The Influence of Quality Policies and Digital Learning Ecosystems on Human Resource Competitiveness in the Industry 5.0 Era

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Abstract. Digital transformation in education had been recognized as important for improving learning quality and strengthening human resource competitiveness in the industry 5.0 era, yet a gap had persisted between policy and classroom implementation. This study aimed to examine the effects of digital-based education quality policies and digital learning ecosystems on human resource competitiveness and to identify the most influential factor. A quantitative explanatory approach had been applied. Data were collected through closed questionnaires, structured interviews, and documentation involving 68 teachers at SMAN 3 Pontianak using total sampling. Analysis was conducted using SEM-PLS to assess relationships among variables. The results showed that digital-based quality policies had significantly influenced competitiveness ($\beta = 0.37$; $p < 0.001$), while digital learning ecosystems had exerted a stronger effect ($\beta = 0.42$; $p < 0.001$). Both variables jointly explained 51% of the variance. The study concluded that the digital learning ecosystem had been the most dominant factor and highlighted its critical role in enhancing education quality and human resource competitiveness.
Keywords: digital education quality policy, digital learning ecosystem, human resource competitiveness, digital transformation of education, industry 5.0.

How to cite (in APA style):
Putranti, N.D., Handoyo, E., Rokhman, F., & Oktarina, N. (2026). The Influence of Quality Policies and Digital Learning Ecosystems on Human Resource Competitiveness in the Industry 5.0 Era. *Proceeding of IJC-MaSTEd*, 1(1), 25-38.

DOI: https://doi.org/10.31571/ijcmasted.v1i1.1021

1. Introduction

Digital transformation in education was a global phenomenon that significantly changed the structure, processes, and governance of modern education systems (Bond et al., 2018; Selwyn, 2021; Bond et al., 2020; Dwivedi et al., 2021; Cabero-Almenara et al., 2022). The *Digital Education Outlook 2023* report published by the OECD (2023) emphasized that the use of digital technology in education was no longer seen as an alternative, but rather as a strategic necessity that systematically improved the quality of learning and the competitiveness of human resources (OECD, 2023; Pedro et al., 2019; Chiu et al., 2021).

In the context of Industry 5.0, education was directed toward a human-centered digital transformation model that emphasized collaboration between humans and intelligent systems to produce sustainable innovation (Xu et al., 2021; Nahavandi, 2019; Javaid et al., 2022). This paradigm demanded the strengthening of 4C skills (critical thinking, creativity, collaboration, and digital literacy) through a transformational learning ecosystem, as well as adaptive capabilities to technological changes (OECD, 2023; Voogt & Roblin, 2012; van Laar et al., 2020; Falloon, 2020).

Recent research showed that the effectiveness of implementing digital transformation in education was greatly influenced by policies integrated with strengthening teacher capacity and institutional governance (Tondeur et al., 2017; Forsstrom et al., 2020; Ertmer & Ottenbreit-Leftwich, 2020; Konig et al., 2020). A study by Forsstrom et al. (2020) found that digital policies based on teacher competency development significantly improved the quality of learning. Furthermore, research by Redecker (2017), using the European Digital Competence Framework for Educators (DigCompEdu), confirmed that teachers' digital competencies were a key determinant of the success of technology-based learning (Redecker, 2017; Ghomi & Redecker, 2019).

In higher education, digital innovation was also shown to drive more collaborative and problem-solving-based pedagogical changes (Bond et al., 2018; Hodges et al., 2020; Rapanta et al., 2020). In addition, the integration of artificial intelligence (AI) into learning systems was found to improve personalized learning and student academic performance (Zawacki-Richter et al., 2019; Holmes et al., 2019; Chen et al., 2020).

However, various international reports indicated that there were still significant gaps between policy direction and implementation at the educational unit level (UNESCO, 2023; OECD, 2023; Schleicher, 2020; Williamson et al., 2020). The results of the Programme for International Student Assessment (PISA) 2022 published by the OECD (2023) described students' literacy and numeracy achievements, with Indonesia remaining below the international average of OECD members. Furthermore, a UNESCO report (2023) identified that gaps in digital infrastructure and technological literacy remained major obstacles to educational transformation in developing countries (UNESCO, 2023; Trucano, 2020; Zhang et al., 2022).

In the national context, disparities in access to technology between urban areas and 3T (frontier, disadvantaged, and remote) areas reinforced inequalities in education quality (World Bank, 2022). A preliminary study conducted by the researchers at SMAN 3 Pontianak through observations, exploratory questionnaires, and limited interviews with 30 teachers revealed a gap in digital policy implementation. A total of 68% of teachers stated that they had used digital devices in learning, but only 41% systematically designed learning based on a Learning Management System. In addition, 57% of teachers admitted that they had not participated in training programs in advanced digital technology pedagogy in the last two years, and 52% of respondents stated that learning evaluation still predominantly used conventional methods without learning data analytics.

From a policy perspective, school documents indicated that digitalization programs were included in annual work plans but had not yet been fully integrated into an internal quality assurance system based on digital performance indicators. This preliminary data indicated that policy implementation remained administrative in nature and had not yet been fully operationalized pedagogically. This finding aligned with previous literature by Tondeur et al. (2017), which explained that the failure of technology integration in educational institutions was often caused by a lack of synchronization between policies, teacher professional development, and institutional quality strategies.

Conceptually, most previous studies tended to analyze aspects of digital transformation only partially, such as teacher competency (Redecker, 2017), pedagogical innovation (Bond et al., 2018), or the integration of intelligent educational systems (Zawacki-Richter et al., 2019), without integrating digital education policies with frameworks for developing learning quality standards and human resource competitiveness within a comprehensive structural model (Selwyn, 2021; Chiu et al., 2021; Dwivedi et al., 2021). Therefore, an integrative strategy was needed to explain the systemic relationships between digital education policies, teacher competencies, learning quality, and the competitive advantage of human resources in the Society 5.0 era (Xu et al., 2021; Javaid et al., 2022; Cabero-Almenara et al., 2022).

Based on the research background regarding digital transformation in education and the importance of increasing human resource competitiveness in the Society 5.0 period, the formulation of the study problem was as follows:

1) What was the effect of digital-based education quality policies on increasing human resource competitiveness?
2) How did the digital learning ecosystem affect the competitiveness of human resources?
3) How did digital-based quality policies and digital learning ecosystems simultaneously influence human resource competitiveness in the Society 5.0 period?
4) What factors contributed most to strengthening the competitiveness of human resources in digital education transformation?

This study aimed to empirically analyze the effects of digital-based education quality development policies on teachers' digital competence and learning quality, and to examine their contribution to increasing human resource competitiveness. Furthermore, this study aimed to develop an integrated digital education policy model as a conceptual framework to strengthen national competitiveness in the industry 5.0 era. The original contribution of this study was the formulation of a holistic model that integrated digital education policies, teachers' digital competence, learning quality, and human resource competitiveness within a single policy-driven model, differing from previous studies that were partial and did not examine systemic relationships among these variables in the context of educational transformation in the Industry 5.0 era in Indonesia.
Based on this conceptual framework, the research hypotheses were as follows:

1) Hypothesis 1 (H1): Digital-based education quality policies had a positive and significant impact on increasing the competitiveness of human resources.
2) Hypothesis 2 (H2): The digital learning ecosystem had a positive and significant impact on increasing the competitiveness of human resources.
3) Hypothesis 3 (H3): Digital-based quality policies and digital learning ecosystems simultaneously had a positive and significant impact on human resource competitiveness.
4) Hypothesis 4 (H4): The digital learning ecosystem had a more dominant influence than digital-based quality policies in increasing the competitiveness of human resources in the Industry 5.0 era.

2. Method

This study used a quantitative approach based on an explanatory design to analyze the causal relationships between digital-based education quality development policies, teachers' digital competence, learning quality, and human resource competitiveness. This design was chosen because the research aimed to test hypotheses and evaluate the direct and indirect effects between variables in a holistic structural model. Data processing used SEM-PLS because this method was suitable for testing predictive patterns with latent variables and mediating relationships simultaneously.

The research was conducted in stages. The first stage consisted of a preliminary study through direct observation of the implementation of digital-based learning and limited interviews with educators and vice principals in charge of curriculum to identify patterns of digital policy implementation in schools. The next stage was the development of a research instrument based on indicators of digital education policy, teacher digital competence, learning quality, and human resource competitiveness synthesized from the research conceptual framework.

The data collection tool was a closed-ended questionnaire using a five-level Likert scale (1 = strongly disagree – 5 = strongly agree). Before being used for primary data collection, the instrument was validated by three experts in education management and learning technology to ensure alignment between indicators and research constructs. Subsequently, validation of the instrument was conducted with 30 teacher respondents outside the research location to test item clarity and initial reliability. After being declared appropriate, primary data collection was conducted both in person and online, depending on respondents' conditions.

The third stage involved instrument validation using expert judgment involving three experts in education management and learning technology. Validation was carried out using an indicator evaluation sheet based on a relevance scale of 1–4. The Content Validity Index (CVI) value was calculated to ensure alignment between indicators and underlying constructs. The instrument was declared valid if the I-CVI value was ≥ 0.78.

The fourth stage was a trial of the instrument on 30 teachers outside the research location to test initial reliability using Cronbach's Alpha with IBM SPSS Statistics version 26. The instrument was declared reliable if α was ≥ 0.70. The fifth stage was the collection of primary data and structural model analysis using SmartPLS version 4.0.9. The significance test used a bootstrapping technique ($n = 5,000$) with resampling to obtain stable and robust path coefficient estimates.

This research was conducted at SMAN 3 Pontianak as a single-site study. The object of the study was the implementation of digital-based education quality development policies at the school. The unit of analysis was all teachers actively teaching in the 2025/2026 academic year and involved in the use of digital technology in the learning process. The study was conducted over three months, covering the preparation phase, data collection, data analysis, and report writing.

The target population of this study included all educators at SMAN 3 Pontianak. Because the population was limited, this study adopted total sampling, where the entire population served as respondents. Therefore, 68 active teachers involved in the use of digital technology in learning were selected as respondents. This method was adopted to obtain a holistic understanding of the implementation of digital policies in the school and to minimize potential bias in sample selection.

Data were collected through three main techniques. First, a closed-ended questionnaire served as the primary instrument, consisting of 27 indicators (nine indicators for each construct) to measure teachers' perceptions of the research variables. The questionnaire was distributed through two channels: Google Forms for online completion and printed questionnaires for in-person responses. Second, semi-structured interviews were conducted during the exploratory stage to deepen understanding of school policies related to educational digitalization. Third, a review of school administrative documents such as school work plans, quality improvement programs, digitalization programs, and internal quality policies related to the use of digital technology was conducted.

The research variables consisted of digital-based education quality development policies as independent variables, teacher digital competence and learning quality as mediating variables, and human resource competitiveness as dependent variables. Digital-based education quality development policies were operationalized as the level of integration of school policies in supporting digital transformation, reflected through internal regulations, provision of ICT infrastructure, digital-based teacher training programs, and data-based monitoring and evaluation systems.

Teacher digital competence was operationalized as technology-based pedagogical competence, measured through digital literacy, technology-based learning design, utilization of digital learning platforms, and digital evaluation practices. Learning quality was operationalized as the level of effectiveness of digital-based learning, indicated by classroom interactivity, a variety of technology-based methods, student engagement, and the quality of feedback. Human resource competitiveness was operationalized as the ability of students to demonstrate 21st-century competencies, as perceived by teachers through indicators of student digital literacy, critical thinking skills, creativity and problem-solving, and adaptability to technology.

Data processing was divided into two steps. The first step was descriptive analysis using SPSS version 26 to calculate mean, standard deviation, minimum, and maximum values to describe respondent characteristics and the distribution of responses. The second step was PLS-SEM analysis using SmartPLS version 4.0.9.9, which included evaluation of the measurement model (outer model) and the structural model (inner model).

Evaluation of the outer model was carried out by testing convergent validity through loading factor values (> 0.70) and Average Variance Extracted (> 0.50), construct reliability through composite reliability (> 0.70), and discriminant validity through HTMT values (< 0.90). Evaluation of the inner model was conducted by analyzing the R^2 value to determine predictive ability and testing the significance of path coefficients through a bootstrapping procedure at a significance level of 0.05.

Testing of the mediation effect was conducted by analyzing indirect effects and calculating the Variance Accounted For (VAF) to determine the type of mediation. Through structured procedures, the use of total sampling, and detailed analysis stages, this research was designed to be replicable and verifiable by other researchers who wished to test the digital-based education quality development policy model in the secondary school context.
The analysis tools used included:
1) IBM SPSS Statistics version 26 for descriptive analysis and initial reliability testing.
2) SmartPLS version 4.0.9.9 for analysis of measurement and structural models.
3) Microsoft Excel 2019 for initial data recapitulation and cleaning.

The instrument validation tool was an expert validation sheet based on construct indicators, assessed using a four-level relevance scale.

3. Results and Discussion

Results

Finding 1: Descriptive Description of the Implementation of Digital-Based Education Quality Policies
Descriptive analysis was conducted on three main variables:
1) Implementation of Digital-Based Education Quality Development Policy (X1)
2) Quality of Digital Learning Ecosystem (X2)
3) Human Resource Competitiveness (Y)

Descriptive analysis was carried out on 68 teacher respondents using IBM SPSS Statistics version 26, with a Likert scale of 1–5 as presented in Table 1.

Table 1. Descriptive statistics of research variables

Variables	N	Minimum	Maximum	Mean	Standard Deviation	Category
Digital-based quality policy (X1)	68	3.10	4.85	4.08	0.52	Tall

Variables	N	Minimum	Maximum	Mean	Standard Deviation	Category
Digital learning ecosystem (X2)	68	2.95	4.80	3.95	0.56	Tall
Human Resource Competitiveness (Y)	68	3.25	4.90	4.15	0.48	Tall

Source: (Research results, 2026)
Information:
1) Number of respondents (N) = 68 teachers.
2) The measurement scale uses Likert 1–5.
3) Mean categorization criteria:
   (1) 1.00–1.80 = Very Low
   (2) 1.81–2.60 = Low
   (3) 2.61–3.40 = Moderate
   (4) 3.41–4.20 = High
   (5) 4.21–5.00 = Very High

All variables had mean values in the range of 3.41–4.20 and were therefore categorized as High, indicating that digital readiness and implementation in schools were at a good level. Table 1 showed that the implementation of digital-based quality policies at SMAN 3 Pontianak had been running relatively well, particularly in aspects such as Learning Management System integration, the use of collaborative platforms, and technology-based teacher training. However, scores on data-based evaluation and learning analytics indicators were relatively lower than other indicators.

Finding 2: Results of Classical Assumption Tests
Before hypothesis testing, assumption tests were conducted as follows:
1. Normality (Kolmogorov–Smirnov)
   Sig. = 0.089 (> 0.05) → data were normally distributed.
2. Multicollinearity
   Tolerance > 0.10 and VIF < 10 → no multicollinearity was observed.
3. Heteroscedasticity (Glejser test)
   Sig. > 0.05 → no heteroscedasticity was detected.

Based on these results, the regression model was declared to meet classical assumptions and was suitable for hypothesis testing (Table 2).

Table 2. Normality test (Kolmogorov–Smirnov test)

Variables	N	Kolmogorov–Smirnov Z	Sig. (2-tailed)	Information
Unstandardized Residual	68	1,221	0.089	Normal

Source: (Research results, 2026)
Information:
The Sig. value = 0.089 (> 0.05) indicates that the residual data is normally distributed.

Table 3. Multicollinearity test

Variables	Tolerance	VIF	Information
Digital-based quality policy (X1)	0.632	1,582	There is no multicollinearity
Digital learning ecosystem (X2)	0.632	1,582	There is no multicollinearity

Source: (Research results, 2026)

Criteria:
- Tolerance > 0.10
- VIF < 10

All variables meet the criteria, so there are no symptoms of multicollinearity.

Table 4. Heteroscedasticity test (Glejser test))

Variables	t	Sig.	Information
Digital-based quality policy (X1)	1,124	0.265	There is no heteroscedasticity
Digital learning ecosystem (X2)	0.874	0.385	There is no heteroscedasticity

Source: (Research results, 2026)
Criteria:
Sig. > 0.05 → There are no symptoms of heteroscedasticity.
Conclusion of assumption test
Based on the results of normality, multicollinearity, and heteroscedasticity tests, the regression model is declared to fulfill classical assumptions, so it is suitable for use in hypothesis testing.

Finding 3: The Influence of Digital-Based Quality Policies on HR Competitiveness

1. The influence of digital-based quality policies (X1) on HR competitiveness (Y):
   $\beta = 0.37$; $t = 3.98$; Sig. = 0.000
   These results indicated that digital-based quality policies had a positive and significant effect on increasing human resource competitiveness in the Industry 5.0 era.
2. The influence of the digital learning ecosystem (X2) on HR competitiveness (Y):
   $\beta = 0.42$; $t = 4.51$; Sig. = 0.000
   The digital learning ecosystem had a stronger influence than formal policies.
3. Simultaneous effect of X1 and X2 on Y:
   $F = 33.74$; Sig. = 0.000; $R^2 = 0.51$
   The model explained 51% of the variation in HR competitiveness, while 49% was influenced by other factors such as leadership, innovation culture, and psychological capital.

Table 5. Results of partial influence test (t-test)

Independent Variables	Dependent Variable	β coefficient
Digital-Based Quality Policy (X1)	Human Resource Competitiveness (Y)	0.37
Digital Learning Ecosystem (X2)	Human Resource Competitiveness (Y)	0.42

Source: (Research results, 2026)
Description: $\alpha = 0.05$

Table 6. Simultaneous test results (F test / ANOVA)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	41,286	2	20,643	33.74	0,000
Residual	39,458	65	0.607		
Total	80,744	67			

Source: (Research results, 2026)

Table 7. Coefficient of determination (model summary)

Model	R	R Square (R^2)	Adjusted R Square	Std. Error	R
1	0.714	0.510	0.495	0.779	0.714

Source: (Research results, 2026)

Description: The research model is able to explain 51% of the variation in HR competitiveness, while 49% is influenced by other variables outside the research model.

Finding 4: Hypothesis Testing (Multiple Linear Regression)

Table 8. Multiple linear regression summary model

Model	R	R Square	Adjusted R Square	Standard Error of the Estimate
1	0.714	0.510	0.495	0.342

Source: (Research results, 2026)

The regression analysis results showed that:

1. R = 0.714 indicated a strong simultaneous correlation between digital-based quality policies and digital learning ecosystems on human resource competitiveness.
2. R^2 = 0.510 indicated that the model was able to explain 51% of the variance in HR competitiveness.
3. Adjusted R^2 = 0.495 showed that the model remained stable after adjustment.
4. The standard error of the estimate (0.342) indicated a relatively low prediction error.

Table 9. Regression coefficient

Variables	Beta	t	Sig.
Digital-Based Quality Policy (X1)	0.37	3.98	0.000
Digital Learning Ecosystem (X2)	0.42	4.51	0.000

Source: (Research results, 2026)

Regression coefficients showed that both variables had positive and significant effects on HR competitiveness ($p < 0.001$).

Outer Model Evaluation (PLS-SEM)

Analysis using SmartPLS 4.0.9.9 with bootstrapping (5,000 resamples) showed that:

1. All loading factors were ≥ 0.70
2. AVE was > 0.50
3. Composite Reliability was > 0.70
4. HTMT was < 0.90

Thus, the measurement model was declared valid and reliable as can be seen in Table 10.

Table 10. Outer model evaluation (PLS-SEM)

Variables / Indicators	Loading Factor	AVE	Composite Reliability	HTML	Information	Variables / Indicators
Variable X1 – Indicator 1	0.82				Valid & Reliable	Variable X1 – Indicator 1
Variable X1 – Indicator 2	0.85	0.62	0.88	0.76	Valid & Reliable	Variable X1 – Indicator 2
Variable X2 – Indicator 1	0.79				Valid & Reliable	Variable X2 – Indicator 1
Variable X2 – Indicator 2	0.83	0.61	0.87	0.73	Valid & Reliable	Variable X2 – Indicator 2
Variable Y – Indicator 1	0.88				Valid & Reliable	Variable Y – Indicator 1

Source: (Research results, 2026)

Notes:

(1) All loading factors ≥ 0.70, indicating that the indicators significantly absorb the construct.

(2) AVE > 0.50, indicates that the variable has good convergent validity.

(3) Composite Reliability > 0.70, indicating adequate internal reliability.
(4) HTMT < 0.90, indicating that discriminant validity is met.

Inner Model Evaluation

The inner model evaluation showed that:

1. R^2 of HR Competitiveness was 0.516
2. f^2 for Digital-Based Quality Policy was 0.18 (medium)
3. f^2 for Digital Learning Ecosystem was 0.24 (medium–strong)
4. Q^2 was 0.392 (> 0), indicating good predictive relevance

Path coefficients indicated that:

1. Digital Quality Policy → HR Competitiveness ($\beta = 0.354$; $p < 0.001$)
2. Digital Learning Ecosystem → HR Competitiveness ($\beta = 0.419$; $p < 0.001$)

The digital learning ecosystem showed the most dominant influence (table 11).

Table 11. Inner model evaluation (PLS-SEM)

Dependent Variable	Independent Variables	β (Path Coefficient)	p-value	f^2 (Effect Size)	Information
Human Resource Competitiveness (HRC)	Digital Quality Policy (DQP)	0.354	<0.001	0.18 (Medium)	Significant, moderate influence
	Digital Learning Ecosystem (DE)	0.419	<0.001	0.24 (Medium-Strong)	Significant, dominant influence

Source: (Research results, 2026)

Model Statistics:
(1) R^2 HRC = 0.516 → the model is able to explain 51.6% of the variability in HR competitiveness.
(2) $Q^2 = 0.392$ (>0) → the model has good predictive relevance.

The results indicated that all paths were significant ($p < 0.001$). The digital learning ecosystem had the most dominant influence on human resource competitiveness. The effects of both independent variables were in the medium to moderately strong category.

Discussion

1. The Influence of Digital-Based Quality Policies on Human Resource Competitiveness

The research analysis showed that digital-based quality policies made a positive and significant contribution to increasing human resource competitiveness. These findings demonstrated that educational policies oriented toward digital transformation could improve the quality of learning systems and strengthen students' adaptive competencies in responding to technological change. Digital education policies served as a strategic framework that guided curriculum development, teacher competency improvement, and technology optimization in learning implementation.

The results of this study reinforced previous empirical evidence that digital policies played a crucial role in accelerating educational transformation. Bond et al. (2018) and Bond et al. (2020) explained that digital transformation in education required institutional policy support capable of systematically integrating technology into the learning process. Furthermore, Dwivedi et al. (2021) stated that the success of digital transformation in organizations, including educational institutions, was largely determined by strategic policies that guided structural and cultural changes.

Previous studies supported this view, Tondeur et al. (2017) argued that digital education policies were a vital factor in encouraging technology integration in schools, especially when accompanied by teacher professional development and institutional support. Forsstrom et al. (2020) demonstrated that digital policies linked to teacher development activities improved the quality of technology-based learning. Furthermore, Ertmer and Ottenbreit-Leftwich (2020) stated that policies supporting technological innovation in education accelerated changes in pedagogical practices toward more effective digital learning.

From a broader perspective, this research supported Selwyn's (2021) view that educational technology was not limited to the use of digital devices but also related to how educational policies shaped the structure, practices, and culture of learning. Therefore, digital-based quality policies played a strategic role in creating learning systems that produced competitive human resources in the era of digital transformation.

2. The Influence of the Digital Learning Ecosystem on Human Resource Competitiveness
Empirical data demonstrated that the digital learning ecosystem had a positive and significant impact on human resource competitiveness. These findings indicated that the quality of the digital learning environment was a critical factor in determining the effectiveness of technology implementation in education. A digital learning ecosystem encompassed various components, including technology infrastructure, digital platforms, learning management systems, collaborative culture, and the utilization of learning data.

These findings supported Redecker's (2017) study, which developed the DigCompEdu framework and stated that the success of technology-based learning was greatly influenced by educators' digital competence and a supportive digital environment. Ghomi and Redecker (2019) also emphasized that teachers' digital competence was a key determinant in creating effective technology-based learning.

Furthermore, Bond et al. (2018) indicated that the use of digital technology in learning encouraged more collaborative and problem-solving-based pedagogical innovation. Rapanta et al. (2020) and Hodges et al. (2020) emphasized that effective digital learning required a combination of technology, pedagogy, and social interaction.

Other studies showed that the development of intelligent technologies such as artificial intelligence improved personalized learning and the quality of students' learning experiences. Chen et al. (2020) and Zawacki-Richter et al. (2019) explained that AI-based learning systems enabled more adaptive and data-driven learning. Moreover, Falloon (2020) and van Laar et al. (2020) emphasized that digital literacy mastery was crucial in enhancing critical thinking, creativity, and problem-solving skills, which were essential components of human resource competitiveness.

Thus, the findings of this study indicated that the digital learning ecosystem did not merely function as a technological tool but served as a dynamic learning environment that facilitated interactions among teachers, students, and technology.

3. The Simultaneous Influence of Digital-Based Quality Policies and Digital Learning Ecosystems on Human Resource Competitiveness
The research results showed that digital-based quality policies and the digital learning ecosystem simultaneously had a significant impact on human resource competitiveness. The research model was able to explain more than half of the variation in human resource competitiveness, indicating that both variables contributed significantly to improving educational quality and student competencies.

These findings reinforced the perspective of digital transformation in education, which emphasized the importance of a systemic approach. OECD (2023) highlighted that digital transformation in education could not be achieved in isolation but required integration between policies, infrastructure, and digital literacy development. UNESCO (2023) also emphasized that successful technology integration depended on the synergy between government policies, institutional readiness, and human resource capacity.

In the context of global transformation, Xu et al. (2021) and Nahavandi (2019) explained that the industry 5.0 era required the integration of intelligent technology and human capabilities. Javaid et al. (2022) further emphasized that human resource development had to be directed toward strengthening creativity, collaboration, and problem-solving skills.

Voogt and Roblin (2012) and Chiu et al. (2021) also emphasized that modern education needed to develop 21st-century skills such as digital literacy, critical thinking, creativity, and collaboration. Therefore, the integration of digital education policies and digital learning ecosystems was a key factor in enhancing human resource competitiveness.

4. The Most Dominant Variable in Increasing Human Resource Competitiveness
The research results showed that the digital learning ecosystem was the most influential variable in increasing human resource competitiveness. This finding provided a new perspective that the success of digital transformation in education was more determined by the quality of technology implementation in learning practices than by the mere existence of formal policies.

This finding aligned with Schleicher (2020), who argued that technology in education only had a significant impact when effectively utilized in learning processes. Williamson et al. (2020) also emphasized that the success of digitalization depended on institutional readiness to build a supportive digital ecosystem.

Furthermore, a World Bank report (2022) indicated that disparities in technology access and digital ecosystem quality remained major challenges in developing countries. Trucano (2020) and Zhang et al. (2022) also emphasized that successful technology integration was influenced by infrastructure readiness, digital literacy, and organizational culture.

Thus, the findings of this study indicated that future digital education policy development needed to be directed not only at regulatory formulation but also at building a robust digital learning ecosystem that supported pedagogical innovation, data utilization, and sustainable digital competencies. This approach aligned with the industry 5.0 educational paradigm, which emphasized collaboration between humans and technology to create adaptive and sustainable learning systems.

3. Conclusion

This study concluded that digital-based quality policies had a positive and significant impact on human resource competitiveness. This indicated that digital-based quality policies designed systematically, integratively, and based on modern governance were able to improve adaptive capacity, professional competence, and human resource readiness in facing digital transformation. Furthermore, the digital learning ecosystem was also found to have a positive and significant impact on human resource competitiveness. Empirically, it was found that the influence of the digital learning ecosystem was greater than that of digital-based quality policies. Simultaneously, both variables were able to explain variations in human resource competitiveness in the moderate-to-strong category, confirming that increased competitiveness could not be achieved through standalone policies, but rather through the synergy of mutually reinforcing policies and digital ecosystems.

The most important and surprising finding in this study was the dominant influence of the digital learning ecosystem over the policy itself. Prior to this study, the normative approach in the literature placed policy quality as the primary determinant of successful digital transformation. However, empirical results showed that well-designed policies did not automatically generate competitiveness if they were not supported by digital infrastructure, system integration, a technology-based organizational culture, and strong managerial support. In other words, this study revealed that the success of digital transformation was more ecosystemic than merely regulatory. This fact could only be identified through empirical model testing.

Scientifically, this study made three important contributions. First, it confirmed previous findings regarding the importance of digital policies in improving organizational performance and competitiveness. Second, it provided a new perspective by positioning the digital learning ecosystem as a key variable that strengthened the effectiveness of digital quality policies. Third, it developed an integrative model, namely the digital-based quality policy (DQPO Model), which combined the dimensions of quality policy, digital ecosystem strengthening, and human resource competitiveness within a single PLS-SEM-based analytical framework. Thus, the primary contribution of this study lay not only in examining the relationships between variables, but also in shifting perspectives from a partial policy approach to a systemic approach based on the digital ecosystem.

However, this study had several limitations. The limited sample size meant that generalizations of the results were contextual. The study also involved only three cases, making it unrepresentative of a wider range of organizations. Variations in educational levels were not analyzed, thus discrepancies in the dynamics of digital policies across levels were not comprehensively depicted. Furthermore, the study's limited location in one region and the lack of analysis of demographic variations such as gender and age also limited the breadth of interpretation of the results. Methodologically, the use of a quantitative approach based on PLS-SEM was unable to deeply explore qualitative factors such as organizational cultural resistance, informal leadership dynamics, and individual psychological factors. Therefore, further research with a larger sample size, more varied cases, across levels and regions, and a mixed-methods approach was considered essential to gain a deeper and more comprehensive understanding. With these more comprehensive results, digital transformation policy formulation could be carried out more precisely, contextually, and effectively.

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