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INDUSTRY PERSPECTIVES ON DIGITAL COMPETENCES AMONG MBKM INTERNS IN INDONESIA

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ABSTRACT

Indonesia's digital economy is expanding at a breakneck pace, highlighting the urgent need for digital competencies that align with industry demands. Addressing this critical issue, the Ministry of Education, Culture, Research, and Technology of Indonesia has initiated the *Merdeka Belajar Kampus Merdeka* (MBKM) program, one of the programs, emphasizing practical internships to enhance undergraduates' digital skills. This research aims to examine the effectiveness of the MBKM initiative in narrowing the disparity between graduates' digital competencies and the evolving needs of various industries, shedding light on the program's role in fostering digital readiness among undergraduatesThis research scrutinizes the impact of the MBKM initiative on bridging the gap between graduates' digital competencies and the expectations of diverse industries. It specifically assesses the efficacy of the program in cultivating essential digital skills through IT-related tasks in various sectors. Employing a Likert-scale questionnaire rooted in the DigComp 2.0 framework, the research surveyed host companies across Jakarta, evaluating the digital proficiency of MBKM interns and their readiness for employment. Analysed through the Smart PLS, the research employed PLS-SEM to unravel the influence of digital competencies on employability. Findings indicate that one digital competence, Digital Content Creation, is significantly associated with employability prospects. Conversely, Information and Data Literacy, Communication and Collaboration, Safety, and Problem Solving did not exhibit a substantial direct effect on employability. This research underlines the critical nature of enhancing specific competencies within the MBKM framework to better prepare Indonesia's workforce for the demands of a digital future. The insights gleaned offer strategic implications for refining educational programs and underscore the importance of continual alignment with industry needs, thereby strengthening the nation's digital talent pool.

Keywords : *Digital Competences; Internship; MBKM*

INTRODUCTION

Indonesia's Digital economy is projected to reach USD 146 billion by 2025 representing approximately 40% of the Southeast Asia digital economy (BI, 2022). Digital transformation plays an important role that contributes to significant economic growth in Indonesia, one of the examples is digitalisation in the finance industry. With society joining the digital era, financial inclusion has increased in which 65.4% of the adult population has a formal bank account with 83.6% of aforementioned population having used financial products and services (BI, 2022). This accomplishment optimistically will bring Indonesia to achieve the target of 90% financial inclusion by 2024. It is predicted that with the immense growth taking place, the digital economy will reach approximately USD 315.5 billion by 2030 (Sekertariat Kabiner, 2021).

Looking at the aforementioned high trajectory of digital economy, an immense digital transformation in every sector has to take place and digital talent demand will definitely increase to serve the digital ecosystem (Gong & Ribiere, 2021). According to the Minister of Communication and Information Technology, Indonesia, at current rate, needs at least 600,000 digital talents every year to navigate the driver of the digital ecosystem (Kementerian Komunikasi dan Informatika, 2022). It is projected that there will be a shortage of 47 million digital talents in 2030 (Kementerian Komunikasi dan Informatika, 2022) and at national level, it is recorded that at least 50% of the talents have only basic and intermediate digital skills while only 1% that have advanced digital skills (Andarningtyas & Ad, 2022).

During the pandemic COVID-19 situation, digital transformation was not delayed, but it even has taken place aggressively. Lots of activities or daily routines that were done offline have shifted online, one of the examples is the education system. During the pre-pandemic, education system was rarely run online whereby students always came to their schools or other education institutions. Due to the rule of physical distancing or social distancing, students had to study at home and familiarise themselves with technologies such as Google Meet, Zoom and any other online medium that helped the education be delivered without having to attend the class physically. This rule-changing condition has also happened in workplaces imposing a new working rule which was Working from Home (WFH) or the other term used was Working from Anywhere (WFA) by which employees did not have to attend the work physically and their performance indicator suddenly changed to result-oriented rather than process-oriented as their superiors could not monitor them closely (UNESCO, 2018).

Innovation and technology have brought a bunch of benefits to today's world, however, there is one thing to remember that digital transformation is a changing process and it's not only applied to the technology, but also to the talents. From the employment perspective, despite digital transformation promotes various new job creations, a new set of digital skills are required to fill those jobs. The talents have to be transformed into digital talents that are equipped with digital skills, therefore, upskilling and reskilling contribute a crucial role in digital transformation. As digital competence is a lifelong learning, digital talents have to keep enhancing their skills in order to adapt to this fast-changing digital ecosystem. Future is unpredictable, hence the ability to adapt to an even more digital future depends on developing the next generation of skills so as to close the gap between talent supply and demand (Frankiewicz & Chamorro-Premuzic, 2020).

In the midst of the enormous demand of digital talent, there is a gap between digital talent availability and job opportunities, simply because current available talents or graduates are considered lacking of digital competence (Vuorikari et al., 2016). While the demand for digital talent is reaching 600,000 every year, Indonesia's unemployment rate in 2022 exists at 5.83% or equals to 8.4 million people currently unemployed with the detailed information provided in Table 1 according to BPS (2022). The highest rank of unemployment is dominated by senior high school (SMA) and vocational high school (SMK) graduates. According to Ali et al. (2020), there is a substantial mismatch between vocational education provider and the needs of the industries due to the limitations in terms of quality human resources, facilities, infrastructure, curricula and work culture that meets industries' standards while vocational education itself should be promoting ready-to-work graduates

Table 1 Unemployment Status

Education	2021		2022
	February	August	February
Not School	20.461	23.905	24.852
Not graduated	342.734	431.329	437.819
Elementary School	1.219.494	1.393.492	1.230.914
Junior High School	1.515.089	1.604.448	1.460.221
Senior High School	2.305.093	2.472.859	2.251.558
Vocational High School	2.089.137	2.111.338	1.876.661
Academy/ Diploma	254.457	216.021	235.359
University	999.543	848.657	884.769
Total	8.746.008	9.102.052	8.402.153

The gap of digital talent in Indonesia has been a huge challenge that needs to be solved in order to promote digital transformation that contributes to the growth of the digital economy. The collaboration between the stakeholders including government, educators and industries will be pivotal to the attainment of a digital ecosystem. Thus, digital talent is one crucial component to support Indonesia in achieving top 10 in world's major economies by 2030 (Sekretariat Kabinet, 2018).

Indonesian digital startups have been growing significantly and it is stated that there are more than 2,000 startups running in 2022. These startups are reinforcing the digital transformation and the formation of the digital economy by supporting the incumbents to become digital. At this rate, digital talent will be hugely demanded not only by the startups, but also by the incumbents and unfortunately, digital talent transformation is not an instant process.

There is a mismatch between graduates' competences and the industry requirements. Lots of industries have difficulty in finding the right digital talent and this is because what industry needs is digital competences, which consist not only the digital hard skills, but also digital soft skills, to adapt with the current situation. Based on the finding obtained by Santoso & Putra (2017), adequate knowledge is not sufficient if the graduates are not equipped with necessary competencies demanded by industries which will affect the chance of employability of the graduates (Oberländer et al., 2020). In addition, the fast development in information and communication technology (ICT) makes it difficult for education institutions to assess the gap between current skills taught and new skills required by the jobs so they fail to instantly adapt to the fast changes of the skills requirements (Mohammad Akhriza et al., 2017).

The homework that is necessary to be accomplished is upgrading existing talents, transforming inadequate talents including the unemployed based on the Table 1, and cultivating the future talents in order to match current and future industry needs or requirements. In conclusion, bridging the digital competences gap between potential talents or graduates and industries is the initial step to increase the employability and reduce the mismatch occurred.

According to Collins (2021), there are several ways to bridge the digital competences gap which are apprenticeship, paid internship, integrating career service into postsecondary institutions, and building strong postsecondary-industry relationship. In Australia and New Zealand, a few models of internships have been promoted and one of the successful programs is cadetship program (Ismail, 2018; Kempegowda & Chaczko, 2018). Cadetship is a mix of industry placement combined with formal study in tertiary education or universities that ensure the students or the cadets gain the right knowledge of technical/hard skills and soft skills through real industry experience (SnelL & Snell-Siddle, 2017). Cadetship programs have shown a positive-proven result and it has been implemented by organizations and industries across Australia and New Zealand to address skills shortage and bridge the skills gap. In Scotland, especially in computing, apprenticeship is more popular because of the integration with work experience and it is a way to ensure that graduates are equipped with the necessary skills for sustainable employment (Taylor-Smith et al., 2019).

In Indonesia, as the initial strategy to address the digital competences gap, the Ministry of Communication and Information Technology (MCIT) has introduced four module of digital literacy which are digital culture, digital safety, digital ethics, and digital skills (Sasongko, 2021). There are three main programs supporting this digital literacy that are categorized into three levels: advanced, intermediate and basic digital skills. In advance level, Digital Leadership Academy (DLA) is initiated to increase the competences of digital decision maker both in public and private sectors, starting with 300 participants conducting online while in intermediate level, there is Digital Talent Scholarship (DTS) that is dedicated to prepare and train 100,000 talents and potential talents including the skills of artificial intelligence, machine learning, cloud computing, cyber security, digital entrepreneurship and digital communication. In the basic level, there is National Digital Literacy Movement (GNLD) Siberkreasi program in collaboration with 34 provincial governments including 514 city governments together with Project Implementation Unit in MICT to address bigger segment that represents 12.4 million Indonesian (Torres-Coronas & Vidal-Blasco, 2011).

Furthermore, The Ministry of Education, Culture, Research and Technology (MoECRT) has also imposed a new policy, named Merdeka Belajar Kampus Merdeka (MBKM), which is a crucial collaboration between universities, industries and government, in relation with cultivating the next wave of digital talents, to achieve and align the goals to minimise the skills gap in Indonesia (Ingsih et al., 2022). MBKM programs are dedicated to give opportunities for undergraduate students exploring their passion and ability outside their current program in university. MBKM offers a variety of activities that can be undertaken by students within or even outside their campus. Students undertake five semesters of their major in the normal circumstances and as part of the MBKM program, they have the right to spend one semester in another major or faculty at the same university and two semesters outside their campus (Rahmawanti & Nurzaelani, 2021). These 3 semesters' activities are designed to assist students to define their real capabilities as well as to equip them with additional knowledge that might not be experienced in their current major and will be useful during their transition into the working world.

There are eight activities offered in MBKM policy which are Student Exchange, Internship, Educational Assistance, Research, Humanity Project, Entrepreneurship, Independent Study, and Community Service Program (Kemeterian Pendidikan, 2020). The most popular activity offered in MBKM that is taken by the students is internship which can be converted into SKS system (Kemeterian Pendidikan, 2020) and the potential host companies have to prepare proper internship material or curriculum that can accommodate the SKS conversion system in order to be accepted and eligible to take the students becoming their interns. This process helps to standardise the industry internship program so the interns can gain valuable experiences more than just administrative working. It is expected that the internship, especially in tech-based companies, can nurture the final year undergraduate students to prepare themselves including their competences when they enter into the digital ecosystem after they graduate from universities so as to increase the chance of employability.

There exists a global framework on digital competences that have been applied and become an integral tool worldwide which is the DigComp 2.0 Framework as detailed in Table 2. The DigComp 2.0 is an EU framework offering a detailed description of all the competences needed to be proficient in today's digital society (Ferrari & Punie, 2013; Law et al., 2018; Martin & Grudziecki, 2006). It encompasses areas like information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. By comprehensively understanding and incorporating this framework, the gap between industry requirements and digital competences of graduates could be bridged.

Table 2 Conceptual Framework DigComp 2.0

Competence Areas (Dimension 1)	Indicators (Dimentions 2)
1. Information and data literacy	1.1. Browsing, searching and filtering, data, information and digital content 1.2. Evaluating data, information and digital content 1.3. Managing data, information and digital content
2. Communication and collaboration	2.1. Interacting through digital technologies 2.2. Sharing through digital technologies 2.3. Engaging in citizenship through digital technologies 2.4. Collaborating through digital technologies 2.5. Netiquette 2.6. Managing digital identity
3. Digital content creation	3.1. Developing digital content 3.2. Integrating and re-elaborating digital content 3.3. Copyright and licences 3.4. Programming
4. Safety	4.1. Protecting devices 4.2. Protecting personal data and privacy 4.3. Protecting health and well-being 4.4. Protecting the environment
5. Problem solving	5.1. Solving technical problems 5.2. Identifying needs and technological responses 5.3. 5.3 Creatively using digital technologies

5.4. 5.4 Identifying digital competence gaps

The MBKM internship aims to provide students with real-world experience and understanding of company needs, hence equipping them with necessary hard and soft skills. Industries, in return, can evaluate and train these future talents, ensuring they meet industry standards upon graduation. The incorporation of the DigComp 2.0 Framework into such initiatives would further bolster the digital competences of graduates.

In conclusion, addressing the digital talent gap is crucial for the continuous growth of Indonesia's digital economy. By leveraging comprehensive tools like the DigComp 2.0 Framework and initiatives like the MBKM program, Indonesia could be better poised to nurture digital talent and reduce the mismatch between potential talents or graduates and industry requirements. As a beginning, this research will therefore focus on assessing the digital competences of the MBKM interns from the industry's perspective.

RESEARCH METHOD

This research aims to assess the digital competences of the MBKM interns with industries serving as the primary stakeholders as they are the ultimate beneficiaries of this digital talent pool. The recent implementation of the MBKM internship program in early 2020 and the paucity of existing data from the industry perspective make this research context unique. The initial step of this research entails identifying the digital competencies that industries expect. This is followed by an evaluation of how the MBKM internship program aligns with these expectations in terms of enhancing the digital competencies of potential graduates.

In light of the lack of comprehensive existing data and the specialized focus of this research, the research will predominantly rely on a primary data collection approach. As such, a Likert-scale questionnaire has been developed to assess the industry's evaluation of the proficiency level in each digital competency exhibited by the MBKM interns. The results obtained from this questionnaire will be analysed using Smart PLS. Moreover, this research will use SEM method which allows for a robust examination of the relationships between observed indicators and latent variables concerning industry-rated digital competencies and the skills exhibited by MBKM interns.

Given the unknown population size of industry representatives who have interacted with the MBKM internship program, a purposive sampling method will be employed (Muijs, 2010). This method facilitates the selection of individuals who have had direct interactions with MBKM interns, thereby ensuring that the responses gathered are informed and relevant to the research objectives.

Aligned with the research questions and hypotheses, the trajectory of this research is exploratory in nature. This approach is geared towards methodically answering the research questions and testing the hypotheses by delving into the relationship between industry expectations, the MBKM internship program, and the digital readiness of potential graduates. Through the exploration and analysis of collected data, the research strives to provide a comprehensive understanding of how the MBKM internship program prepares the digital competencies of potential graduates, and whether this aligns with the expectations of the industry stakeholders. This endeavour is crucial as it informs on the efficacy of the MBKM internship program in preparing graduates for the digital demands of the modern workforce.

The research will begin with gathering responses through a Likert-scale questionnaire which. The aim is to understand what digital skills industries expect from potential employees and how well MBKM interns demonstrate these skills according to industry representatives. serves as a pivotal tool for this research, designed to assess industry representatives' perceptions of the proficiency levels of MBKM interns across various digital competencies and their employability rates within the industry. This questionnaire, based on the DigComp 2.0 framework, ensures comprehensive coverage of digital competence areas and aligns with the research objectives. Prior to administering the questionnaire, a validation process is undertaken to confirm the eligibility and experience of industry representatives in evaluating digital skills. Once validated, data collection proceeds, targeting industry representatives overseeing MBKM interns, particularly those from IT-related host companies, through purposive sampling (Palinkas et al., 2015). This approach ensures a minimum of 60 respondents, in line with SEM guidelines, for a robust analysis of the relationships between interns' digital competencies and their employability rates.

The responses collected will be analysed using Smart PLS. Initially, basic statistics will be used to see if there are any clear trends in the data and following this, a deeper analysis to test the hypotheses will be conducted using SEM method. SEM will help understand the complex relationships between the proficiency levels of MBKM interns and the employability chance for the interns (Pagano, 2012).

Before diving into SEM, validation and reliability tests will be conducted to ensure the data is accurate and consistent. This step is crucial to ensure the trustworthiness of the data before proceeding to test the hypotheses and drawing conclusions regarding the digital competences of the MBKM interns.

Table 3 Research Flow Summary

Research Processes	Summary
Data Collection	• A survey will be conducted utilizing a questionnaire informed by the DigComp 2.0 Framework to assess digital competencies. • The focus is on host companies across Jakarta with MBKM interns engaged in IT-related tasks. • Data of minimum 60 samples will be collected, to provide a representation of industry perspective.
Data Validation	• Preliminary validation will use 30 respondents to test the instrument’s validity and reliability. • R values should be above 0.361 in order to indicate a valid instrument. • Cronbach’s Alpha will be utilized and value above the accepted threshold of 0.7 will indicate high reliability.
Data Analysis	• Smart PLS software will be employed to analyse the data, utilizing descriptive and inferential statistics. • PLS-SEM will be applied to investigate the relationships among digital competencies, perceived proficiency levels of MBKM interns, and their employability. • The analysis will reveal the level of industry’s perception on proficiency levels of key digital competencies.
Hypotheses Testing	• Five hypotheses will be tested using PLS-SEM. • The result is expected to indicate a significant relationship for each digital competencies with employability, through the threshold value of p-value < 0.05 and t-statistics >1.96 which will imply statistical significance, as well as the value of path coefficient which will show the relationship positivity.
Conclusion	• The research will conclude which digital competence is more influential in determining the employability of MBKM interns from the industry perspective. • Whether the MBKM internship program positively impacts digital competency development • The research's implications will also be provided to suggest an urgent need to align educational initiatives with industry expectations to optimize the digital talent pool in Indonesia's evolving digital economy.

RESULT AND DISCUSSION

PLS-SEM Analysis

In this research, the influence between variables will be analysed using the PLS-SEM analysis technique. The stages in PLS-SEM analysis consist of testing the outer model and testing the inner model (Hair et al., 2017). This research model includes six latent variables: Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, Problem Solving, and Employability. All these variables are first-order latent constructs measured by several indicators. The Information and Data Literacy construct is a first-order construct with 3 measurement indicators, the Communication and Collaboration construct is a first-order construct with 6 indicators, the Digital Content Creation construct is a first-order construct with 4 indicators, the Safety construct is a first-order construct with 4 indicators, the Problem Solving construct is a first-order construct with 4 indicators, and the Employability construct is a first-order construct with 10 measurement indicators. The PLS-SEM model specification to be estimated in this research is pictured in Figure 1 SEM-PLS Model Specification.

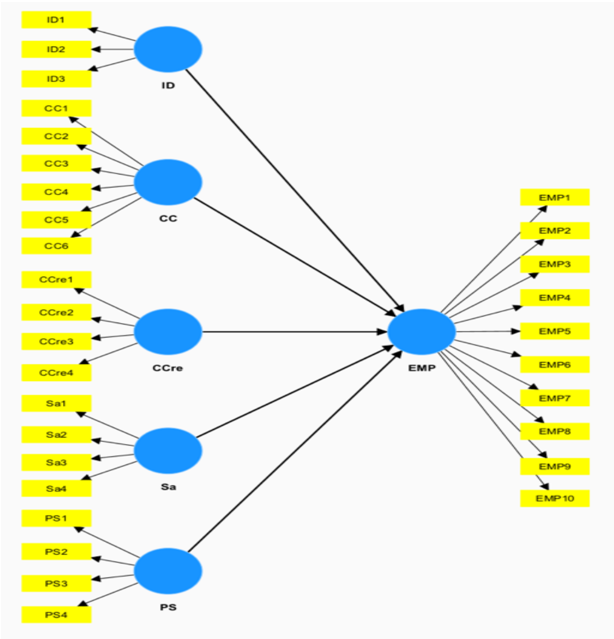

Figure 1 PLS-SEM Model Specification

1. Testing the Outer Model

The measurement model testing phase includes the assessment of Convergent Validity, Discriminant Validity, and Composite Reliability. The results of the PLS analysis can be used to test research hypotheses if all indicators in the PLS model meet the criteria for convergent validity, discriminant validity, and composite reliability. To generate the results of the outer model test, the PLS model must be estimated using an algorithm technique. The figure 2 is the results of the PLS-SEM model estimation after being estimated using the algorithm technique.

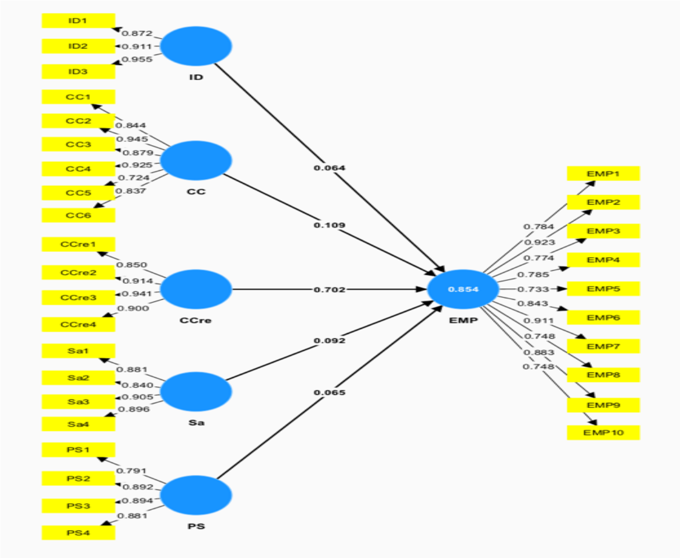

Figure 2 Initial Phase SEM Model Estimation Results

a. Convergent Validity

Based on the SEM model estimation results shown in Figure 2, all remaining variables in the model are valid in their measurement, allowing the testing to proceed to the Average Variance Extracted (AVE) stage. The loading factor values and AVE of the model can be more clearly seen in Table 4 Convergent Validity Test Results.

Table 4 Convergent Validity Test Results

Variable	Indicator	Loading factor	Cut Value	AVE	Convergent Validity
Communication and Collaboration	CC1	0.844	0.7	0.743	Valid
	CC2	0.945	0.7		Valid
	CC3	0.879	0.7		Valid
	CC4	0.925	0.7		Valid
	CC5	0.724	0.7		Valid
	CC6	0.837	0.7		Valid
Digital Content Creation	CCre1	0.850	0.7	0.813	Valid
	CCre2	0.914	0.7		Valid
	CCre3	0.941	0.7		Valid
	CCre4	0.900	0.7		Valid
Employability	EMP1	0.784	0.7	0.666	Valid
	EMP10	0.748	0.7		Valid
	EMP2	0.923	0.7		Valid
	EMP3	0.774	0.7		Valid
	EMP4	0.785	0.7		Valid
	EMP5	0.733	0.7		Valid
	EMP6	0.843	0.7		Valid
	EMP7	0.911	0.7		Valid
	EMP8	0.748	0.7		Valid
	EMP9	0.883	0.7		Valid
Information and Data Literacy	ID1	0.872	0.7	0.834	Valid
	ID2	0.911	0.7		Valid
	ID3	0.955	0.7		Valid
Problem Solving	PS1	0.791	0.7	0.749	Valid
	PS2	0.892	0.7		Valid

	PS3	0.894	0.7		Valid
	PS4	0.881	0.7		Valid
Safety	SA1	0.881	0.7	0.776	Valid
	SA2	0.840	0.7		Valid
	SA3	0.905	0.7		Valid
	SA4	0.896	0.7		Valid

The SEM model estimation results in Table 4 show that all constructs are valid and have an Average Variance Extracted (AVE) > 0.5, meaning that they meet the required convergent validity based on loading factor and AVE values.

b. Discriminant Validity

Discriminant validity is essential for ensuring that each latent variable in a model distinctly captures its intended construct, separate from others in the model. An established criterion for assessing discriminant validity is the Fornell-Larcker criterion, which posits that a model exhibits strong discriminant validity when the square root of the AVE (Average Variance Extracted) for each construct is greater than the construct's correlations with other constructs. Table 5~~3~~ presents the results of the discriminant validity assessment.

Table 5 Discriminant Validity according to the Fornell-Larcker Criterion

	CC	**CCre**	**EMP**	**ID**	**PS**	**SA**
CC	0.862					
CCre	0.564	0.902				
EMP	0.588	0.915	0.816			
ID	0.004	0.353	0.353	0.913		
PS	0.465	0.731	0.715	0.188	0.865	
SA	0.562	0.875	0.839	0.303	0.795	0.881

The results from Table 5 largely support the discriminant validity of the constructs within the PLS model, as the square roots of the AVEs for most constructs are higher than their inter-construct correlations, as per the Fornell-Larcker criterion. There are some instances where the correlations slightly exceed the square roots of the AVEs.

However, these instances are minimal and do not significantly detract from the overall discriminant validity of the model. This is further corroborated by additional robustness checks through cross-loadings, where each indicator's loading on its own construct is compared with its cross-loadings on other constructs. According to this criterion, an indicator demonstrates adequate discriminant validity if its loading on its own construct is higher than on any other construct. These results underscore the distinctiveness of the constructs and support the validity of the model, reinforcing the reliability of the findings and the soundness of the PLS model's application in this research.

Table 6 Discriminant Validity according to Cross Loading Values

	CC	**CCre**	**EMP**	**ID**	**PS**	**SA**
CC1	0.844	0.580	0.575	0.128	0.468	0.593
CC2	0.945	0.553	0.555	-0.013	0.453	0.559
CC3	0.879	0.461	0.488	-0.017	0.478	0.513
CC4	0.925	0.532	0.535	0.048	0.420	0.491
CC5	0.724	0.309	0.365	-0.179	0.245	0.314
CC6	0.837	0.425	0.485	-0.018	0.295	0.382
CCre1	0.514	0.850	0.745	0.324	0.577	0.756
CCre2	0.412	0.914	0.835	0.411	0.662	0.792
CCre3	0.572	0.941	0.889	0.315	0.701	0.817
CCre4	0.538	0.900	0.824	0.225	0.690	0.790

EMP1	0.509	0.635	0.784	0.287	0.423	0.612
EMP10	0.416	0.572	0.748	0.163	0.391	0.521
EMP2	0.577	0.889	0.923	0.341	0.657	0.798
EMP3	0.459	0.671	0.774	0.185	0.580	0.554
EMP4	0.508	0.655	0.785	0.234	0.667	0.643
EMP5	0.300	0.678	0.733	0.201	0.668	0.665
EMP6	0.414	0.887	0.843	0.397	0.634	0.800
EMP7	0.588	0.866	0.911	0.367	0.659	0.792
EMP8	0.425	0.703	0.748	0.284	0.504	0.668
EMP9	0.571	0.806	0.883	0.341	0.600	0.714
ID1	-0.030	0.244	0.249	0.872	0.036	0.160
ID2	-0.105	0.287	0.271	0.911	0.169	0.267
ID3	0.096	0.399	0.407	0.955	0.260	0.360
PS1	0.349	0.671	0.588	0.255	0.791	0.762
PS2	0.514	0.631	0.683	0.149	0.892	0.692
PS3	0.385	0.650	0.604	0.154	0.894	0.677
PS4	0.345	0.580	0.590	0.096	0.881	0.623
SA1	0.485	0.826	0.752	0.275	0.769	0.881
SA2	0.566	0.794	0.747	0.289	0.560	0.840
SA3	0.456	0.721	0.746	0.291	0.700	0.905
SA4	0.472	0.738	0.709	0.210	0.775	0.896

Based on the results in Table 6, all indicators have the highest loading on their respective constructs, fulfilling the discriminant validity requirements. Besides the Fornell-Larcker and cross-loading tests, discriminant validity can also be assessed using the Heterotrait-Monotrait Ratio (HTMT) between constructs. HTMT, an alternative method recommended for assessing discriminant validity, uses a multitrait-multimethod matrix as its basis. The HTMT value should be less than 0.9 to ensure discriminant validity between two reflective constructs (Henseler et al., 2015). In this testing, constructs in the PLS model meet discriminant validity if the HTMT value between constructs does not exceed 0.9.

Table 7 HTMT Between Latent Constructs

	CC	CCre	EMP	ID	PS	S
CC						
CCre	0.599					
EMP	0.620	0.968				
ID	0.126	0.372	0.357			
PS	0.499	0.807	0.774	0.201		
S	0.603	0.958	0.900	0.317	0.890	

Based on the results in Table 7, while most construct pairs in PLS model are well within this threshold, a few constructs pairs exhibit HTMT values marginally above it. Despite these minimal exceedances, the overall pattern of HTMT values supports the assertion that the constructs in the PLS model retain distinct conceptual definitions. The instances where the HTMT values slightly surpass the threshold can be attributed to the inherent complexity and interrelatedness of the constructs under study, which does not substantially compromise the model's discriminant validity. The outer model of the PLS, therefore, still demonstrates a robust discriminant validity.

a. Construct Reliability

Construct reliability is assessed by the Cronbach's Alpha and Composite Reliability values of each construct. The recommended values for composite reliability and Cronbach's Alpha are more than 0.7.

Table 8 Composite Reliability

Construct	Cronbach's Alpha	Composite Reliability	Reliability
CC	0.929	0.945	Reliable
CCre	0.923	0.946	Reliable
EMP	0.943	0.952	Reliable
ID	0.902	0.938	Reliable
PS	0.887	0.922	Reliable
Sa	0.903	0.933	Reliable

Based on the analysis in Table 8, the composite reliability and Cronbach's Alpha values of all constructs exceed 0.7, indicating that all constructs meet the required reliability. Considering the overall results of the validity and reliability tests in the outer model testing phase, it can be concluded that all indicators validly measure their constructs and all constructs are reliable, allowing the testing to proceed to the next phase, the inner model testing.

2. Testing the Inner Model

a. Testing the Goodness of Fit of the Model

The goodness of fit of a PLS model can be determined by the R Square, Q Square, and SRMR (Standardized Root Mean Square Residual) values. The R Square value indicates the model's strength in predicting dependent variables, Q Square indicates the level of predictive relevance of the model, and SRMR indicates the goodness of fit of the model, categorizing it as either perfect fit, fit, or bad fit.

- Assessment of R Square Model

According to Chin (2013), an R Square value > 0.67 indicates a strong PLS model in predicting endogenous variables, an R Square between 0.33 – 0.67 indicates a moderately strong model, and an R Square between 0.19 – 0.33 indicates a weak model in predicting endogenous variables. The analysis results in Table 9 show that the R Square for employability is 0.854, categorizing it as strong.

Table 9 R Square Values

Variable	R Square	Criteria
Employability	0.854	Strong

- Assessment of Q Square Model

Q Square indicates the predictive relevance of the model. A Q Square value between 0.02 – 0.15 indicates low predictive relevance, a Q Square between 0.15 – 0.35 indicates moderate predictive relevance, and a Q Square > 0.35 indicates high predictive relevance (Chin, 2013). The analysis results in Table10 show that the Q Square for employability falls into the category of high predictive relevance.

Table 10 Q Square Values

Variable	Q Square	Criteria
Employability	0.824	High

- Assessment of SRMR Model

In addition to R Square and Q Square values, the goodness of fit of the model is also assessed by the SRMR of the estimated model. A model is considered a perfect fit if the SRMR is < 0.08 and fit if the SRMR is between 0.08-0.10. The analysis results in the table 11 show that the SRMR of the estimated model is 0.086, categorizing it as a fit.

Table 11 SRMR

Component	SRMR	Criteria
Saturated Model	0.086	Fit
Estimated Model	0.086	

b. Multicollinearity

Multicollinearity assessment within the PLS-SEM framework is conducted through the Variance Inflation Factor (VIF) of the inner model constructs. A VIF value below 5.00 typically suggests an absence of multicollinearity, ensuring that the regression model's estimates remain unbiased and reliable. According to the value presented in Table 12, the VIF values for the majority of constructs in the inner model are comfortably below the threshold, signifying a multicollinearity-free model. However, one construct marginally exceeds this limit with a VIF value of 5.639, which suggests a need for a more nuanced interpretation (Fisher, 1922).

This slightly elevated VIF value warrants further inspection but does not necessarily imply a significant multicollinearity issue within the model. Given the conservative nature of the VIF threshold, values that marginally exceed 5.00 may not dramatically affect the validity of the regression estimates. Consequently, while the presence of a VIF value above 5.00 merits acknowledgement and consideration, it does not invalidate the model. The integrity of the PLS-SEM model is upheld by the overall pattern of low VIF values across the constructs, and the analysis proceeds with a mindful recognition of the indicated multicollinearity check.

Table 12 VIF Inner Model

	CC	CCre	EMP	ID	PS	SA
CC			1.617			
CCre			4.765			
EMP						
ID			1.239			
PS			2.802			
SA			5.639			

c. Testing Direct Effects

In PLS analysis, after the model is proven to be fit, testing the influence between variables can be conducted. This includes testing direct effects, indirect effects, and total effects. The following Figure 3 shows the results of the PLS-SEM model estimation using the bootstrapping method.

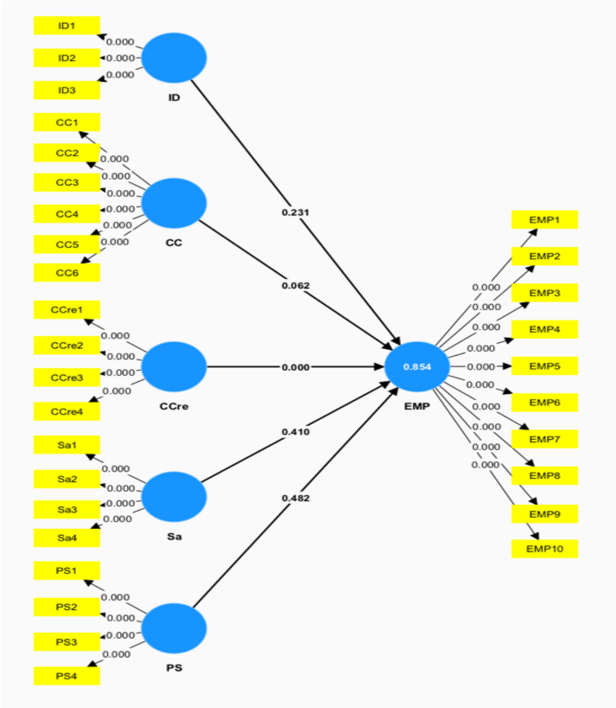

Figure 3 Bootstrapping Model Estimation Results

Based on the PLS model estimation results using the bootstrapping technique with 500 samples, the following Table 13 are the results of the testing of the influence between variables.

Table 13 Results of Testing Direct Effects

Path	Path Coefficient	T-Statistics	P-Values
CC -> EMP	0.109	1.874	0.062
CCre -> EMP	0.702	5.391	0.000
ID -> EMP	0.064	1.200	0.231
PS -> EMP	0.065	0.703	0.482
SA -> EMP	0.092	0.825	0.410

Direct effects, often referred to as direct impact, are the influences of exogenous variables directly on endogenous variables without going through other (intervening) variables. In PLS-SEM analysis, the significance and direction of direct effects are determined by the p-value, t-statistics, and path coefficients for each path connecting endogenous and exogenous variables. If the p-value obtained in the relationship between variables is < 0.05 and t-statistics > 1.96 (two-tailed t-value, α 5%) and t-statistics > 1.65 in one-tailed tests, it is concluded that the exogenous variable significantly influences the endogenous variable in the direction indicated by the sign of its path coefficient. Conversely, if the p-value is > 0.05 and t-statistics < 1.96 (two-tailed t-value, α 5%) in two-tailed tests and t-statistics < 1.65 in one-tailed tests, it is concluded that the exogenous variable does not significantly influence the endogenous variable (Hair et al., 2019). Based on these test results, the following conclusions are drawn:

- Communication and Collaboration → Employability

The relationship between communication and collaboration and employability, while positive, is not statistically significant with a p-value of $0.062 > 0.05$. The path coefficient is 0.109, and the t-statistics are $1.874 < 1.96$, just below the conventional significance threshold. This suggests that the influence of communication and collaboration on employability, although present, is not significant.

- Digital Content Creation → Employability

The analysis reveals a strong positive relationship between digital content creation and employability. The path coefficient of 0.702 signifies a substantial effect, and with t-statistics of 5.391 > 1.96, this relationship is statistically significant beyond the 0.05 p-value threshold. The findings suggest that proficiency in digital content creation is a key driver of employability, reflecting the growing demand for these skills in the job market.

- Information and Data Literacy → Employability

The relationship between information and data literacy and employability is observed with a path coefficient of 0.064. However, the associated t-statistics of 1.200 indicate that this effect is not statistically significant, as the p-value of 0.231 > 0.05. This suggests that, within the scope of this analysis, information and data literacy do not have a direct measurable impact on employability.

- Problem Solving → Employability

Problem-solving is not statistically significant to employability, as reflected by a p-value of 0.482 > 0.05 and t-statistics of 0.703 < 1.96. This indicates a weak influence of problem-solving skills on employability.

- Safety → Employability

Safety's influence on employability is not statistically significant with a p-value of 0.410 > 0.05 and t-statistics of 0.825 < 1.96. This suggests that the level of safety does not have a strong predictive power or does not have a significant influence on employability.

d. Coefficient of Determination

In a structural model, the exogenous variables in the research model simultaneously influence the endogenous variable. The extent of the contribution of all exogenous variables to the endogenous variable can be seen from the coefficient of determination. The coefficient of determination is indicated by the Adjusted R Square value, which ranges between 0-1, or can also be interpreted as a percentage (0-100%). A higher coefficient of determination indicates a greater proportion of the variance in the endogenous variable explained by its exogenous variables, while a lower coefficient of determination suggests a relatively low influence of the exogenous variables on the endogenous variable. This is because there are still many factors outside of these exogenous variables that can influence the endogenous variable.

Table 14 Coefficient of Determination

	R Square	R Square Adjusted
Employability	0.854	0.842

The analysis results in Table 14 show that the adjusted R square for employability is 0.842, meaning that 84.2% of the variance in employability is influenced by Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem Solving, while the remaining 15.8% of employability is influenced by other factors outside of Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem Solving.

Hypothesis Testing

The hypothesis testing in this research is based on the results of the PLS-SEM analysis. Below is a summary of the hypothesis testing results in this research as disclosed in Table 15~~3~~.

Table 15 Hypothesis Testing Results

No.	Hypothesis	Regression Coefficients	Conclusion
H1	Information and Data Literacy has significant relationship with Employability	Path Coefficient = 0.064; T-Statistics = 1.200; P-Value = 0.231	Not Significant
H2	Communication and Collaboration has significant relationship with Employability	Path Coefficient = 0.109; T-Statistics = 1.874; P-Value = 0.062	Not Significant
H3	Digital Content Creation has significant relationship with Employability	Path Coefficient = 0.702; T-Statistics = 5.391; P-Value = 0.000	Significant
H4	Safety has significant relationship with Employability	Path Coefficient = 0.092; T-Statistics = 0.825; P-Value = 0.410	Not Significant
H5	Problem Solving has significant relationship with Employability	Path Coefficient = 0.065; T-Statistics = 0.703; P-Value = 0.482	Not Significant

The explanations of the hypothesis testing results are as follows:

- **Hypothesis 1 (H1)**: states that information and data literacy have a positive, but not significant effect on employability. The analysis results show a p-value of 0.231, t-statistics of 1.200, and a positive path coefficient of 0.064. Since the p-value is > 0.05 and t < 1.96, it can be concluded that information and data literacy positively, but not significantly affect employability, therefore, this result indicates a rejection of H1.
- **Hypothesis 2 (H2)**: states that communication and collaboration have a positive, but not significant effect on employability. The analysis results show a p-value of 0.062, t-statistics of 1.874, and a positive path coefficient of 0.109. Since the p-value is > 0.05 and t < 1.96, it can be concluded that communication and collaboration positively, but not significantly affect employability, therefore, this result indicates a rejection of H2.
- **Hypothesis 3 (H3)**: states that digital content creation has a positive and significant effect on employability. The analysis results show a p-value of 0.000 and t-statistics of 5.391. Since the p-value is < 0.05 and t > 1.96, it can be concluded that digital content creation positively and significantly affects employability, therefore, this result indicates a clear confirmation of H3. Furthermore, digital content creation has the highest path coefficient among other digital competence components which indicates this digital competence influences employability more than the other digital competencies.
- **Hypothesis 4 (H4)**: states that safety has a positive, but not significant effect on employability. The analysis results show a p-value of 0.410, t-statistics of 0.825, and a positive path coefficient of 0.092. Since the p-value is > 0.05 and t < 1.96, it can be concluded that safety positively, but not significantly affects employability, therefore, this result indicates a rejection of H4.
- **Hypothesis 5 (H5)**: states that problem solving has a positive, but not significant effect on employability. The analysis results show a p-value of 0.482, t-statistics of 0.703, and a positive path coefficient of 0.065. Since the p-value is > 0.05 and t < 1.96, it can be concluded that problem solving positively, but not significantly affects employability, therefore, this result indicates a rejection of H5.

Discussion on each Digital Competencies

a. Re-evaluating the Role of Information and Data Literacy in Employability
The research indicates that information and data literacy, while positively associated with employability, does not have a statistically significant impact. This finding prompts a re-examination of how these competencies are perceived and valued in the industry. While data literacy remains a critical skill for navigating a data-driven landscape, its direct correlation to employability may not be significant. This nuanced understanding calls for a broader approach to developing digital competencies that reflect the multifaceted nature of employability.

b. Communication and Collaboration's Subtler Influence on Employability
The research suggests that communication and collaboration, essential skills in the workplace, contribute positively but not significantly to employability. This nuanced result challenges the assumption of their direct impact on job prospects. While these competencies are undoubtedly valued, the findings imply that additional factors may play a more pivotal role in employability, necessitating a more comprehensive skill set for MBKM interns.

c. Digital Content Creation as a Key Driver of Employability
In a significant finding, digital content creation emerges as a vital competence with a substantial and significant positive effect on employability. This marks the positioning creative digital skills as a critical component for the graduates seeking to stand out in the job market. The research underscores the necessity of integrating digital content creation into curricular activities to enhance job readiness and align with industry trends.

d. Safety's Unexpected Minor Role in Employability
In this research, safety does not significantly influence employability, though it maintains a positive relationship. This suggests that while important, safety competencies alone may not be sufficient indicators of job readiness. This insight calls for a re-evaluation of safety within the digital competence framework, potentially integrating it with broader skill sets to meet the complex demands of the digital workforce.

e. Re-thinking the Impact of Problem-Solving Skills on Employability
This research highlights that problem-solving, while positively aligned with employability, does not significantly determine job prospects. This unexpected outcome indicates that while problem-solving is critical, it may operate synergistically with other skills rather than independently influencing employability. It suggests that a holistic approach, combining problem-solving with other digital and non-digital competencies, might better prepare MBKM interns for the multifarious challenges of the modern workplace.

Managerial Implications

The important findings of this research have been summarized, followed by the managerial responses as well as the persons who are responsible to take such implications as shown in Table14.

Table 16 Managerial Implications of the Research

No.	Research Finding	Managerial Response	Executors
1	Digital Content Creation as a Key Competency	Amplify focus on Digital Content Creation within MBKM training, recognizing its substantial impact on employability.	Educational Institutions and MBKM Program Coordinators
2	Moderate Proficiency in Information and Data Literacy, Communication and Collaboration, Safety and Problem Solving	Intensify training in Information and Data Literacy, Communication and Collaboration, Safety and Problem Solving for MBKM interns, given their moderate proficiency and positive relationship on employability.	MBKM Program Developers and Educational Institutions

3	Alignment with Industry Standards	Strengthen the synergy between educational institutions and industries to customize MBKM programs to industry-specific digital skill requirements.	Educational Institutions, Industry Partners, and MBKM Program Developers
4	Policy Development	Advocate for policies that facilitate the integration of digital competencies in MBKM programs, particularly those most impactful on employability.	Government Bodies, Educational Policy Makers, and Industry Leaders

Limitation of the Research

Despite the insights gained from this research, it's important to acknowledge certain limitations that may have influenced the outcomes, including sample specificity and methodological constraints.

a. Sample Specificity: The research focused on IT-related tasks, potentially overlooking the importance of competencies in non-IT sectors.
b. Small Sample Size: The limited sample size might not fully represent the diverse digital competency landscape across industries.
c. Industry Specificity: The research centered primarily on IT-related industries, possibly neglecting the needs of other sectors
d. Temporal Scope: The research's timeframe may not capture the evolving nature of digital competencies and industry requirements.
e. Methodological Limitations: Reliance on self-report questionnaires could introduce biases.
f. Limited Generalizability: The findings may not be broadly applicable outside the Indonesian context.

Recommedation for Future Research

Building upon the findings and limitations, several recommendations emerge for future research and practical applications, aiming to address gaps in knowledge and enhance the effectiveness of educational programs in aligning with industry needs.

a. Diversify Research Focus: Investigate the importance of different competencies across various industry contexts.
b. Curriculum Enhancement: Integrate key findings into educational programs to better prepare students for employability.
c. Industry-Education Collaboration: Foster closer collaboration between industries and educational institutions to ensure relevance and alignment of training programs.
d. Policy Alignment: Formulate policies that align educational programs with industry needs.
e. Promote Lifelong Learning: Encourage continuous skill development to keep pace with technological advancements.

CONCLUSION

In conclusion, this research provides valuable insights into the alignment between the digital competencies of MBKM interns and industry requirements in Indonesia. Through rigorous analysis, it has identified Digital Content Creation as a crucial competency directly impacting employability, emphasizing the significance of creative and technical skills in the digital realm. However, there exists a moderate perception gap in proficiency levels among interns, particularly in competencies like Information and Data Literacy and Safety, suggesting a need for recalibration in educational programs to better meet industry demands.

The MBKM internship program demonstrates a positive influence on competency development, bridging theoretical knowledge with practical application. Yet, the diversity in competency significance underscores the necessity for a nuanced program design. Prioritizing digital content creation skills within MBKM could ensure interns possess both theoretical knowledge and practical capabilities highly sought after in today's job market.

Moving forward, it is imperative to acknowledge the limitations of this research, such as the focus on IT-related tasks and the small sample size. These constraints inform the interpretation of findings and guide future research endeavours. Addressing these limitations involves broadening research focus across industries, integrating diverse methodological approaches, and considering longitudinal studies to track competency evolution over time.

The main implications of these findings are twofold: firstly, educational programs, particularly the MBKM initiative, should prioritize the development of digital content creation skills to enhance interns' job readiness; secondly, stakeholders, including educational institutions, industry partners, government bodies, and policymakers, should collaborate to tailor educational programs to industry needs, ensuring graduates are equipped with the necessary digital competencies for the evolving job market

Recommendations stemming from this research highlight the need for future studies to delve into the varying importance of competencies across different industry contexts. Additionally, integrating insights from this study into curriculum development, fostering closer collaboration between industries and educational institutions, and formulating policies to align educational programs with industry needs are crucial steps forward.

In essence, this research lays a foundational blueprint for enhancing the MBKM internship program's efficacy in Indonesia. By aligning program objectives with identified digital competencies, stakeholders can ensure interns are equipped not only for current digital demands but also for future technological advancements. This alignment is pivotal for sustaining Indonesia's growth and competitiveness in the global digital landscape, fostering a workforce adaptable to the rapid changes defining this era of digital transformation.

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