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From Digital Readiness to Employability: Mediating Role of Artificial Intelligence Competence and the Moderating Influence of Policy Support among Malaysian Graduates

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Abstract

The fourth industrial revolution (4IR) emphasises the demand for graduates with both digital readiness and artificial intelligence (AI) skills, which are aligned with labour market demands. Although prior studies link digital skills to employability, empirical evidence is scarce, and there is little research on how digital readiness translates into employment outcomes in AI-driven, particularly developing, economies. Hence, considering AI competence as a mediating mechanism and government policy support as a moderator, this study investigates the effects of digital literacy, technological self-efficacy, and digital learning engagement on graduate employability. Grounded in human capital theory, social cognitive theory, and institutional theory, this study employed a quantitative, cross-sectional design and collected data from 400 final-year students and recent graduates at Malaysian universities. PLS-SEM were used examine the proposed relationships among variables. The findings revealed that digital literacy has a direct impact on employability, whereas technological self-efficacy and digital learning engagement have indirect impacts on employability through AI competence. AI competence emerges as a central mechanism that converts digital readiness into labour market value. Additionally, government policy support strengthens the relationship between AI competence and employability, emphasising the importance of an enabling institutional environment. This study extends employability research by emphasising applied AI skills within a policy-supported framework and highlights the roles of

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universities, students, and policymakers in establishing graduate employability in the 4IR era.

Keywords: Digital Readiness, Artificial Intelligence Competence, Employability, Policy Support, Malaysian Graduates

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1.0 Introduction

The fourth industrial revolution (4IR) has transformed the global landscape of work, education, and employability. Driven by rapid digitalisation, artificial intelligence (AI), and shifting labour-market demands, it has redefined the competencies expected of modern graduates. Across both developed and developing economies, the integration of automation, data analytics, and AI is reshaping job structures and educational priorities (Anwar et al., 2025; Gulati et al., 2025; Schwab & Zahidi, 2023). In leading industrialised economies, including the United States, the United Kingdom, and South Korea, universities are embedding AI literacy, computational thinking, and data fluency into curricula (Atkinson-Toal & Guo, 2024; Hong et al., 2024). Meanwhile, developing nations, including those in Southeast Asia, continue to face challenges in narrowing digital skills gaps and ensuring the inclusive availability of digital resources for learning. This transition is especially crucial in Malaysia, where the digital economy is the core of national development. While 89% of Malaysian workers understand that they should upskill to a technology-driven environment, the majority of graduates continue to experience discrepancies between training and industry requirements (Dzulkifli, 2025; Randstad Malaysia, 2024). The Portulans Institute (2024) has observed similar issues in Indonesia, India, and Vietnam, where digital preparedness initiatives expand rapidly and unevenly.

Despite Malaysia's strong commitment to digital transformation, graduate employability remains a persistent national concern. Recent findings show that many Malaysian graduates are underemployed, have skills mismatch, and experience delayed entry to the workforce, especially in technology-intensive sectors (Dzulkifli, 2025; Halik Bassah et al., 2025). Employers increasingly report that while graduates possess basic digital skills, they often lack applied competencies, especially in artificial intelligence (AI), data-driven decision-making, and problem-solving, which are critical in the Fourth Industrial Revolution (Kamaruddin et al., 2024; Tee et al., 2024). This disconnection between the outputs of higher education and the expectations of the labour market has become more pronounced as the rate of adoption of AI has been increasing across different industries, leading to changes in jobs and skill requirements (Gulati et al., 2025; Schwab & Zahidi, 2023). Consequently, with digitalisation, graduate employability in

Malaysia is not about academic qualifications but the ability to convert digital readiness into job-relevant AI competence in an enabling policy environment.

The impact of digital literacy on graduate employability has not been extensively studied, despite Malaysian research associating digital literacy with academic performance and learning preparedness (Md Yusof et al., 2023; Wan Mokhtar et al., 2022). The literature predominantly deals with work settings, including the efficacy of oil and gas sector employees using AI tools (Abas et al., 2019), and studies concerning AI competence, as the capacity of graduates to utilise AI devices is only beginning to develop (Brougham & Haar, 2022; Yusnilzahri et al., 2025). There are limited studies that have combined various aspects of digital readiness (digital literacy, technological self-efficacy, and digital learning engagement) to identify the effects of their combination on employability via AI competence, acting as a mediating mechanism that generates a gap in employability studies. Although self-efficacy also improves online learning (Sriwiyanti et al., 2021) and digital literacy predicts online engagement (Shuhidan et al., 2023), it is not clear how the two contribute to employability.

This research addresses these gaps by examining the roles of digital literacy, technological self-efficacy, and digital learning engagement in developing AI competence and, consequently, enhancing graduate employability in the 4IR environment. Digital literacy reflects an individual's ability to access, examine, and apply digital resources for personal or professional development (Khan et al., 2022). Similarly, technological self-efficacy indicates a person's confidence in effectively using and making the best use of new technologies (Bandura, 1997; Huang & Hew, 2022). Digital learning engagement has behavioural and motivational participation (Kuo et al., 2021), and AI competence encompasses the required knowledge, competence, and ethical awareness for the use of AI (Saetra, 2024).

This study also adds government policy support as a moderator of the relationship between AI competence and employability. Malaysian initiatives, such as the MyDIGITAL Blueprint and Industry4WRD, have the potential to enhance technological and human skills development to support sustainable employability (Economic Planning Unit, 2021; Ministry of Higher Education Malaysia, 2022). Similarly, global

frameworks, e.g. EU Digital Education Action Plan and Singapore's Smart Nation Initiatives, also accentuate the role of government in positioning education to fulfil the requirements of modern AI-driven economies (European Commission, 2023; UNESCO, 2024). By empirically validating this integrated model in Malaysia's higher-education context, the study extends human capital and digital competence theories and offers practical insights for curriculum design, pedagogy, and policy to enhance graduate employability in AI-driven labour markets.

2.0 Literature Review and Hypotheses Development

2.1 Graduate Employability in the 4IR Era

The employability of graduates in the modern economy means more than just getting a job, and encompasses the ability to acquire, maintain, and advance in a job in a fast-changing digital economy (Hernandez, 2023; Hussain & Phulpoto, 2024; Moo & Wan, 2022). The fourth industrial revolution (4IR), which is automation-driven, digitally based, and artificial intelligence (AI) based, is transforming the nature of jobs, skills, and education (Han et al., 2025; Izzah & Subbarao, 2025; Tee et al., 2024). Critics worldwide have informed employers that data analytics, the sophistication of AI tools, and digital communication have become crucial competencies to sustain in the modern job market. However, universities still struggle to match the results of the curriculum to workforce expectations, especially in developing economies (Abelha et al., 2020; Nyagope, 2025).

Based on human capital theory (HCT; Becker, 1964), employability shows the extent to which individuals invest in developing skills and applying knowledge to increase productivity and market value (Becker, 1964). Meanwhile, social cognitive theory (SCT; Bandura, 1997) focuses on self-efficacy and behaviour as antecedents to the acquisition and performance of a skill. At the macro level, institutional theory (IT; Scott, 2008) advocates that policy structures and institutional reinforcements define how individual human capital is transformed into labour-market outcomes (Scott, 2008). These theories collectively frame the model in which digital readiness fosters AI competence through psychological (self-efficacy and engagement) and human capital development pathways, subsequently fostering employability outcomes.

Collectively, these theories frame our integrated model: HCT explains the investment in and value of digital and AI skills (digital literacy, AI competence, and employability). SCT describes individual motivation for skills acquisition (technological self-efficacy and digital learning engagement). IT explains the contextual boundary condition, which strengthens this process (government policy support as a moderator). Thus, digital readiness enabled by psychological and behavioural factors (SCT) leads to AI competence (HCT), which interacts with the policy environment (IT) to produce enhanced employability.

2.2 Digital Literacy

The ability of an individual to create, access, analyse, and communicate information using digital technologies reflects digital literacy (Rahim et al., 2023). In the context of developing countries, such as Malaysia, digital literacy is positively related to the adaptability of online learning, problem-solving, and job performance (Anwar et al., 2025; Wan Mokhtar et al., 2022). A recent systematic review suggests that digital literacy is a critical but under-theorised antecedent of employability and innovation behaviour (Caroline et al., 2025). From the human capital theory perspective, digital literacy constitutes an investment in human capital that enhances employability. Empirical work demonstrates that graduates with higher digital literacy engage more with AI tools and online job search platforms (Anwar et al., 2025; Bah, 2025). However, gaps remain: many digital literacy measures focus on access and basic usage rather than strategic creation, evaluation, and adaptation (Damayanti et al., 2024). The employability literature questions whether digital literacy alone is sufficient to drive job readiness or whether AI competence, conceptualised as a mediating construct in the present study, plays a significant role in linking digital skills to better employability prospects (Caroline et al., 2025; Portocarrero Ramos et al., 2025). This study aims to determine the foundational relationship before testing this complex mediated pathway and frames its first hypothesis as follows:

H1: Digital literacy has a positive effect on graduate employability.

2.3 Technological Self-Efficacy

Technological self-efficacy reflects an individual's confidence and convenience in adopting, using, adapting to, and dealing with technology (Bandura, 1997). In social cognitive theory (SCT) (Bandura, 1997), self-efficacy determines effort, persistence, and resilience in learning complex technologies. Recent empirical research has revealed that technological self-efficacy is an indicator of greater involvement in digital tools and preparation for artificial intelligence (AI) environments (Anwar et al., 2025; Jamil & Loke, 2024). For instance, in a study on remote work in Indonesia, digital self-efficacy mediated the association between technology support and perceived employability (Siregar & Syahrizal, 2024). Despite its conceptual appeal, the direct links between self-efficacy and employability are mixed. Some studies indicate that self-efficacy must translate into applied competence to gain employability (Akçay, 2025; Getenet et al., 2024). In the context of the fourth industrial revolution (4IR), confidence would only be useful when coupled with the ability to use an AI tool and induce innovation by gaining AI skills. This leads to the understanding that self-efficacy functions indirectly through AI competence (Zhan et al., 2024). However, other perspectives posit that confidence, manifesting as persistence, positive self-presentation, and adaptability, may carry independent value in the labour market, thereby enhancing employability (Cheng et al., 2025; Nikou et al., 2022). To comprehensively evaluate its role, we test both potential pathways. Accordingly, while technological self-efficacy is theorised to enhance employability mainly through the development of AI competence, a direct relationship is also empirically tested to assess whether confidence alone yields labour-market value. Therefore, the study frames its next hypothesis as follows:

H2: Technological self-efficacy has a positive effect on graduate employability.

2.4 Digital Learning Engagement

Consistent with social cognitive theory, digital learning engagement encompasses learners' behavioural, cognitive, and emotional involvement in technology-enhanced environments (Fredricks et al., 2004). It reflects the motivated behavioural enactment of self-efficacy, in which confident individuals invest greater effort and persistence in

digital learning activities. Empirical research links digital engagement to creative problem-solving, communication skills, and career adaptability, attributes valued in the 4IR labour market (Aziz, 2023). However, while engagement supports learning, its direct connection to employability remains underexplored. Many engagement studies stop at academic performance rather than tracking workforce transitions (Fish et al., 2025; Kim et al., 2019). In 4IR settings, the challenge is: does active engagement translate into applied AI competence and, thereby, job readiness? We argue yes, but engagement alone may not suffice without competence (Fish et al., 2025; Magallanes, 2022).

H3: Digital learning engagement has a positive effect on graduate employability.

2.5 Role of AI Competence

The term AI competence refers to the knowledge, technical skills, and ethical awareness needed to use and implement artificial intelligence technologies academically and professionally, responsibly and effectively (Long & Magerko, 2020). The literature on digitalisation and employability clearly states that graduates with a high level of AI-related skills are in a better position to secure AI-intensive occupational positions and have higher career opportunities (Gulati et al., 2025). Likewise, more digitally capable people will be more flexible in AI-controlled workplaces and more productive at work (Anwar et al., 2025). In terms of human capital theory and social cognitive theory, AI competence is high-level human capital, which is created by digital literacy, technological self-efficacy, and participation in digital learning contexts (Becker, 1964; Bandura, 1997).

2.5.1 Predictors of AI Competence

Previous studies have advocated that digital readiness contributes to the development of AI competence in individuals. Digital literacy facilitates the understanding, evaluation, and application of complex digital and AI tools. This forms the cognitive basis for AI skill acquisition (Caroline et al., 2025). Technological self-efficacy further enables this development by improving individuals' confidence in dealing with and exploiting emerging AI technologies. Simultaneously, digital learning engagement augments

experience, practice, and sustained interaction with an AI-enabled learning platform (Anwar et al., 2025). Consequently, this study proposes that all these constructs influence and act as potential predictors of AI competence.

H4: Digital literacy positively influences AI competence.

H5: Technological self-efficacy positively influences AI competence.

H6: Digital learning engagement positively influences AI competence.

2.5.2 Effect of AI Competence on Graduate Employability

AI competence has increasingly been recognised as a critical determinant of graduate employability in the Fourth Industrial Revolution. Empirical evidence suggests that AI competence enables graduates to translate digital readiness into applied, job-relevant capabilities, thereby improving employability outcomes (Filo et al., 2024). AI competence as a type of highly skilled human capital improves the capacity of graduates to perform complex work, be innovative, and remain relevant in technology-driven labour markets (Gulati et al., 2025). Thus, it is assumed that AI competence has a direct positive influence on graduate employability.

H7: AI competence has a positive effect on graduate employability.

2.5.3 Mediating Role of AI Competence

Beyond its direct effect, AI competence is conceptualised as a mediating mechanism that bridges digital readiness and employability. According to the research results of previous studies, digital literacy, technological self-efficacy, and digital learning engagement might not necessarily lead to the outcomes of employability unless converted into applied AI-related skills (Bah, 2025; Caroline et al., 2025). AI competence is therefore an essential channel through which digital readiness is transformed into labour-market value. Based on this, this study hypothesises that AI competence mediates the

relationships among digital literacy, technological self-efficacy, digital learning engagement, and graduate employability.

H8a: AI competence mediates the relationship between digital literacy and graduate employability.

H8b: AI competence mediates the relationship between technological self-efficacy and graduate employability.

H8c: AI competence mediates the relationship between digital learning engagement and graduate employability.

2.6 Moderating Role of Government Policy Support

When investing in digital and AI capacities, the institutional environment dictates how this is translated into an employment benefit. Institutional theory states that organisational and governmental structures influence the results of individuals by providing legitimacy, resources, and supportive norms as individuals perceive them (Scott, 2008). In Malaysia, frameworks such as the MyDIGITAL Blueprint and National AI Roadmap (2021–2025) reflect strategic policies to boost AI literacy and workforce readiness (MDEC, 2024). However, the effectiveness of such initiatives depends on graduates' perceptions of the availability, accessibility, and usefulness of government policy support, rather than objective exposure alone. Cross-national studies have shown that policy environments moderate the translation of digital skills into employability (Gulati et al., 2025). Therefore, graduates' AI competence will yield greater employability benefits in contexts of robust perceived policy support. Conversely, weak policy settings may constrain the value of individual investments.

H9: Government policy support positively moderates the relationship between AI competence and graduate employability, such that the relationship is stronger under higher perceived policy support.

3.0 Conceptual Framework

This study combines human capital theory (Becker, 1964), social cognitive theory (Bandura, 1997), and institutional theory (Scott, 2008) to identify the impact of digital readiness on graduate employability in the Malaysian 4IR context. According to human capital theory, investments in digital competencies, such as digital literacy, technological self-efficacy, and digital learning engagement, enhance productivity and employability. Social cognitive theory emphasises the importance of confidence and behavioural involvement in learning and using new technologies; thus, self-efficacy and engagement are central psychological facilitators of employability. AI competence serves as a mediating mechanism that transforms digital readiness into employability. Therefore, digitally literate, confident, and engaged graduates have an increased chance of developing AI-related skills, making them more relevant in the workforce.

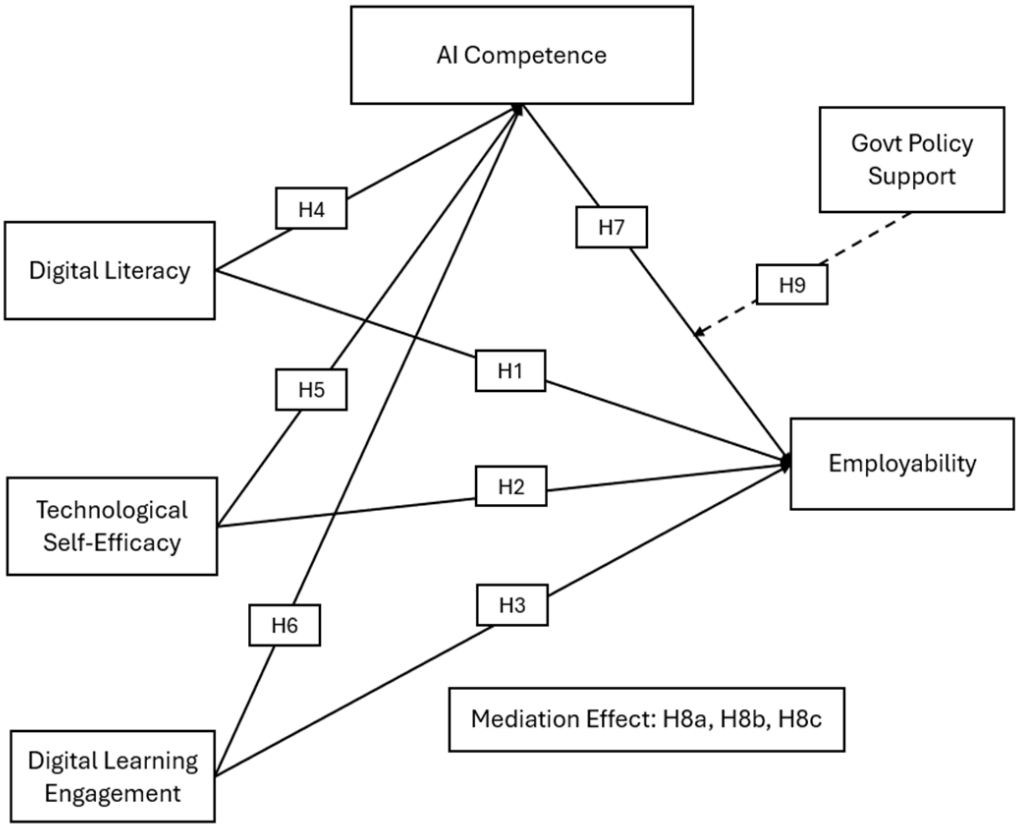

Figure 1: Conceptual Framework of Digital Readiness, AI Competence, and Graduate Employability

4.0 Methodology

4.1 Research Design

This study adopts a quantitative, cross-sectional methodological approach and empirically examines the relationships among digital literacy, technological self-efficacy, digital learning engagement, AI competence, government policy support, and graduate employability. This method is appropriate for objective measurements of variables, hypothesis testing, and generalising the results to the entire population (Creswell & Creswell, 2018). In addition, structural equation modelling (SEM) is used as the main analytical methodology, which enables the investigation of several relationships, mediation, and moderating influence of AI competence and government policy support. This method is also welcomed in educational and management research when testing complex models with latent constructs is required (Hair et al., 2022).

4.2 Population and Sampling

This study targeted final-year undergraduate students and recent graduates (less than one year) from Malaysian universities. These participants are well-educated and adequately exposed to digital environments and are aware of AI-related technologies, which is consistent with the study's objectives. In addition to recent graduates, final-year undergraduate students were selected as respondents because they are at the transition point between higher education and labour market entry, making them suitable proxies for assessing graduate employability readiness. Research on graduate employability and skill development frequently includes final-year students as a valid proxy population because their assessed competencies and perceptions strongly predict early career outcomes and are highly correlated with data from recent graduates (Delcker et al., 2024; Elkhayma & Ezzaidi, 2025). This study employed a non-probability purposive sampling technique and selected respondents who are Malaysian nationals, currently enrolled in the final year or have recently graduated, and, most importantly, participants who possess basic digital or AI-enabled learning modules. The target population of this study

comprised 400 respondents, which would guarantee sufficient statistical power and model stability (Hair et al., 2022).

4.3 Measurement of Variables

The study variables were measured using validated multi-item instruments adapted from established prior research, as presented in Table 1. Digital literacy, technological self-efficacy, and digital learning engagement were operationalised using the scale endorsed by Chang and Kuo (2025). For AI competence (Filo et al., 2024), graduate employability (Llinares Insa et al., 2018), and government policy support, the scale by Li and Wang (2024) was adapted. A five-point Likert-type scale was employed, anchored from 1 (strongly disagree) to 5 (strongly agree).

Table 1: Measurement Constructs

Construct	Items	Measurement	Description
Digital Literacy	4	(Chang & Kuo, 2025)	Captures individuals' proficiency in obtaining, evaluating, creating, and communicating information in digital environments.
Technological Self-Efficacy	5	(Chang & Kuo, 2025)	Captures individuals' confidence in learning, adopting, and effectively using digital technologies.
Digital Learning Engagement	4	(Chang & Kuo, 2025)	Examine behavioural, emotional, and cognitive engagement during digital or AI-enabled learning activities.
AI Competence	4	(Filo et al., 2024)	Assesses understanding, ethical awareness, and application of AI tools in learning and professional contexts.
Graduate Employability	4	(Llinares Insa et al., 2018)	Measures perceived and objective employability, including adaptability, career management, and transferable skills.
Government Policy Support	4	(Li & Wang, 2024)	Measures the extent to which perceived government policies support digital learning, AI skill application, and employability.

4.4 Data Collection Procedure and Pilot Testing

First, a pilot study was conducted in which 50 respondents participated to determine the reliability, clarity, and consistency of the questionnaire items. The internal reliability of all constructs was satisfactory, and the values of Cronbach's alpha were over the recommended 0.70 (Hair et al., 2022). Minor wording changes were made to enhance understanding, particularly for the constructs of AI competency and digital learning engagement. After the pilot test, the tested questionnaire was sent to the target population via a Google Forms link, and in-person data collection was also conducted. The questionnaire was distributed by university networks, student associations, and online learning platforms such as WhatsApp, LinkedIn, and institutional emails. Participation was voluntary, and respondents were guaranteed confidentiality and anonymity. Approximately 650 prospective participants were contacted through these channels. Data collection spanned 6–8 weeks. After the collection period, a total of 432 responses were received. Following a screening process to remove incomplete responses and those showing inconsistent answer patterns (e.g., straight-lining), 400 valid and usable responses were retained, yielding a final response rate of 61.5%.

4.5 Data Analysis Techniques

The study utilised partial least squares structural equation modelling (PLS-SEM) and SmartPLS 4 to test the hypotheses because it is an appropriate tool for use in a complex model of mediating and moderating variables and is predictive in nature (Hair et al., 2022). The analysis was conducted in two steps. In the first step, Convergent validity, internal consistency reliability, and discriminant validity using the Fornell–Larcker criterion and HTMT ratio (< 0.90) were used to assess the measurement model. Second, the structural model tested direct effects (H1–H7), mediation by AI competence (H8a–c), and moderation by government policy support (H9), using path coefficients (β), t-values, and p-values ($p < 0.05$). Model quality was evaluated via R^2, Q^2, f^2, and SRMR (≤ 0.08). Bootstrapping with 5,000 resamples was used to test mediation, interaction terms to test moderation, and VIF values to test multicollinearity. Because the study employed a self-report questionnaire and collected data from a single source, common

method bias was evaluated through Harman's single-factor test by entering all 25 items into an unrotated principal component analysis. The first factor accounted for 26.8% of the variance, falling well below the 50% criterion and suggesting minimal common method bias. The researcher ensured that ethical issues were considered when collecting, analysing, or presenting the data in accordance with the Personal Data Protection Act 2010 of Malaysia.

5.0 Data Analysis and Results

5.1 Demographic Profile of Respondents

A total of 400 responses were collected from final-year undergraduate students and newly graduated students. Table 2 presents their demographic characteristics.

Table 2: Demographic Profile of Respondents (N = 400)

Demographics	Category	Frequency	Percentage (%)
Gender	Male	182	45.5
	Female	218	54.5
Age	21–22 (Final Year Undergrad)	160	40.0
	23–25 (New Graduates)	160	40.0
	26–28 (Postgraduates)	80	20.0
Programme Level	Undergraduate	240	60.0
	Postgraduate	160	40.0
Field of Study	STEM	180	45.0
	Social Sciences	140	35.0
	Business/Management	80	20.0
Exposure to AI Learning	Low	70	17.5
	Moderate	210	52.5
	High	120	30.0

Table 2 presents the sample of 400 participants, comprising 45.5% men and 54.5% women, which reflects Malaysia's higher education enrolment. Most respondents (80 %) were aged 21–25 (final-year undergraduates and new graduates), and 20% were postgraduates. Diversity in disciplines was achieved by having participants from (45%) particular, social science (35%), and business/management (20%) disciplines. The

majority of the reported moderate (52.5) to high (30) exposure to AI learning, which means that they are generally familiar with AI tools, and this supports the study's focus on AI competence.

5.2 Measurement Model Assessment

5.2.1 Indicator Reliability (Outer Loadings)

Outer loadings for all indicators are presented in Table 3. All loadings exceeded the recommended threshold of 0.70 (Hair et al., 2022), indicating acceptable indicator reliability. No items were removed, as all exceeded minimum loading requirements.

Table 3: Indicator Loadings (Outer Loadings)

Construct	Items	Loading
Digital Literacy	DL1	0.78
	DL2	0.81
	DL3	0.76
	DL4	0.79
Technological Self-Efficacy	TSE1	0.74
	TSE2	0.78
	TSE3	0.80
	TSE4	0.76
	TSE5	0.79
Digital Learning Engagement	DLE1	0.82
	DLE2	0.79
	DLE3	0.76
	DLE4	0.81
AI Competence	AIC1	0.77
	AIC2	0.80
	AIC3	0.83
	AIC4	0.78
Graduate Employability	GE1	0.75
	GE2	0.78
	GE3	0.80
	GE4	0.72
Government Policy Support	GPS1	0.73
	GPS2	0.76
	GPS3	0.71
	GPS4	0.74

5.2.2 Internal Consistency and Convergent Validity

Cronbach's α values (0.80–0.86) and composite reliability (0.83–0.89) exceeded the recommended thresholds (≥0.70). The AVE values ranged from 0.52 to 0.60, confirming adequate convergent validity.

Table 4: Reliability and Validity Indicators

Construct	Cronbach's α	Composite Reliability	AVE
Digital Literacy	0.84	0.87	0.58
Technological Self-Efficacy	0.81	0.85	0.55
Digital Learning Engagement	0.85	0.88	0.60
AI Competence	0.86	0.89	0.59
Graduate Employability	0.82	0.86	0.57
Government Policy Support	0.80	0.83	0.52

5.2.3 Collinearity Assessment (VIF) and Discrinminant Validity

To evaluate multicollinearity, the variance inflation factor (VIF) values were assessed for all measurement indicators. All VIF values fell between 1.25 and 2.30, well below the conservative threshold of 3.3, indicating no collinearity concerns (Hair et al., 2022). These results confirm that collinearity is not an issue and that the constructs are measured distinctly. In addition, Table 5 shows the discriminant validity, where the bold diagonal entries denote the square roots of the AVE, with construct correlations reported below the diagonal and HTMT ratios above it. All HTMT values are below 0.85, supporting adequate discriminant validity.

Table 5: Discriminant Validity

Construct	1	2	3	4	5	6
1. Digital Literacy	**0.76**	0.64	0.65	0.69	0.62	0.59
2. Technological Self-Efficacy	0.43	**0.74**	0.61	0.61	0.61	0.61
3. Digital Learning Engagement	0.52	0.48	**0.77**	0.65	0.62	0.65
4. AI Competence	0.58	0.45	0.54	**0.77**	0.69	0.69
5. Graduate Employability	0.49	0.38	0.42	0.52	**0.75**	0.71
6. Government Policy Support	0.41	0.39	0.44	0.47	0.43	**0.72**

5.3 Structural Model Assessment

5.3.1 Structural Model Results – Direct Effects

Table 6 presents the direct associations among the study constructs. Digital literacy has a positive and significant effect on graduate employability ($\beta = 0.18$, $t = 2.95$, $p = 0.003$), supporting H1 and aligning with prior evidence that digitally literate graduates are more adaptable and labour-market ready (Vuorikari et al., 2022). In contrast, technological self-efficacy ($\beta = 0.08$, $t = 1.65$, $p = 0.10$) and digital learning engagement ($\beta = 0.07$, $t = 1.20$, $p = 0.23$) showed no significant direct effects on employability, rejecting H2 and H3. This indicates that confidence in technology use or engagement alone does not enhance employability without advanced competencies, such as AI skills.

All three predictors significantly influence AI competence digital literacy ($\beta = 0.40$, $t = 6.50$, $p < 0.001$), technological self-efficacy ($\beta = 0.22$, $t = 3.90$, $p < 0.001$), and digital learning engagement ($\beta = 0.28$, $t = 4.10$, $p < 0.001$), supporting H4–H6 and suggesting a cumulative development process. Finally, AI competence has a strong positive effect on graduate employability ($\beta = 0.35$, $t = 5.90$, $p < 0.001$), confirming H7 and reinforcing its role as advanced human capital in the 4IR era (Brynjolfsson & McAfee, 2017). Overall, while basic digital skills contribute to employability, their impact is maximised through AI competence, which bridges digital readiness and labour-market performance.

Table 6: Structural Model Results – Direct Effects

Hypothesis	Path	β	t-value	p-value	Result
H1	Digital Literacy-> Employability	0.18	2.95	0.003	**Supported**
H2	Technological Self-Efficacy -> Employability	0.08	1.65	0.10	Not Supported
H3	Digital Learning Engagement -> Employability	0.07	1.20	0.23	Not Supported
H4	Digital Literacy -> AI Competence	0.40	6.50	<0.001	**Supported**
H5	Technological Self-Efficacy-> AI Competence	0.22	3.90	<0.001	**Supported**

Hypothesis	Path	β	t-value	p-value	Result
H6	Digital Learning Engagement -> AI Competence	0.28	4.10	<0.001	**Supported**
H7	AI Competence -> Employability	0.35	5.90	<0.001	**Supported**

5.3.2 Coefficient of Determination (R^2) and Effect Sizes (f^2)

The structural model exhibits strong explanatory capability, with the predictors accounting for 48% of the variance in AI competence and 57% of the variance in graduate employability, indicating a strong model fit for social science research. Effect size (f^2) analysis shows that digital literacy and AI competence exert the strongest influence within the model, whereas technological self-efficacy and digital learning engagement contribute modest yet meaningful effects.

Table 7: Model Fit Indices, Explanatory Power (R^2), and Effect Sizes (f^2)

Construct / Path / Fit Index	Value	Benchmark / Effect Size	Interpretation
SRMR	0.068	≤ 0.08	Good model fit
AI Competence (R^2)	0.48	--	48% variance explained
Graduate Employability (R^2)	0.57	--	57% variance explained
Digital Literacy → AI Comp.	--	0.12 (Medium)	Strongest predictor of AI competence
Tech. Self-Efficacy → AI Comp.	--	0.05 (Small)	Minor contribution
Digital Learning Engage. → AI Comp.	--	0.08 (Small–Medium)	Moderate effect
AI Competence → Employability	--	0.15 (Medium)	Substantial influence

Note:SRMR = Standardised Root Mean Square Residual. R^2 = Coefficient of determination. f^2 = Effect size.

5.3.3 Mediation Analysis

The mediation results show that AI competence significantly mediates the effects of all independent constructs on graduate employability. Digital literacy positively and

significantly indirectly influences employability through AI competence (b = 0.14, t = 4.80, p < 0.001), indicating that it is partially mediated by digital literacy, which also has a direct impact. The indirect effect of technological self-efficacy in AI competence is significant (b = 0.08, t = 3.50, p < 0.001), which signifies that TSE has complete mediation; that is, it has an impact on employability only when it is converted into AI skills. In like manner, there is a significant indirect impact of digital learning engagement through AI competence (b = 0.10, t = 4.00, p < 0.001), which is a full mediation.

Table 8: Mediation Results – AI Competence

Path (IV → Mediator → DV)	Indirect Effect (β)	t-value	p-value	Mediation Type
DL -> AI Competence -> Employability	0.14	4.80	< 0.001	Partial Mediation
TSE -> AI Competence -> Employability	0.08	3.50	< 0.001	Full Mediation
DLE -> AI Competence -> Employability	0.10	4.00	< 0.001	Full Mediation

5.3.4 Moderation Analysis

Table 9 presents the results of the moderation analysis examining the role of perceived government policy support (GPS) in the relationship between AI competence and graduate employability. The interaction term **(**AI competence × government policy support**)** was found to be positive and statistically significant (β = 0.12, *t* = 2.75, *p* = 0.006), supporting the hypothesised moderating effect. To facilitate interpretation of the interaction effect, high and low levels of the moderator were plotted at one standard deviation above and below the mean, following standard PLS-SEM practice. For interpretation purposes, government policy support was categorised into high, medium, and low levels based on the mean score and ±1 standard deviation.

Table 9: Moderation Results – Government Policy Support

Interaction	β	t-value	p-value	Interpretation
AI Competence × Government Policy Support -> Employability	0.12	2.75	0.006	Supported

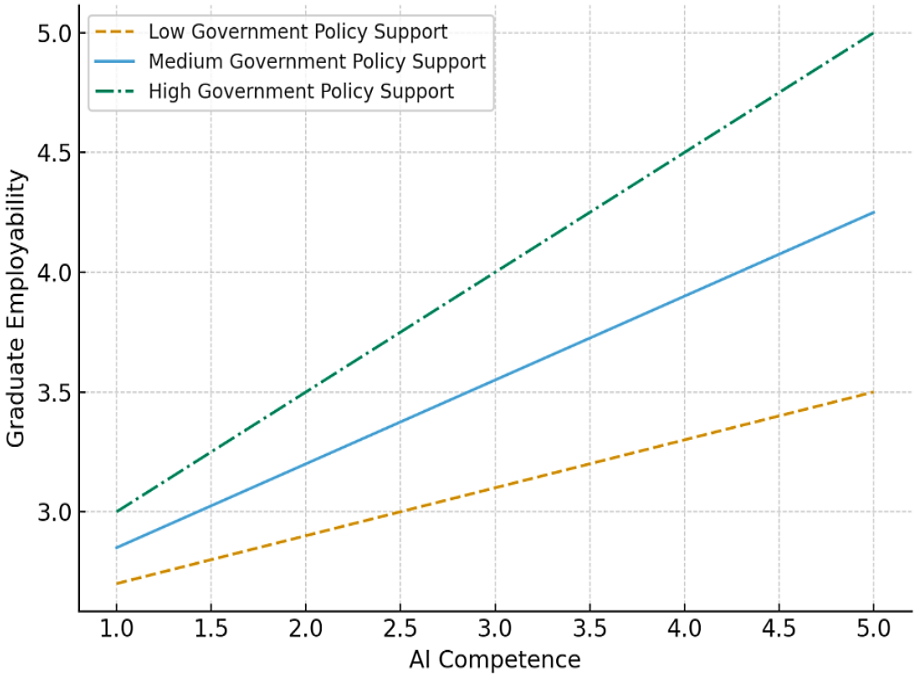

Figure 2: Interaction plot showing the moderating effect of Government Policy Support on the relationship between AI Competence and Graduate Employability

Figure 2 shows that AI competence has a stronger positive effect on graduate employability when perceived government policy support is high. Under strong policy conditions, employability increases sharply with increasing AI competence, whereas under low policy support, the relationship is weaker, indicating that government initiatives amplify the benefits of AI competence on employability.

6.0 Discussion and Conclusion

Digital literacy is a direct predictor of high employability, which coincides with human capital theory, which claims that investments in skills add value to the labour market (Becker, 1964). Digital application, information management, and online collaboration skills enable graduates to better meet workplace demands, which is consistent with Malaysian (Kamaruddin et al., 2024; Wan Mokhtar et al., 2022) and international evidence (OECD, 2023; World Bank, 2024). Nevertheless, AI competence reinforces

this effect to a considerable degree, meaning that digital skills will need to become applied AI functions to remain relevant in the 4IR era (Sima et al., 2020). In a broader understanding of sustainability, this observation promotes Sustainable Development Goal 4 (quality education), which focuses on equipping graduates with pertinent digital and technological skills to increase their readiness to meet future changes in the labour market. Technological self-efficacy and digital learning engagement have not emerged as direct predictors of employability, which means that confidence and engagement on the Internet do not suffice without practical abilities. This is consistent with social cognitive theory, which considers self-efficacy as mediating the effect across results by developing competence (Bandura, 1997). As such, the two factors influence employability; however, this is mediated by AI competence.

AI competence has emerged as an influential mediator, connecting technological self-efficacy completely and partially digital literacy and digital learning engagement to employability. This highlights its transformative capability in digital preparedness for labour-market outcomes, in line with worldwide data that displays AI skills as the key to employability (Kaur and Ching, 2024; Long and Magerko, 2020). Based on human capital theory, AI-skilled graduates are high-value human capital in the current economy. This study directly contributes to SDG 8 (Decent Work and Economic Growth) by demonstrating that developed digital capabilities can be used to enhance productive employment in an AI-driven economy because of AI competence.

Perceived government policy support is another factor that strengthens the relationship between AI competence and employability, thereby extending institutional theory (Scott, 2008). Initiatives such as the MyDIGITAL Blueprint and National AI Roadmap (2021–2025) have established an enabling ecosystem between education, industry, and policy (MDEC, 2024), which is a manifestation of effective digitalisation policies in Singapore and South Korea (Chen et al., 2024; Lim et al., 2023). Generally, the findings integrate human capital, social cognitive, and institutional theories with the model of multilevel employability, the fact that AI competence mediates the impact of the digital preparedness variable, and the government policy enhances it. This highlights the strategic imperative of providing higher education that is AI literate, sustaining the enabling ecosystems by policymakers, and creating adaptive future-oriented skills

required by individuals to be updated with the 4IR workforce. These findings also contribute to SDGs 4 and 8 by endorsing how AI-oriented education, consistent with the national policy that consequently enhances workforce readiness, leads to increased innovation capabilities and sustainable economic engagement.

6.1 Implications of the Study

This study has theoretical and practical implications for graduate employability in the midst of contemporary digital transformation. Theoretically, the results are congruent with the literature on digital readiness for employability by empirically demonstrating the mediating role of AI competence in the process of interpreting digital literacy, technological self-efficacy, and digital learning engagement into employability. By combining human capital theory, social cognitive theory, and institutional theory, this study explains how the factors of digital readiness are transformed into labour-market value through advanced AI-related capabilities. From a practical perspective, these outcomes highlight the importance of integrating AI competence development into curricula. Universities and higher education institutions should move beyond basic digital skills training and prioritise applied AI-related learning experiences that enhance students' confidence, engagement, and readiness for AI-driven work environments. Policymakers and educational planners may also leverage these findings to inform national digital education strategies aimed at improving graduate employability by aligning academic training with evolving industry demands.

7. 0 Limitations and Future Research

As the study employs a cross-sectional design, which restricts the ability to make causal inferences, longitudinal or experimental designs should be utilised in future studies to determine how digital skills and employability change over time (Podsakoff et al., 2012). Second, the non-probability sample of digitally active students limits generalisability, and it is possible to say that broader and more representative samples across institutions will be required (Hair et al., 2022). Third, the data provided by them can be biased; subsequent research can use the ratings of employers or performance history as

confirmation. The research is also based on the context of Malaysia, in which institutional structures such as the MyDIGITAL Blueprint determine the outcome of employability. Institutional differences could be better described through comparative studies across countries (Scott, 2008). Lastly, it is possible to further apply this framework to additional theories, such as job demands–resources (JD-R) or technological pedagogical content knowledge (TPACK) models, to gain a better understanding of digital competencies in their interaction with the workplace and learning conditions.

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