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AI-DRIVEN TECHNOLOGICAL DISRUPTION, DIGITAL LITERACY, AND ALUMNI EMPLOYABILITY: A QUANTITATIVE STUDY OF UNIVERSITY GRADUATE

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Abstract

Introduction: The rapid development of artificial intelligence (AI) and digital transformation has created both challenges and opportunities for graduate employability, making digital literacy increasingly important in the labor market. This study aims to analyze the effect of AI technological disruption and digital literacy on the employability of FEBI UIN Ar-Raniry alumni. Methods: This research employs a descriptive quantitative approach involving 138 alumni selected through snowball sampling. Data were analyzed using validity and reliability tests, classical assumption tests, multiple linear regression, and hypothesis testing (t-test, F-test, and coefficient of determination) using RStudio. Result: The findings demonstrate that AI technological disruption and digital literacy have a significant positive effect on employability, both individually and simultaneously.

Keywords: *Artificial Intelligence, Digital Literacy, Digitalization, Employability, Human Capital*

1. INTRODUCTION

Globalization, digital transformation, and the integration of artificial intelligence have significantly transformed the structure of the workforce (Ferns et al., 2019). These disruptions have led to a mismatch between workforce skills and industry needs (Comyn & Strietska-Ilina, 2019), meaning that workers are required to adapt to these change to remain relevant to industry needs (Valerio et al., 2016). The skills required are an individual's ability to acquire, maintain, and develop themselves in the fase of change in labor market, defined as employability by the United Nations Educational, Scientific and Cultural Organization (UNESCO, 2025), thus making it a tangible indicator of the gap between higher education and industry (Ramos et al., 2025). A college degree is viewed as investment that should increse one's employment oppurtunities, in line with human capital theory (Becker, 1964). In Indonesia, however, the unemployment rate for college graduates, according to the Central Statistics Agency (BPS), remains relatively high at 9.7%. The OUR measures the working age population actively seeking employment but who have not yet secured a job (BPS, 2025).

This reflects the weak employability of the educated workforce, particularly in terms of adaptability and the utilization of new technologies in Indonesia (Setyanti et al., 2022), including in Aceh, where the OUR rate in August 2025 for higher education graduates specifically Diploma IV, Bachelors (S1), Masters (S2), and Doctorate (S3) holders stood at 6.35% (BPS Aceh, 2025). This indicates that graduates have not been fully absorbed into the workforce due to various factors (Iqlima, 2021), as well as a gap between the demands of the industrial revolution era and university graduates (Taufik & Amirulkamar, 2023).

These challenge is also felt directly by alumni of the Faculty of Islamic Economics and Business (FEBI), as evidenced by a preliminary study conducted to understand the relationship between employability and five FEBI alumni with varying statuses. Alumni A (graduate, 2020) explained that they obtained their current job through a network within an organization due to a lack of work skills and a mismatch with the formal job qualifications required; Alumni B (graduate, 2025) is still undergoing an internship due to intense competition; Alumni C (graduate, 2024; graduating in 2025) has not yet secured a job in the formal sector due to a lack of individual skills; and Alumni D (graduating in 2025) is currently preparing to pursue a masters degree abroad and plans to work there due to the limited job market domestically.

Even with different statuses, each individual shows the same variation regarding AI-driven technological disruption, such as the use of ChatGPT to maximize job performance in their respective fields strong digital literacy skills that can help graduates find employment and employability, which graduates view as a long-term goal rather than merely initial preparation.

Unlike previous studies that mainly examine digital literacy or AI-related competencies separately, this study integrates AI-driven technological disruption and digital literacy into a single predictive model of alumni employability. The study also offers contextual evidence from FEBI UIN Ar-Raniry alumni, thereby enriching the discussion on graduate employability in Indonesian higher education. There is a lack of empirical studies on AI technology disruption that explain how AI disruption can change work structures and digital literacy as prerequisite skills in the 21st century, as well as studies that examine AI technology disruption and digital literacy simultaneously in relation to employability, particularly from the graduates own perspective. These limitations are identified as research gaps in this study and offer novelty in the local context, while also utilizing two key determinants to predict alumni employability.

The study aims to analyze the relationship between these two determinants and graduate employability, both individually and collectively. In practical terms, the findings of this study are expected to serve as a foundation for developing curriculum policies and programs to enhance alumni's employability, enabling them to adapt to the changing needs of the job market in the era of digital transformation.

The relationship between ai-driven technological disruption and employability

This study examines how technological change tends to increase labor demand through shifts in the structure of labor demand, consistent with the theory of skill-biased technological change (Katz & Murphy, 1992). Several studies report that the adoption of AI technology has a direct impact on graduates employability through automation and changes in job structures (WEF, 2025), driving competitive advantage (Govindaraj et al., 2025), and creating demands for new competencies (Pathania & Malik, 2025). This also impacts workers with technical skills that are irrelevant to technological needs (Rickardo & Meiriele, 2023). Thus, they risk experiencing a skills mismatch and difficulty entering the labor market (James et al., 2017), whereas on the other hand, the use of generative AI technologies like ChatGPT has proven more productive in jobs aligned with their expertise (Ramos et al., 2025).

Its rapid development and adoption in Indonesia also follow patterns aligned with global trends (Rasyid, 2024). These changes reflect the occurrence of AI-driven technological disruption a condition where AI-based innovations alter or potentially replace human roles in various work activities through automation and digitalization (Susanto et al., 2025). Furthermore, Rahman et al., (2025) found that graduates employability depends on their ability to utilize AI to enhance efficiency and productivity. This phenomenon reinforces the notion that the disruptive effects of this technology determine the employability of college graduates.

The relationship between digital literacy and employability

The rapid technological advancements of the 21st century have had a profound impact on workers, making it rare to find an educational system capable of keeping pace with the ever-changing demands that continually reshape the way we work (Khan et al., 2022). The United Nations Educational, Scientific and Cultural Organization (UNESCO) highlights the importance of fundamental competencies rooted in digital knowledge and the digital economy, which serve as essential prerequisites and play a crucial role in an individuals employability a concept represented within this framework by digital literacy (UNESCO, 2018), defined as the ability to safely access, manage, understand, integrate, evaluate, and create information through the use of digital technology (Vuorikari et al., 2022), a concept introduced by Glister (1998), as a 21st-century skill for understanding and utilizing information from various digital sources. These skills are crucial to an individual's employability given the rapid pace of technological change (Van Laar et al., 2017).

Furthermore, empirical research demonstrates that digital literacy has a positive impact on individual employability (Diana et al., 2025), particularly among higher education graduates preparing to enter the job market (Putri et al., 2021). This aligns with the view of Peersia et al., (2024), who argue that initial work readiness is an early indicator that directly contributes to employability.

2. RESEARCH METHOD

This study was conducted at the Faculty of Islamic Economics and Business (FEBI) at Ar-Raniry State Islamic University in Banda Aceh using a descriptive and quantitative approach. A snowball sampling method was used to determine the sample size of 138 respondents; this method was employed to facilitate reaching alumni, given constraints such as inaccurate information, including contact details within the database. The population for this study consisted of FEBI alumni from the 20th and 21st graduating classes, with a sample size of 138 individuals, this batch was chosen because they experienced firsthand the development of AI, especially chatbots that can be used as assistants in doing daily tasks, both in helping to support the use of technology to support individual professionalism in the world of work.

In this study, data was collected through the distribution of a google form questionnaire using a likert scale of 1-6 to obtain answers. A scale of 1-6 is used so as not to cause bias, so that it can be more precise in identifying respondents' agreement and disagreement with the questionnaire given. The operationalized variables are derived from employability, Artificial Intelligence (AI) Technology Disruption dan Digital Literacy. Employability is understood as a sustainable ability through optimal use of competencies. This concept emphasizes that employability is not only for the status of individuals who are already employed or not working, but a process that allows individuals to remain relevant and adaptive to changes in the job market (Van der Heijde & Van der Heijden, 2006). Employability in this study was measured using a self perceived employability approach based on a framework Rothwell & Arnold (2007) i.e. consists of two main internal and external dimensions.

Disruption of artificial intelligence (AI) technology refers to changes that can provide two sides, which can provide efficiency benefits in work processes and operational costs and can cause disruption and threats to the human workforce (Susanto et al., 2025). Variables use 3 dimensions that can represent the disruption of AI technology quoted from the research Ramos et al., (2025) including the level of knowledge on AI, the impact on the world of work and the impact of AI on the way of working.

Digital literacy is defined as the ability of individuals to use digital technology effectively and efficiently in supporting work activities (Glister, 1999), then adopted the 21st century Digital Skills framework developed by van Laar et al., (2017) consisting of seven core skills in supporting various types of work, these are adopted as dimensions that can represent these variables, consisting of technical, information management, communication, collaboration skills, creativity, critical thinking and problem solving.

Validity and reliability test

In this study, the validity test was carried out by comparing the value of r calculated with the r table. A statement is considered valid if the r-calculated value > r of the table is at a significance level of 0.05 or 5% (Chiang et al., 2015). In this study, in ensuring the reliability of the instruments used, a reliability test was carried out using the Cronbach's alpha method. Which is where the questionnaire variable is acceptable if Cronbach's alpha value is 0.6 (Griethuijsen et al., 2015) or 0.7 (Fein et al., 2021).

Classic assumption test

Next, classical assumption tests were conducted, including tests for normality, multicollinearity and heteroscedasticity. The data normality test is carried out using the Shapiro-Wilk method on the residual regression model, if the significance level of >0.05 or 5% can be concluded that the data is normally distributed and meets the normality assumption. The multicollinearity test was carried out to determine whether or not there is a high correlation between independent variables in the regression model by looking at the tolerance value and the Variance Inflation Factor (VIF). If the tolerace value is >0.10 or the VIF value is <10, then it is stated that there is no multicollinearity, and vice versa. Heteroscedasticity was tested to determine whether there is non-constant variance in the residuals. The test was conducted using a scatter plot of fitted values against residuals.p;;

Multiple linear regression analysis

Multiple linear regression analysis was used to test the simultaneous and partial influence of independent variables on dependent variables in this study. To test the influence between AI Technology Disruption (DTI) and Digital Literacy (LDG) on Employability (EPY), analysis was carried out using multiple linear regression which is formulated as follows:

$$EPY = \alpha + \beta_1 DTI + \beta_2 LDG + e$$

Where EPY is the dependent variable, DTI and LDG is the independent variable, α is a constant, β is the coefficient of the variable DTI and LDG, and e is an error term. Based on this regression equation, the following hypothesis tests can be conducted: t-test(partial), F-test (simultaneous) and determination of coefficient (R2). The t-test or partial test is used to determine the influence of each independent variable on the dependent variable. This test was carried out by comparing the significance value (p-value) with the predetermined significance level ($\alpha = 0.05$). If the significance value < 0.05, then the independent variable is declared to have a significant effect on the dependent variable. The F test is used to determine the simultaneous influence of independent variables on dependent variables. Next, the F-statistic was used to test the significance of the simultaneous effect of the two variables on EPY, with the criterion that a p-value < 0.05 indicates that the two variables have a significant simultaneous effect on EPY. Conversely, there is no significant effect.

furthermore, determination of coefficient (R^2) test is used to show how much an independent variable is capable of explaining the dependent variable. The value of the determination coefficient ranges from 0 to 1.

3. RESULTS AND DISCUSSION

3.1 Data description

Table 1 provides a descriptive overview of the demographic characteristics of the study respondents. This table summarizes key attributes, including gender, employment status and age of alumni to illustrate sample diversity.

Table 1 Description of Research Respondent

Category	Detail	Amount	Percentage
Gender	Men	73	53%
	Woman	65	47%
Employment Status	Already	70	51%
	Not yet, looking for	57	41%
	Intership	9	7%
	Other	2	1%
Year of Graduation	2020	77	56%
	2021	61	44%

Note: Data were analyzed using Rstudio
***Source:** Data Processed, 2026*

Based on Table 1, the respondents consisted of 138 individuals, with a gender proportion of 53% Male and 47% female. Regarding employment status, most of the respondents already have a job, 51% of respondents already have a job and 41% have not or are looking for others, followed by another 2%, these are respondents who continue their master's program.

Table 2 Descriptive statistics and correlation matrixs

Descriptive statistics			
	Employability	Digital literacy	AI Technology Disruption
Minimum	3.5	3	2

Maximum	6	6	6
Mean	4.911	4.888	4.537
Std. Dev	0.5419	0.5225	0.6096
Sample	138	138	138
Correlation matrixs			
Employability	1		
Digital literacy	0.631	1	
AI Disruption	0.301	0.269	1

Note: Data were analyzed using Rstudio

Source: *Data Processed, 2026*

Descriptive statistics show that all variables are in the high category. Employability has an average of 4.911 (SD = 0.5419), digital literacy of 4.888 (SD = 0.5225), and AI disruption of 4.537 (SD = 0.6096). This indicates that respondents tend to have a high level of digital literacy and employability, and are quite sensitive to AI disruption with relatively low answer variation. Overall, these results show that digital literacy is a more dominant factor than AI disruption in increasing employability, although the two still have a significant relationship. The correlation results showed that all variables had a positive and significant relationship ($p < 0.01$). Digital literacy had a strong relationship with employability ($r = 0.631$), followed by AI disruption which had a moderate relationship ($r = 0.301$).

In addition, digital literacy is also positively correlated with AI disruption ($r = 0.269$). These findings indicate that digital literacy is a more dominant factor in increasing employability than AI disruption. Overall, these results show that digital literacy is a more dominant factor than AI disruption in increasing employability, although the two still have a significant relationship.

3.2 Validity and reliability test result

In this study, the data quality test used a validity test and a reliability test. The results of both are explained in the discussion below.

Table 3 Result of the validity and reliability tests

No	Variable	Item	Validity test			Reliability test	
			r value	r table	Stat	Cronbach's alpha	Stat
1	AI technology disruption (DTI)	DTI1	0.521	0.167	Valid	0.683	Reliable
		DTI2	0.596				
		DTI3	0.511				
		DTI4	0.519				
		DTI5	0.518				

		DTI6	0.660				
		DTI7	0.619				
		DTI8	0.543				
2	Digital literacy(LDG)	LDG1	0.590	0.167	Valid	0.731	Reliable
		LDG2	0.574				
		LDG3	0.505				
		LDG4	0.507				
		LDG5	0.531				
		LDG6	0.566				
		LDG7	0.536				
		LDG8	0.528				
		LDG9	0.546				
		LDG10	0.529				
3	Employability (EPY)	EPY1	0.590	0.167	Valid	0.629	Reliable
		EPY2	0.708				
		EPY3	0.649				
		EPY4	0.488				
		EPY5	0.520				
		EPY6	0.582				

Note:Data were analyzed using Rstudio
***Source:** Data Processed, 2026*

3.3 Result of classic assumption test
3.3.1 Data normality test

The data normality test is carried out using the Shapiro-Wilk method on the residual regression model, if the significance level of >0.05 or 5% can be concluded that the data is normally distributed and meets the normality assumption.

Table 4 Normality test result

Variable	Statistic(W)	p-value	Decision
Residuals	0,981	0,053	Normal

Note: Data were analyzed using RStudio. Significance level α = 0.05.
***Source:** Data Processed, 2026*

Based on table 4, it is known that the normality test uses the Shapiro-Wilk method, the data shows a sig value, of 0.53 which can be concluded that the data is normally distributed.

3.3.2 Multicollinearity test

The multicollinearity test was carried out to determine whether or not there is a high correlation between independent variables in the regression model by looking at the tolerance value and the Variance Inflation Factor (VIF). If the tolerace value is >0.10 or the VIF value is <10, then it is stated that there is no multicollinearity, and vice versa.

Table 5 Multicollinearity test result

Variable	Tolerance	VIF	Decision
DTI	0.927	1.078	No Multicollinearity
LDG	0.927	1.078	No Multicollinearity

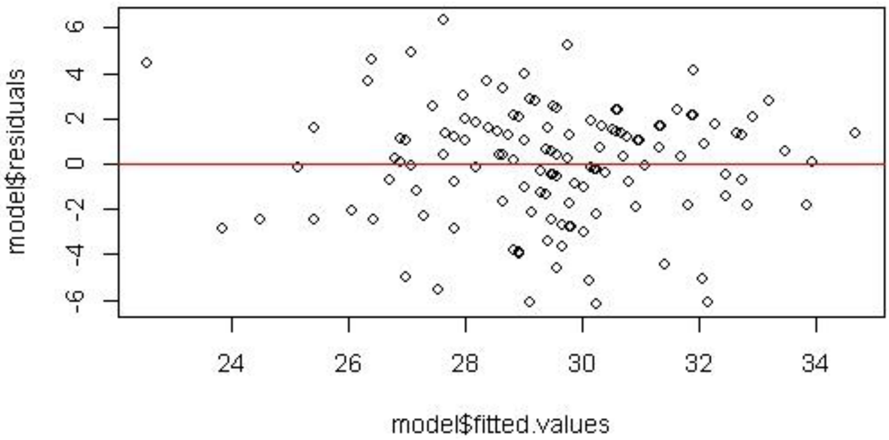
Note: Data were analyzed using RStudio.
Source: *Data Processed, 2026*

Table 5 shows that the tolerance and VIF values for these results are greater than 0.10 and less than 10, respectively, indicating the lack of multicollinearity

3.3.2 Heteroscedasticity

Heteroscedasticity was tested to determine whether there is non-constant variance in the residuals. The test was conducted using a scatter plot of fitted values against residuals.

Figure 1. Scatterplot of Residuals versus Fitted Values



Source: *Data Processed, 2026*

Based on the scatterplot of residuals against fitted values, the points are randomly distributed without a clear pattern, indicating the absence of heteroscedasticity in the regression model.

3.4 Result of the multiple linear regression analysis

Based on the results of the multiple linear regression analysis, the regression model is formulated as follows:

$$EPY = 7.997 + 0.095\ DTI + 0.369\ LDG$$

The constant value of 7.997 indicates that when AI Technology Disruption (DTI) and Digital Literacy (LDG) are equal to zero, Employability (EPY) is 7.997. The regression coefficient of DTI (0.095) indicates that a one-unit increase in AI Technology Disruption leads to an increase of 0.095 in Employability, holding other variables constant. The results show that DTI has a positive and significant effect on Employability ($p < 0.05$). The regression coefficient of LDG (0.369) indicates that a one-unit increase in Digital Literacy increases Employability by 0.369, ceteris paribus. LDG also has a positive and significant effect on Employability ($p < 0.05$).

Table 6 Results of the multiple linear regression analysis

Constant & independent variables	Dependent Variable: Employability				
	Estimate coefficient	Stand. error	T test	p-value	VIF
Constant	7.997	2.287	3,496	0,001	-
DTI	0,095	0,045	2,084	0,039	1.078
LDG	0.369	0,042	8.686	0,000	1.078

$R^2 = 0.417$; Adjusted $R^2 = 0.408$; $F = 48.28$ ($p < 0.001$).
Note: Data were analyzed using RStudio.
Source: *Data Processed, 2026*

Based on the test results in Table 6, the following conclusions can be drawn:

The first hypothesis states that AI-driven technological disruption has a positive and significant effect on employability. The results of the t-test show a calculated t-value of 2.084 with a significance level of 0.039 < 0.05. This indicates that DTI has a positive and significant effect on employability. Therefore, H1 is accepted.

The second hypothesis states that digital literacy has a positive and significant effect on employability. Based on the results of the t-test, a t-count value of 8.686 was obtained with a significance level of 0.000 < 0.05. This shows that digital literacy has a positive and significant effect on employability. Thus, H2 is accepted.

The F test is used to determine the simultaneous influence of independent variables on dependent variables. Based on the test results, an F value of 48.28 was obtained with a significance of 0.000 < 0.05. This shows that the disruption of AI technology and digital literacy simultaneously has a significant effect on employability, so the research hypothesis is accepted.

The determination coefficient (R^2) test is used to show how much an independent variable is capable of explaining the dependent variable. The value of the determination coefficient ranges from 0 to 1. Based on the results of the analysis, the Adjusted R Square value was obtained of 0.408. This shows that 40.8% of employability variations are influenced by AI technology disruption variables and digital literacy, while the remaining 59.2% are influenced by other factors that were not observed in this study.

3.5. Discussion

Based on the results of the research, in table 6 the results can be seen;

P-value < sig value (0.039 < 0.05), this study has succeeded in proving that AI technology disruption has a significant effect on employability. This is in line with previous research that explains that AI technology is starting to play a significant role in employability (Ramos et al., 2025). As explained at the outset, this predictor is not merely about understanding and utilising AI, but also about how its impact can disrupt the environment within the context of the structure of the world of work. Other factors also influence the use of AI, which can affect individuals and even other groups, including demands for its use, new competencies, and new requirements. All these factors can be described as AI-driven technological disruption, which encourages individuals or groups to use it more efficiently in their work. AI is tangible evidence of an industrial revolution capable of transforming traditional ways of life (albeit not entirely), due to factors related to the preservation of traditions and culture.

In this study, we will not address these issues, but will instead discuss the SBTC theory (skill-biased technological change) proposed by Katz and Murphy (1992). This economic concept explains that rapid advances in modern technology can increase the demand for and productivity of skilled (highly educated) workers compared to unskilled workers. This is evidenced by the results of the questionnaire as many as 68.84% stated that AI encourages the frequent use of AI technology in work activities in individual environments. Another impact is that individuals use AI (chatbot) as an assistant to support doing daily tasks, this is also evidenced by the results of the questionnaire as many as 57.25% who said they agreed, the percentage increased to 85.51% if added with the response "quite agreed", this is considered by individuals with as many as 60.15% of respondents agreeing with the statement that if AI is used properly and correctly will support individual professionalism In the world of work, then the individual will agree to use AI for daily tasks if used in a good and correct way.

Furthermore, in the second predictor, namely digital literacy, the results of p-value < sig value (0.000 < 0.05) prove that digital literacy has a significant effect on employability. This is in line with the results of the research Diana et al., (2025) where digital literacy can increase the employability of trainee alumni. These findings also demonstrate the significant impact of digital literacy on employability; this is undeniable, as digital literacy is a 21st-century skill that is essential to master (Van Laar et al., 2017), given the pace of current technological developments that can lead to a shift in digital terms from various sectors.

These findings also demonstrate that there is a need for a combination of skills directly related to AI namely, digital literacy which are required today and will continue to be needed in the years to come. This combination is evidenced by the fact that AI incorporates several core skills of digital literacy, namely critical thinking in assessing the accuracy of digital information before trusting it, and problem-solving in decision-making. This demonstrates that AI and digital literacy are interrelated and correlated; for example, an individual may understand the use of digital technology and computing, and someone already familiar with digital technology will be able to automate tasks more effectively by utilising generative AI-based chat systems.

4. CONCLUSION

This study concludes that AI-driven technological disruption and digital literacy have positive and significant effects on FEBI UIN Ar-Raniry alumni employability. Among the two predictors, digital literacy has a stronger influence, indicating that practical digital skills are essential for graduates' adaptability in the contemporary labour market.

Ultimately, both factors have been shown to significantly support graduates employability, which is a multidimensional concept that goes beyond simply securing a job; it also involves an individual's ability to retain their position and have opportunities for growth over time. These findings contribute to Becker's (1964) human capital theory. In fact, education is not the only factor that can enhance an individual's ability to compete in the labour market; indeed, university graduates also contribute to unemployment through educational unemployment, as they rely solely on their degrees and fail to realise that technological skills are also in demand and constitute key qualifications in many industries.

In practical terms, the findings of this study indicate that enhancing graduates employability requires more than just relying on educational qualifications; it must be supported by the ability to utilise AI technology and the strengthening of digital literacy. Therefore, educational institutions and stakeholders need to pay greater attention to the development of practical digital skills and prepare graduates to be better equipped to meet the demands of an ever-evolving job market.

This study has limitations, particularly in its use of questionnaire-based instruments that rely on individual perceptions; consequently, the results obtained may be influenced by respondents' subjectivity. Moreover, this study focuses solely on the variables of AI-related disruptions and digital literacy, without incorporating other factors that may also influence competitiveness in the labour market. Future research is recommended to expand this model by employing more robust research methods, refining the constructs, and incorporating additional constructs that directly influence work ability, as well as further exploring methods to measure individual skills beyond questionnaires, which are fundamentally based on personal assumptions that may vary depending on behaviour. Furthermore, future research could focus on testing not only whether AI disruption and digital literacy affect work ability, but also how and under what conditions these effects occur.

Specifically, future research could aim to test mediating mechanisms such as adaptability or self efficacy, as well as moderating factors such as labour market dynamics or fields of study, to broaden our understanding of the processes underpinning graduate employability. From a methodological perspective, further studies are also recommended to use longitudinal designs to capture changes in employability over time, mixed-methods to deepen contextual understanding, and performance-based assessment approaches to complement the self-perception measures used in this study. It is hoped that these new directions, objectives, and methodological approaches will yield a more comprehensive research model and strengthen the development of similar studies in the future.

Therefore, higher education institutions and stakeholders must pay closer attention to the graduates they produce to ensure they are better prepared to enter the world of work. By collaborating with relevant parties such as municipal training centres that can provide dedicated quotas for new graduates and by inviting and working alongside key figures to enhance individual capabilities, we can ensure that, as technology advances, we create an environment that is responsive to these macro level issues. This is crucial for driving economic growth and sustainability. In short, individual employability will continue to improve if the two approaches outlined above are utilised effectively to create an inclusive human resources ecosystem.

REFERENCES

Badan Pusat Statistik. (2025). *Keadaan ketenagakerjaan indonesia agustus 2025*. https://www.bps.go.id/id/pressrelease/2025/11/05/2479/tingkat-pengangguran-terbuka--tpt--sebesar-4-85-persen--rata-rata-upah-buruh-sebesar-3-33-juta-rupiah-.html

Badan Pusat Statistik Provinsi Aceh. (2025). *Keadaan ketenagakerjaan agustus 2025 Provinsi Aceh(1)2025-11-05*. https://aceh.bps.go.id/id/infographic?id=476

Becker, G. S. (1964). Human capital : a theoretical and empirical analysis, with special reference to education. *National Bureau of Economic Research / The University of Chicago Press*. https://www.nber.org/books-and-chapters/human-capital-theoretical-and-empirical-analysis-special-reference-education-first-edition/front-matter-preface

Chiang, I.-C. A., Jhangiani, R. S., Price, P. C., & Victoria, B. (2015). Research methods in psychology 2nd canadian edition. https://pressbooks.com

Comyn, Paul., & Strietska-Ilina, Olga. (2019). *Skills and jobs mismatches in low- and middle-income countries*. International Labor Office.

Diana, R. D., Fahmy, R., & Rivai, H. A. (2025). Pengaruh literasi digital terhadap employability dengan efikasi diri sebagai mediasi pada alumni peserta pelatihan kompetensi kerja. *Jurnal Informatika Ekonomi Bisnis*, *7*, 162–168. https://doi.org/10.37034/infeb.v7i2.1116

Eko Susanto, M Abzar D, & Abdul Majid. (2025). Disrupsi kecerdasan buatan dan reduksi peran manusia dalam dunia kerja. *Journal Scientific of Mandalika*, *6*(4). http://ojs.cahayamandalika.com/index.php/jomla

Fein, E. C., Gilmour, J., Machin, T., And, ;, & Hendry, L. (2021). Statistics for research students. www.jamovi.org.

Ferns, S., Dawson, V., & Howitt, C. (2019). A collaborative framework for enhancing graduate employability. *International Journal of Work-Integrated Learning*, *20*, 99–111.

Glister, P. (1999). Digital literacy. New York: John Wiley & Sons.

Gomes Rickardo, & Santos Meiriele. (2023). Artificial intelligence: Its impact on employability. *World Journal of Advanced Research and Reviews*, *18*(3), 198–203. https://doi.org/10.30574/wjarr.2023.18.3.1056

Govindaraj, M., Varya, N. S., & Amri, K. (2025). Exploring the emergence of ai-driven service marketing paradigms. In intersecting natural language processing and fintech innovations in service marketing (pp. 179–202). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-9944-6.ch011

Iqlima. (2021). Pengaruh kesempatan kerja, tingkat pendidikan dan jumlah penduduk terhadap pengangguran di provinsi Aceh.

Katz Lawrence F, & Murphy Kevin M. (1992). Change in relative wages, 1963-1987: supply and demand factors. *The Quartely Journal of Economics*, *107*(1).

Khan, N., Sarwar, A., Chen, T. B., & Khan, S. (2022). Connecting digital literacy in higher education to the 21st century workforce. *Knowledge Management and E-Learning*, *14*(1), 46–61. https://doi.org/10.34105/j.kmel.2022.14.004

Manyika James, Lund Susan, Chui Michael, Bughin Jacques, Woetzel Jonathan, Batra Parul, Ko Ryan, & Sanghvi Saurabh. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation. www.mckinsey.com/mgi.

Pathania, M., & Malik, R. (2025). A study on the impact of ai tools on graduate employabillity. *International Journal of Multidisciplinary Research in Science*, *12*(6), 1876. www.ijmrsetm.com

Peersia, K., Rappa, N. A., & Perry, L. B. (2024). Work readiness: definitions and conceptualisations. In higher education research and development (Vol. 43, Number 8, pp. 1830–1845). Routledge. https://doi.org/10.1080/07294360.2024.2366322

Portocarrero Ramos, H. C., Cruz Caro, O., Sánchez Bardales, E., Quiñones Huatangari, L., Campos Trigoso, J. A., Maicelo Guevara, J. L., & Chávez Santos, R. (2025). Artificial intelligence skills and their impact on the employability of university graduates. *Frontiers in Artificial Intelligence*, *8*. https://doi.org/10.3389/frai.2025.1629320

Putri, A. , N. T. , & Haryanto, A. (2021). Peran mahasiswa dalam proses perencanaan pembangunan daerah melalui program magang. *Ekonomi Dan Kebijakan Pembangunan*, *12*(1), 34–45.

Rahman, A., Lattu, A., & Permana, M. A. (2025). Analisis kesiapan kerja mahasiswa menghadapi transformasi ai menuju society 5.0 pada mahasiswa universitas xyz. *Jurnal Sistem Informasi*, *14*(6), 3052–3069. http://sistemasi.ftik.unisi.ac.id

Rasyid Nur Aini. (2024, February 22). 10 negara pengguna AI terbanyak, Indonesia salah satunya. GoodStats. https://data.goodstats.id/statistic/10-negara-pengguna-ai-terbanyak-indonesia-salah-satunya-RLlmC

Rothwell, A., & Arnold, J. (2007). Self-perceived employability: Development and validation of a scale. *Personnel Review*, *36*(1), 23–41. https://doi.org/10.1108/00483480710716704

Setyanti, A. M., Ashar, K., Santoso, D. B., & Badriyah, N. (2022). Will finding employment be easier for higher education graduates? *Proceedings of the Brawijaya International Conference on Economics, Business and Finance 2021 (BICEBF 2021)*, *206*. https://doi.org/10.2991/aebmr.k.220128.031

Taufik, & Said Amirulkamar. (2023). Triple helix; tantangan kolaborasi pemerintah, universitas, dan industri dalam pengembangan sumber daya manusia di provinsi Aceh. *Mimbar : Jurnal Penelitian Sosial Dan Politik*, *12*(2), 219–229. https://doi.org/https://doi.org/10.32663/782fmd80

UNESCO IESALC. (2025). Breaking barriers the role of higher education in advancing employability for all. https://www.unesco.org/en/open-access/cc-sa

UNESCO Institute for Statistics. (2018). A global framework of reference on digital literacy skills for indicator 4.4.2. http://www.uis.unesco.org

Valerio, A., Laura, M., Puerta, S., Tognatta, N., & Monroy-Taborda, S. (2016). Are there skills payoffs in low-and middle-income countries? empirical evidence using step data (7879; policy research working paper). World Bank. http://econ.worldbank.org.

Van Der Heijde, C. M., & Van Der Heijden, B. I. J. M. (2006). A competence-based and multidimensional operationalization and measurement of employability. *Human Resource Management*, *45*(3), 449–476. https://doi.org/10.1002/hrm.20119 van Griethuijsen, R. A. L. F., van Eijck, M. W., Haste, H., den Brok, P. J., Skinner, N. C., Mansour, N., Savran Gencer, A., & BouJaoude, S. (2015). Global patterns in students views of science and interest in science. *Research in Science Education*, *45*(4), 581–603. https://doi.org/10.1007/s11165-014-9438-6

van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, *72*, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

Vuorikari, Riina., Kluzer, Stefano., & Punie, Yves. (2022). DigComp 2.2*,* The digital competence framework for citizens, skills and attitudes. *Publications Office of the European Union*. https://doi.org/10.2760/115376

World Economic Forum. (2025). The future of jobs report 2025. https://www.weforum.org/publications/the-future-of-jobs-report-2025/