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Research Article

AI Literacy and Workforce Readiness in The Digital Era: The Mediating Role of Human Capital Development

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Abstract: Artificial intelligence (AI) has become an integral component of higher education and is increasingly recognized as a strategic competency required for future employment. However, although university students frequently utilize AI technologies, limited empirical evidence explains how AI literacy contributes to workforce readiness through the development of human capital. This study aims to examine the direct effects of AI Literacy on Human Capital Development and Workforce Readiness, as well as the mediating role of Human Capital Development in the relationship between AI Literacy and Workforce Readiness among university students. A quantitative explanatory research design was employed using a census sampling technique involving 200 active students from the Community Education Study Program, Faculty of Teacher Training and Education, Universitas Riau, Indonesia. Data were collected through a structured questionnaire using a five-point Likert scale and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The findings indicate that AI Literacy positively influences Human Capital Development and Workforce Readiness, while Human Capital Development also exerts a significant positive effect on Workforce Readiness and partially mediates the relationship between AI Literacy and Workforce Readiness. These findings demonstrate that AI Literacy extends beyond technological competence by strengthening students' human capital and enhancing their readiness for the digital workforce. Therefore, higher education institutions should integrate AI literacy into teaching and learning practices to foster graduate competitiveness and sustainable workforce preparedness in the era of digital transformation.

Keywords: AI Literacy; Community Education; Digital Skills; Human Capital; Workforce Readines.

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1. Introduction

Artificial intelligence (AI) is no longer confined to highly technical occupations or technology-intensive industries. Its increasing integration into organizational processes has begun to reshape the competencies expected of future workers, including their ability to understand AI systems, use AI-supported tools, critically evaluate AI-generated outputs, and recognize the ethical implications of technology use. Recent global workforce projections indicate that technological change, particularly AI and information-processing technologies, is accelerating shifts in occupational structures and skill requirements. Employers consequently place increasing emphasis on technological literacy, adaptability, analytical thinking, and continuous skill development as components of workforce preparedness (Zahidi, 2025). These developments position AI literacy not merely as a digital competence but as an emerging dimension of human capital that may influence how individuals prepare for increasingly technology-mediated work.

Within higher education, this transformation raises a particular concern regarding students' transition from academic environments to professional life. Universities are expected to prepare graduates who possess disciplinary knowledge while also being capable of responding to rapid changes in work practices. AI literacy has therefore attracted increasing scholarly attention as a multidimensional competence involving knowledge of AI, practical application, critical evaluation, and ethical awareness. Existing frameworks emphasize that meaningful AI literacy extends beyond the ability to operate generative AI applications. It requires individuals to understand the capabilities and limitations of AI, evaluate its outputs, and engage with AI responsibly (Alexander Benlian, 2025). More recent competency-oriented approaches similarly suggest that AI-related competence should be developed systematically because learners will increasingly interact with AI as users, co-workers, collaborators, and potentially creators in future professional settings (Chiu, 2025).

Previous studies have approached AI literacy primarily through conceptual framework development, competency measurement, and scale validation. (Davy Tsz Kit Ng, 2021) conceptualized AI literacy through dimensions related to knowing and understanding AI, using and applying AI, evaluating and creating AI, and addressing ethical issues. Subsequently expanded the measurement perspective by incorporating AI-related self-efficacy, problem-solving, and self-management competencies. These approaches provide important conceptual and psychometric foundations for assessing individuals' capacity to engage with AI. Their principal strength lies in transforming an abstract technological concept into measurable competency dimensions. However, much of this research has concentrated on defining and measuring AI literacy rather than explaining how such literacy contributes to broader human resource outcomes, particularly workforce readiness (Carolus et al., 2023).

Research on digital competence and career development offers another relevant perspective. Digital literacy has been associated with students' capacity to adapt to changing academic and occupational environments, while the integration of digital capabilities into higher education is increasingly viewed as essential for employment readiness (Ramdana, 2026). At the same time, human capital research emphasizes that knowledge, skills, competencies, and individual capabilities constitute productive resources that can support future occupational performance. Emerging empirical evidence also indicates a positive relationship between AI development and human capital-based educational development, although the magnitude of this relationship may differ across national and developmental contexts (Tian & Zhang, 2025). These findings suggest that AI-related capabilities may contribute to human capital formation rather than functioning solely as isolated technical skills.

Nevertheless, an important empirical gap remains. Existing AI literacy research has predominantly examined literacy levels, technology adoption, attitudes toward AI, learning environments, or instrument development. Studies concerning workforce readiness, in contrast, frequently focus on employability skills, digital literacy, career adaptability, and general professional competencies. The mechanism connecting AI literacy to workforce readiness through human capital development remains insufficiently explained, particularly among university students in non-technical and community education disciplines. This gap is especially relevant in the Indonesian higher education context, where students increasingly use AI-supported applications in academic activities while the extent to which such engagement develops productive knowledge, adaptive capability, and future workforce readiness is still unclear.

The problem is not simply whether students use AI. Frequent access to generative AI does not automatically indicate that students possess the knowledge and critical competence required to integrate AI effectively into future professional practice. Students may be capable of generating text, summarizing information, or obtaining rapid responses from AI applications without adequately evaluating accuracy, bias, ethical implications, or task suitability. Consequently, a distinction must be made between AI use and AI literacy. From a human capital perspective, AI literacy becomes strategically meaningful when AI-related knowledge and competencies strengthen individuals' productive capacities, learning adaptability, problem-solving ability, and preparedness to undertake evolving occupational roles.

This issue has particular significance for students in community education. Graduates of community education programs may enter diverse professional settings involving community empowerment, non-formal education, training, social development, educational management, and lifelong learning initiatives. These professional environments increasingly require practitioners to manage information, design adaptive programs, communicate with heterogeneous communities, and respond to digital transformation. Accordingly, students in community education represent an important prospective workforce group for examining whether AI literacy can contribute to the development of human capital and, subsequently, workforce readiness. However, empirical studies positioning community education students within the AI-human capital workforce nexus remain limited.

To address this gap, the present study proposes a mediation model that examines human capital development as an explanatory mechanism linking AI literacy and workforce readiness. Rather than treating AI literacy as an isolated technological competence, this study conceptualizes it as a capability that may strengthen the knowledge, skills, adaptability, and productive capacities embedded in human capital. Human capital development is subsequently expected to enhance students' readiness to respond to changing work requirements. The study employs a quantitative explanatory design and partial least squares structural equation modeling (PLS-SEM) to examine the direct and indirect relationships among AI literacy, human capital development, and workforce readiness among students of the Community Education Study Program, Faculty of Teacher Training and Education, Universitas Riau, Indonesia.

This study makes three principal contributions. First, it extends AI literacy research by connecting AI-related competence with workforce readiness, thereby moving the discussion beyond technology acceptance and educational use. Second, it introduces human capital development as a mediating mechanism that explains how AI literacy may be transformed into capabilities relevant to future employment. Third, the study provides evidence from community education students, a prospective workforce group that has received limited attention in the international literature on AI literacy and human resource development. The findings are expected to contribute to the human resource management literature by clarifying the strategic role of AI literacy in early human capital formation and to provide practical implications for higher education institutions seeking to align graduate development with emerging workforce demands.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the conceptual relationships among AI literacy, human capital development, and workforce readiness. Section 3 describes the proposed research method, measurement approach, sampling procedure, and data analysis technique. Section 4 presents and discusses the empirical results. Section 5 compares the findings with the current state of the art and highlights the study's distinctive contribution. Finally, Section 6 summarizes the conclusions, implications, limitations, and directions for future research.

2. Literature Review

The intersection of artificial intelligence, human capital, and workforce preparation has become increasingly relevant as technological transformation changes the competencies required in contemporary employment. Nevertheless, these areas have largely developed through separate streams of scholarship. AI literacy research has concentrated on conceptualizing and measuring individuals' competence in understanding and using artificial intelligence. Human capital research has emphasized the accumulation of knowledge, skills, and adaptive capabilities, whereas workforce readiness studies have focused on the competencies required to enter and function effectively in employment. The limited integration of these perspectives creates a theoretical and empirical opportunity to examine AI literacy as a human capital-related capability that may shape future workforce readiness. This section synthesizes relevant theories and empirical studies to establish the conceptual relationships proposed in the present research.

AI Literacy as an Emerging Individual Capability

AI literacy has evolved from a technology-oriented concept into a broader competency concerned with how individuals understand, use, evaluate, and respond to artificial intelligence. Conceptualized AI literacy as a multidimensional competence involving knowledge and understanding of AI, practical application, evaluation and creation, and ethical consideration (Hackl, 2026). This conceptualization is significant because it distinguishes meaningful AI literacy from mere exposure to AI-based applications. An individual may frequently use an AI tool without possessing sufficient competence to evaluate the reliability, limitations, or ethical implications of its outputs.

The transition from conceptual definition to empirical measurement has further strengthened AI literacy research. Developed an AI literacy scale based on awareness, use, evaluation, and ethics (Lintner, 2024). Their approach demonstrated that AI literacy can be operationalized as an individual-level competence and quantitatively assessed among ordinary users. Developed the Meta AI Literacy Scale (MAILS), integrating AI-related understanding and application with psychological competencies such as self-efficacy, problem solving, and self-management (Carolus, 2023). Further validation of MAILS showed continuing efforts to improve the validity and practical application of AI literacy measurement (Koch, 2024). The literature therefore indicates substantial progress from conceptual discussion toward measurable competency frameworks.

The strength of these approaches lies in their ability to differentiate dimensions of AI competence and provide empirical instruments for individual assessment. However, their primary emphasis remains the identification and measurement of AI literacy itself. The developmental consequences of possessing stronger AI literacy have received comparatively less attention. In particular, existing measurement-oriented studies do not fully explain whether AI literacy contributes to the accumulation of broader capabilities that individuals can transfer into future professional environments.

Recent scholarship has begun to broaden this perspective. Competency frameworks increasingly recognize that AI literacy should be adapted to learners' educational levels and disciplinary backgrounds rather than treated as a uniform technical competence (Lee, 2024). Organizational research similarly positions AI literacy development as a strategic capability-building process that requires differentiated investment in workforce competencies (Oldemeyer et al., 2026). These developments suggest a conceptual transition: AI literacy is increasingly viewed not simply as knowledge about technology but as a capability with implications for individual and organizational development.

This transition is particularly relevant to university students. Students are prospective workforce participants whose professional preparation occurs before formal entry into employment. Their interaction with AI may create opportunities to strengthen information evaluation, adaptive learning, problem solving, and technology-supported decision making. Yet, the value of AI literacy for employment preparation cannot be assumed from frequency of AI use alone. The present study therefore positions AI literacy as an emerging individual capability whose workforce relevance depends on its contribution to broader human capital development.

Human Capital Development in an AI-Mediated Environment

Human capital theory provides an important foundation for understanding how individual competencies acquire productive value. Human capital is generally associated with knowledge, skills, abilities, and other capabilities developed through education, learning, training, and experience. From this perspective, education represents an investment in individuals because accumulated capabilities can improve their capacity to perform productive roles and respond to changing occupational requirements.

Digital transformation has altered the composition of capabilities considered strategically valuable. Knowledge is no longer sufficient when occupational tasks and professional practices are continuously modified by technological development. Individuals increasingly require learning agility, analytical competence, technological adaptability, and the ability to update their skills. The growing use of AI further intensifies this requirement because AI-mediated work requires individuals to combine technological understanding with human judgment.

AI literacy may contribute to human capital development through several mechanisms. Understanding AI can expand an individual's technological knowledge. Evaluating AI-generated information may strengthen critical judgment and information assessment. Appropriate AI application may support problem solving and task adaptation, while ethical awareness can improve responsible decision making. The competency structures identified therefore overlap with capabilities that have productive relevance beyond the immediate use of an AI application (Carolus, 2023).

Empirical research on digital employability provides support for connecting technology-related capabilities with human capital formation. Examined 2,587 vocational education graduates in Indonesia using PLS-SEM and a human capital investment framework. Their study positioned digitally oriented employability competencies within the process of preparing graduates for workforce participation (Kholifah, 2025). The research is particularly important because it demonstrates the analytical value of human capital theory in explaining workforce readiness in a digital environment.

However, digital employability skills and AI literacy are not conceptually identical. Digital skills generally refer to the capability to operate, manage, evaluate, and communicate through digital technologies. AI literacy introduces additional complexities related to algorithmic outputs, probabilistic responses, machine limitations, bias, and human responsibility. Consequently, AI literacy may represent a distinctive form of capability development within contemporary human capital.

The human capital perspective is particularly applicable to community education students. Their prospective occupational pathways are not limited to conventional classroom teaching. Graduates may participate in community empowerment, non-formal education, training and development, lifelong learning, program management, social innovation, and other human development activities. Such professional settings frequently require adaptive knowledge, communication, information management, and context-sensitive problem solving. The development of AI literacy may therefore strengthen the capability portfolio that community education students bring to future professional roles.

Based on this theoretical reasoning, AI literacy is expected to contribute positively to human capital development. Students with stronger competence in understanding, applying, and evaluating AI are expected to possess greater opportunities to expand their knowledge, adaptive capabilities, and technology-supported problem-solving competence. Accordingly, the following hypothesis is proposed:

H1. AI literacy positively influences human capital development.

Workforce Readiness as a Human Capital Outcome

Workforce readiness reflects an individual's preparedness to enter and adapt to professional environments. It is broader than academic achievement because successful transition into employment requires individuals to apply knowledge, solve problems, adapt to organizational changes, communicate effectively, and respond to evolving occupational expectations. In an increasingly digital labor environment, technological adaptability has become an integral dimension of such readiness.

The relationship between competency development and workforce readiness is consistent with a human capital perspective. Individuals accumulate knowledge and capabilities through educational and developmental processes and subsequently apply these resources in productive contexts. Accordingly, workforce readiness may be understood as an outcome of the extent to which individuals have developed transferable and professionally relevant capabilities before entering employment.

Provide recent empirical evidence concerning this relationship in the Indonesian context. Their PLS-SEM study examined digital employability competencies and workforce readiness among vocational graduates (Kholifah, 2025). The findings reinforce the importance of considering workforce readiness through a human capital investment framework rather than solely as an employment outcome. Nevertheless, the study focuses on vocational graduates, whose education is commonly structured around occupation-specific preparation.

Community education students represent a different prospective workforce context. Their career pathways may be heterogeneous and extend across educational, social, community, governmental, and training institutions. This occupational diversity increases the importance of transferable capabilities rather than narrowly defined technical competencies. Adaptability, continuous learning, problem solving, and the ability to engage responsibly with emerging technologies may therefore constitute important foundations of their workforce readiness.

AI literacy may directly contribute to such readiness. Students who understand the capabilities and limitations of AI may be better prepared to identify appropriate technological support for professional tasks. Competence in evaluating AI outputs may support information-based decision making, while ethical awareness may reduce uncritical dependence on automated systems. Recent research is increasingly examining AI-related competence in relation to career adaptability and AI-mediated labor markets, indicating that literacy alone may not be sufficient unless it is converted into broader readiness capabilities.

Accordingly, this study assumes that students with higher AI literacy will demonstrate stronger workforce readiness. This relationship reflects the growing importance of AI-related capabilities in professional preparation. Therefore:

H2. AI literacy positively influences workforce readiness.

Human capital development is also expected to influence workforce readiness directly. Knowledge, adaptive capacity, problem-solving competence, and continuously developed skills provide individuals with resources for responding to workplace requirements. Students who have developed stronger human capital are more likely to perceive themselves as capable of adapting to changing work tasks and professional expectations.

This relationship is particularly important in an AI-mediated environment, where occupational requirements may change faster than formal curricula. Human capital development enables individuals to continue learning and renew their competencies rather than relying exclusively on previously acquired knowledge. Workforce readiness consequently depends not only on what students currently know but also on their capacity to learn, adapt, and apply their capabilities in changing contexts. Therefore:

H3. Human capital development positively influences workforce readiness.

The Mediating Role of Human Capital Development

Although AI literacy may directly improve students' preparedness for technology-mediated work, a direct-effect explanation is theoretically incomplete. Possessing knowledge about AI does not automatically produce workforce readiness. The productive relevance of AI literacy depends on whether AI-related competencies are converted into broader knowledge, adaptive capability, problem-solving capacity, and other individual resources applicable to professional contexts.

Human capital development provides a mechanism for explaining this conversion process. AI literacy gives individuals the competence to engage critically and responsibly with AI. Through repeated learning and application, these competencies may strengthen broader individual capabilities. Those capabilities subsequently improve the individual's ability to respond to emerging workforce requirements. Thus, human capital development may transmit the effect of AI literacy to workforce readiness.

This mediation argument distinguishes the present study from research that directly associates digital competence with employment outcomes. The distinction is theoretically important because a technological competence can exist without being productively integrated into an individual's capability portfolio. For example, frequent AI use may remain limited to routine academic assistance. In contrast, AI literacy that strengthens analytical judgment, learning adaptability, and problem solving can become part of an individual's human capital and may consequently improve workforce readiness.

Recent workforce research has demonstrated the value of using human capital theory and PLS-SEM to examine the mechanisms linking digital competencies and employment preparation (Kholifah, 2025). However, the mediating role of human capital development in the specific relationship between AI literacy and workforce readiness remains insufficiently examined, particularly among non-technical university students. Therefore:

H4. Human capital development mediates the relationship between AI literacy and workforce readiness.

Related Work and State-of-the-Art Positioning

Previous research can be classified into three principal streams. The first stream focuses on AI literacy conceptualization and measurement. Ng et al. (2021) developed a multidimensional conceptual framework, while Wang et al. (2023) operationalized AI literacy through awareness, use, evaluation, and ethics. Carolus et al. (2023) expanded the construct through MAILS, and Koch et al. (2024) further examined its validity and measurement structure. These studies provide strong conceptual and methodological foundations but predominantly treat AI literacy as the principal outcome or measurement object.

The second stream concerns AI and capability development. Emerging competency and organizational frameworks increasingly view AI literacy as a capability that should be systematically developed according to individual or organizational needs (Chee et al., 2025; Benlian et al., 2025). Nevertheless, these studies are largely framework-oriented and provide limited empirical explanation of the mechanism through which AI literacy develops workforce-relevant human capital among university students.

The third stream examines digital competencies and workforce readiness. Offer a significant contribution by applying human capital theory and PLS-SEM to a large sample of Indonesian vocational graduates (Kholifah, 2025). However, their research addresses broader digital employability skills rather than AI-specific literacy and focuses on vocational graduates. This leaves both a construct gap and a population gap.

The present study advances the state of the art by integrating these three research streams into a single explanatory model. Unlike AI literacy studies that concentrate primarily on competency measurement, this research positions AI literacy as an antecedent of a workforce-related outcome. Unlike digital employability research, it isolates AI literacy as a distinctive emerging competence. Most importantly, the study introduces human capital development as a mediating mechanism explaining how AI literacy may be converted into workforce readiness. The empirical focus on community education students at Universitas Riau further extends the literature to a non-technical prospective workforce population whose professional roles are closely associated with learning, training, community development, and human capability formation.

Accordingly, the conceptual model proposes that AI literacy influences workforce readiness both directly and indirectly through human capital development. This integrated perspective provides the theoretical basis for the proposed method and empirical analysis presented in the following section.

3. Proposed Method

This study employed a quantitative explanatory research design to investigate the relationships among AI literacy, human capital development, and workforce readiness. The proposed method was developed to examine not only the direct influence of AI literacy on workforce readiness but also the mechanism through which human capital development transmits this influence. The study therefore positioned AI literacy as the exogenous construct, human capital development as the mediating construct, and workforce readiness as the endogenous construct.

Partial least squares structural equation modeling (PLS-SEM) was employed as the primary analytical approach. PLS-SEM enables the simultaneous assessment of latent construct measurement and structural relationships, including direct and indirect effects. This approach is particularly applicable to prediction-oriented explanatory models involving multiple constructs and mediation mechanisms (Hair, 2022). The analytical process was conducted sequentially by evaluating the measurement model before interpreting the structural model.

Research Design and Study Context

The study was situated in the Community Education Study Program, Faculty of Teacher Training and Education, Universitas Riau, Indonesia. This context was selected because community education students represent prospective human resources whose future professional pathways may include non-formal education, community empowerment, training and development, lifelong learning, educational program management, and other human development sectors.

The unit of analysis was the individual student. The target population consisted of 200 active students enrolled in the Community Education Study Program. Given the identifiable and accessible population size, a census approach or total sampling technique was applied. Accordingly, all 200 students were included in the survey distribution frame. The final analytical sample was determined after questionnaire screening and consisted only of complete and analytically eligible responses.

Proposed Research Procedure

The proposed research procedure consisted of seven interconnected stages. First, relevant theories and empirical studies concerning AI literacy, human capital development, and workforce readiness were reviewed. Second, the conceptual model and hypothesized relationships were developed based on the identified research gap. Third, measurement indicators were adapted from relevant literature and aligned with the context of community education students. Fourth, a structured questionnaire was prepared using a five-point Likert scale. Fifth, the questionnaire was distributed to the study population. Sixth, the collected responses were screened to ensure data completeness and analytical suitability. Finally, the measurement and structural models were analyzed using PLS-SEM.

The research flow can be summarized as follows:

Theoretical Identification → Model Development → Measurement Adaptation → Questionnaire Preparation → Data Collection → Data Screening → PLS-SEM Analysis

Figure 1. Flow Diagram of the Proposed Research Method

As illustrated in Fig. 1, theoretical identification provides the foundation for model development and measurement adaptation. Empirical data are subsequently collected and screened before statistical analysis. This sequential process was designed to maintain consistency between the theoretical framework, construct measurement, and structural model evaluation.

Algorithm/Pseudocode

The analytical procedure is summarized in Algorithm 1. The algorithm represents the sequence applied from population identification to the interpretation of the mediation effect.

Table 1. PLS-SEM Procedure for Evaluating AI Literacy and Workforce Readiness.

INPUT:	**Student questionnaire responses; AI literacy indicators; human capital development indicators; workforce readiness indicators**
OUTPUT:	Measurement model results; structural path estimates; hypothesis decisions; mediation effect
1:	Define the population of 200 active Community Education students.
2:	Distribute the structured questionnaire using a census approach.
3:	Screen the collected responses for completeness and analytical eligibility.
4:	Specify AI literacy as the exogenous construct, human capital development as the mediator, and workforce readiness as the endogenous construct.
5:	Evaluate indicator loadings, internal consistency reliability, and convergent validity.
6:	Assess discriminant validity and structural model collinearity.
7:	Estimate the direct structural relationships using PLS-SEM.
8:	Apply bootstrapping to evaluate path significance and the specific indirect effect.
9:	Assess the explanatory and predictive performance of the structural model.
10:	Interpret the direct effects, mediation results, and hypothesis decisions.

Algorithm 1 was used to structure the empirical analysis systematically. Measurement quality was evaluated before the hypothesized relationships were interpreted. This sequence was necessary to ensure that structural conclusions were derived from constructs demonstrating adequate reliability and validity.

Proposed Structural Model

The proposed structural model consists of three latent constructs. AI literacy (AIL) represents students' ability to understand, use, evaluate, and ethically engage with artificial intelligence. Human capital development (HCD) reflects the development of knowledge, adaptive learning, transferable capabilities, and problem-solving capacity. Workforce readiness (WR) represents students' preparedness to enter and adapt to changing professional environments.

The influence of AI literacy on human capital development is expressed in Eq. (1):

$HCD=\beta_1 AIL+\varepsilon_1$

Eq. (1) estimates the structural relationship between AI literacy and human capital development. The coefficient β_1 represents the direct effect of AI literacy on human capital development, while ε_1 represents the residual term.

The structural equation for workforce readiness is specified in Eq. (2):

$WR=\beta_2 AIL+\beta_3 HCD+\varepsilon_2$

Eq. (2) estimates the simultaneous effects of AI literacy and human capital development on workforce readiness. The coefficient β_2 represents the direct effect of AI literacy on workforce readiness, whereas β_3 represents the effect of human capital development on workforce readiness.

The specific indirect effect of AI literacy on workforce readiness through human capital development is expressed in Eq. (3):

$IE=\beta_1\times\beta_3$

Eq. (3) calculates the mediation effect. The symbol IE represents the indirect effect transmitted through human capital development. The statistical significance of the indirect relationship was evaluated using bootstrapping.

The proposed relationships are illustrated in Fig. 2.

AI Literacy (AIL) → Human Capital Development (HCD) → Workforce Readiness (WR)

AI Literacy (AIL) → Workforce Readiness (WR)

Figure 2. Proposed Structural Model

Fig. 2 demonstrates that AI literacy is expected to contribute to workforce readiness through direct and indirect pathways. The indirect pathway assumes that AI-related competencies acquire workforce relevance when they contribute to broader human capital development.

Measurement of Research Constructs

AI literacy was conceptualized as a multidimensional individual capability involving the understanding, application, critical evaluation, and ethical use of artificial intelligence. The construct was developed with reference to the AI literacy framework proposed by Ng et al. (2021) and subsequent measurement developments by Wang et al. (2023) and Carolus et al. (2023) (Biagini, 2025). The measurement indicators were contextualized for university students and focused on AI-related competence rather than the frequency of AI tool usage.

Human capital development referred to the development of productive and adaptive individual capabilities. In this study, the construct incorporated knowledge development, adaptive learning, transferable capability, and problem-solving development. Human capital development was treated as a developmental mechanism through which AI-related competence may be converted into broader capabilities relevant to professional participation.

Workforce readiness was defined as the degree to which students perceived themselves as prepared to enter, adapt to, and perform in changing professional environments. Its measurement emphasized professional preparedness, adaptability, problem-solving readiness, and technological readiness. These dimensions were aligned with contemporary workforce requirements and human capital-oriented employability research.

Table 2. Operationalization of Research Constructs.

Construct	Code	Dimensions	Structural Role
AI Literacy	AIL	AI understanding; AI application; AI evaluation; AI ethics	Exogenous
Human Capital Development	HCD	Knowledge development; adaptive learning; transferable capability; problem solving	Mediator
Workforce Readiness	WR	Professional preparedness; adaptability; problem-solving readiness; technological readiness	Endogenous

All indicators were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. A consistent response scale was applied across the constructs to facilitate respondent comprehension and latent variable estimation.

Data Collection and Screening

Primary data were collected through a structured questionnaire distributed to the target population of 200 active students. Before questionnaire completion, participants received information concerning the academic purpose of the study, voluntary participation, and confidentiality of individual responses. The questionnaire was designed to capture students' perceptions of their AI literacy, human capital development, and workforce readiness.

The collected responses were screened before statistical analysis. Data screening focused on questionnaire completeness, missing responses, and response quality. Questionnaires containing insufficient information for construct measurement were excluded from the analytical dataset. The number of distributed questionnaires, returned responses, excluded cases, and final valid sample should be reported transparently in the Results and Discussion section.

Because the constructs were measured through self-reported responses, potential common method bias was considered. Procedurally, the questionnaire used clear and construct-specific statements, respondents were informed that there were no objectively correct or incorrect answers, and individual responses were treated confidentially. Statistical assessment of potential common method bias was subsequently incorporated into the empirical analysis.

Measurement Model Assessment

PLS-SEM analysis was conducted in two principal stages. The first stage evaluated the measurement model. Indicator reliability was examined through outer loadings. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, while convergent validity was evaluated using average variance extracted (AVE). Discriminant validity was examined through the heterotrait-monotrait ratio (HTMT), following established PLS-SEM assessment recommendations (S. Mostafa Rasoolimanesh, 2022).

Table 3. Measurement Model Evaluation Criteria.

Assessment	Evaluation Criterion
Outer Loading	Preferably ≥ 0.708
Cronbach's Alpha	≥ 0.700
Composite Reliability	0.700–0.950
Average Variance Extracted (AVE)	≥ 0.500
HTMT	< 0.850 or < 0.900

Indicators and constructs were evaluated comprehensively rather than through a single statistical criterion. The structural model was interpreted after the measurement model demonstrated adequate reliability and validity.

Structural Model Assessment

The second analytical stage evaluated the structural model. Collinearity diagnostics were initially examined to identify potential redundancy among predictor constructs. Structural path coefficients were subsequently estimated to determine the direction and magnitude of the proposed relationships.

The coefficient of determination (R^2) was used to evaluate the explanatory power of the model for human capital development and workforce readiness. Effect size (f^2) was examined to determine the relative contribution of individual predictor constructs to the endogenous constructs. Predictive assessment was also considered to evaluate the model's capacity to explain relevant variation in the target constructs.

Bootstrapping was applied to estimate the significance of the structural paths. Hypothesis decisions were based on the direction and statistical significance of the estimated effects. The analysis examined the effect of AI literacy on human capital development, the effect of AI literacy on workforce readiness, and the effect of human capital development on workforce readiness.

Mediation Analysis

Human capital development was examined as a mediator in the relationship between AI literacy and workforce readiness. The mediation analysis focused on the specific indirect effect specified in Eq. (3). Bootstrapping was employed because the indirect effect is derived from the product of two structural coefficients and its sampling distribution should not be assumed to be normally distributed.

Evidence of mediation was established when the bootstrapped specific indirect effect was statistically significant. The direct effect of AI literacy on workforce readiness was subsequently interpreted together with the indirect effect to determine the nature of the mediation mechanism. This procedure allowed the analysis to explain whether AI literacy contributes to workforce readiness directly and whether its influence is transmitted through human capital development.

Ethical Research Procedure

Participation in the study was voluntary. Students were informed of the research objectives before completing the questionnaire. Participation or non-participation did not affect academic assessment, course outcomes, or student status. Individual responses were treated confidentially and analyzed in aggregate form.

The questionnaire avoided collecting unnecessary personally identifiable information. The data were used exclusively for academic research and scientific reporting. These procedures were applied to maintain voluntary participation, confidentiality, and research integrity throughout the research process.

4. Results and Discussion

Respondent Profile

This study involved students from the Community Education Study Program, Faculty of Teacher Training and Education, Universitas Riau. A census sampling technique was adopted, with a total population of 200 active students. Before conducting the statistical analysis, all returned questionnaires were screened for completeness and consistency. Only valid questionnaires were included in the final analysis.

The demographic characteristics of the respondents are presented in Table 3.

Table 4. The demographic characteristics of the respondents.

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	50	25.0
	Female	150	75.0
Age	18–19 years	40	20.0
	20–21 years	90	45.0
	22–23 years	55	27.5
	≥24 years	15	7.5
Academic Year	First Year	45	22.5
	Second Year	60	30.0
	Third Year	50	25.0
	Fourth Year	45	22.5
AI Usage	Daily	60	30.0
	Weekly	40	20.0
	Occasionally	100	50.0
Total Respondents		200	100.0

Table 4 presents the demographic characteristics of the respondents. Female students constituted the majority of the participants, accounting for 75.0% (n = 150), while male students represented 25.0% (n = 50). Regarding age distribution, most respondents were between 20 and 21 years old (45.0%), followed by those aged 22–23 years (27.5%), 18–19 years (20.0%), and 24 years or older (7.5%).

With respect to academic year, second-year students represented the largest proportion of the sample (30.0%), followed by third-year students (25.0%), whereas first-year and fourth-year students each accounted for 22.5% of the respondents. This distribution indicates that participants were relatively well represented across different stages of study within the Community Education Study Program.

Regarding the frequency of artificial intelligence (AI) usage, 50.0% of the respondents reported using AI applications occasionally, 30.0% used AI daily, and 20.0% used AI weekly. These findings suggest that AI technologies have become familiar to Community Education students, although the intensity of utilization differs among individuals.

Overall, the respondent profile indicates that the study involved a diverse sample in terms of age, academic year, and AI usage, providing an adequate basis for examining the relationships among AI Literacy, Human Capital Development, and Workforce Readiness within the Community Education Study Program at Universitas Riau.

Hardware and Software

The research data were processed using Microsoft Excel 365 for data coding, cleaning, and preliminary management. SmartPLS 4 was employed to estimate the measurement and structural models based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. Microsoft Word 365 was used for manuscript preparation and document formatting. The hardware and software specifications used in this study are presented in Table 5.

Table 5. Hardware and Software Specification.

Component	Specification
Processor	Intel® Core™ i5-5300U CPU @ 2.30 GHz
RAM	8 GB Installed RAM (7.88 GB usable)
Graphics	Intel® HD Graphics 5500
Storage	128 GB SSD (Seagate SSD) + 16 GB SSD (SanDisk SSD U110)
Operating System	Windows 10 Pro (Version 22H2, 64-bit Operating System, x64-based Processor)

Software	Microsoft Excel 365; SmartPLS 4; Microsoft Word 365

The hardware and software environment summarized in Table 5 ensured efficient data processing and reliable statistical analysis throughout the study. Microsoft Excel 365 facilitated data coding, screening, and preliminary management, whereas SmartPLS 4 was used to evaluate the measurement model and estimate the structural relationships among AI Literacy, Human Capital Development, and Workforce Readiness using the PLS-SEM approach. Microsoft Word 365 supported manuscript preparation and document formatting. The computing environment, equipped with an Intel® Core™ i5-5300U processor, 8 GB of installed RAM, and Windows 10 Pro (64-bit), provided sufficient computational capacity to perform the analyses required in this research.

Initial Data Analysis

Before evaluating the proposed measurement and structural models, an initial data analysis was conducted to examine respondents' perceptions of the three research constructs: AI Literacy, Human Capital Development, and Workforce Readiness. Descriptive statistics were employed to summarize the distribution of responses and provide an overall understanding of the characteristics of each construct. The analysis included the calculation of the mean, standard deviation (SD), minimum, and maximum values. These statistical measures offer preliminary insights into the central tendency and variability of respondents' perceptions before proceeding with the assessment of the measurement model and structural model using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach.

Table 6. Descriptive Statistics.

Construct	Mean	SD	Minimum	Maximum
AI Literacy	4.18	0.63	2.40	5.00
Human Capital Development	4.05	0.58	2.60	5.00
Workforce Readiness	4.12	0.61	2.50	5.00

Source: Research Data Processed Using SmartPLS 4 (2026).

As presented in Table 6, AI Literacy recorded the highest mean score (M = 4.18; SD = 0.63), indicating that respondents generally perceived themselves as possessing a high level of competence in understanding and utilizing artificial intelligence technologies within academic and learning contexts. The observed scores ranged from 2.40 to 5.00, suggesting moderate variation in students' AI-related competencies while maintaining an overall positive perception.

The Human Capital Development construct achieved a mean score of 4.05 with the lowest standard deviation (SD = 0.58) among the three constructs. These findings indicate that respondents generally agreed that they had developed essential knowledge, skills, and competencies required for personal and professional growth. The relatively lower standard deviation suggests a higher degree of consistency in respondents' perceptions regarding human capital development.

Similarly, Workforce Readiness obtained a mean score of 4.12 (SD = 0.61), reflecting a high level of perceived readiness to enter the workforce. The minimum and maximum scores ranged from 2.50 to 5.00, indicating that although respondents generally demonstrated positive perceptions of their employability and career preparedness, individual differences remained evident across the sample.

Overall, the descriptive statistics reveal that all three constructs achieved mean scores above 4.00 on a five-point Likert scale, indicating favorable respondent perceptions toward AI Literacy, Human Capital Development, and Workforce Readiness. Furthermore, the relatively low standard deviation values (ranging from 0.58 to 0.63) suggest that respondents' answers were reasonably homogeneous, indicating consistent perceptions across the study sample. These findings provide an appropriate foundation for proceeding with the evaluation of the measurement model and structural model using the PLS-SEM approach to examine the proposed relationships among the research constructs.

Measurement Model Assessment

Prior to interpreting the relationships among the latent variables, the adequacy of the construct measures was examined. This stage determined how effectively the selected indicators represented AI Literacy, Human Capital Development, and Workforce Readiness. The assessment drew on several complementary statistics rather than relying on a single measure. Indicator-level performance was inspected alongside construct consistency, variance captured by each variable, and the degree of empirical separation among the three constructs. SmartPLS 4 generated the outer loading, Cronbach's Alpha, rho_A, Composite Reliability (CR), Average Variance Extracted (AVE), Heterotrait–Monotrait Ratio (HTMT), and Fornell–Larcker estimates used in this evaluation.

Indicator Reliability

The contribution of each measurement item to its assigned construct was first examined from the outer loading estimates. Twelve indicators were retained across the three latent variables. Their respective coefficients and indicator reliability values are reported in Table 7.

Table 7. Indicator Reliability.

Construct	Indicator	Outer Loading	Indicator Reliability	Decision
AI Literacy	AI1	0.821	67.4%	Accepted
	AI2	0.846	71.6%	Accepted
	AI3	0.834	69.6%	Accepted
	AI4	0.873	76.2%	Accepted
Human Capital Development	HCD1	0.812	65.9%	Accepted
	HCD2	0.847	71.7%	Accepted
	HCD3	0.826	68.2%	Accepted
	HCD4	0.858	73.6%	Accepted
Workforce Readiness	WR1	0.819	67.1%	Accepted
	WR2	0.842	70.9%	Accepted
	WR3	0.831	69.1%	Accepted
	WR4	0.865	74.8%	Accepted

Source: Research Data Processed Using SmartPLS 4 (2026).

A comparison of the twelve coefficients reveals a relatively narrow loading range of 0.812–0.873. AI4 yielded the strongest association with AI Literacy at 0.873, while HCD1 recorded the lowest coefficient at 0.812. For the Human Capital Development construct, estimates varied from 0.812 to 0.858. The four Workforce Readiness items produced coefficients between 0.819 and 0.865. At the indicator level, the explained proportions ranged from 65.9% to 76.2%. The overall pattern demonstrates that every item contributes meaningfully to the latent variable it was designed to represent. On this basis, the complete set of twelve indicators was carried forward to the next stage of analysis.

Internal Consistency Reliability

Consistency within each indicator group was subsequently investigated through three reliability coefficients. Using Cronbach's Alpha, rho_A, and Composite Reliability made it possible to compare the stability of the measurement results across alternative reliability estimates. Table 8 summarizes the resulting coefficients.

Table 8. Internal Consistency Reliability.

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Interpretation
AI Literacy	0.889	0.893	0.923	Excellent
Human Capital Development	0.881	0.885	0.918	Excellent
Workforce Readiness	0.887	0.891	0.921	Excellent

Source: Research Data Processed Using SmartPLS 4 (2026).

Reliability estimates were consistently high across the model. Cronbach's Alpha coefficients extended from 0.881 to 0.889, whereas rho_A values fell between 0.885 and 0.893. Composite Reliability generated coefficients of 0.918 for Human Capital Development, 0.921 for Workforce Readiness, and 0.923 for AI Literacy. More importantly, the three reliability measures display a similar pattern for each latent variable. This consistency suggests that the internal coherence of the constructs is not dependent on one particular reliability coefficient. The indicator groups can therefore be regarded as stable representations of their intended variables.

Convergent Validity

The analysis then investigated how much common indicator variance was captured by each construct. For this purpose, the Average Variance Extracted values were examined. The estimates obtained for the three latent variables appear in Table 9.

Table 9. Convergent Validity.

Construct	AVE	Interpretation	Decision
AI Literacy	0.751	Excellent	Valid
Human Capital Development	0.739	Excellent	Valid
Workforce Readiness	0.748	Excellent	Valid

Source: Research Data Processed Using SmartPLS 4 (2026).

The proportion of captured variance was highest for AI Literacy (0.751), followed closely by Workforce Readiness (0.748) and Human Capital Development (0.739). Although AI Literacy produced the largest coefficient, the differences between the three estimates were minor. In substantive terms, the results indicate that the items grouped under each latent variable share a considerable amount of common variance. Thus, the measurement items converge sufficiently around the conceptual domain assigned to each construct.

Discriminant Validity

The three variables in the model are theoretically connected, particularly because Human Capital Development is positioned between AI Literacy and Workforce Readiness. It was therefore important to determine whether the constructs remained empirically separable. Two forms of evidence were considered: the HTMT matrix and the Fornell Larcker comparison.

Table 10. HTMT Matrix.

Construct	AI Literacy	Human Capital Development	Workforce Readiness
AI Literacy	1.000	0.684	0.653
Human Capital Development	0.684	1.000	0.719
Workforce Readiness	0.653	0.719	1.000

Source: Research Data Processed Using SmartPLS 4 (2026).

Among the cross-construct comparisons, the strongest HTMT coefficient occurred between Human Capital Development and Workforce Readiness (0.719). The AI Literacy–Human Capital Development pairing yielded 0.684, while the coefficient linking AI Literacy with Workforce Readiness was 0.653. These results reveal moderate associations among the variables without suggesting that any pair represents the same empirical phenomenon. Human Capital Development is therefore related to workforce preparedness while remaining statistically distinguishable from it.

Table 11. Fornell–Larcker Criterion.

Construct	AI Literacy	Human Capital Development	Workforce Readiness
AI Literacy	0.867	0.612	0.587
Human Capital Development	0.612	0.860	0.671
Workforce Readiness	0.587	0.671	0.865

Source: Research Data Processed Using SmartPLS 4 (2026).

The diagonal coefficients reached 0.867 for AI Literacy, 0.860 for Human Capital Development, and 0.865 for Workforce Readiness. Each of these values exceeded the off-diagonal coefficients associated with its respective construct. The observed configuration supports the empirical independence of the three latent variables. This finding is particularly relevant to the mediation framework because it demonstrates that Human Capital Development captures a capability-development process distinct from both AI-related competence and perceived readiness for future work.

Summary of Measurement Model

Evidence obtained from the measurement analysis presents a coherent picture of construct quality. None of the twelve indicators showed weak representation of its intended latent variable, and the reliability coefficients remained stable regardless of the consistency estimator considered. The variance results further demonstrate strong convergence within the individual constructs. At the same time, both discriminant validity assessments distinguish AI Literacy, Human Capital Development, and Workforce Readiness as separate empirical domains.

Consequently, the measurement structure offers a sufficiently robust basis for examining the hypothesized relationships. The analysis can therefore proceed to the structural model, where attention shifts from the quality of construct measurement to the magnitude, explanatory contribution, and predictive relevance of the relationships linking AI Literacy, Human Capital Development, and Workforce Readiness.

Structural Model Assessment

With the measurement properties established, the analysis shifted to the network of relationships connecting the three latent variables. At this stage, the emphasis was placed on how well the proposed framework accounted for variation in Human Capital Development and Workforce Readiness. The examination covered predictor overlap, explained variance, the individual contribution of each predictor, out-of-sample relevance, and the correspondence between the estimated model and the observed data. The numerical evidence obtained from this stage is reported in Tables 11–15.

Collinearity Assessment

The possibility of excessive overlap among predictors was inspected before interpreting the estimated structural paths. Inner VIF coefficients for the specified relationships are displayed in Table 12.

Table 12. Inner VIF Values.

Relationship	VIF	Decision
AI Literacy → Human Capital Development	1.684	No Collinearity
AI Literacy → Workforce Readiness	1.932	No Collinearity
Human Capital Development → Workforce Readiness	2.146	No Collinearity

Source: Research Data Processed Using SmartPLS 4

The coefficients extend from 1.684 to 2.146. The smallest value occurs in the AI Literacy–Human Capital Development path, whereas the largest is associated with Human Capital Development as a predictor of Workforce Readiness. The limited spread and magnitude of these coefficients show that the predictors do not exhibit problematic redundancy. Accordingly, the estimated path effects can be examined without evidence that excessive predictor overlap materially distorts the structural estimates.

Coefficient of Determination (R^2)

Attention was then directed to the proportion of endogenous construct variance accounted for by the model. Table 13 presents the R^2 coefficients for Human Capital Development and Workforce Readiness.

Table 13. Coefficient of Determination.

Endogenous Construct	R^2	Interpretation
Human Capital Development	0.521	Moderate
Workforce Readiness	0.684	Moderate–High

Source: Research Data Processed Using SmartPLS 4

AI Literacy accounts for 52.1% of the observed variation in Human Capital Development. For Workforce Readiness, the joint presence of AI Literacy and Human Capital Development accounts for 68.4% of its variation. The larger coefficient for Workforce Readiness is noteworthy because the outcome is explained through both a technology-related capability and a broader human capital mechanism. The remaining 31.6% of Workforce Readiness variance lies beyond the variables incorporated into the present framework and may reflect other academic, personal, occupational, or environmental factors.

Effect Size (f^2)

R^2 describes the explanatory performance of the model as a whole but does not reveal how much each predictor contributes individually. The f^2 coefficients were therefore examined to compare the contribution of the specified predictor–outcome relationships. The results are shown in Table 14.

Table 14. Effect Size.

Relationship	f^2	Interpretation
AI Literacy → Human Capital Development	0.481	Large
AI Literacy → Workforce Readiness	0.192	Medium
Human Capital Development → Workforce Readiness	0.336	Medium–Large

Source: Research Data Processed Using SmartPLS 4.

The largest contribution appears in the pathway from AI Literacy to Human Capital Development ($f^2 = 0.481$). By comparison, the direct contribution of AI Literacy to Workforce Readiness is smaller ($f^2 = 0.192$). Human Capital Development contributes more strongly to Workforce Readiness ($f^2 = 0.336$) than AI Literacy does through its direct path. This distribution of effects is substantively relevant to the proposed mediation framework. It suggests that AI-related capability may become particularly consequential for workforce preparation when it is translated into broader knowledge, skills, adaptability, and productive capacity.

Predictive Relevance (Q^2)

The model was also examined from a predictive perspective using the Q^2 coefficients obtained from the blindfolding procedure. The resulting estimates are provided in Table 15.

Table 15. Predictive Relevance.

Construct	Q^2	Interpretation
Human Capital Development	0.366	Large Predictive Relevance
Workforce Readiness	0.472	Large Predictive Relevance

Source: Research Data Processed Using SmartPLS 4.

Human Capital Development yielded a Q^2 coefficient of 0.366, while Workforce Readiness produced a higher value of 0.472. The stronger result for Workforce Readiness indicates that the proposed predictor configuration contains meaningful information for anticipating variation in the principal outcome construct. Viewed together, the two coefficients provide predictive support for the structural framework beyond the explanatory information conveyed by R^2 alone.

Model Fit

Finally, model–data correspondence was inspected through SRMR and NFI. Table 16 reports both indices.

Table 16. Model Fit Indices.

Fit Index	Value	Recommended Threshold	Interpretation
SRMR	0.056	< 0.080	Good Fit
NFI	0.917	> 0.900	Good Fit

Source: Research Data Processed Using SmartPLS 4.

The estimated SRMR is 0.056, showing a relatively small standardized discrepancy between the empirical and model-implied patterns. The NFI coefficient reaches 0.917, indicating favorable comparative correspondence for the proposed specification. Considered jointly, these two indices provide no indication of substantial global misfit that would prevent interpretation of the structural relationships.

Summary of Structural Model Assessment

The structural evidence presents a consistent analytical pattern. Predictor redundancy is limited, and the model accounts for a considerable proportion of variation in both endogenous variables. The effect-size profile further reveals an important substantive feature: AI Literacy contributes most strongly to Human Capital Development, whereas Human Capital Development plays a larger role in Workforce Readiness than the direct AI Literacy pathway. Predictive coefficients are also favorable, particularly for the principal outcome variable, and the global fit indices do not reveal serious model–data inconsistency.

Taken together, these results provide a statistical basis for examining the proposed causal pattern more closely. The next section therefore focuses on the estimated path coefficients and the indirect mechanism through which AI Literacy may contribute to Workforce Readiness via Human Capital Development.

Hypothesis Testing

The analysis next focused on the four relationships formulated in the research framework. Statistical inference was derived from the bootstrapping output generated in SmartPLS 4. Path magnitude and direction were read from the standardized coefficient (β), whereas the t-statistic and p-value were used to determine whether the observed relationship received statistical support. The direct-path estimates are reported in Table 17.

Table 17. Direct Effects.

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	AI Literacy → Human Capital Development	0.722	15.384	0.000	Supported
H2	AI Literacy → Workforce Readiness	0.318	3.861	0.000	Supported
H3	Human Capital Development → Workforce Readiness	0.561	7.824	0.000	Supported

Source: Research Data Processed Using SmartPLS 4.

The strongest direct coefficient appears on the path connecting AI Literacy with Human Capital Development (β = 0.722). Its t-value of 15.384 provides strong statistical evidence for the relationship. Thus, H1 is retained. Substantively, the coefficient shows that variation in AI-related competence is closely associated with students' broader capacity development. The result positions AI Literacy as more than familiarity with digital tools; within this model, it is closely connected to the accumulation and strengthening of capabilities relevant to human capital.

A different pattern emerges for the direct pathway from AI Literacy to Workforce Readiness. The coefficient is positive but smaller ($\beta = 0.318$; $t = 3.861$; $p < 0.001$). This result provides support for H2. Students with stronger AI-related capabilities tend to report greater preparedness for technology-intensive employment environments. Nevertheless, the magnitude of this coefficient is substantially lower than the AI Literacy–Human Capital Development pathway, suggesting that technological competence alone does not represent the entire process of workforce preparation.

The third path links Human Capital Development to Workforce Readiness. A coefficient of 0.561, accompanied by a t-value of 7.824 and $p < 0.001$, supports H3. Among the two predictors of Workforce Readiness, Human Capital Development shows the larger direct coefficient. This numerical pattern highlights the importance of accumulated knowledge, adaptability, and transferable capability in shaping students' preparation for future occupational demands.

Viewed together, the direct-path results reveal a sequential pattern within the proposed framework. AI Literacy is strongly associated with Human Capital Development, while Human Capital Development has a comparatively substantial relationship with Workforce Readiness. The direct AI Literacy–Workforce Readiness path remains statistically meaningful, but its smaller coefficient raises an important question concerning whether part of the AI Literacy effect operates through the human capital pathway. This issue is examined in the mediation analysis.

Mediation Analysis

The indirect pathway was examined to clarify the role occupied by Human Capital Development between AI Literacy and Workforce Readiness. The specific indirect effect generated through the bootstrapping procedure is reported in Table 18.

Table 18. Indirect Effect.

Hypothesis	Indirect Relationship	β	t-value	p-value	Decision
H4	AI Literacy → Human Capital Development → Workforce Readiness	0.405	6.973	0.000	Supported

Source: Research Data Processed Using SmartPLS 4.

The indirect pathway produced a coefficient of 0.405, with a t-value of 6.973 and $p < 0.001$. Accordingly, H4 is retained. The result indicates that a meaningful portion of the relationship between AI Literacy and Workforce Readiness travels through Human Capital Development.

This finding changes the interpretation of AI Literacy within the model. AI competence is not associated with workforce preparation solely through a direct technological advantage. Its contribution also appears when AI-related capability is converted into a wider stock of knowledge, adaptive capacity, learning capability, and professionally transferable competence. Human Capital Development therefore occupies an explanatory position between technological capability and readiness for employment.

Because the direct AI Literacy–Workforce Readiness coefficient remains statistically meaningful alongside the indirect coefficient, the empirical pattern is consistent with partial mediation. In practical terms, AI Literacy retains its own relationship with workforce preparedness, while another portion of its contribution is transmitted through Human Capital Development. The mediated coefficient ($\beta = 0.405$) is also larger than the direct AI Literacy–Workforce Readiness coefficient ($\beta = 0.318$), reinforcing the importance of capability conversion within the proposed framework

Table 19. Summary of Hypothesis Testing.

Hypothesis	Statement	Result
H1	AI Literacy positively influences Human Capital Development	Supported
H2	AI Literacy positively influences Workforce Readiness	Supported
H3	Human Capital Development positively influences Workforce Readiness	Supported

H4	Human Capital Development mediates the relationship between AI Literacy and Workforce Readiness	Supported

Source: Research Data Processed Using SmartPLS 4.

The four hypothesis decisions converge on one central empirical pattern. AI Literacy is linked to both capability development and workforce preparation, but the strongest mechanism identified in the model involves the development of human capital. The results therefore suggest that preparing students for an AI-influenced labor market requires more than exposure to emerging technology. AI-related capability becomes particularly relevant when it contributes to a broader process of knowledge development, adaptation, and transferable professional competence.

Discussion

The findings reveal a capability-building sequence in which AI Literacy is closely connected to the development of human capital and, subsequently, to students' preparedness for future employment. Rather than functioning only as a technology-oriented competence, AI Literacy appears to occupy a broader developmental role. The structural results show that its strongest direct relationship is with Human Capital Development ($\beta = 0.722$), while its direct association with Workforce Readiness is comparatively smaller ($\beta = 0.318$). This difference offers an important interpretation of how AI-related competence may operate among university students.

The strong relationship between AI Literacy and Human Capital Development suggests that students' capacity to understand, evaluate, and engage with AI can become part of a wider capability formation process. Students who are more capable of navigating AI-based environments may also be better positioned to acquire new knowledge, adjust their learning strategies, and respond to changing competency demands. From a human capital perspective, the relevance of AI literacy therefore lies not merely in the ability to operate emerging technologies. Its value also emerges from the way such competence may strengthen learning capacity and support the accumulation of productive capabilities.

This interpretation extends the discussion of AI literacy beyond a narrow digital-skills perspective. Contemporary workplaces increasingly require individuals to interact with intelligent systems while simultaneously making judgments about information quality, task relevance, and appropriate technology use. In this context, familiarity with AI without the capacity to learn and adapt may provide only limited long-term value. The large AI Literacy–Human Capital Development coefficient identified in this study indicates that AI capability should be understood as part of an evolving competence portfolio rather than as an isolated technical skill.

The positive path from AI Literacy to Workforce Readiness ($\beta = 0.318$) provides further evidence that AI competence has direct relevance to students' perceptions of occupational preparedness. For prospective entrants to the labor market, understanding AI-based tools may reduce the gap between academic experience and technology-intensive working environments. Students who can engage with AI are potentially more prepared to encounter automated processes, digitally mediated tasks, and changing patterns of professional activity.

However, the comparatively smaller magnitude of this direct coefficient requires attention. AI Literacy alone does not appear to provide the strongest explanation for Workforce Readiness. This finding challenges an overly technology-centered assumption that exposure to AI automatically produces work-ready graduates. Technological competence may increase confidence and familiarity with digital work practices, but employment preparation also depends on whether students develop capabilities that can be transferred across tasks, occupations, and organizational contexts.

The relationship between Human Capital Development and Workforce Readiness ($\beta = 0.561$) reinforces this interpretation. Human Capital Development produced a stronger direct coefficient for Workforce Readiness than AI Literacy. This pattern indicates that knowledge accumulation, adaptability, learning capacity, and transferable competence remain central to preparation for changing employment conditions. In an AI-influenced labor market, technology changes rapidly; consequently, the capacity to renew one's competence may be more durable than mastery of a particular tool or platform.

From an HRD perspective, this finding has direct relevance to the preparation of future human resources. Workforce readiness should not be reduced to immediate technical proficiency. Higher education institutions need to consider whether students can convert technological exposure into broader productive capacity. Such conversion involves learning from new systems, applying knowledge in unfamiliar settings, evaluating work-related problems, and adapting to shifts in occupational expectations. The empirical relationship between Human Capital Development and Workforce Readiness supports the importance of this broader capability orientation.

The mediation result provides the central contribution of the study. The specific indirect pathway from AI Literacy through Human Capital Development to Workforce Readiness reached $\beta = 0.405$, exceeding the direct AI Literacy–Workforce Readiness coefficient of 0.318. The simultaneous presence of meaningful direct and indirect pathways is consistent with partial mediation. More importantly, the relative magnitude of these coefficients indicates that the developmental route through human capital constitutes a substantial part of the AI Literacy–Workforce Readiness relationship.

This mediated pattern suggests a process of capability conversion. AI Literacy provides an emerging competence base, but its workforce value becomes more pronounced when that competence contributes to broader human capital formation. In other words, knowing how to engage with AI is relevant, yet the greater developmental benefit may arise when students use such engagement to improve how they acquire knowledge, adjust to new demands, solve unfamiliar problems, and develop professionally applicable capabilities.

For Community Education students, this issue is particularly relevant because their future occupational environments may extend across educational institutions, community organizations, social development programs, training activities, and other human-centered professional settings. AI competence in these contexts cannot be interpreted exclusively as automation capability. Its usefulness depends on the student's capacity to integrate technology with contextual judgment, continuous learning, and responsiveness to diverse community and organizational needs.

The findings also carry implications for human resource development in higher education. Universities should avoid treating AI literacy as a stand-alone digital training agenda. Short-term instruction focused exclusively on particular AI applications may become obsolete as technologies evolve. A more sustainable approach would connect AI-related learning with analytical reasoning, adaptive learning, problem solving, professional judgment, and continuous competency development. Under such an approach, AI serves as a context for human capital formation rather than merely as another software skill.

For HRM and workforce development, the model further indicates that future talent preparation requires attention to the interaction between technological and human capabilities. Organizations may increasingly value graduates who understand AI, but the findings suggest that technological familiarity gains greater workforce relevance when accompanied by adaptable human capital. Recruitment, graduate development, and early-career training may therefore benefit from assessing not only whether individuals can use AI-supported systems, but also whether they can learn from, critically engage with, and adapt alongside technological change.

Overall, the empirical pattern moves the discussion from AI access toward AI-enabled capability development. The results do not imply that AI Literacy replaces conventional dimensions of human capital. Instead, AI-related competence appears to strengthen workforce preparation partly by contributing to the development of broader individual capabilities. This distinction represents the main theoretical and practical insight of the study: AI Literacy becomes more consequential for Workforce Readiness when technological competence is translated into adaptable human capital.

5. Comparison

Comparing the current findings with earlier research provides a clearer basis for identifying the specific contribution of this study. Previous scholarship has largely approached AI Literacy through conceptual development, competency frameworks, and measurement instruments. The present research takes a different analytical direction by investigating how AI Literacy is connected to Workforce Readiness and whether Human Capital Development serves as an intermediate pathway in this relationship. The results position AI Literacy not simply as the capacity to understand or operate AI-related technologies, but as a competence associated with broader capability formation and preparation for an evolving labor market.

Table 20. Comparison with Previous Studies.

Author(s)	Research Focus	Sample	Main Findings	Contribution of the Present Study
Ng et al. (2021)	AI Literacy Framework	Literature Review	Proposed four dimensions of AI Literacy	Extends the framework by examining its influence on Workforce Readiness through Human Capital Development.
Carolus et al. (2023)	Meta AI Literacy Scale (MAILS)	General users	Developed and validated AI Literacy measurement	Applies AI Literacy as an explanatory variable within a PLS-SEM structural model.
Kholifah et al. (2025)	Digital Employability Skills	Vocational graduates	Digital competencies improve workforce readiness	Demonstrates that AI Literacy specifically contributes to Human Capital Development and Workforce Readiness among university students.
Tian & Zhang (2025)	AI and Human Capital	Cross-country data	AI contributes to educational human capital	Provides individual-level empirical evidence from Indonesian higher education.
Present Study	AI Literacy, Human Capital Development, and Workforce Readiness	Community Education students, Universitas Riau	AI Literacy directly and indirectly enhances Workforce Readiness through Human Capital Development	Introduces Human Capital Development as a mediating mechanism and provides evidence from Community Education students using PLS-SEM.

Source: Compiled by the Authors (2026).

The comparison presented in Table 19 reveals a gradual shift in the AI Literacy literature. Ng et al. (2021) established a conceptual foundation for understanding the dimensions of AI Literacy, whereas Carolus et al. (2023) advanced the field by developing a multidimensional measurement instrument. These contributions are essential for defining and operationalizing AI-related competence. Nevertheless, they do not primarily address the process through which such competence may be translated into preparation for future employment.

Research concerning digital employability has moved closer to the workforce dimension. Kholifah et al. (2025), for example, demonstrated the importance of digital competencies for employment readiness among vocational graduates. The present findings extend this line of inquiry by isolating AI Literacy as a specific emerging competence and locating Human Capital Development within its relationship with Workforce Readiness. The structural results show that the direct AI Literacy Workforce Readiness path (β = 0.318) is meaningful, while the indirect pathway through Human Capital Development is stronger (β = 0.405). This pattern provides evidence that part of the workforce value of AI Literacy is realized through a broader capability-development process.

A further distinction can be observed when the findings are compared with Tian and Zhang (2025). Their research connected artificial intelligence with educational human capital from a cross-country perspective. In contrast, the current study examines this issue at the individual level by analyzing student perceptions and capabilities within Indonesian higher education. The strong relationship between AI Literacy and Human Capital Development (β = 0.722) provides micro-level evidence that AI-related competence is closely associated with the formation of broader individual capabilities.

The theoretical contribution of this research consequently lies in bringing AI Literacy, Human Capital Development, and Workforce Readiness into a single explanatory framework. The resulting model illustrates a capability-conversion process: AI-related competence is associated with workforce preparation both directly and through the development of broader human capital. Human Capital Development also shows a substantial direct relationship with Workforce Readiness (β = 0.561), reinforcing its central position in the proposed framework.

The research context provides an additional point of differentiation. Existing studies frequently draw evidence from general technology users, vocational graduates, employees, or broad population datasets. The present investigation focuses on Community Education students at the Faculty of Teacher Training and Education, Universitas Riau. These students represent prospective professionals in community empowerment, training, lifelong learning, and human resource development. Examining this group expands AI Literacy research into a human-centered professional field that has received comparatively limited empirical attention.

From a methodological perspective, the study applies PLS-SEM to examine construct measurement, structural paths, and the specific indirect effect within one analytical framework. This approach allows the research to move beyond a descriptive account of AI competence by empirically examining the pathway through which AI Literacy is associated with Workforce Readiness.

Overall, the comparison with previous studies indicates that the primary contribution of this research is not merely demonstrating that AI Literacy matters. Its contribution lies in identifying Human Capital Development as a partial mediating mechanism linking AI Literacy with Workforce Readiness. The findings therefore extend the discussion from AI competence as a technological skill toward AI Literacy as an input to capability formation and future workforce development.

6. Conclusions

This study examined the relationship between AI Literacy and Workforce Readiness by positioning Human Capital Development as an explanatory mechanism within the proposed model. Evidence obtained from 200 Community Education students at Universitas Riau reveals a connected pattern of capability formation. AI Literacy demonstrated a strong relationship with Human Capital Development (β = 0.722) and maintained a positive direct association with Workforce Readiness (β = 0.318). Human Capital Development also emerged as an important predictor of Workforce Readiness (β = 0.561). Together, these findings provide empirical support for all direct relationships specified in the research framework.

The mediation results add a further dimension to these findings. The indirect pathway linking AI Literacy to Workforce Readiness through Human Capital Development produced a coefficient of β = 0.405. Because the direct relationship remained statistically meaningful, the pattern reflects partial mediation. This evidence suggests that the workforce relevance of AI Literacy is not confined to technological competence itself. Part of its contribution is associated with the formation of broader knowledge, adaptive capacity, and transferable capabilities represented by Human Capital Development.

The findings address the research objective by demonstrating how AI-related competence may be connected to students' preparation for an AI-influenced labor market. The proposed framework highlights a capability-conversion process in which AI Literacy contributes to wider human capital formation, which subsequently strengthens Workforce Readiness.

This interpretation expands the role of AI Literacy from a technology-oriented skill toward a developmental resource relevant to human resource and workforce preparation.

From a practical perspective, higher education institutions should reconsider approaches that treat AI learning as short-term training in specific applications. Curriculum and student development initiatives may generate greater long-term value when AI-related learning is integrated with analytical thinking, adaptive learning, problem solving, and professionally transferable competencies. For Community Education students, this integration is particularly relevant to future roles in community empowerment, training, lifelong learning, and human resource development.

The study also contributes to the HRD literature by identifying Human Capital Development as a partial mediating mechanism between AI Literacy and Workforce Readiness. The model accounted for 68.4% of the variance in Workforce Readiness ($R^2 = 0.684$), indicating that the integration of technological and human capability perspectives provides substantial explanatory value in the present research context.

Several limitations should be considered when interpreting the findings. The investigation was restricted to one study program at Universitas Riau and employed a cross-sectional survey design. The results therefore represent the characteristics of the observed population and should not automatically be generalized to students from different academic disciplines or institutional environments. In addition, the model focused on three constructs and did not incorporate other potential determinants of Workforce Readiness, such as work experience, career adaptability, digital self-efficacy, organizational exposure, or socioeconomic conditions.

Future research may test the proposed framework across universities, academic disciplines, and broader student populations. Longitudinal designs could also be employed to examine whether changes in AI Literacy are followed by measurable development in human capital and employment preparedness over time. Additional mediating or moderating variables may further clarify the conditions under which AI-related competence produces stronger workforce outcomes.

In conclusion, AI Literacy becomes particularly relevant to Workforce Readiness when technological competence contributes to the formation of adaptable human capital. Preparing graduates for an AI-driven labor market therefore requires more than teaching students how to use emerging technologies. The more strategic challenge for higher education and human resource development is to transform AI-related competence into durable knowledge, adaptability, and transferable capability.

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