Exploring drivers of business performance in web-enabled supply chains: the role of web technology training and supply chain integration. *Journal of Enterprise Information Management*, *36*(4). https://doi.org/10.1108/JEIM-09-2022-0318

Nakabuye, Z., Mayanja, J., Bimbona, S., & Wassermann, M. (2023). Technology orientation and export performance: the moderating role of supply chain agility. *Modern Supply Chain Research and Applications*, *5*(4). https://doi.org/10.1108/mscra-01-2023-0006

Putra, A.P., Nuraisah, F., & Kuswantoro, M.W. (2024). The Role of Digital Transformation on The Performance of Indonesia's Biggest Dry Bulk Port. *Procedia Computer Science* 234 (2024) 900–908.

QU Zheng. (2024). Digital Readiness and Digital Competences Influence on Information Management System: Organizational Support as Moderator. *Profesional de La Información*, 33(4). https://doi.org/10.3145/epi.2024.ene.0408

Shinkevich, A. I., Baygildin, D. R., & Vodolazhskaya, E. L. (2020). Management of a sustainable development of the oil and gas sector in the context of digitalization. *Journal of Environmental Treatment Techniques*, *8*(2).

Sugiyono. (2022). *Metode Penelitian Kuantitatif, Kualitatif, dan R&D*. Alfabeta CV.

Tjahjadi, B., Soewarno, N., Nadyaningrum, V., & Aminy, A. (2022). Human capital readiness and global market orientation in Indonesian Micro-, Small- and-Medium-sized Enterprises business performance. *International Journal of Productivity and Performance Management*, 71(1), 79–99. https://doi.org/10.1108/IJPPM-04-2020-0181.

Uraon, R. S., & Gupta, M. (2020). Do HRD practices affect perceived market performance through operational performance? Evidence from software industry. *International Journal of Productivity and Performance Management*, 69(1), 85–108. https://doi.org/10.1108/IJPPM-06-2018-0207.

Whitman Cobb, W. N. (2020). Racing into the future. In *Privatizing Peace*. https://doi.org/10.4324/9780429321917-7

Yu, J., & Moon, T. (2021). Impact of digital strategic orientation on organizational performance through digital competence. *Sustainability* 2021, 13, 9766. https://doi.org/10.3390/su13179766.