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UNDERSTANDING EMPLOYMENT CONSTRUCTS ACROSS BORDERS: A CROSS-NATIONAL COMPARISON OF MALAYSIA AND INDONESIA

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ABSTRACT
In today's digital age, digital literacy has emerged as a vital skill that shapes employability and workforce preparedness. The research examines the impact of digital literacy on employability among employees in Malaysia and Indonesia through a quantitative methodology and purposive sampling. Data were collected from 469 participants (238 Malaysians and 231 Indonesians) via structured questionnaires. Results show that nationality does not significantly moderate the link between digital literacy and employability, suggesting that perceptions of these constructs are consistent in both countries. This finding implies that initiatives to improve digital literacy can be applied similarly across these contexts. The study highlight the consistent relationship between digital literacy, employability, and related factors such as media literacy and perceived ease of use across different nationalities. For managers, policymakers, educators, and corporate trainers, this suggests that standardized frameworks may be effective in fostering digital skills and employability, supporting a cohesive regional strategy.

Keywords: *Computer literacy, communication literacy, digital literacy, employability skills, media and visual literacy*

1. INTRODUCTION

In 21st-century workplace, digital literacy is foundational for preparing the future workforce. As global economies become increasingly digitalized, digital literacy has emerged as a critical factor in improving employability. While information literacy encompasses a broad set of skills for handling information to achieve diverse objectives, digital literacy is specifically oriented toward effectively using Information and Communication Technologies (ICTs) to search, retrieve, and apply information. For example, Gilbert (2017) highlighted that organizations value diverse information literacy skills, such as the use of various resources, information synthesis, evaluation, practical application, and collaboration. The demand for digital skills is particularly strong in virtual work environments, as individuals with robust digital competencies are better equipped to secure employment and advance their careers (Zahoor et al., 2023).

Digital literacy foster active participation in society, extending beyond social and digital inclusion to enhance individual employability and contribute to economic growth (Ferrari, 2012). With digital technologies becoming integral to multiple sectors and daily life, digital literacy is now essential for many jobs. Although some roles are at risk of automation, many existing jobs now demand updated skills and knowledge, shaped by industry-specific, regional, and occupational factors, as well as the adaptability of stakeholders to social, economic, and political shifts (World Economic Forum, 2016). Numerous studies have observed an increased need for digital literacy and competencies due to digitization (OECD, 2014).

Both theoretical and practical perspectives underscore the growing importance of ICT proficiency across various jobs. The European Commission (2016) notes that over 90% of jobs now require at least basic computer skills, with ICT-focused positions making up a significant portion of the EU15 economy as of 2010 (OECD, 2016). Digital literacy encompasses diverse competencies, including communication, media or visual and computer literacy, which are all essential for navigating today's digital environment (Ng, 2012; Zahoor et al., 2023). Information literacy entailing the ability to effectively use information which complements digital literacy and is equally crucial in a digital economy. Together, these literacies equip individuals to adapt to technological advancements and respond to job market demands.

Despite the extensive research on digital literacy and employability, cross-national studies in this area remain scarce. This study seeks to assess the stability of the relationship between digital literacy and employability across different national contexts, focusing on Malaysia and Indonesia. The findings will provide valuable insights into whether strategies to enhance digital literacy can be standardized across these countries, informing policymakers, educators, and corporate trainers on effective methods to boost employability through digital literacy programs.

This study's theoretical framework builds upon the research by Nikou et al. (2022) and Reddy et al. (2023), modified to address the evolving requirements of employability skills. To analyze factors influencing technology adoption in workplace settings, the study incorporates the Technology Acceptance Model (TAM) to investigate the role of digital literacy in employability. Enhancing digital literacy can improve individuals' perceptions of digital tools, thereby encouraging greater technology use and enhancing employability (Reddy et al., 2023). This research introduces both information and digital literacy as new precursors within the model (see Figure 1).

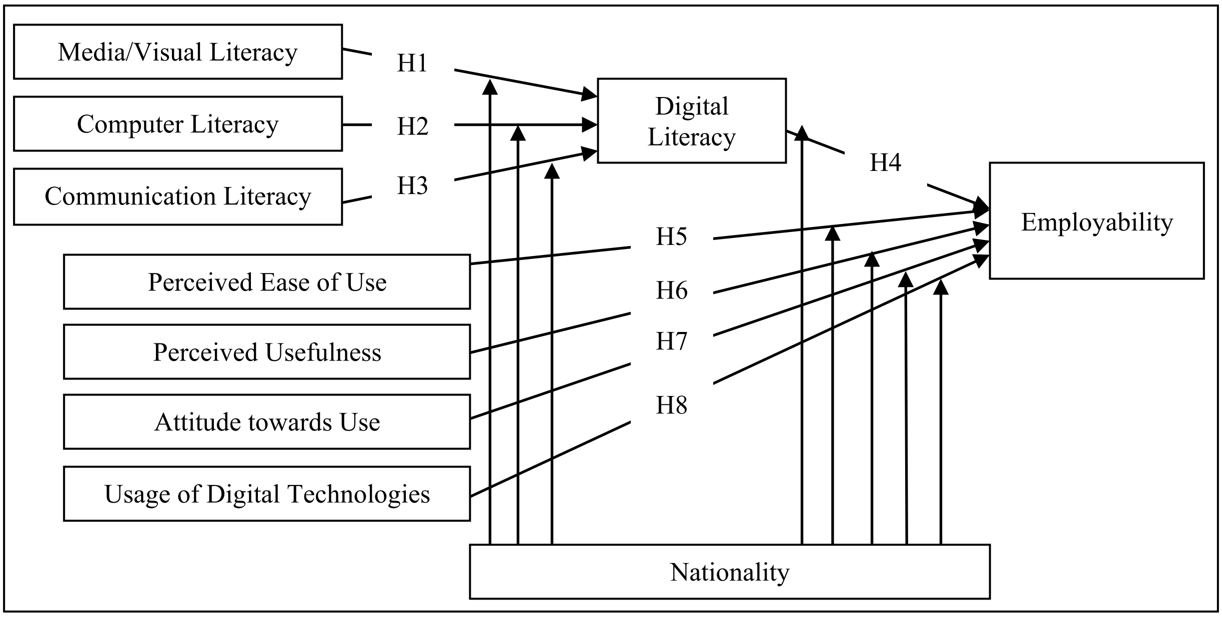

Figure 1. Conceptual Framework
Source: Nikou, S., Reuver, M.D., and Kanafi, M.M, 2022; Reddy, P., Chaudhary, K., and Hussein, S., 2023

Digital Literacy

Digital literacy skill set includes media/visual literacy, communication literacy, and computer literacy (Ng, 2012), which are crucial for individuals to swift digital changes and foster both personal and professional development (Zahoor et al., 2023). Research suggests that those with strong digital literacy are more likely to find employment and progress in careers, as they are more adept at completing tasks efficiently with technology (Ukwoma & Iwundu, 2016).

H1: Media and visual literacy significantly influence digital literacy.
H2: Computer literacy significantly influences digital literacy.
H3: Communication literacy significantly influences digital literacy.
H4: Digital literacy significantly influences employability among employed individuals.

Perceived Ease of Use (PEOU)

PEOU is a central element of the Technology Acceptance Model (TAM) and is critical for an individual's understanding technology adoption (Davis, 1989). Research has demonstrated that when people find digital tools easy to use, they are more likely to incorporate them, which boosts productivity (Venkatesh & Davis, 2000).

H5: PEOU significantly influences the use of digital technologies among employed individuals.

Perceived Usefulness (PU)

PU describes the degree to which individuals believe that using a technology will enhance their job performance (Davis, 1989). As a foundational TAM component, PU has been extensively researched, showing that when users view a technology as valuable, they are more likely to use it, resulting in improved job performance and employability (Venkatesh & Davis, 2000).

H6: Perceived usefulness significantly influences the use of digital technologies among employed individuals.

Attitude

Attitude towards technology denotes an individual's positive or negative disposition toward using specific digital tools (Ajzen & Fishbein, 1980). In relation to digital literacy and employability, a favorable attitude toward technology is importan to influences the willingness to engage with and use these tools. Research suggests that a positive attitude increases PEOU and PU, leading to higher technology adoption and job performance (Taylor & Todd, 1995; Nikou et al., 2021).

H7: Attitude towards digital technologies significantly influences the use of digital technologies among employed individuals.

Usage of Digital Technologies

Digital technology usage indicates the level of individuals' engagement with digital tools in their routine tasks. Regular and proficient use of these tools is associated with enhanced digital literacy and increased employability. Studies emphasize that individuals who consistently use digital technologies are better equipped to handle the demands of the digital workforce (Hargittai, 2010).

H8: Usage of digital technologies significantly influences employability among employed individuals.

Employability

Employability encompasses the skills, knowledge, and attributes that enhance an individual's likelihood of securing and advancing in employment (Yorke, 2004). In the digital era, employability is increasingly tied to digital literacy, as employers seek candidates proficient in digital tools. Consequently, improving digital literacy is essential to boost employability, equipping individuals with the competencies necessary for success in today's workforce (Zahoor et al., 2023).

H9: Nationality moderates the relationship between factors and employability.

2. RESEARCH METHOD

In order to meet the research objectives and evaluate the proposed outcomes, this study adopted a quantitative research approach and used purposive sampling to focus on individuals currently employed. Determining an appropriate sample size is an essential step in both social science and business research, commonly achieved through power analysis (Faul et al., 2007). Based on Cohen's (1988), G*Power software was used to calculate the sample size of the study where the minimum sample size of 118 participants, with parameters set at $\alpha = 0.01$ and $1-\beta = 0.95$. To fulfill this criterion, 238 responses were gathered from employed individuals in Malaysia, and 231 responses from Indonesia.

The questionnaire was designed to facilitate effective data collection while maintaining simplicity for participants. Section A focused on evaluating independent variables related to digial and information literacy. Sections C, D, and E included items to measure perceived ease of use, perceived usefulness, and attitudes toward technology. Section F explored employability as the dependent variable, and Section H gathered respondents demographic information. Items in Sections B through F were rated using a five-point Likert scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The digital literacy questions were adapted from the works of Zahoor et al. (2023), Simon et al. (2017), Ukwoma et al. (2016), and Ng (2012), while information literacy items were based on Zahoor et al. (2023) and Ukwoma and Iwundu (2016). Questions on attitude, perceived ease of use, and perceived usefulness were adapted from Reddy et al. (2023), and employability questions were based on Zahoor et al. (2023).

Four human resource specialists were selected for pre-testing to ensure the clarity and practicality of the questionnaire. After confirming that the statements were clear, the main data collection phase began. Following the recommendations of Morris and Rosenbloom (2017) and Worthington and Whittaker (2006), 50 questionnaires were then distributed for the pilot study.

3. RESULTS AND DISCUSSIONS

This research developed an enhanced model to evaluate employment potential by integrating eight key constructs. To determine the structure of these variables and investigate their relationships, an exploratory factor analysis (EFA) was initially performed on a pilot sample of 50 participants, followed by confirmatory factor analysis (CFA) and covariance based structural equation modeling (CB-SEM) on a larger sample of 469 participants (238 from Malaysia and 231 from Indonesia).

Descriptive Analysis

Table 1 shows the respondents demographic profiles from Malaysia and Indonesia. In Malaysia, most respondents are female, making up 66.0% of the sample, compared to 50.6% in Indonesia. Conversely, the proportion of male respondents is higher in Indonesia at 49.4%, whereas in Malaysia it is lower at 34.0%. The age distribution shows that most Malaysian respondents are between 30 and 39 years old, representing 72.7% of the sample, while in Indonesia, a significant portion, 60.2%, are aged 29 and below. This indicates a younger demographic in Indonesia compared to Malaysia. The percentage of respondents aged 40 and above is relatively low in both countries, with Malaysia at 15.1% and Indonesia at 10.8%.

Regarding education levels, most Malaysian respondents hold a diploma or lower (64.2%), whereas in Indonesia, a larger proportion has a bachelor's degree (66.2%) or a postgraduate degree (25.1%). This suggests that Indonesian respondents generally have higher educational attainment compared to their Malaysian counterparts. In terms of industry sectors, both countries have a high proportion of respondents working in the private sector—76.1% in Malaysia and 81.8% in Indonesia. The public sector employs 19.7% of Malaysians and 9.5% of Indonesians, while the not-for-profit sector has a minor presence in both countries.

The data on firm age reveals that in Malaysia, most respondents are employed in firms that are ten years or older, with 66.4% in this category. In Indonesia, a similar pattern is observed, with 56.3% working in firms of the same age range. Additionally, there is a higher proportion of Indonesian respondents working in firms that are less than one year old (6.1%) and those aged 1 to 3 years (16.0%), compared to their Malaysian counterparts.

Table 1. Demographic Profile of Respondents (Malaysian=238; Indonesian=231)

Variable	Malaysia	Indonesia	Variables	Malaysia	Indonesia
Gender			**Industry Sector**		
Male	34.0	49.4	Public Sector	19.7	9.5
Female	66.0	50.6	Private Sector	76.1	81.8
			Not-For-Profit Sector	4.2	1.7
Age			Others	0.0	6.9
29 and below	12.2	60.2			
30 to 39	72.7	29.1	**Firm Age (Years)**		
40 and above	15.1	10.8	Less than 1 year	0.4	6.1
			1 - 3	0.4	16.0
Education Level			4 - 6	6.7	14.3
Diploma and below	64.2	8.6	7 - 9	26.1	7.4
Bachelor’s degree	27.7	66.2	10 and above	66.4	56.3
Postgraduate	7.9	25.1			

For the EFA of the 25 items, principal axis factoring with Promax rotation was used, in line with the recommendations of Costello and Osborne (2005) for social science research, where factors tend to correlate. Factor loadings were assessed based on the criteria established by Hair et al. (2010), with a threshold of 0.40 considered significant for sample sizes of 100 or more. The results of Bartlett’s test of sphericity were significant at $p < 0.01$ (Field, 2013), and the Kaiser-Meyer-Olkin (KMO) measure was 0.899, indicating excellent adequacy of the sample size (Hutcheson and Sofroniou, 1999). One item was excluded due to communalities score lower than 0.5 (Field, 2013). The extracted factors accounted for 63.012% of the total variance, surpassing the 50% threshold recommended by Podsakoff and Organ (1986), with the first factor explaining 12.978% of the variance, suggesting that no single factor dominates the data.

Model Fi Indicators

Table 2 provides the fit indices for the measurement model, summarizing the model's overall suitability through absolute, incremental, and parsimonious fit measures. Hair et al. (2010) recommend evaluating at least one index from each category to confirm model fit in structural equation odelling. The primary fit indices are divided into absolute, incremental, and parsimonious categories.

Absolute fit indices gauge the model's direct alignment with the observed data without referencing a baseline model. In this study, the GFI (0.932) and AGFI (0.908) exceed the recommended thresholds respectively, demonstrating a good fit. Additionally, the RMSEA value of 0.040 and SRMR of 0.037 are well below the acceptable 0.08 threshold (Steiger, 1990; Hu & Bentler, 1999), supporting a strong absolute fit.

Incremental fit indices assess how well the model performs compared to a null model. Here, all four incremental fit measures indicate a good fit. The NFI (0.916) exceeds the recommended threshold of 0.80 (Bentler & Bonnet, 1980), and the CFI (0.961) surpasses the 0.90 guideline (Byrne, 2010). Additionally, the TLI (0.952) and IFI (0.962) are both above the 0.90 threshold (Tucker & Lewis, 1973; Bollen, 1990), confirming the model's robustness. Parsimonious fit indices reflect model fit while accounting for model complexity. The Chisq/df ratio of 1.763 falls within the acceptable range of 1.00 to 5.00 (Kline, 2010), suggesting an appropriate balance between fit and simplicity. Furthermore, PGFI (0.685) and PNFI (0.730) exceed the 0.50 guideline (James et al., 1982; Bentler & Bonnet, 1980), indicating efficient fit without excessive complexity.

Table 2. Goodness-of-Fit Indices

Category	Index	Adequate of Model Fit	Result	Fit
Absolute Fit Measure	GFI	> 0.90	0.932	Yes
	AGFI	> 0.80	0.908	Yes
	RMSEA	< 0.08	0.040	Yes
	SRMR	< 0.08	0.037	Yes
Incremental Fit Measure	NFI	> 0.80	0.916	Yes
	CFI	> 0.90	0.961	Yes
	TLI	> 0.90	0.952	Yes
	IFI	> 0.90	0.962	Yes
Parsimonious Fit Measure	Chisq/df	1.00-5.00	1.763	Yes
	PGFI	> 0.50	0.685	Yes
	PNFI	> 0.50	0.730	Yes

Notes: The indexes are recommended by Awang (2014)

Construct Reliability

Reliability for the six main latent variables was validated through Cronbach's alpha and Composite Reliability (CR) coefficients. The Cronbach's alpha scores ranged from 0.651 to 0.855, all above the 0.60 threshold (Nunnally & Bernstein, 1994), establishing internal consistency. CR values for all constructs were between 0.893 and 0.966, surpassing the 0.70 minimum recommended (Fornell & Larcker, 1981), indicating that the constructs are reliable with minimal error, as shown in Table 3.

Indicator Reliability

Indicator reliability assesses the extent to which individual items align with their constructs. According to Hair et al. (2013), high factor loadings indicate strong commonality with the construct. All items in this study had loadings above the 0.50 threshold, ranging from 0.504 to 0.611 (Hair et al., 2010), demonstrating that no items needed removal from the scale, as they contributed reliably. Items with loadings between 0.40 and 0.70 were retained, as their exclusion would not significantly enhance CR or AVE values (Hair et al., 2011).

Convergent Validity

Convergent validity, evaluated using the Average Variance Extracted (AVE), measures the extent to which a construct accounts for the variance in its indicators. For convergent validity to be considered satisfactory, the AVE values should be at least 0.50 (Hair et al., 2013). In this study, the AVE values ranged between 0.507 and 0.611, indicating that the constructs adequately explain more than 50% of the variance in their indicators, as detailed in Table 3.

Table 3. Model Fit Indicators for the Full Model

Construct	Items	Cronbach Alpha (>0.6)	Factor Loading (>0.5)	CR (>0.7)	AVE (>0.5)	Skewness	Kurtosis
Media and Visual Literacy	MV1	0.835	0.707	0.963	0.566	-1.017	1.367
	MV2		0.689			-0.911	0.936
	MV3		0.781			-0.911	1.703
	MV4		0.827			-0.907	0.775
Computer Literacy	CL1	0.651	0.806	0.893	0.507	-1.063	2.191
	CL2		0.604			-1.562	4.232
Communication Literacy	COML1	0.697	0.696	0.911	0.538	-0.988	1.780
	COML2		0.769			-0.904	1.193
Perceived Ease of Use	PEOU1	0.855	0.751	0.980	0.598	-0.487	-0.040
	PEOU2		0.787			-0.876	1.817
	PEOU3		0.803			-0.469	-0.254
	PEOU4		0.753			-0.329	-0.254
Perceived Usefulness	PU1	0.720	0.789	0.925	0.565	-0.601	-0.302
	PU2		0.713			-0.550	-0.438
Attitude	ATTI1	0.699	0.748	0.920	0.542	-0.285	-0.735
	ATTI2		0.724			-0.844	1.428
Digital Literacy	DL1	0.759	0.784	0.900	0.611	-0.847	0.372
	DL2		0.779			-0.765	1.718
Employability	EMP1	0.749	0.662	0.966	0.504	0.667	0.554
	EMP2		0.746			-0.713	0.770
	EMP3		0.721			-0.747	0.667
Usage of Digital Technologies	UG2	0.818	0.734	0.954	0.540	-0.666	-0.396
	UG3		0.819			-0.752	-0.735
	UG4		0.767			-0.689	-0.654
	UG5		0.601			-0.857	-0.708

Discriminant Validity

Table 4 displays the discriminant validity results using the Fornell-Larcker criterion, which assesses whether each construct is distinct from others. The square root AVE for Media and Visual Literacy (MV) is 0.566, which is greater than its correlations with constructs like Computer Literacy (CL) at 0.317 and Digital Literacy (DL) at 0.521, confirming that MV is distinct. All constructs met this criterion, verifying discriminant validity.

Table 4. Fornell-Lacker Criterion

	MV	CL	COML	DL	PEOU	PU	ATT	EMP	UG
MV	0.566								
CL	0.317	0.507							
COML	0.432	0.477	0.538						
DL	0.521	0.347	0.524	0.611					

PEOU	0.485	0.417	0.473	0.524	0.598				
PU	0.229	0.358	0.334	0.293	0.341	0.565			
ATT	0.389	0.239	0.301	0.348	0.473	0.274	0.542		
EMP	0.385	0.314	0.367	0.476	0.485	0.482	0.443	0.504	
UG	0.266	0.202	0.202	0.222	0.246	0.103	0.247	0.196	0.540

Structural Model Assessment

After validating the measurement model, the structural model was assessed to explore the relationships between the constructs. This model outlines the interactions between exogenous and endogenous variables, offering a clearer understanding of how the constructs are connected (Hair et al., 2010; Ho, 2006). Evaluating the structural model ensures that the theoretical framework is supported by empirical evidence and helps determine whether the hypotheses are consistent with the data (Hair et al., 2013). The findings of the structural model are presented in Figures 2 and 3.

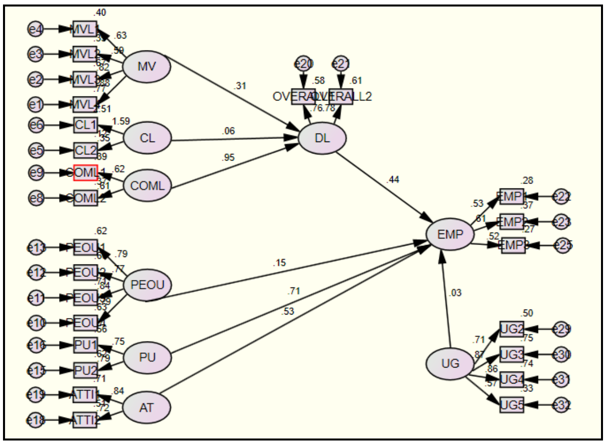

Figure 2. Structural Model (Indonesia)

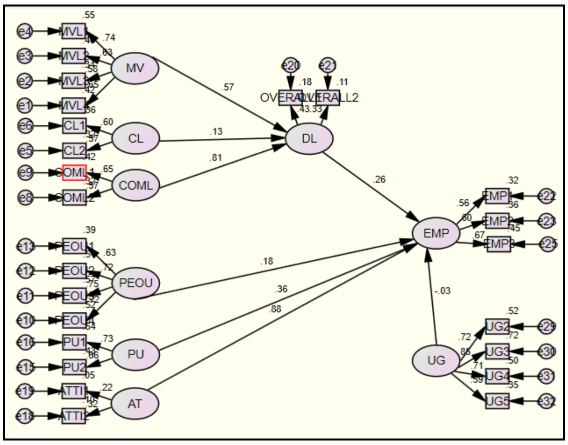

Figure 3. Structural Model (Malaysia)

Hypothesis Tests

Based on the detailed results and discussion of Table 5 and Table 6, the moderation effect of nationality (Malaysia vs. Indonesia) on the overall model was examined. However, despite differences in the magnitude of relationships between constructs in both groups, the multi-group analysis reveals no significant moderation effect of nationality.

Table 5. Moderation Effect of Marital Status on Overall Model

Model	CMIN	DF	P value
Unconstrained	1600.529	538	0.000
Measurement residuals	2230.501	594	0.000
Model Comparison	629.972	56	0.000

The multi-group analysis (Table 6) assesses whether nationality (Malaysian or Indonesian) significantly moderates the structural paths. For moderation to occur, the beta coefficients between the two groups should show significant differences. However, the following conditions, which indicate a lack of moderation where Beta for Group 1 (e.g., Indonesian) is significant while Group 2 (e.g., Malaysian) is not: For example, the impact of Communication Literacy (COML) towards Digital Literacy (DL) is significant for both Indonesia ($\beta = 1.075$, $p < 0.001$) and Malaysia ($\beta = 0.397$, $p < 0.001$), but the strength of the relationship is stronger in Indonesia. Although there is a difference in beta values, both are in the same direction (positive). This suggests that the relationship exists in both groups, but at varying strengths, meaning nationality does not moderate the effect fundamentally. Secondly, if both groups show significant results, but one is positive and the other negative, none of the relationships in this model display this kind of opposing result. For instance, in the relationship between Usage of Digital Technologies (UG) and Employability (EMP), neither group shows significance (p-values of 0.678 and 0.714, respectively). This consistency further suggests that nationality does not fundamentally alter the perception of how these constructs interact.

Surprisingly, the result shows that perception is consistent across both nationalities. Although some paths show stronger or weaker effects based on nationality, this does not constitute a moderation effect. Rather, it suggests that both Indonesian and Malaysian respondents share the same overall perception, with differences only in the strength of certain relationships.

The impact of Media and Visual Literacy (MV) towards Digital Literacy (DL) is significant for both nationalities, but slightly stronger for Malaysians ($\beta = 0.284$) compared to Indonesians ($\beta = 0.232$). However, since the relationship is in the same direction and significant in both groups, it implies that nationality does not alter the fundamental perception of this relationship.

While the relationship between Computer Literacy (CL) and Digital Literacy (DL) shows no significant in either group, with p-values of 0.698 (Indonesia) and 0.495 (Malaysia). This suggests that computer literacy does not significantly impact digital literacy in either country.

Moreover, the relationship between Communication Literacy (COML) and Digital Literacy (DL) shows that there is a stark difference between the two countries. In Indonesia, the impact is very strong ($\beta = 1.075$) and highly significant ($p < 0.001$), whereas in Malaysia, the relationship is significant but weaker ($\beta = 0.397$, $p < 0.001$). This suggests that communication literacy plays a much larger role in influencing digital literacy in Indonesia compared to Malaysia.

Both countries show a significant positive relationship between digital literacy and employability. However, this relationship is stronger in Malaysia ($\beta = 0.440$, $p = 0.020$) than in Indonesia ($\beta = 0.258$, $p < 0.001$), suggesting that digital literacy has a greater influence on employability for Malaysians.

While the relationship between PEOU and EMP also shows significance for both groups, with a slightly stronger effect for Malaysians ($\beta = 0.136$) than Indonesians ($\beta = 0.093$). Despite the difference in magnitude, the relationship holds for both groups, indicating a shared perception of how ease of use affects employability.

In both Indonesia and Malaysia, perceived usefulness significantly impacts employability. However, the effect is much stronger in Indonesia ($\beta = 0.525$, $p < 0.001$) than in Malaysia ($\beta = 0.269$, $p = 0.003$), highlighting the greater role of usefulness perception in shaping employability in Indonesia.

Interestingly, attitude toward employability differs greatly between the two countries. In Indonesia, the effect is moderate ($\beta = 0.314$, $p < 0.001$), but in Malaysia, it is much stronger ($\beta = 2.201$, $p = 0.016$). This suggests that attitude is a major factor in determining employability in Malaysia.

The path between Usage of Digital Technologies (UG) and Employability (EMP) is not significant for either group, indicating that the usage of digital technologies does not have a meaningful impact on employability in either Indonesia or Malaysia.

In conclusion, Since the beta coefficients for the two groups are either both significant or both not significant, and none of the paths show opposing signs (i.e., one positive and one negative), it can be concluded that nationality does not significantly moderate the relationships in the model. The chi-square results and model comparison also indicate no significant moderation effect, as the difference in model fit was significant, but the pattern of beta coefficients did not meet the criteria for moderation.

Thus, despite the slight differences in how strong certain constructs relate to each other, both Malaysian and Indonesian respondents perceive these constructs in a similar way. Nationality does not meaningfully alter the relationships in this model, reinforcing that no moderation effect of nationality exists based on the multi-group analysis results.

Table 6. Structural Path Analysis Result

Hypothesis				Indonesian			Malaysian		
				Estimate	S.E	P Value	Estimate	S.E	P Value
H_1	DL	←	MV	0.232	0.048	***	0.284	0.088	0.001***
H_2	DL	←	CL	0.031	0.080	0.698	0.073	0.106	0.495
H_3	DL	←	COML	1.075	0.129	***	0.397	0.125	0.001***
H_4	EMP	←	DL	0.258	0.051	***	0.440	0.189	0.020**
H_5	EMP	←	PEOU	0.093	0.044	0.033**	0.136	0.066	0.038**
H_6	EMP	←	PU	0.525	0.086	***	0.269	0.090	0.003***
H_7	EMP	←	ATT	0.314	0.063	***	2.201	0.912	0.016**
H_8	EMP	←	UG	0.015	0.037	0.678	-0.012	0.034	0.714

***Significant at 0.01

4. CONCLUSION AND SUGGESTIONS

In conclusion, the study reveals no significant moderation effect of nationality between Malaysia and Indonesia on the constructs related to digital literacy and employability. This finding highlights the consistency of perceptions across both countries and suggests that interventions to improve digital literacy can be applied uniformly in these contexts. This study able to demonstarte the relationships between digital literacy, employability, and related constructs, such as media literacy and perceived ease of use, remain consistent across different nationalities (Malaysia and Indonesia). The findings suggest that nationality does not moderate these relationships, providing further validation for the generalizability of theoretical models across different cultural contexts.

For managers and policymakers, this research indicates that strategies aimed at enhancing digital literacy and employability can be applied consistently across both Malaysian and Indonesian markets. Marketing efforts focused on improving digital competencies and perceived ease of use are likely to yield similar results in both countries, allowing for a unified regional approach. Practitioners, such as educators and corporate trainers, can adopt similar frameworks to enhance digital literacy and employability skills, knowing that nationality does not significantly impact the effectiveness of these interventions. Training programs can be designed with a standardized approach for both Malaysian and Indonesian audiences, improving efficiency in implementation.

This study is limited by its focus on only two nationalities and a specific set of constructs. Future research could expand the scope to include additional countries or explore other potential moderating variables, such as socio-economic status or education level, to provide a more comprehensive understanding of how these factors influence the relationships in the model.

REFERENCES

Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. Prentice-Hall.

Awang, Z. (2014). *Structural Equation Modeling Using AMOS*, University Teknologi MARA Publication Center, Shah Alam.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. Practical Assessment, Research and Evaluation, 10(7), 1-9.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

European Commission. (2016). Europe's Digital Progress Report 2016. Brussels. Retrieved from https://ec.europa.eu/digital-single-market/en/download-scoreboard-reports

Faul, F., Erdfelder, E., Lang, A. G., and Buchner, A. (2007). G* power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behav. Res. Methods 39, 175–191. https://doi: 10.3758/BF03193146

Ferrari, A. (2012). Digital Competence in Practice: An Analysis of Frameworks. JRC Technical Report, European Commission - Joint Research Centre, Publications Office of the European Union.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). Sage Publications Ltd, London.

Fornell, C., & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50. https://doi.org/10.2307/3151312

Gilbert, S. (2017). Information literacy skills in the workplace: examining early career advertising professionals. *Journal of Business and Finance Librarianship, 22(*2), 111-134.

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson, NJ.

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2013). *A Primer on Partial Least Squares Structural Equation Modeling (PLS- SEM),* Sage Publications, CA.

Hair, J.F., Ringle, C.M., & Starstedt, M. (2011). PLS-SEM: indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139-151. https://doi.org/10.2753/MTP1069-6679190202

Hargittai, E. (2010). Digital na(t)ives? Variation in internet skills and uses among members of the 'Net generation'. *Sociological Inquiry, 80*(1), 92-113.

Ho, R. (2006). Handbook of Univariate and Multivariate Data Analysis and Interpretation with SPSS, Chapman & Hall/CRC, Taylor & Francis Group, Boca Raton, FL.

Hu, L., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modelling*, 6, 1-55.

Hutcheson, G.D., & Sofroniou, N. (1999). *The Multivariate Social Scientist*, Sage, London.

Joreskog, K. G., & Sorbom, D. (1989). LISREL 7: *A guide to the program and applications. Chicago*: SPSS, Inc.

Kang, H. (2021). Sample size determination and power analysis using the G* power software. J. Educ. Eval. Health Prof. 18(17). https://doi: 10.3352/jeehp.2021.18.17

Morris, N. S., and Rosenbloom, D. A. (2017). Defining and understanding pilot and other feasibility studies. *The American journal of nursing*, 117, 38–45.

Ng, W. (2012). Can we teach digital natives digital literacy? *Computers and Education, 59(*3), 1065-1078.

Nikou, S., De Reuver, M., & Mahboob Kanafi, M. (2021). Workplace literacy skills—how information and digital literacy affect adoption of digital technology. *Journal of Enterprise Information Management, 34(*6), 1649-1672. https://doi.org/10.1108/JEIM-01-2020-0010

Nunnally, J.C., & Bernstein, I.H. (1994). *Psychometric Theory*, McGraw-Hill, New York, NY.

OECD. (2016). New Skills for the Digital Economy: *Measuring the Demand for ICT Skills at Work*. OECD Digital Economy Papers No. 258, OECD Publishing.

Podsakoff, P.M., & Organ, D.W. (1986). Self-reports in organizational research: problems and prospects. Journal of Management, 12(4), 531-544. https://doi.org/10.1177/014920638601200408

Reddy, P., Chaudhary, K., & Hussein, S. (2023). *A digital literacy model to narrow the digital literacy skills gap*. Heliyon, 9, e14878.

Simon, M., Meeus, W., & T'sas, J. (2017). Developing a questionnaire for assessing teachers' competencies in media literacy education. *Journal of Media Literacy Education, 9*(1), 99-115.

Taylor, S., & Todd, P. A. (1995). Assessing IT usage: The role of prior experience. *MIS Quarterly, 19(*4), 561-570.

Ukwoma, S., Iwundu, N.E., & Iwundu, I. E. (2016). Digital literacy skills among students of UNN: Implications for effective learning and performance. *New Library World, 117*(11/12), 702-720.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

World Economic Forum. (2016). The Future of Jobs. *Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution*. Geneva.

Worthington, R.L., & Whittaker, T.A. (2006). Scale development research: a content analysis and recommendations for best practices. Counseling Psychologist, 34(6), 806-838. https://psycnet.apa.org/doi/10.1177/0011000006288127

Yorke, M. (2004). Employability in Higher Education: What It Is – What It Is Not. *Higher Education Academy/ESECT.*

Zahoor, N., Zopiatis, A., Adomako, S., & Lamprinakos, G. (2023). The micro-foundations of digitally transforming SMEs: Exploring the interplay between digital literacy, technology, and managerial attributes. *Journal of Business Research, 159*(113755), 1-12.

Zahoor, Z., et al. (2023). Digital literacy and employability: A comparative study. *Journal of Information Technology Education: Research, 22*, 123-140.