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HUMAN RESOURCE CAPACITY DEVELOPMENT MODEL MANUFACTURING SECTOR IN THE ERA OF DIGITAL TRANSFORMATION

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ABSTRACT

This study aims to analyze the impact of Education and Training, Organizational Culture, Policy Support, and Technology Investment on Digital HR Capacity, with Digital Competence, Media Literacy, and HR Adaptability serving as intervening variables. Employing a quantitative approach, data were collected from the manufacturing workforce and analyzed using the Structural Equation Modeling-Partial Least Squares (SEM-PLS) method. The results indicate that Education and Training, Organizational Culture, and Technology Investment have a significant direct influence on enhancing Digital Competence and HR Adaptability. These findings confirm that digital competence acts as a strategic asset that significantly boosts HR capacity. However, the study reveals that Media Literacy and HR Adaptability do not have a significant direct impact on Digital HR Capacity within the context of structured manufacturing operations. This suggests that adaptive attitudes and information literacy require the mediation of technical competence to be converted into functional capacity. The study's implications highlight the importance of harmonizing national policies and sustaining technology investment to bridge the skills gap in the era of digital transformation.

ABSTRAK

Penelitian ini bertujuan untuk menganalisis pengaruh Pendidikan dan Pelatihan, Budaya Organisasi, Dukungan Kebijakan, dan Investasi Teknologi terhadap Kapasitas SDM Digital, dengan Kompetensi Digital, Literasi Media, dan Adaptabilitas SDM sebagai variabel intervening. Menggunakan pendekatan kuantitatif, data dikumpulkan dari tenaga kerja di sektor manufaktur dan dianalisis menggunakan metode Structural Equation Modeling-Partial Least Square (SEM-PLS). Hasil penelitian menunjukkan bahwa Pendidikan dan Pelatihan, Budaya Organisasi, serta Investasi Teknologi memiliki pengaruh langsung yang signifikan terhadap peningkatan Kompetensi Digital dan Adaptabilitas SDM. Temuan ini mengukuhkan bahwa kompetensi digital berperan sebagai aset strategis (strategic asset) yang secara signifikan meningkatkan Kapasitas SDM. Namun, penelitian ini menemukan bahwa Literasi Media dan Adaptabilitas SDM tidak memiliki pengaruh langsung yang signifikan terhadap Kapasitas SDM Digital dalam konteks operasional manufaktur yang terstruktur. Hal ini mengindikasikan bahwa sikap adaptif dan literasi informasi memerlukan mediasi kompetensi teknis agar dapat dikonversi menjadi kapasitas fungsional. Implikasi penelitian ini menekankan pentingnya harmonisasi kebijakan nasional dan investasi teknologi yang berkelanjutan guna menutup celah kesenjangan keterampilan (*skill gap*) di era transformasi digital

INTRODUCTION

The fourth industrial revolution (Industry 4.0) has triggered a profound paradigm shift across the global manufacturing landscape. Driven by the convergence of the Industrial Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, artificial intelligence (AI), and advanced robotics, modern industrial organizations are transitioning toward intelligent, automated, and hyper-connected production ecosystems (Lasi *et al*., 2014; Vial, 2019). In emerging economies such as Indonesia, this technological wave is recognized as an unprecedented strategic window to revitalize the domestic industrial base, escape the middle-income trap, and achieve the national ambition of ranking among the world's top ten economies by 2030. To steer this structural transformation, the Indonesian government launched the national strategic initiative "Making Indonesia 4.0" in 2018, designating key focus sectors that represent the backbone of national manufacturing output: food and beverages, textiles and clothing, automotive, electronics, chemicals, and subsequently expanded to include pharmaceuticals and medical devices (Ministry of Industry, 2018; Aryani *et al*., 2024).

Nevertheless, navigating the transition to Industry 4.0 presents multifaceted challenges that transcend mere capital expenditure on advanced machinery and software. Empirical assessments consistently indicate that the primary bottleneck hindering industrial digitization in developing nations is the acute deficit in human capital readiness and the institutional misalignment of regulatory governance (Yuwono *et al*., 2025). The World Economic Forum (2023) Future of Jobs and Digital Readiness reports ranked Indonesia 54th out of 141 nations, reflecting a pervasive competence mismatch: while modern smart factories require high-level technical expertise in programmable logic controllers (PLCs), industrial data analytics, and automated maintenance, the majority of the domestic industrial workforce remains concentrated in secondary and lower-level educational qualifications with predominantly manual proficiencies. The national Indonesia Industry 4.0 Readiness Index (INDI 4.0) assessments further illuminate severe structural disparities; whereas select multinational automotive, machinery, and pharmaceutical enterprises have attained "lighthouse" status, the vast majority of medium-scale enterprises in consumer commodities, textiles, and agro-processing remain entrenched in Industry 2.0 or transitional 3.0 stages.

Compounding this skills gap is the systemic fragmentation of institutional policies. In Indonesia, vocational training governance, labor regulations, educational curricula, and industrial fiscal incentives are distributed across disparate government bodies, including the Ministry of Industry, the Ministry of Manpower, the Ministry of Education, and regional governments (Bappenas, 2020; Farhan *et al*., 2025). Policy instruments designed to foster industrial innovation such as the Super Tax Deduction for vocational training and R&D activities often face low private-sector utilization due to bureaucratic complexities, ambiguity in operational guidelines, and limited industry involvement in curriculum co-design (Dharmanu Yudartha *et al*., 2026; Kristanti *et al*., 2024). Consequently, despite substantial state rhetoric regarding industrial modernization, the operational shop floors of Indonesian manufacturing still grapple with low workforce productivity, fear of technological displacement, cultural resistance to digital monitoring, and an inability to translate raw informational flows into shop-floor operational efficiencies (Rohida, 2018; World Bank, 2021).

A critical synthesis of the prevailing literature reveals several prominent conceptual and empirical gaps. First, prior scholarship on industrial digitization in emerging Southeast Asian economies has focused predominantly on macroeconomic feasibility studies, overarching policy evaluations, or macroeconomic econometric modeling (Bappenas, 2020; World Bank, 2021). These studies provide broad diagnostic overviews but lack actionable, micro-level organizational mechanisms that explain how individual firms can systematically construct workforce capabilities from the ground up. Second, while regional inquiries on technical and vocational education and training (TVET) (e.g., ADB, 2022; ILO, 2021) have examined public educational pipelines, they rarely examine the internal organizational dynamics specifically the interplay between internal training architectures, corporate culture, technological investments, and

shop-floor capability conversion within operational production facilities.

Third, and most importantly, while contemporary strategic human resource management (SHRM) and dynamic capabilities literature in advanced economies demonstrates that strategic HR practices mediate operational agility and digital performance (Galanti *et al*., 2023; Nicolás-Agustín *et al*., 2021; Strohmeier, 2020), these theoretical models are almost exclusively situated within high-tech European, American, or East Asian manufacturing environments. Applying these models uncritically to developing industrial ecosystems overlooks critical contextual idiosyncrasies, such as severe baseline educational deficits, organizational hierarchies steeped in paternalistic management cultures, and fragmented technology adoption pathways where manual assembly lines coexist alongside semi-automated robotics (Buer *et al*., 2018; Powell & Romero, 2024). Furthermore, existing empirical inquiries have rarely modeled the multidimensional mediating mechanisms connecting institutional inputs and individual competencies; specifically, how technical execution capabilities (*Digital Competence*), cognitive information evaluation (*Media Literacy*), and psychological/behavioral openness (*HR Adaptability*) simultaneously act as pathways toward building holistic, enterprise-level *Digital HR Capacity* (Febriawan *et al*., 2025; Firmansyah *et al*., 2022; Pahlan, 2025).

To bridge this literature gap, this study develops and empirically validates an integrative structural model of human resource capacity development tailored specifically to the operational realities of the Indonesian manufacturing sector. Rooted in the convergence of the Resource-Based View (Barney, 1991), Human Capital Theory (Becker, 1964), Dynamic Capabilities Theory (Teece *et al*., 1997), and Strategic Human Resource Management (Wright & McMahan, 1992), this research addresses the following core research questions, (a) How do structural organizational interventions (Education and Training, Organizational Culture, Policy Support, and Technology Investment) directly influence the development of intermediate workforce capabilities (Digital Competence, Media Literacy, and HR Adaptability)? (b) Do these intermediate cognitive, technical, and behavioral capabilities exert direct and significant influences on the overarching construct of Digital HR Capacity within the structured environment of manufacturing operations? and (c) What are the structural and managerial implications for enterprise leadership and national industrial policymakers in optimizing digital upskilling programs under the Making Indonesia 4.0 framework?.

By executing a comprehensive Structural Equation Modeling–Partial Least Squares (SEM-PLS) analysis across 330 industrial human resource and manufacturing division leaders, this study offers dual academic and practical novelties. Theoretically, it delineates the functional boundaries between cognitive-behavioral dispositions and technical competencies, elucidating why psychological adaptability alone is insufficient to enhance performance in precision manufacturing without certified technical mastery. Practically, it establishes a data-driven diagnostic framework that aligns internal enterprise human resource strategies with national industrial readiness indicators (INDI 4.0), providing clear guidelines for corporate managers and industrial policymakers striving to achieve sustainable competitive advantage in the digital transformation era.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Resource-Based View (RBV)

The Resource-Based View (RBV), initially formulated by Wernerfelt (1984) and formalized into strategic management by Barney (1991), posits that an enterprise's competitive advantage and superior long-term performance derive fundamentally from its internal resource endowments rather than its external market positioning. To serve as a source of sustained competitive advantage, organizational resources must satisfy the VRIN criteria: they must be *Valuable* (exploiting environmental opportunities or neutralizing threats), *Rare* (not widely held by current or prospective competitors), *Inimitable* (incapable

of being easily replicated due to unique historical conditions, path dependency, causal ambiguity, or social complexity), and *Non-substitutable* (lacking strategically equivalent structural substitutes) (Barney, 1991). In the digital manufacturing paradigm, physical technology assets—such as industrial robotics, server infrastructures, and commercial software packages—are widely accessible on global capital markets and therefore rarely fulfill the criteria of rarity or inimitability on their own. Instead, RBV dictates that it is the socially complex, path-dependent human capital that integrates, operates, programs, and refines these cyber-physical assets that constitutes the true VRIN resource of the enterprise (Galanti *et al*., 2023). Within the conceptual architecture of this study, *Digital HR Capacity* and *Digital Competence* are operationalized as core VRIN capabilities. The unique combination of accumulated shop-floor tacit knowledge, specialized technical troubleshooting proficiencies, and collective organizational routines cannot be readily purchased or replicated by competitors, thereby serving as the primary internal engine of manufacturing resilience.

Human Capital Theory (HCT)

Pioneered by Schultz (1961) and systematically elaborated by Becker (1964), Human Capital Theory (HCT) conceptualizes individuals' cumulative knowledge, practical skills, cognitive capabilities, and physical health as a form of capital asset that yields economic returns to both the individual and the employing firm. Becker differentiated between *general human capital* competencies that are equally valuable across diverse organizational settings (such as foundational literacy, numeracy, and general media fluency)—and *specific human capital*, which represents skills, technical know-how, and procedural expertise that are idiosyncratic to a specific firm or production process. In the context of Industry 4.0 manufacturing, HCT provides the primary theoretical justification for institutional investments in formal vocational education, continuous upskilling, and apprenticeships (*Education and Training*). As industrial machinery shifts from mechanical logic to digital and computerized control, the marginal productivity of manufacturing labor becomes entirely contingent upon continuous capital investments in targeted technical learning. Technical training programs focusing on programmable automation, industrial IoT architecture, and digital maintenance serve as specific human capital investments that directly elevate employee productive efficiency and prevent human capital obsolescence amid rapid technological lifecycles (Mustofa *et al*., 2024; Wicaksono & Prasetiyo, 2023).

Dynamic Capabilities Theory (DCT)

While RBV provides a robust account of resource sustainability under equilibrium conditions, it has frequently been critiqued for its static orientation in rapidly shifting environments. To address this limitation, Teece *et al*., (1997) formulated Dynamic Capabilities Theory (DCT), defining dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." Teece *et al*., (1997) subsequently disaggregated dynamic capabilities into three distinct managerial and organizational clusters: (1) *Sensing* local and global technological opportunities and customer shifts; (2) *Seizing* structures, business models, and investments to capture value from those opportunities; and (3) *Transforming* (or reconfiguring) legacy organizational assets, organizational designs, and workforce skill profiles. In this research, digital transformation in the manufacturing sector represents a classic high-velocity, turbulent industrial environment characterized by technological disruption and shifting regulatory regimes. Within this context, *Organizational Culture* and *HR Adaptability* function as foundational dynamic capabilities. An organizational culture characterized by openness, psychological safety, and cross-functional collaboration facilitates the sensing and seizing of emerging technologies (Chatman & O'Reilly, 2023). Concurrently, HR adaptability represents the micro-foundation of reconfiguring: the cognitive flexibility, willingness to learn, and emotional resilience of workers required to unlearn legacy manual routines and reconfigure their day-to-day operations around cyber-physical workflows (Febriawan *et al*., 2025; Siahaan, 2023).

Strategic Human Resource Management (SHRM)

Strategic Human Resource Management (SHRM) emerged from the seminal work of Wright and McMahan (1992), who defined it as "the pattern of planned human resource deployments and activities intended to enable an organization to achieve its goals." Unlike traditional, transactional personnel administration, SHRM emphasizes the critical importance of *vertical fit* (the tight alignment between HR policies and the overarching strategic objectives of the firm) and *horizontal fit* (the mutual coherence and synergy among various HR practices, including selection, training, performance appraisal, and compensation). In modern manufacturing, achieving the digital vision outlined in roadmaps such as Making Indonesia 4.0 requires an unambiguous SHRM approach (Nicolás-Agustín *et al*., 2021). The deployment of advanced technologies (ERP, automated production lines, cloud monitoring) must be vertically aligned with targeted training initiatives, progressive organizational cultures, and national industrial policies. When training initiatives, cultural incentives, and capital investments operate in a synchronized manner, they create high-performance work systems (HPWS) that systematically foster workforce competencies, which subsequently translate into superior organizational capacity (O'Higgins, 2023; Strohmeier, 2020).

Digital Transformation in the Manufacturing Domain

Digital transformation within industrial operations is not merely an incremental IT upgrade; it represents an exhaustive organizational transformation wherein physical manufacturing operations are deeply fused with virtual computations, cognitive computing, and digital networks (Vial, 2019). Operationally conceptualized as "Smart Manufacturing" or "Lean 4.0," this domain utilizes digital instrumentation (smart sensors, automated vision systems, digital kanban) to monitor production in real time, conduct predictive maintenance, eliminate micro-stoppages, and achieve real-time optimization of energy, material, and labor (Buer *et al*., 2018; Powell & Romero, 2024). Consequently, the traditional role of manufacturing workers as manual tool operators is rendered obsolete; shop-floor personnel must transition into knowledge-driven roles as system controllers, analytical troubleshooters, and continuous-improvement coordinators.

Digital HR Capacity as the Target Construct

In contrast to individual competency, which captures the localized knowledge, skills, and attitudes of a specific employee, *Human Resource Capacity* represents an aggregate, firm-level capability. It reflects the comprehensive institutional readiness, quality, infrastructure, and collective organizational competence required to deploy human capital toward strategic objectives (Hecklau *et al*., 2016; Ulrich *et al*., 2012). In this study, *Digital HR Capacity* encompasses five interconnected operational dimensions: (1) alignment of targeted training with corporate digital roadmaps; (2) interactive and simulation-based learning methodologies; (3) organizational support, leadership commitment, and cross-departmental engagement; (4) autonomous shop-floor technology adoption; and (5) the cultural institutionalization of digital continuous improvement (Fenech *et al*., 2019; Noe, 2020; Sari *et al*., 2021).

Hypothesis Development

Education and Training and Digital Competence

Under the principles of Human Capital Theory, structured technical training programs constitute the primary formal mechanism for closing operational knowledge gaps (Becker, 1964). In the manufacturing environment, operating computerized numeric control (CNC) machinery, navigating SCADA systems, and interfacing with industrial IoT gateways require highly specialized technical know-how that cannot be acquired through informal socialization alone (Azhari & Kurniawan, 2023). Empirical inquiries by Mustofa

et al. (2024) and Wicaksono and Prasetiyo (2023) confirm that targeted technical upskilling directly improves operators' algorithmic logic, system-level comprehension, and diagnostic problem-solving abilities. When enterprises provide regular, relevant, and rigorously evaluated digital curricula, employee proficiency in specialized software and operational technology expands significantly. Therefore, it is hypothesized:

H1: Education and Training have a significant positive effect on Digital Competence.

Organizational Culture and HR Adaptability

Drawing from Dynamic Capabilities Theory, an organization's capacity to reconfigure operational processes depends directly on the shared values, norms, and behavioral expectations of its workforce (Teece *et al*., 1997). In manufacturing plants undergoing digital transformation, workers frequently experience profound technostress, fear of automation-induced layoffs, and cognitive dissonance when established manual habits are disrupted. An organizational culture characterized by participative leadership, psychological safety, and a "safe-to-fail" learning orientation provides the supportive climate necessary to mitigate employee anxiety (Chatman & O'Reilly, 2023; Siahaan, 2023). Studies by Isnada (2025) and Lopes and Sulislastuti (2025) demonstrate that when corporate culture encourages collaborative experimentation and eliminates punitive responses to honest operational errors during technology trials, shop-floor workers exhibit markedly higher cognitive flexibility, willingness to learn new digital systems, and resilience in the face of workplace disruption. Hence:

H2: Organizational Culture has a significant positive effect on HR Adaptability.

Policy Support and Media Literacy

From an institutional theory perspective, external institutional environments provide the legitimacy, standardization, and normative rules that shape organizational behavior (Dixit & Pindyck, 1994). In Indonesia, national initiatives such as Making Indonesia 4.0, technical guidelines issued by the Ministry of Industry, and data security frameworks establish formal expectations regarding how industrial data should be managed, audited, and protected (Ministry of Industry, 2018; Tuscany, 2017). Policy support, including subsidized training, vocational certification standards (SKKNI), and transparent digital guidelines, lowers information ambiguity for manufacturing personnel. When government and corporate policies provide clear standard operating procedures regarding digital data usage, industrial cybersecurity, and digital information ethics, workers are better positioned to critically interpret digital dashboards, verify information authenticity, and manage shop-floor digital communication platforms effectively (Firmansyah *et al*., 2022; Isnainul *et al*., 2020). Therefore:

H3: Policy Support has a significant positive effect on Media Literacy.

Technology Investment, Digital Competence, and Media Literacy

Capital expenditure on advanced manufacturing infrastructure such as cyber-physical machinery, networked sensors, enterprise resource planning (ERP) platforms, and edge-computing devices—creates an experiential, technology-rich physical environment (Klasean & Suwito, 2024; Tahir *et al*., 2022). In accordance with experiential learning theory, technical competencies cannot develop in an abstract theoretical environment; they require sustained, hands-on physical interaction with modern industrial equipment (Hadjimanolis, 2022). As enterprises invest in smart hardware and automated workflows, workers are compelled through daily operational necessity to master software interfaces, understand system parameters, and troubleshoot machine-network communication faults (Vial, 2019).

Simultaneously, the physical digitization of production lines transforms the nature of shop-floor information exchange. Manual paper logs, physical kanban cards, and verbal shift handovers are replaced by synchronized digital dashboards, real-time telemetry charts, and cloud-based reporting systems (Schmidt & Green, 2014). This continuous influx of digital signals necessitates the cultivation of media

and data literacy: shop-floor personnel must learn to read complex visual data, extract meaningful operating indicators from digital noise, and communicate across virtual and hybrid operational interfaces (Azhari & Kurniawan, 2023; Puteri & Asyari, 2023). Accordingly, technological capital investments simultaneously stimulate both direct technical capabilities and cognitive data-handling competencies:

H4: Technology Investment has a significant positive effect on Digital Competence.

H5: Technology Investment has a significant positive effect on Media Literacy.

The Mediating Roles Leading to Digital HR Capacity

Within modern industrial operations, the overarching construct of *Digital HR Capacity* reflects the collective capability of an enterprise's workforce to execute agile production, minimize unexpected downtime, and continuously innovate within cyber-physical environments (Hecklau *et al*., 2016; Ulrich *et al*., 2012). Under the Resource-Based View, this aggregate capacity is constructed from distinct intermediate individual competencies that fulfill the VRIN criteria.

First, *Digital Competence* serves as a direct technical pillar of HR capacity. In precision manufacturing, operational success hinges on technicians possessing the specific skills required to program robotic cells, adjust automated tooling, interpret SCADA system diagnostics, and conduct predictive maintenance (Pahlan, 2025; Silalahi, 2025). High individual digital competence directly translates into organizational-level capacity by maximizing Overall Equipment Effectiveness (OEE) and minimizing operational interruptions (Galanti *et al*., 2023).

Second, *Media Literacy* provides the cognitive information infrastructure. Workers operating in smart manufacturing settings must possess the capability to process dense operational data streams, evaluate the reliability of automated alerts, communicate cross-functionally via enterprise platforms, and adhere strictly to data privacy and cybersecurity protocols (Livingstone, 2004; Schmidt & Green, 2014). An organization whose workforce lacks critical information discernment risks severe operational delays, data misinterpretations, and vulnerability to industrial cyber threats.

Third, *HR Adaptability* acts as the behavioral and psychological catalyst. Rapid technology life cycles require workers who actively embrace continuous unlearning and relearning, demonstrate behavioral agility when shifting across operational roles, and maintain psychological resilience amid continuous automation updates (Febriawan *et al*., 2025; Sutrisno, 2021). Without adaptive attitudes, technical investments encounter passive resistance, sabotage, or underutilization. Consequently, these three intermediate competencies represent the vital mediating mechanisms through which institutional and organizational investments are transformed into sustainable, high-level organizational HR capacity:

H6: Digital Competence has a significant positive effect on HR Capacity.

H7: Media Literacy has a significant positive effect on HR Capacity.

H8: HR Adaptability has a significant positive effect on HR Capacity.

The research framework illustrates that this study consists of dependent and independent variables. Referring to the conceptual framework and research objectives, an operational framework and hypotheses were developed. This operational research framework illustrates the relationship between education and training, organizational culture, policy support, technology investment, digital competence, media literacy, human resource adaptability, and human resource capacity.

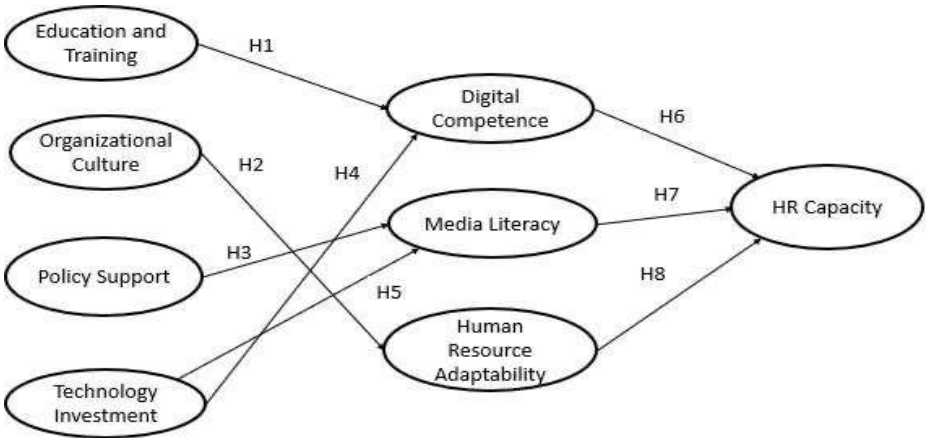


Figure 1. Operational Thinking Framework

RESEARCH METHOD

The population of this study is all medium and large scale manufacturing industry companies in Indonesia in the 7 priority sectors of Making Indonesia 4.0 in 2025 with a total of 1285 companies. The research sample selection technique in this study uses the purposive sampling method. The purposive sampling technique is a sampling technique based on certain criteria from a population. The selected respondents are HRD/HC Managers or Heads of Production Divisions or Digital Transformation Divisions (who can represent Human Capital/HRD). The research sample selection criteria are based on (1) industrial sector (representing 7 priority sectors), (2) company scale (medium and large), and (3) digital readiness level (referring to the INDI 4.0 classification: readiness level low, moderate, high).

The sample size for processing using SEM-PLS is recommended to be at least 5–10 times the number of indicators. Assuming 33 indicators, a minimum of 200–300 respondents are required. The sample size in this study was 330 respondents based on the theory of Hair *et al*. (2014), which states that the sample size requirement must be at least 5–10 times the number of indicators. The quantitative method used was Structural Equation Modeling-Partial Least Squares (SEM-PLS) analysis as a statistical approach, to formulate a model for developing human resource capacity in the manufacturing sector in the era of digital transformation.

The research framework illustrates that this study consists of dependent, intervening, and independent variables. Referring to the conceptual framework and research objectives, an operational framework and hypotheses were developed. This operational research framework illustrates the relationship between education and training, organizational culture, policy support, technology investment, digital competence, media literacy, human resource adaptability, and human resource capacity. To ensure construct validity and operational clarity prior to evaluating the measurement model, all latent variables are operationalized into specific indicators adapted from established literature. The exogenous construct of Education and Training (X_1) is captured through four indicators adapted from Vial (2019), Wicaksono and Prasetiyo (2023), and Mustofa *et al*. (2024), comprising training frequency ($X_{1.1}$), material relevance ($X_{1.2}$), employee participation rate ($X_{1.3}$), and evaluation of training outcomes ($X_{1.4}$). Organizational Culture (X_2) is measured using four indicators reflecting leadership support ($X_{2.1}$), cross-functional team collaboration ($X_{2.2}$), change orientation ($X_{2.3}$), and technological openness ($X_{2.4}$), drawing on Naveed *et al*. (2022), Isnada (2025), and Lopes and Sulislastuti (2025). Policy Support (X_3) incorporates institutional dimensions including digital workforce regulation ($X_{3.1}$), reskilling incentives ($X_{3.2}$), vocational and internship facilitation ($X_{3.3}$), and accessibility of technical assistance ($X_{3.4}$), as formulated by Dixit and Pindyck (1994), Bukht and Heeks (2017), Tuscany (2017), and Isnainul *et al*. (2020). Technology Investment (X_4) encompasses four indicators based on Tahir *et al*. (2022) and Klasean and Suwito (2024),

measuring digital investment budg*et al*location ($X_{4.1}$), advanced technology adoption ($X_{4.2}$), IT infrastructure connectivity ($X_{4.3}$), and system-wide process digitalization ($X_{4.4}$).

The three mediating constructs are operationalized to represent workforce cognitive, technical, and behavioral readiness. Digital Competence (M1) reflects practical execution capabilities and is evaluated through software proficiency (M1.1) with two indicators (M1_1 and M1_2), system problem-solving (M1.2) with two indicators (M1_3 and M1_4), digital data analysis (M1.3) with two indicators (M1_5 and M1_6), and work efficiency (M1.4) with two indicators (M1_7 and M1_8), based on Vial (2019), Pahlan (2025), and Silalahi (2025). Media Literacy (M2), which specifically encompasses data and information processing competencies, is measured using four indicators based on Schmidt and Green (2014), Livingstone (2004), Firmansyah *et al*. (2022), Puteri and Asyari (2023), and Widiyanti *et al*. (2024); these include data reading (M2.1) with two indicators (M2_1 and M2_2), data processing (M2.2) with two indicators (M2_3 and M2_4), data utilization for decision-making (M2.3) with two indicators (M2_5 and M2_6), and awareness of data ethics and cybersecurity (M2.4) with two indicators (M2_7 and M2_8). Human resource adaptability (M3) encompasses dynamic adjustment through operational flexibility (M3.1) with two indicators (M3_1 and M3_2), willingness to learn (M3.2) with two indicators (M3_3 and M3_4), responsiveness to change (M3.3) with two indicators (M3_5 and M3_6), and readiness to face disruption (M3.4) with two indicators (M3_7 and M3_8), adapted from Teece *et al*., (1997), Sutrisno (2021), and Febriawan *et al*. (2025).

Finally, the target endogenous construct Human Resource Capacity (Y) is operationalized as an aggregate multidimensional capability comprising five key dimensions: training focus (Y1) with two indicators (Y_1 and Y_2), learning methodology (Y2) with two indicators (Y_3 and Y_4), organizational support and engagement (Y3) with two indicators (Y_5 and Y_6), technology adoption (Y4) with two indicators (Y_7 and Y_8), and the integration of leadership and digital culture (Y5) with two indicators (Y_9 and Y_10); this conceptualization is derived from a synthesis of the work of Hecklau *et al*. (2016), Lee (2018), Schwalbe (2018), Fenech *et al*. (2019), Sari *et al*. (2021), and Noe (2020). All indicator items are assessed using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"), serving as the basis for the measurement codes analyzed in the Results section.

RESULTS AND DISCUSSION

The *path diagram* of this research consists of the variables of education and training, organizational culture, policy support, technology investment, digital competence, media literacy, human resource adaptability, and human resource capacity. There are five exogenous latent variables: education and training with four indicators, organizational culture with four indicators, policy support with four indicators, and technology investment with four indicators. The digital competence variable consists of four indicators, media literacy with four indicators, human resource adaptability with four indicators, and human resource capacity with five indicators.

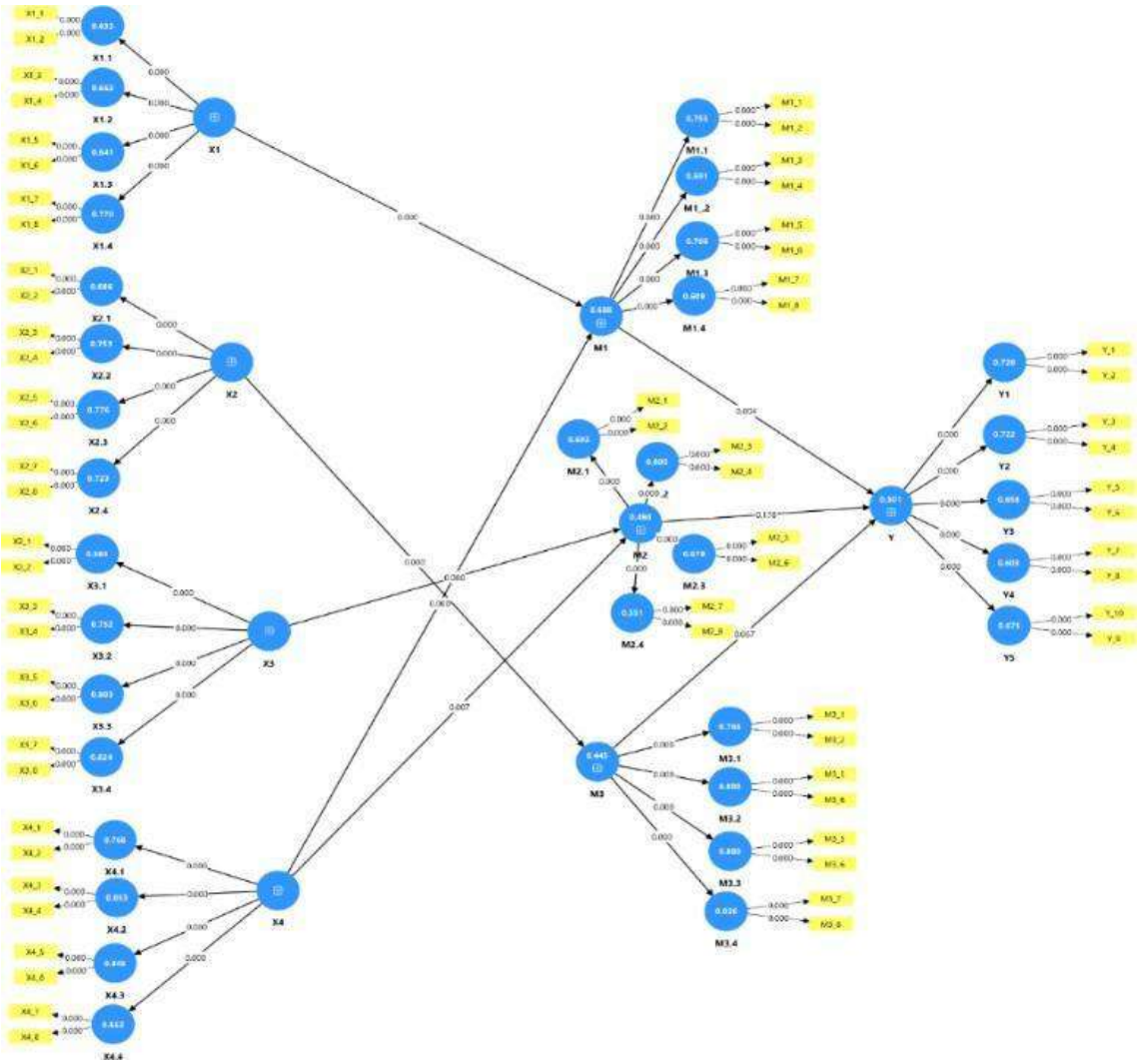


Figure 2. SEM-PLS Output

The results of the analysis for the initial stage of exploration of valid indicators and items as measuring variables with the criteria of *loading factor values* > 0,5. A *loading factor* value of 0,50 or more is considered to have sufficient validation to explain latent constructs (Hair *et al.,* 2010). The assessment of the reflective measurement model commenced with the examination of convergent validity. Factor loadings, Average Variance Extracted (AVE), and reliability coefficients are reported in Table 1.

Table 1. Measurement Model Reliability and Convergent Validity Results

Latent Variable & Sub-Dimensions	Cronbach's Alpha (α)	Composite Reliability (ρa)	Composite Reliability (ρc)	Average Variance Extracted (AVE)	Status
Digital Competence (M1)	**0,918**	**0,919**	**0,933**	**0,636**	**Reliable and Valid**
- M1.1 (Software Proficiency)	0,897	0,897	0,951	0,906	Reliable and Valid
- M1.2 (System Troubleshooting)	0,852	0,852	0,931	0,871	Reliable and Valid
- M1.3 (Digital Data Analysis)	0,887	0,889	0,947	0,898	Reliable and Valid

Latent Variable & Sub-Dimensions	Cronbach's Alpha (α)	Composite Reliability (ρa)	Composite Reliability (ρc)	Average Variance Extracted (AVE)	Status
- M1.4 (Work Efficiency)	0,934	0,934	0,968	0,938	Reliable and Valid
Media Literacy (M2)	**0,905**	**0,909**	**0,923**	**0,603**	**Reliable** and **Valid**
- M2.1 (Data Reading)	0,828	0,829	0,921	0,854	Reliable and Valid
- M2.2 (Data Processing)	0,905	0,905	0,955	0,913	Reliable and Valid
- M2.3 (Decision-Making)	0,871	0,874	0,940	0,886	Reliable and Valid
- M2.4 (Information Ethics)	0,860	0,866	0,934	0,877	Reliable and Valid
HR Adaptability (M3)	**0,943**	**0,945**	**0,953**	**0,716**	Reliable and Valid
- M3.1 (Operational Flexibility)	0,888	0,888	0,947	0,899	Reliable and Valid
- M3.2 (Continuous Learning)	0,829	0,830	0,921	0,854	Reliable and Valid
- M3.3 (Change Responsiveness)	0,829	0,830	0,921	0,854	Reliable and Valid
- M3.4 (Disruption Readiness)	0,913	0,913	0,958	0,920	Reliable and Valid
Education and Training (X1)	**0,886**	**0,889**	**0,910**	**0,559**	Reliable and Valid
- X1.1 (Training Frequency)	0,696	0,696	0,868	0,767	Reliable and Valid
- X1.2 (Material Relevance)	0,732	0,732	0,882	0,788	Reliable and Valid
- X1.3 (Participation Rate)	0,796	0,798	0,908	0,831	Reliable and Valid
- X1.4 (Outcome Evaluation)	0,894	0,894	0,950	0,904	Reliable and Valid
Organizational Culture (X2)	**0,897**	**0,899**	**0,917**	**0,582**	Reliable and Valid
- X2.1 (Leadership Support)	0,699	0,700	0,869	0,768	Reliable and Valid
- X2.2 (Collaboration)	0,670	0,673	0,858	0,752	Reliable and Valid
- X2.3 (Change Orientation)	0,790	0,792	0,905	0,826	Reliable and Valid
- X2.4 (Technological Openness)	0,786	0,793	0,903	0,824	Reliable and Valid
Policy Support (X3)	**0,917**	**0,920**	**0,933**	**0,636**	Reliable and Valid
- X3.1 (Workforce Regulation)	0,873	0,877	0,940	0,887	Reliable and Valid
- X3.2 (Fiscal Incentives)	0,950	0,950	0,976	0,953	Reliable and Valid
- X3.3 (Vocational Linkage)	0,783	0,789	0,902	0,821	Reliable and Valid
- X3.4 (Technical Assistance)	0,736	0,736	0,883	0,791	Reliable and Valid
Technology Investment (X4)	**0,927**	**0,930**	**0,941**	**0,666**	Reliable and Valid
- X4.1 (Capital Allocation)	0,828	0,830	0,921	0,853	Reliable and Valid
- X4.2 (Advanced Technology)	0,818	0,819	0,916	0,846	Reliable and Valid
- X4.3 (IT Infrastructure)	0,912	0,912	0,958	0,919	Reliable and Valid
- X4.4 (System Digitization)	0,735	0,743	0,882	0,790	Reliable and Valid
Digital HR Capacity (Y)	**0,897**	**0,900**	**0,916**	**0,522**	Reliable and Valid
- Y1 (Training Focus)	0,775	0,792	0,898	0,815	Reliable and Valid
- Y2 (Learning Methodology)	0,677	0,680	0,861	0,756	Reliable and Valid
- Y3 (Organizational Support)	0,741	0,741	0,885	0,794	Reliable and Valid
- Y4 (Technology Adoption)	0,644	0,645	0,849	0,737	Reliable and Valid
- Y5 (Digital Culture)	0,686	0,692	0,864	0,761	Reliable and Valid

As demonstrated in Table 2, all overarching latent constructs and second-order sub-dimensions exhibited Cronbach's alpha and Composite Reliability (rho_c) values exceeding the recognized benchmark of 0,70 (ranging from 0,849 to 0,976), confirming exceptional internal consistency. Convergent validity was fully

verified: all Average Variance Extracted (AVE) values exceeded the 0,50 threshold, ranging from 0,522 (*Digital HR Capacity*) to 0,716 (*HR Adaptability*), indicating that the constructs capture over half of the variance in their respective measurement indicators (Hair *et al*., 2014, 2022). Furthermore, individual factor loadings across all primary indicators surpassed the minimum threshold of 0,50, with the vast majority exceeding 0.708 (ranging between 0,645 and 0,976, see Figure 2 and Table 1 in source data), confirming that each item reliably reflects its target construct. Discriminant validity was established through the Fornell-Larcker criterion. In accordance with statistical rules, the square root of the AVE for every latent construct (diagonal elements) was greater than its highest correlation with any other construct in the model.

Structural Model Evaluation (Inner Model)

Following measurement validation, the structural model was examined to test the hypothesized relationships. Structural fit, explanatory power (R^2), effect sizes (f^2), predictive relevance (Q^2), and path coefficients were systematically calculated.

Table 2. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Latent Construct	R^2 Value	R^2 Adjusted	Predictive Relevance (Q^2)	Evaluation
Digital Competence (M1)	0,688	0,682	0,437	Substantial Explanatory Power
Media Literacy (M2)	0,480	0,470	0,289	Moderate Explanatory Power
HR Adaptability (M3)	0,445	0,439	0,318	Moderate Explanatory Power
Digital HR Capacity (Y)	0,501	0,486	0,261	Moderate-to-Substantial Power

The coefficient of determination (R^2) for the target endogenous variable, *Digital HR Capacity (Y)*, was **0,501** (adjusted R^2 = 0,486). This indicates that 50,1% of the total variance in overall manufacturing HR capacity is explained simultaneously by Digital Competence, Media Literacy, and HR Adaptability. For the intermediate variables, *Digital Competence* exhibited a substantial R^2 of **0,688**, indicating that 68.8% of technical competence variance is driven by Education and Training and Technology Investment. *Media Literacy* (R^2 = 0,480) and *HR Adaptability* (R^2 = 0,445) displayed moderate explanatory power. The Stone-Geisser predictive relevance (Q^2) values across all endogenous constructs were substantially above zero, yielding an aggregate system predictive relevance of Q^2 = 0,999, confirming that the model demonstrates excellent out-of-sample predictive relevance.

Table 3. Model Fit Test Results (Goodness of Fit)

Goodness of Fit Index	Cut-Off Criteria	Saturated Model	Estimated Model	Conclusion
SRMR	≤ 0,08	0,078	0,142	Good Fit (Saturated Model)
d_ULS	> 0,05	55,897	186,568	Good Fit
d_G	> 0,05	0,331	0,363	Good Fit
Chi-Square	Smaller than df	456,127	456,127	Acceptable Fit
NFI	≥ 0,90	0,851	0,851	Marginal / Acceptable Fit

The Standardized Root Mean Square Residual (SRMR) for the saturated model was **0,078**, satisfying the recognized benchmark (≤ 0,08) for acceptable model fit (Hu & Bentler, 1999). Geodesic distance (d_G = 0,331) and unweighted least squares discrepancy (d_ULS = 55,897) confirmed absence of structural misspecification. The Normed Fit Index (NFI) reached 0,851, which is deemed acceptable for complex, multi-tiered structural models in organizational research (Hair *et al*., 2022).

Structural Model Evaluation (*Inner Model*)

Each relationship was tested using a *Bootstrapping simulation* on the sample. This test aims to minimize the problem of disharmony in the research data. The results of the *Bootstrapping test* using the PLS values are shown in Figure 3.

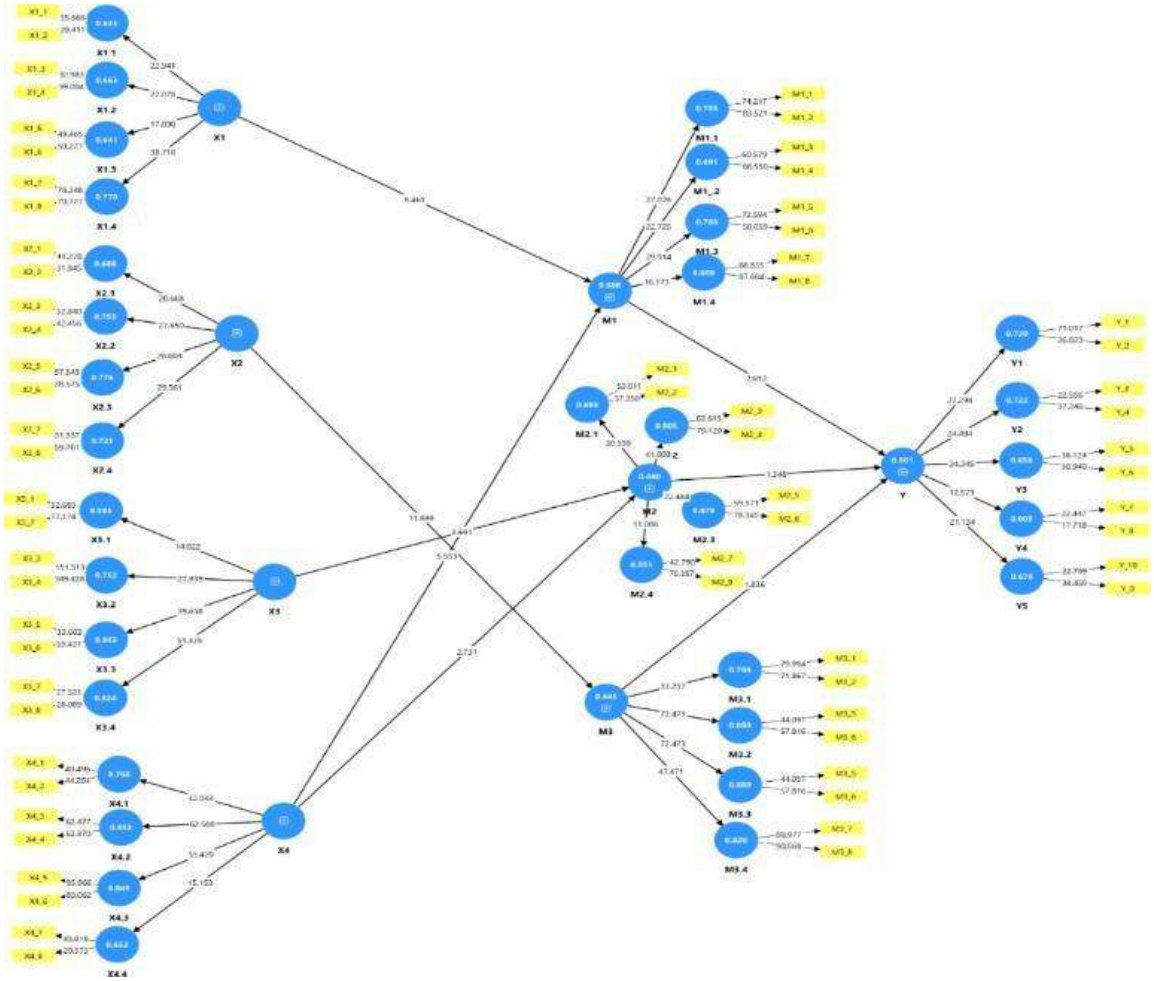


Figure 3. *Bootstrapping output* (*t-value)*

To assess the significance of the predictive model in structural model testing, the t-statistic value between the independent and dependent variables in the direct influence table (*path coefficient*) can be seen. Table 4 shows the results of the structural model hypothesis testing in the study. Based on the results of the hypothesis testing, it is known that six hypotheses are accepted.

Hypothesis Testing: Direct Effect

Testing in this study includes direct and total effects.

Table 4. Hypothesis Testing Results

Hypothesis	Path (Relationship)	t-value 5% (≥1,96)	Influence		Hypothesis Conclusion
			Direct	Total	
H1	X1 →M1	5,461	0,464	0,464	Accepted
H2	X2 →M3	11,699	0,667	0,667	Accepted
H3	X3→M2	3,691	0,406	0,406	Accepted
H4	X4 →M1	5,553	0,473	0,473	Accepted
H5	X4 →M2	2,731	0,343	0,343	Accepted
H6	M1→ Y	2,912	0,356	0,356	Accepted
H7	M2 → Y	1,348	0,171	0,171	**Rejected**
H8	M3 → Y	1,836	0,234	0,234	**Rejected**

This section discusses the results of the research hypothesis testing. The discussion of the research findings is based on descriptive and verification analyses, which are then compared with theory and previous research findings.

H 1 : Direct influence of education and training on digital competence

Education and Training exerts a substantial positive effect on Digital Competence. This confirms Human Capital Theory (Becker, 1964): structured, continuous technical instruction serves as the indispensable knowledge-transfer mechanism in manufacturing. Operating computerized numeric control (CNC) equipment, programming robotics, and managing cyber-physical systems cannot be learned through unguided socialization. When curricula focus on programmable logic controllers, industrial IoT architectures, and predictive analytics, workers transition rapidly from manual operators into skilled industrial technicians. This aligns with findings by Mustofa *et al*. (2024) and Wicaksono and Prasetiyo (2023), confirming that rigorous vocational modules directly close operational execution gaps.

H 2 : Direct influence of Organizational Culture on HR Adaptability.

Organizational Culture displays the largest direct effect size in the entire model, driving HR Adaptability. Grounded in Dynamic Capabilities Theory (Teece *et al*., 1997), an organization's agility to reconfigure routines depends on internal cultural norms. Introducing cyber-physical automation inherently induces acute technostress and fear of job obsolescence. A progressive culture that champions psychological safety, open communication, and cross-functional collaboration creates a "safe-to-fail" learning environment. As evidenced by Chatman and O'Reilly (2023) and Lopes and Sulislastuti (2025), when manufacturing leadership encourages continuous experimentation and eliminates punitive measures for operational errors during trial runs, workers exhibit superior mental flexibility and behavioral resilience.

H 3 : Direct influence of Policy Support on Media Literacy.

Support significantly enhances Media Literacy. Institutional clarity embodied in national frameworks like Making Indonesia 4.0, standardized vocational guidelines (SKKNI), and corporate standard operating procedures removes information ambiguity (Dixit & Pindyck, 1994; Tuscany, 2017). Clear regulatory mandates guide workers in interpreting industrial notifications, operating digital dashboards, and complying with industrial cybersecurity standards. However, the moderate effect size (f^2 = 0.158) highlights that while policy frameworks establish the necessary regulatory foundation, internal plant-level execution is required to transform broad public guidelines into ingrained shop-floor informational habits.

H 4 : Direct influence of Technology Investment on Digital Competence.
Technology Investment significantly drives Digital Competence. Hands-on interaction with modern manufacturing technology creates an active "learning-by-doing" environment (Hadjimanolis, 2022). Capital expenditures on cyber-physical equipment, automated assembly lines, and ERP platforms force operators to acquire practical technical proficiencies to program, monitor, and maintain these integrated assets (Klasean & Suwito, 2024). This finding explains the persistent competence divide in Indonesia: large enterprises with sustained capital investments build advanced talent pools, whereas capital-constrained medium enterprises remain trapped in legacy operational habits.

H 5 : Direct influence of Technology Investment on Media Literacy.
Technology Investment positively affects Media Literacy. The physical digitization of production lines shifts operational communication from manual paper logs to synchronized telemetry, digital kanban, and computerized dashboards (Schmidt & Green, 2014; Vial, 2019). This exposure requires workers to cultivate data literacy to filter operational noise from urgent alerts. Nevertheless, the modest effect size indicates that acquiring hardware and software alone does not guarantee critical information literacy; absent continuous pedagogical guidance, excessive technology investments risk inducing data overload rather than systematic analytical discernment.

H 6 : Direct influence of Digital Competence on HR Capacity.
Digital Competence has a statistically significant, direct positive effect on Digital HR Capacity. This confirms the Resource-Based View (Barney, 1991): specialized digital technical competence fulfills the VRIN criteria. In highly automated production environments, organizational capacity is determined by workers who master industrial software, execute rapid robotic line reconfiguration, and conduct predictive maintenance to prevent costly machine downtime. As shown by Galanti *et al*. (2023), Pahlan (2025), and Silalahi (2025), functional technical mastery is the operational engine that converts technological investments into institutionalized manufacturing capability.

H 7 : Direct influence of Media Literacy on Human Resource Capacity.
Media Literacy does not exert a significant direct effect on Digital HR Capacity. While media and data literacy enable employees to read dashboards, navigate digital communication interfaces, and comprehend cybersecurity rules, these cognitive capabilities do not automatically translate into aggregate manufacturing capacity. In precision manufacturing, possessing general informational literacy is an auxiliary skill. Reading a machine telemetry alert does not equate to the engineering capability required to recalibrate an automated tooling path or repair a failing PLC unit. This finding corroborates the workplace literacy thesis: general digital literacy facilitates interaction with technology interfaces, but its impact on operational outcomes remains latent unless coupled with job-specific technical competencies (Chong & Mohamed Zainal, 2024). Specific indirect effect testing confirmed that the pathways X3 □ M2 □ Y and X4 □ M2 □ Y were also statistically non-significant, reinforcing that media literacy serves as a foundational cognitive baseline rather than an independent driver of industrial capacity.

H 8 : Direct influence of HR Adaptability on HR Capacity.
HR Adaptability does not demonstrate a statistically significant direct impact on Digital HR Capacity at the conventional 5% significance level. This empirical result provides a vital theoretical nuance to the Dynamic Capabilities literature within industrial engineering contexts. In high-precision manufacturing, an employee's behavioral willingness to embrace change, cognitive agility, and positive attitude toward automation cannot compensate for a lack of verified technical competence. An operator may possess an

exceptionally agile and enthusiastic mindset; however, without certified technical competence, that worker cannot debug a robotic welding cell or optimize computerized batch parameters. In standardized manufacturing environments governed by strict Standard Operating Procedures (SOPs), unchanneled behavioral adaptability unanchored by technical expertise can even introduce unauthorized process deviations that compromise product quality. Consequently, adaptability functions effectively as an antecedent that accelerates skill acquisition (as supported in H2), but it does not serve as a standalone determinant of shop-floor operational capacity.

CONCLUSION

This study demonstrates that the development of human resource capacity in the Indonesian manufacturing sector is primarily driven by targeted technical competencies rather than generalized behavioral or information readiness. The empirical findings confirm that structured education and training, organizational culture, and continuous technology investment serve as foundational drivers that enhance digital competence and workforce adaptability. In turn, digital technical competence emerges as a critical strategic asset satisfying the VRIN criteria, exerting a direct, significant influence on overall HR capacity by enabling workers to operate complex cyber-physical systems, conduct autonomous troubleshooting, and minimize operational downtime. Conversely, media literacy and HR adaptability do not exhibit a direct significant effect on HR capacity within precision manufacturing environments. This crucial empirical divergence indicates that cognitive openness and generalized information literacy remain latent unless they are systematically channeled through specialized, hands-on technical proficiencies governed by strict industrial Standard Operating Procedures.

These findings generate actionable managerial and policy implications to accelerate digital readiness across manufacturing enterprises. From an organizational management perspective, corporate leaders and HR practitioners must move beyond generic digital training by prioritizing hands-on, certified upskilling in high-impact domains such as programmable logic controllers, industrial IoT, and predictive maintenance while cultivating a "safe-to-fail" organizational culture that provides psychological safety for continuous learning. Furthermore, physical capital expenditures in smart machinery must be coupled with structured technical assistance and simulator modules to prevent acquired technologies from becoming underutilized assets. At the policy level, inter-ministerial synchronization between the Ministry of Industry, the Ministry of Education, and relevant regulatory agencies is essential to eliminate regulatory fragmentation, harmonize vocational curricula with SKKNI 4.0 standards, and expand fiscal incentives like the Super Tax Deduction to support capital-constrained small and medium-sized enterprises. Ultimately, sustaining long-term industrial competitiveness under the Making Indonesia 4.0 roadmap necessitates an integrative strategy where government policy, targeted technology investment, and human-centric competence development operate cohesively.

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