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# Investigation of workplace literacy in Indonesia to enhance employability opportunities

# David Sukardi Kodrat<sup>a\*</sup>, Damelinda Basauli Tambunan<sup>a</sup> and Wendra Hartono<sup>a</sup>

| <sup>a</sup> Universitas | Cinutra | Surabaya  | Indonesia |
|--------------------------|---------|-----------|-----------|
| Universitus              | Cipuira | surabaya, | maonesia  |

| CHRONICLE   | A B S T R A C T   |
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| Article history:<br>Received: October 10, 2023<br>Received in revised format:<br>November 20, 2023<br>Accepted: February 4, 2024<br>Available online:<br>February 4, 2024<br>Keywords:<br>Indonesians cultural<br>Digital literacy<br>Employability<br>Information literacy<br>Workplace literacy | Indonesia's enduring vision 2045 requires sustained growth driven by productivity and human resources quality. A goal attainable only through a workforce proficient in critical thinking and digital literacy. Despite the acknowledged significance of digital literacy, there is limited empirical evidence on its effects, especially concerning employment prospects. While information and digital literacy are increasingly recognized as vital competencies within organizations, existing literature has somewhat overlooked the literacy levels of employees. This study aims to explore the impact of information and digital literacy on employees' perspectives regarding the utility and user-friendliness of digital technologies, subsequently assessing the implications for their overall employability in Indonesia. A survey involving 258 Indonesians. Data collecting is conducted through questionnaires and analysis using structural equation modeling investigates the factors influencing employability using the Technology Acceptance Model. The findings reveal that in Indonesia, there is a heightened emphasis on computer literacy and information literacy in both educational and professional realms. This might be due to the Indonesian education system and industry standards prioritizing these specific digital competencies, considering them essential for navigating technology, accessing information, and effectively utilizing digital tools in the professional sphere. |
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# 1. Introduction

Workplace has experienced a gradual shift towards greater integration of technology, the emergence of new roles, and the elimination of old ones (Khan, et al., 2022). At the same time, the education sector continues to experience evolution driven by major changes in the fields of information and technology (Kolbjornsrud, et al., 2016; Dewi et al., 2021). Now, modern education is not just about factual knowledge, but prioritizes the development of soft skills, including communication, creative thinking, and adaptability (Khan, et al., 2022) to create a more humanistic education (Fahmi, 2021). The skills sought are not only academic qualifications, but also prioritizing the ability to analyze and interpret data, as well as apply knowledge effectively in the workplace.

Traditionally, the three Rs (reading, writing, and basic arithmetic) serve as a benchmark for knowledge, communication skills, and predictors of success in the workplace (Jose, 2016). However, today's workplace shows that traditional literacy skills are still lacking (Jose, 2016) requiring a focus on judgment work, treating Intelligent Machines as "Colleagues", working like a designer, and developing social skills and networks (Kolbjornsrud, et al. , 2016). This new literacy includes communication, problem solving, analysis, assessing, evaluation, collaboration, construction, creation, and proficiency in information technology and digital tools (Jose, 2016). Growing trends suggest that mastery of these literacies is critical to achieving success in an interconnected world, as researchers such as Kist (2013) and Dudeney (2014) observe.

\* Corresponding author. E-mail address: <u>david.kodrat@ciputra.ac.id</u> (D. S. Kodrat)

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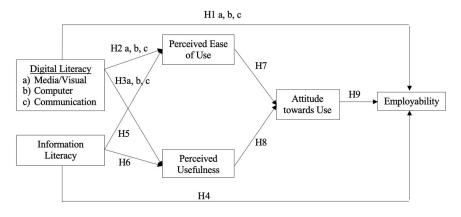
The term "digital literacy" was first coined in the 1980s. Initial understanding shows the ability to use a computer for work. Gilster (1997) has expanded the concept of digital literacy by defining it as a set of attitudes, understanding, and skills required to handle and communicate information effectively through various media and formats. In contrast to a rigid list of skills, Gilster's concept encapsulates a broader idea, aligned with contemporary interpretations of literacy, involving the proficient use of technology to write, read, and handle information. On the other hand, Martin (2008) defines digital literacy as the ability to understanding their effective use and awareness of their social impact. Digital literacy will improve communication, work efficiency and productivity, especially in collaboration with other people who have similar abilities (Martin, 2008). In today's highly competitive market, digital literacy is considered not only a necessity in the workplace but also an important life skill (Morris, 2018). This can empower individuals to create, manage, and derive value from information and turn it into practical use (Khan, et al., 2022).

Dudeney (2015) highlights that new literacies, such as communication, interaction, analysis, collaboration and creation, can be applied to both analog and digital domains. Warschauer's (2011) pedagogical framework focuses on content, community, construction, and composition as areas for incorporating digital literacy into educational contexts. These practices contribute to increased information literacy, community building through online networking, multimedia document creation, and composition skills essential for collaborative writing and skills required in work and academic environments.

Indonesia's Vision for 2045 has 4 pillars, namely: (1) human development and mastery of science and technology, (2) sustainable economic development, (3) equitable development, and (4) strengthening national resilience and governance (Ministry of National Development Planning / Bappenas, 2019). This vision requires sustainable, productivity-driven growth through a critically thinking and digitally literate workforce (Kahn, et. al., 2022). Although there is extensive research on the impact of digital literacy in the workplace, attention still needs to be paid to professionals' perceptions and reactions to technological innovations (Chiu & Wang, 2008). Students' attitudes towards digital literacy in the workplace are very important, because a lack of consideration will hinder the implementation of e-learning applications (Admiraal & Lockhorst, 2009). Rapid technological developments encourage the need to explore the impact of individual digital literacy on employability. Digital literacy includes the use of software or digital devices, complex cognitive, emotional and sociological skills that are important in a digital environment (Mohammadyari and Singh, 2015). However, research exploring the factors that encourage employees to become digitally literate in the 21st century workforce is still limited (Khan, et. al., 2022). There is no proper framework or guidance, further exacerbating this gap. Therefore, regular updating of these skills is necessary to keep pace with changing circumstances and the ever-evolving digital information environment. As the labor market undergoes a global transformation, it is necessary to update Computer Information Technology knowledge and skills so that digital literacy emerges as a significant influence on educational outcomes and the labor market. Despite this importance, there is little evidence regarding the impact of digital literacy on academic performance and employment opportunities. Although information and digital literacy has received attention as an important competency for individuals in organizations, employee literacy levels are still neglected in the existing literature. This research aims to investigate the influence of information and digital literacy on employees' perspectives regarding the usefulness and ease of use of digital technology, then assess the implications for their overall employability.

# 2. Literature Review

The theoretical basis of this research is based on the research of Nikou et al. (2022), modified to align with current job skill requirements. To assess and analyze factors that influence work ability by integrating the Technology Acceptance Model (TAM). As an introduction to this research model, new information and digital literacies will be introduced.



**Fig. 1.** Conceptual Framework Source: Nikou, S., Reuver, M.D., and Kanafi, M.M, (2022)

# 2.1 Employability

Digital skills are increasingly recognized as having increasing prospects in the world of work. However, there is a significant research gap in terms of understanding the broader implications of digital literacy on employability due to the greater emphasis on technical proficiency. Existing questions often focus on the acquisition of specific digital competencies, such as the use of software or programming languages, and ignore broader aspects of digital literacy that are important for employability in today's digital era.

Recent investigations have explored various factors influencing employability, including human resource practices (Ybema et al., 2017), career competencies, achievements, graduate employability factors (Finch et al., 2013), social mobility aptitude, technical skills, soft skills, and the role of educators (Choukade & Ingalagi, 2020). However, the research does not directly mention digital skills as one of the causes.

This research aims to fill the existing gap by examining the complexity of digital and information literacy and its implications for employment potential. By considering these dimensions, this research seeks to provide a comprehensive understanding of the impact of digital and information skills on employability. Additionally, this investigation will explore how digital and information literacy intersects with job prospects across a variety of industries and job roles. This research will analyze whether specific industries prioritize different dimensions of digital literacy and how demand for digital skills varies across sectors.

# 2.2 Digital Literacy

The 21st century world of work raises digital literacy as a basic element, which places those who are experts in this field as the main key in the future workforce such as digital platforms and apps; e-commerce and digital business; and Artificial Intelligence (WEF, 2023). While Information Literacy (IL) provides a comprehensive framework for managing and utilizing information, Digital Literacy (DL) specifically focuses on interacting with technology and utilizing Information and Communication Technologies (ICT) for the retrieval and application of information (European Commission, 2016). Digital literacy, skills and competencies have an important role in encouraging community involvement. In addition to social and digital inclusiveness, these skills play an important role in improving one's employability and driving economic progress (Ferrari, 2012). Considering that digital literacy aims to consolidate and distribute work-related knowledge and has a positive correlation between digital literacy and work ability (Ali-Hassan et al., 2011). Even though the results are significant, the impact of digital literacy on employees still receives less attention. Most research focuses on factors that support digital literacy acceptance or the relationship between e-learning acceptance and organizational performance (Ong et al., 2004). At the individual level, few researchers have explored the impact of digital literacy acceptance on individual users. Most studies only examine user satisfaction (Goh, Elliott, & Quon, 2012; Johnson et al., 2008; Roca & Gagne, 2008). This research aims to fill this gap by examining the relationship between digital literacy and its impact on employability. Digital literacy has been proven to reduce stress levels and increase individuals' self-confidence in their performance achievements (Eastin & LaRose, 2000). In the context of e-learning, individuals with low levels of digital literacy have less positive perceptions of its ease of use and usefulness (Ferro et al., 2011). In contrast, those with a high level of digital literacy have confidence in using digital technology to improve performance, making it easier to access, evaluate and adapt the system to their learning needs. High digital literacy reduces cognitive load, as individuals are familiar with the interface, access options, terminology, and norms of new tools.

 $H_1$ : There is a significant relationship between digital literacy (media/visual; computer; and communication) and employability.

**H<sub>2</sub>:** There is a significant relationship between digital literacy (media/visual; computers; and communication) and perceived ease of use.

**H<sub>3</sub>:** There is a significant relationship between digital literacy (media/visual; computers; and communication) and perceived usefulness.

# 2.3 Information literacy

Gilbert (2017) sees the need to cultivate a variety of information literacy competencies including: proficient resource utilization, information synthesis, evaluation, practical application, and collaborative skills. Additionally, there is an increasing demand for digital proficiency in the virtual professional domain. Information literacy involves the skillful application of digital technology to discover, identify, analyze, and integrate resources. This includes assessing resource credibility, using appropriate citation methods, complying with legal and ethical considerations regarding resource use, and formulating research questions appropriately, effectively, and efficiently (Reddy et al., 2021). According to Lloyd and Williamson (2008), information literacy is experienced differently in the work environment. Information skills learned during education may not be transferable to work contexts (Forster, 2017). The performance of work activities requires employees to engage with information in a variety of ways, which means employees' abilities to understand the environment and generally accepted practices must be developed and maintained (Lloyd, 2017).

Yu et al. (2017) argue that information literacy empowers individuals to master information content, broaden investigative horizons, recognize the need for information, and be adept at finding, evaluating, and applying necessary information. Ng (2012) also argues that an information literate individual is an intelligent thinker who is able to effectively find and evaluate web-based information wisely. The two studies, namely Yu et al. (2017) and Ng (2012) contributed to defining information literacy, emphasizing the competencies and skills essential for navigating the complex modern information landscape.

In professional contexts, the scarcity of effective information literacy training often underlies the limited levels of information literacy in the world of work (Gilbert, 2017; Kirton and Barham, 2005). For example, Naveed and Rafique (2018) researched the information literacy of scientists revealing their confidence and proficiency in using search tools and electronic information services, although there were still shortcomings in assessing the certainty of the quality of the information collected. This study aims to bridge this gap by exploring the impact of information literacy on employability outcomes.

H4: There is a significant relationship between information literacy and employability.
H5: There is a significant relationship between information literacy and perceived ease of use.
H6: There is a significant relationship between information literacy and perceived usefulness.

# 2.4 Perceived Ease of Use (PEU) and Perceived Usefulness (PU)

The Technology Acceptance Model (TAM) introduced by Davis in 1989 is a widely accepted and applied conceptual framework for analyzing the adoption and integration of new technology solutions at the individual level and in organizational contexts. This model consists of two main factors: perceived ease of use (PEU), which reflects the user's personal perception of the simplicity associated with interacting with a particular system, and perceived usefulness (PU), which focuses on the user's subjective belief that the use of a particular technology can improve performance their work. The influence of perceived usefulness is clearly visible in shaping individuals' behavioral intentions, which functions as a predictor of their tendency to adopt new technology (Sudaryanto, Hendrawan and Andrian, 2023). As highlighted by Damerji and Salimi (2021), the perceived benefits of digital learning have a significant impact on technology adoption among students in higher education, thereby helping them in completing various tasks. The positive impact of perceived usefulness that perceived ease of use has an important role in shaping students' tendencies to adopt artificial intelligence. The rationale behind this is that easy-to-use technology improves students' perceived performance, thereby influencing the adoption of artificial intelligence. These insights collectively underscore the importance of perceived usefulness and ease of use in driving technology adoption in various fields. In the context of this research, PEU and PU will act as mediators, facilitating understanding of how digital literacy and use of digital technology impacts employee attitudes.

**H**<sub>7</sub>: *There is a significant relationship between perceived ease of use and attitude.* **H**<sub>8</sub>: There is a significant relationship between perceived usefulness and attitude.

# 2.5 Attitude towards Use (ATU)

Attitude in this context refers to consumers' psychological assessment of a product (Ahmmadi et al., 2021). Previous research has succeeded in establishing a relationship between individuals' Attitude Towards Use (ATU) towards smart factory technology and their positive experiences and acceptance of new technology (Oh et al., 2019). The researchers concluded that the success of a business significantly depends on organizational and individual factors, including employees' ATU towards the technology and their perception of ease of use (Oh et al., 2019). Ng (2012) found that students showed more positive attitudes towards the application of e-learning technology after completing a course, indicating a positive change in their perceptions. Kimiloglu et al. (2017) examined ATU e-learning technology for corporate training, revealing positive views from companies who recognized the benefits of integrating such technology into their current practices. With the increasing demand for digital literacy among entrepreneurs and its widespread implementation, it is important to explore the relationship between individual attitudes towards digital literacy and the actual development of digital competencies. Current research has somewhat neglected the impact of attitudes on the formation of individual motivation and engagement during skill development. Therefore, gaining deeper insight into how individuals' attitudes towards digital literacy contribute to directing their employability is critical.

This research aims at addressing this knowledge gap by investigating the influence of attitudes towards the use of digital skills on individual mastery of those skills. Specifically, this research seeks to explore how positive attitudes toward digital skills, including perceived ease of use and perceived usefulness, act as motivational drivers, encouraging individuals to actively participate in learning and refine their digital skills. Ultimately, this active engagement contributes to their overall job security and employability.

# H<sub>9</sub>: There is a significant relationship between attitude and work ability.

# 3. Methodology

To achieve the specified objectives and validate the hypothesized results, a quantitative research methodology was used. A purposive sampling approach was used, targeting currently employed individuals to participate in the survey. In social science and business research, it is common to estimate appropriate sample sizes through power analysis (Faul et al., 2007). G\*Power is a tool that uses various statistical methods, recommended for calculating sample sizes (Kang, 2021). For the ANOVA test, Cohen suggests "small," "medium," and "large" effect sizes of 0.02, 0.15, and 0.35, respectively. In this study, a moderate effect size was applied, resulting in an estimated minimum sample size of 118 ( $\alpha = 0.01$ ,  $1-\beta = 0.95$ ). To ensure that the minimum sample size was met, 258 questionnaires were collected from respondents who were currently working. Data were collected using carefully designed questionnaires to be effective and ensure their length was manageable for respondents. Part A consists of independent variable statements measuring information literacy and digital literacy, including media/visual literacy, communication literacy, and computer literacy. Parts C, D, and E each contain mediator variable questions related to perceived ease of use, perceived usefulness, and attitude. Part F relates to the dependent variable, namely employability. Part H is the respondent's demographic profile consisting of gender, monthly income, age and education level.

Statements in Parts B to F are measured using a five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). Digital literacy statement adapted from Zahoor et al. (2023), Ukwoma et al. (2016), Simon et al. (2017), and Ng (2012), while the variable "information literacy" was adapted from Zahoor et al. (2023) and Ukwoma and Iwundu (2016). Attitude statements, perceived ease of use, and perceived usefulness were adapted from Reddy et al. (2023), and the employability statement was adopted from Zahoor et al. (2023). Online and offline field surveys were conducted in November 2023. To ensure the clarity and feasibility of the questionnaire, a pre-test was given to four randomly selected human resources experts. All statements were deemed clear, leading to the start of pilot data collection. Following Morris and Rosenbloom's (2017) recommendations, 50 survey questionnaires were administered for the pilot study. The reliability of the measurement was validated using Cronbach's Alpha, exceeding the recommended value of 0.7, which indicates a high level of reliability (Nunnally and Bernstein, 1994).

#### 4. Data Analysis and Results

The main goal of this research is to create an improved model for predicting employability. This model consists of five main constructs: digital literacy (encompassing media/visual, computer, and communication skills), information literacy, perceived ease of use, perceived usefulness, and attitude. To ensure the structure of these variables and explore their relationships, exploratory factor analysis (EFA) was carried out with a sample size of 50 respondents, following the recommendations of Worthington and Whittington (2006) and Field (2013). Next, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were used using AMOS, involving a sample of 258 respondents. This approach aims to assess hypotheses derived from existing theory, validate the factor structure (Hair et al., 2013), and reveal relationships between specified constructs.

## 4.1 Descriptive Analysis

Demographic details in Indonesia show that 49.2 percent are men and 50.8 percent are women, as shown in Table 1.

| Variable            | %    | Variables             | %    |  |
|---------------------|------|-----------------------|------|--|
| Gender              |      | Industry Sector       |      |  |
| Male                | 49.2 | Public Sector         | 8.5  |  |
| Female              | 50.8 | Private Sector        | 82.9 |  |
|                     |      | Not-For-Profit Sector | 1.6  |  |
| Age                 |      | Others                | 7.0  |  |
| 18 to 24            | 29.1 |                       |      |  |
| 25 to 29            | 26.7 | Firm Age (Years)      |      |  |
| 30 to 34            | 19.4 | Less than 1 year      | 8.5  |  |
| 35 to 39            | 12.8 | 1 - 3                 | 82.9 |  |
| 40 to 44            | 6.2  | 4 - 6                 | 1.6  |  |
| 45 to 49            | 5.0  | 7 - 9                 | 7.0  |  |
| 50 to 54            | 0.8  | 10 and above          | 0.0  |  |
| Education Level     |      |                       |      |  |
| Secondary Education | 3.9  |                       |      |  |
| Diploma             | 4.7  |                       |      |  |
| Bachelor's degree   | 65.5 |                       |      |  |
| Master              | 22.9 |                       |      |  |
| PhD                 | 3.1  |                       |      |  |

#### Table 1

Summary of Demographic Profile of Respondents (n=258)

There is a trend that women entering the world of work are starting to increase. Based on an analysis of job distribution, Indonesian society shows a higher prevalence in the private sector, namely 82.9 percent, 8.5 percent in the public sector, and 1.6 percent in the non-profit sector. Based on length of service, the majority of Indonesian citizens, 82.9 percent, work in companies with an operational period of 1 to 3 years. This shows the high growth of start-ups in Indonesia with the government's program to create one million new entrepreneurs by 2024. In terms of age, 29.1 percent of Indonesia's population is between 18 and 24 years old. This shows that Indonesia is starting to enjoy a demographic bonus. Regarding educational attainment, 65.5 percent of Indonesians have a bachelor's degree. This is due to the large number of universities in Indonesia, namely around 4,004. Of this number, 184 are state universities, the remaining 3,820 are private universities.

# 4.2 Exploratory Factor Analysis

Exploratory factor analysis (EFA) was used to assess the 41 items using the Principal Axis Factoring (Promax) oblique rotation method. The decision to use oblique rotation was influenced by the recognition that factors in social science research often show interrelationships, in line with Costello and Osborne's (2005) recommendations. The agreement with the statistical assumptions, outlined in Table 2, further validates the feasibility of this analytical approach.

#### Table 2

| Criteria                      | Requirement   |   | Value  |
|-------------------------------|---|---|--------|
| Bartlett's test of sphericity | p<0.01 (Field, 2013)  |   | 0.000  |
| Kaiser-Meyer-Olkin (KMO)      | is marvellous (Hutcheson and Sofroniou, 1999)<br>> 0.90           |   | 0.927  |
| Communalities                 | Removed a communalities value that is less than 0.5 (Field, 2013) | Communication Literacy (3<br>items) were removed due to the<br>value is less than 0.5 |        |
| Total variance explained      | > 50% minimum requirement (Podsakoff and Organ, 1986)             |   | 65.094 |
| First factor's variance       | < 50% threshold (Podsakoff and Organ, 1986)                       |   | 13.211 |

#### 4.3 Measurement Model Assessment and CFA

#### 4.3.1 Model Fi Indicators

Table 3 presents the goodness-of-fit indices for the measurement model, and the recommended benchmarks for each indicator. Based on the guidelines of Hair et al. (2010) regarding structural equation modeling, and comprehensive model suitability assessment by combining indicators from three categories, namely: parsimonious fit, incremental fit, and absolute fit. The Absolute fit indicators are RMSEA of 0.054 and SRMR of 0.052, indicating that both indicators are acceptable. In addition, the GFI coefficient of 0.840 and AGFI of 0.810 also supports this conclusion. In addition, four additional fit indices (NFI, CFI, TLI, and IFI) of 0.852, 0.931, 0.923, and 0.932 respectively all showed acceptable fit values. The parsimony fit index contributed to the overall positive assessment, namely: x2/df value of 1.737, PGFI of 0.707, and PNFI of 0.762. All of these values are considered acceptable. This collective evidence shows that the model effectively fits the data. Next, appropriate models are checked for psychometric aspects such as: indicator reliability, discriminant validity, convergent validity, and concept reliability to provide a more comprehensive evaluation.

#### Table 3

Goodness-of-Fit Indices for the Measurement Model

| Name of Category     | Name of Index                                   | Adequate of Model Fit | Result |
|----------------------|---|-----------------------|--------|
| Absolute Fit Measure | Goodness-of-fit (GFI)                           | > 0.90                | 0.840  |
|                      | Adjusted goodness-of-fit index (AGFI)           | > 0.80                | 0.810  |
|                      | Root mean square error of approximation (RMSEA) | < 0.08                | 0.054  |
|                      | Standardized root mean square residual (SRMR)   | < 0.08                | 0.052  |
| Incremental Fit      | Normed fit index (NFI)                          | > 0.80                | 0.852  |
| Measure              | Comparative-fit-index (CFI)                     | > 0.90                | 0.931  |
|                      | Tucker-Lewis coefficient index (TLI)            | > 0.90                | 0.923  |
|                      | The increment fit index (IFI)                   | > 0.90                | 0.932  |
| Parsimonious Fit     | Chisq/df  | 1.00-5.00             | 1.737  |
| Measure              | Parsimony Goodness-of-Fit Index (PGFI)          | > 0.50                | 0.707  |
|                      | Parsimony normed fit index (PNFI)               | > 0.50                | 0.762  |

# 4.3.2 Construct Reliability

Individual Cronbach coefficients for all latent variables ranged from 0.696 to 0.915, exceeding the acceptable threshold of 0.60, as recommended by Kannana and Tan (2005). In addition, the composite reliability (CR) value exceeds the required threshold, namely 0.7, in accordance with Fornell and Larcker (1981), which indicates that the construct reliability criteria

# 4.3.3 Reliability Indicators

Following the criteria outlined by Hair et al. (2013), high loading structures show strong correlations between related metrics. It is recommended to consider eliminating only loadings in the 0.4 to 0.7 range if this can increase the Composite Reliability (CR) or Average Variance Extracted (AVE) values. Items with loadings below 0.40 should be removed from the scale, as suggested by Hair et al. (2011). In this study, item loadings ranged from 0.681 to 0.898. These values exceed the recommended threshold of 0.4, according to Hair et al. (2011).

# 4.3.4 Convergent Validity

Convergent validity assesses how well a measure correlates with other measures of the same construct, and Average Variance Extracted (AVE) serves as a tool to evaluate this validity (Hair et al., 2013). When AVE is equal to or greater than 0.50, this indicates that the construct accounts for more than half of the variance in the indicator. In contrast, an AVE below 0.50 indicates that conceptual variation cannot fully explain item errors (Hair et al., 2013). Table 4 displays the results of convergent validity assessment using AVE. Media/visual literacy data, as indicated by four items, was excluded from the study because the Average Variance Extracted (AVE) value was below the 0.50 threshold. This decision is consistent with the criteria for ensuring satisfactory construct validity in the overall model.

# Table 4

| Construct             | Items | Cronbach<br>Alpha<br>(>0.6) | Factor<br>Loading<br>(>0.4) | CR<br>(>0.7) | AVE<br>(>0.5) | Skewness | Kurtosis |
|-----------------------|-------|-----------------------------|-----------------------------|--------------|---------------|----------|----------|
|                       | EMP1  | 0.888                       | 0.733                       | 0.982        | 0.552         | -1.017   | 1.077    |
|                       | EMP2  |                             | 0.702                       |              |               | -0.928   | 0.521    |
|                       | EMP3  |                             | 0.759                       |              |               | -0.968   | 0.715    |
| Employability         | EMP4  |                             | 0.738                       |              |               | -0.924   | 0.714    |
|                       | EMP5  |                             | 0.799                       |              |               | -1.173   | 1.503    |
|                       | EMP6  |                             | 0.725                       |              |               | -1.191   | 2.587    |
|                       | ATT1  | 0.812                       | 0.756                       | 0.953        | 0.614         | -1.071   | 0.993    |
| Attitude ATT4         | ATT2  |                             | 0.898                       |              |               | -0.776   | 0.058    |
|                       | ATT3  |                             | 0.681                       |              |               | -0.989   | 1.491    |
|                       | PEOU1 | 0.868                       | 0.774                       | 0.966        | 0.625         | -0.574   | -0.194   |
| Let I Free CIL        | PEOU2 |                             | 0.799                       |              |               | -0.669   | -0.035   |
| Perceived Ease of Use | PEOU3 |                             | 0.824                       |              |               | -0.466   | -0.756   |
|                       | PEOU4 |                             | 0.765                       |              |               | -0.650   | 0.371    |
|                       | PU1   | 0.885                       | 0.697                       | 0.993        | 0.527         | -1.027   | 0.807    |
|                       | PU2   |                             | 0.707                       |              |               | -1.126   | 0.981    |
|                       | PU3   |                             | 0.688                       |              |               | -1.171   | 1.279    |
| Perceived Usefulness  | PU4   |                             | 0.724                       |              |               | -1.307   | 3.620    |
|                       | PU5   |                             | 0.740                       |              |               | -0.760   | 0.277    |
|                       | PU6   |                             | 0.788                       |              |               | -0.680   | -0.510   |
|                       | PU7   |                             | 0.736                       |              |               | -0.897   | 0.367    |
|                       | IL1   | 0.915                       | 0.780                       | 0.991        | 0.558         | -0.901   | 0.361    |
|                       | IL2   |                             | 0.815                       |              |               | -0.585   | 0.201    |
|                       | IL3   |                             | 0.724                       |              |               | -0.767   | 0.603    |
| C                     | IL4   |                             | 0.757                       |              |               | -0.660   | -0.133   |
| nformation Literacy   | IL5   |                             | 0.728                       |              |               | -0.591   | 0.109    |
|                       | IL6   |                             | 0.781                       |              |               | -0.794   | 0.664    |
|                       | IL7   |                             | 0.740                       |              |               | -0.750   | 0.242    |
|                       | IL8   |                             | 0.752                       |              |               | -1.033   | 1.336    |
|                       | MVL1  | 0.812                       | 0.632                       | 0.947        | 0.615         | -0.880   | 0.306    |
| Media/Visual Literacy | MVL2  |                             | 0.810                       |              |               | -0.886   | 0.417    |
| 5                     | MVL3  |                             | 0.888                       |              |               | -0.715   | -0.005   |
| ат.'.                 | CL1   | 0.696                       | 0.738                       | 0.895        | 0.537         | -1.000   | 0.551    |
| Computer Literacy     | CL2   |                             | 0.728                       |              |               | -1.362   | 2.654    |

Loading, Cronbach's Alpha, CR, and AVE for the Full Model

# 4.3.5 Discriminant Validity

Discriminant validity analysis aims to determine whether a construct is different from other constructs empirically, which means that the construct captures a unique phenomenon that is not represented by other constructs in the model (Hair et al., 2013). Discriminant validity testing in the measurement model uses Fornell and Larcker (1981) criteria. Table 5 presents the correlations between the main constructs, which show that these constructs are highly related to their respective indicators compared to other constructs in the model. This shows good discriminant validity (Hair et al., 2013). The correlation between exogenous constructs is less than 0.85 so that it meets the criteria for discriminant validity of the entire

model as a whole (Awang, 2014). Therefore, the analysis confirms that each construct is unique and captures aspects not represented by other constructs in the model.

| Results of Di | Results of Discriminant Validity by Fornell-Lacker Criterion |       |       |       |       |       |       |
|---------------|--|-------|-------|-------|-------|-------|-------|
|               | EMP  | ATT   | PEOU  | PU    | IL    | MVL   | CL    |
| EMP           | 0.552  |       |       |       |       |       |       |
| ATT           | 0.586  | 0.614 |       |       |       |       |       |
| PEOU          | 0.470  | 0.450 | 0.625 |       |       |       |       |
| PU            | 0.552  | 0.577 | 0.493 | 0.527 |       |       |       |
| IL            | 0.539  | 0.528 | 0.692 | 0.568 | 0.588 |       |       |
| MVL           | 0.435  | 0.371 | 0.440 | 0.409 | 0.548 | 0.615 |       |
| CL            | 0.333  | 0.322 | 0.407 | 0.484 | 0.404 | 0.290 | 0.537 |

Table 5

Notes: PEOU, perceived ease of use; PU, perceived usefulness; ATT, attitude; EMP, employability; IL, information literacy; MVL, media/visual literacy; CL, computer literacy; CR, critical value.

#### 4.4 Structural Model Assessment

The structural model describes the relationships between constructs after the measurement model is validated. This articulates the relationship between exogenous variables and endogenous variables providing insight into the complex network of relationships between variables (Hair et al., 2010; Ho, 2006). Structural model analysis is used to measure the extent to which empirical data is in line with the underlying theory and ascertain whether the theory has been proven empirically (Hair et al., 2013). A graphical representation of the results of the research structural model can be seen in Figure 2 which was produced using AMOS (version 21).

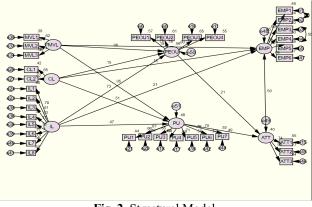


Fig. 2. Structural Model

#### 4.4.1 Hypothesis Tests

Structural Equation Modeling (SEM) is used to investigate the correlation between independent variables and employability. The results of hypothesis testing can be found in Table 6. The results of path analysis testing show that computer literacy and information literacy have a significant impact on perceived ease of use (CL:  $\beta = 0.150$ , t = 2.487, p < 0.05; IL:  $\beta = 0.741$ , t = 10.042, p < 0.01) and perceived benefits (CL:  $\beta = 0.352$ , t = 5.730, p < 0.01; IL:  $\beta = 0.329$ , t = 7.041, p < 0.01). In addition, perceived ease of use ( $\beta = 0.188$ , t = 2.978, p < 0.01) and perceived usefulness ( $\beta = 0.663$ , t = 6.262, p < 0.01) had a significant impact on attitudes. Surprisingly, all independent variables, including media/visual literacy ( $\beta = 0.188$ , t = 3.084, p < 0.01), computer literacy ( $\beta = 0.177$ , t = 2.549, p < 0.05), information literacy ( $\beta = 0.202$ , t = 3.122, p < 0.01), and attitude ( $\beta = 0.538$ , t = 5.910, p < 0.01), have a significant influence on work ability. Therefore, only hypotheses H1 and H2 are rejected. In the field of technology adoption, Oluwole (2016) identified resistance to information systems as a major obstacle hindering the adoption of new technologies and the achievement of information literacy. This objection is particularly relevant when considering individuals with higher proficiency in information technology, as they tend to foster positive perceptions of the ease of use and usefulness of technology in the workplace, thereby enhancing their employability. Alamri's (2019) research underlines the important role of perceived ease of use in shaping respondents' attitudes towards the application of artificial intelligence. According to Yu et al. (2017), information literacy is a key empowerment factor, which enables individuals to master information content, expand investigative horizons, recognize the need for information, and skillfully find, evaluate, and apply necessary information. Additionally, a relationship between individuals' Attitude Toward Use (ATU) toward smart factory technologies and their positive experiences and acceptance of new technologies has been found in previous research ( Oh et al., 2019 ). This relationship highlights the importance of positive attitudes in influencing the successful integration of new technologies, emphasizing the interconnectedness of attitudes, experiences, and technology acceptance. This shows that respondents' perceptions are formed by attitudes, experiences, expectations and emotions, so it is called constructivist perception (Gregory, 1974).

|                 | Dependent<br>Variable |   | Independent<br>Variable | β     | S.E.  | C.R.<br>(t-value) | Decision      |
|-----------------|-----------------------|---|-------------------------|-------|-------|-------------------|---------------|
| $H_1$           | PEOU                  | ÷ | MVL                     | 0.064 | 0.056 | 1.141             | Not Supported |
| $H_2$           | PU                    | ← | MVL                     | 0.034 | 0.041 | 0.818             | Not Supported |
| H3              | PEOU                  | ← | CL                      | 0.150 | 0.060 | 2.487**           | Supported     |
| $H_4$           | PU                    | ← | CL                      | 0.352 | 0.061 | 5.730***          | Supported     |
| H5              | PEOU                  | ← | IL                      | 0.741 | 0.074 | 10.042***         | Supported     |
| $H_6$           | PU                    | ÷ | IL                      | 0.329 | 0.047 | 7.041***          | Supported     |
| $H_7$           | ATT                   | ÷ | PEOU                    | 0.188 | 0.063 | 2.978***          | Supported     |
| $H_8$           | ATT                   | ÷ | PU                      | 0.663 | 0.106 | 6.262***          | Supported     |
| H9              | EMP                   | ← | MVL                     | 0.188 | 0.061 | 3.084***          | Supported     |
| $H_{10}$        | EMP                   | ← | CL                      | 0.177 | 0.069 | 2.549**           | Supported     |
| I11             | EMP                   | ← | IL                      | 0.202 | 0.065 | 3.122***          | Supported     |
| I <sub>12</sub> | EMP                   | ÷ | ATT                     | 0.538 | 0.091 | 5.910***          | Supported     |

# Table 6 Structural Path Analysis Result

Notes: PEOU, perceived ease of use; PU, perceived usefulness; ATT, attitude; EMP, employability; IL, information literacy; MVL, media/visual literacy; CL, computer literacy; CR, critical value.

\*\*\*Significant at 0.01, \*\* Significant at 0.05

#### 5. Discussion and Conclusion

The results of hypothesis testing underscore the complexity of contextual and cultural nuances that shape the perceived significance of computer literacy in influencing perceived ease of use, perceived usefulness, and employability in Indonesia. The differences seen between workers in Indonesia can be caused by various factors, indicating differences in culture, educational landscape and business environment. Computer literacy is the ability to use computers and modern technology effectively (Vishnu, 2023).

The perception of the importance of computer literacy compared to media/visual literacy can occur because the factors that influence media/visual literacy are relatively lower. Digital literacy is related to the ability to read information in digital media, the ability to search, identify, evaluate and use the information obtained. This may be due to variations in educational frameworks, cultural emphases, or industry requirements that prioritize different skills or competencies. Apart from that, the skill of assessing the meaning of each type of message, organizing the meaning so that it is useful, then constructing the message to convey to other people is also very low.

In Indonesia, there is an increasing emphasis on computer literacy and information literacy in both educational and professional fields. In the field of education, the education system and industry standards in Indonesia have prioritized these specific digital competencies, considering them essential for navigating technology, accessing information, and effectively utilizing digital tools in the professional field. In 2019, the Indonesian government again implemented computer technology learning in schools. The aim of including computer technology learning in schools is to improve the ability to use computers from an early age.

In the Indonesian job market, the perceived importance of computer literacy and information literacy in influencing perceived ease of use and perceived usefulness shows that employees associate these competencies with increased capacity to interact and utilize digital technology efficiently. There is a strong link with employability, further implying that employers really value prospective workers who have the skills/ability to operate computers as a condition for employee acceptance and good information literacy. In an evolving job market where technology plays an important role, individuals with these competencies are considered more adaptable, qualified, and valuable contributors to the world of work. In addition, information literacy skills are the core of lifelong learning to search for, evaluate, use and create information.

# 5.1 Theoretical Contributions

This research begins by emphasizing that cultural examination of digital literacy has the aim of increasing employability prospects and has the potential to make a major contribution in improving the Technology Acceptance Model (TAM). This expected contribution includes integrating valuable insights gained from the digital literacy domain into the TAM framework.

Furthermore, this research explores the influence of digital literacy in various aspects including media/visual literacy and computer literacy, on perceived ease of use and perceived benefits within the TAM framework. By exploring the complex relationship between various aspects of digital literacy and individuals' perceptions of technology, this research seeks to enrich the TAM model. This involves recognizing the important role of various digital competencies in the technology adoption process.

In addition, this research expands its exploration to identify specific components of digital literacy that have a significant impact on employability. This investigation aims to uncover the complex mechanisms that link digital literacy with technology acceptance, thereby influencing a person's employability. Identification of these main components is seen as

potentially contributing to improving the TAM model. The results suggest that different cultures and educational systems will emphasize different forms of digital literacy. These improvements will introduce a new dimension related to digital literacy, which is considered important for improving employability prospects, especially in diverse cultural environments. In addition, the resulting model is expected to provide a more comprehensive understanding of the relationship between digital literacy, cultural context, and technology acceptance. The practical implications of this understanding include designing technological interventions that align with the digital and cultural realities of individuals in Indonesia. Overall, this research contributes to a holistic understanding of the important role that digital literacy plays in shaping technology acceptance and work outcomes across diverse cultural contexts. It is hoped that the insights gained will inform the design of effective technology interventions tailored to the digital landscape and individual culture.

# 5.3 Implications for Practice

A cultural investigation into digital literacy that focuses on increasing employment, produces pragmatic implications and broad implications in various sectors. Educational institutions can benefit greatly by modifying their curricula to meet digital literacy needs. These adaptations ensure students gain essential skills, aligning their education with the dynamic demands of an ever-evolving job market.

Additionally, the findings of this study have direct relevance to recruitment practices for employers and human resources professionals. Integrating digital literacy assessments, especially media/video literacy, computer literacy, and information literacy, into the recruitment process allows organizations to determine candidates who have the desired skills. Aligning job descriptions with the identified digital literacy landscape can attract individuals with the necessary competencies. Internally, organizations can leverage the study's insights to tailor training initiatives, address digital literacy gaps among existing employees, and strengthen overall workforce capabilities.

Practical implications also include professional development providers being able to adapt courses to address the digital literacy gaps identified in this research. Tailoring offerings to meet the specific needs of professionals in Indonesia will enhance their career prospects and align professional development with the evolving digital landscape. Therefore, this study acts as a catalyst for strategic initiatives that bridge the gap between digital literacy and employability, ultimately shaping the future work landscape in Indonesia's diverse cultural context.

#### 5.4 Limitations and Suggestions for Future Work

The applicability of this study may be limited in terms of generalizability due to the unique cultural and contextual elements in Indonesia. Although the aim is to look at the role of culture in terms of digital literacy and employability, this research does not cover all the complex variations within each country by ignoring sub-regional, ethnic, or socio-economic differences. In addition, the current dynamism of digital literacy and the employment landscape may not represent a trend that will last for long. Evolving factors such as changes in technology, education, or economic conditions may influence the relevance of these findings. Therefore, it is recommended to conduct longitudinal studies to gain a more comprehensive understanding of the dynamic nature of digital literacy and its long-term impact on employability. This longitudinal approach can facilitate the identification of trends, emerging patterns, and long-term implications.

Expanding research to include stakeholder perspectives, including insights from a broader spectrum of stakeholders such as employers, educators, and policymakers, can enrich understanding of the ecosystem that influences digital literacy and employability. By considering multiple viewpoints, holistic strategies can be better informed, thereby increasing the overall comprehensiveness of the research.

# References

- Admiraal, W., & Lockhorst, D. (2009). E-Learning in small and medium-sized enterprises across Europe attitudes towards technology, learning and training. *International Small Business Journal*, 27(6), 743e767.
- Ahmmadi, P., Rahimian, M., & Movahed, R. G. (2021). Theory of planned behavior to predict consumer behavior in using products irrigated with purified wastewater in Iran consumer. *Journal of Cleaner Production*, 296, 126359.
- Alamri, M. M., et al. (2019). Towards Adaptive E-Learning among University Students: by Applying Technology Acceptance Model (TAM). *Internatioal Journal of Engineering Advanced Technology*, 8(6).
- Ali-Hassan, H., Nevo, D., Kim, H., & Perelgut, S. (2011). Organizational social computing and employee job performance: the knowledge access route. In Proceedings of the 44th Hawaii International Conference on System Sciences (HICSS).
- Awang, Z. (2014). Structural Equation Modeling Using AMOS, University Teknologi MARA Publication Center, Shah Alam.
- Chiu, C. M., & Wang, E. T. G. (2008). Understanding Web-based learning continuance intention: the role of subjective task value. *Information & Management*, 45(3), 194e201.
- Choukade, G., & Ingalagi, N. S. (2022). A study on the role of teachers in enhancing and minimizing factors affecting employability skills. *Educational Quest- An International Journal of Education and Applied Social Sciences*, 11(2), 69-74.

- 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.
- Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. Accounting Education, 30(2), 107–130.
- Dewi, R. S., Fahrurrozi, Hasanah, U., & Zuhri, M. (2021). Analysis study of factors affecting student's digital literacy competency. *Ilkogretim Online - Elementary Education Online*, 20(3), 424–431.
- Dudeney, G. (2015). 21st-century skills and digital literacy in action. Retrieved from https://www.teachingenglish.org.uk/
- Dudeney, G., Hockly, N., & Pegrum, M. (2014). Digital literacies: Research and resources in language teaching. New York, NY: Routledge.
- Eastin, M. S., & LaRose, R. (2000). Internet self-efficacy and the psychology of the digital Divide. *Journal of Computer-Mediated Communication*, 6(1). http://dx.doi.org/10.1111/j.1083-6101.2000.tb00110.x.
- European Commission. (2016). Europe's Digital Progress Report 2016. Brussels. Retrieved from https://ec.europa.eu/digital-single-market/en/download-scoreboard-reports
- Fahmi, M. (2021) Evolusi Pendidikan dan Tantangan Nilai. https://beritabaru.co/evolusi-pendidikan-dan-tantangan-nilai/
- 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. 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.
- Ferro, E., Helbig, N. C., & Gil-Garcia, J. R. (2011). The role of IT literacy in defining digital divide policy needs. Government Information Quarterly, 28(1), 3e10.
- Field, A. (2013). Discovering Statistics Using IBM SPSS Statistics (4th ed.). Sage Publications Ltd, London.
- Finch, D. F., Hamilton, L. K., Riley, B., & Zehner, M. (2013). An exploratory study of factors affecting undergraduate employability. *Education & Training*, 55(7), 681-704. http://dx.doi.org/10.1108/ET-07-2012-0077.
- 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
- Forster, (2017). How is information literacy experienced in the workplace. In M. Forster (Ed.), *Information literacy in the workplace* (pp. 11-28). London: Facet Publishing.
- Gilbert, S. (2017). Information literacy skills in the workplace: examining early career advertising professionals. *Journal* of Business and Finance Librarianship, 22(2), 111-134.
- Gilster, P. (1997). Digital Literacy. Wiley Computer Publications.
- Goh, S. C., Elliott, C., & Quon, T. K. (2012). The relationship between learning capability and organizational performance: a meta-analytic examination. *The Learning Organization*, 19(2), 92e108.
- Gregory, R.L. (1974). Concept and Mechanisms of Perception. UK: Duckworth.
- 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
- Ho, R. (2006). Handbook of Univariate and Multivariate Data Analysis and Interpretation with SPSS, Chapman & Hall/CRC, Taylor & Francis Group, Boca Raton, FL.
- Hutcheson, G.D., & Sofroniou, N. (1999). The Multivariate Social Scientist. Sage, London.
- Johnson, R. D., Hornik, S., & Salas, E. (2008). An empirical examination of factors contributing to the creation of successful e-learning environments. *International Journal of Human-Computer Studies*, *66*(5), 356e369.
- Jose, K. (2016). Digital Literacy Matters: Increasing Workforce Productivity Through Blended English Language Programs. *Higher Learning Research Communications*, 6(4), 1-27.
- Kang, H. (2021). Sample size determination and power analysis using the G\* power software. J. Educ. Eval. Health Prof. 18(17). doi: 10.3352/jeehp.2021.18.17
- Kementerian PPN / Bappenas. (2019). Indonesia 2045: Berdaulat, Maju, Adil, dan Makmur. https://perpustakaan.bappenas.go.id/e-library/file\_upload/koleksi/migrasi-data-
- publikasi/file/Policy\_Paper/Ringkasan%20Eksekutif%20Visi%20Indonesia%202045\_Final.pdf
- Khan, N., Sarwar, A., Chen, T. B., & Khan, S. (2022). Connecting digital literacy in higher education to the 21st-century workforce. *Knowledge Management & E-Learning*, 14(1), 46–61. https://doi.org/10.34105/j.kmel.2022.14.004
- Kimiloglu, H., Ozturan, M., & Kutlu, B. (2017). Perceptions about and attitude toward the usage of e-learning in corporate training. *Computers in Human Behavior*, 72, 339-349. doi: 10.1016/j.chb.2017.02.062.
- Kirton, J., & Barham, L. (2005). Information literacy in the workplace. The Australian Library Journal, 54(4), 365-376.
- Kist, W. (2013). New literacies and the common core. *Technology-Rich Learning*, 70, 38–43. Retrieved from http://www.ascd.org/
- Kolbjornsrud, V., Amico, R., & Thomas, R.J. (2016). How Artificial Intelligence Will Redefine Management, *Harvard Business Review*. https://hbr.org/2016/11/how-artificial-intelligence-will-redefine-management
- Lawson-Body, A., Willoughby, L., Lawson-Body, L., & Tamandja, E. M. (2018). Students' acceptance of E-books: An application of UTAUT. *Journal of Computational Information System*, 60(3), 256–267.

- Lloyd (2017). Learning within for beyond: exploring a workplace information literacy design. In M. Forster (Ed.), *Information literacy in the workplace* (pp. 97-112). London: Facet Publishing.
- Lloyd, & William, K. (2008). Towards an understanding of information literacy in context: implications for research. Journal of Librarianship and Information Science, *40*(1), 3-12.
- Martin, A. (2008). Digital literacy and the 'digital society'. Digital Literacies: Concepts, 151e176.
- Mohammadyari, S., & Singh, H. (2015). Understanding the effect of e-learning on individual performance: The role of digital literacy. *Computer and Education*, 82, 11-25.
- Morris, N. S., and Rosenbloom, D. A. (2017). Defining and understanding pilot and other feasibility studies. *The American Journal of Nursing*, 117, 38–45.
- Morris, W. (2018). Why it is important to be digitally in the 21st century. Retrieved from https://medium.com/literate-schools/why-it-is-important-to-be-digitally-literate-in-the-21st-century-583000ac8fc0
- Naveed, M. A., & Rafique, F. (2018). Information literacy in the workplace: a case of scientists from Pakistan. *Libri*, 68(3), 247-257.
- Ng, W. (2012). Can we teach digital natives digital literacy? Computers and Education, 59(3), 1065-1078.
- Nikou, S., Reuver, M. D., & Kanafi, M. M. (2022). Workplace literacy skills—how information and digital literacy affect adoption of digital technology. *Journal of Documentation*, 78(7), 371-391.
- Nunnally, J.C., & Bernstein, I.H. (1994). Psychometric Theory. McGraw-Hill, New York, NY.
- Oh, J. H., Seo, J. H., & Kim, J. D. (2019). The effect of both employees' attitude toward technology acceptance and ease of technology use on smart factory technology introduction level and manufacturing performance. *Journal of Information Technology Applications and Management*, 26(2), 13-26.
- Oluwole, D. (2016). Technology Acceptance Model as a predictor of using information system to acquire information literacy skills. *Library Philosophy & Practice (e-journal)*, 1450, 1-27.
- Ong, C. S., Lai, J. Y., & Wang, Y. S. (2004). Factors affecting engineers' acceptance of asynchronous e-learning in hightech companies. *Information & Management*, 41(6), 795e804.
- 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.
- Roca, J. C., & Gagne, M. (2008). Understanding e-learning continuance intention in the workplace: a self-determination theory perspective. *Computers in Human Behavior*, 24(4), 1585e1604.
- 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.
- Sudaryanto, M. R., Muhammad, A. H., & Andrian, T. (2023). The effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students' artificial intelligence technology adoption. Les Ulis: EDP Sciences. doi:https://doi.org/10.1051/e3sconf/202338804055
- 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.
- Warschauer, M. (2011). *Learning in the cloud: How (and why) to transform schools with digital media.* New York, NY: Teachers College Press.
- WEF. (2023). Future of Jobs Report 2023. https://www.coorpacademy.com/en/blog/learning-innovation-en/the-top-softskills-to-develop-by-2027-future-of-jobs-world-economic-forum-2023-report/
- Wisnu. (2023). Literasi Komputer: Definisi, Manfaat, dan Cara Meningkatkannya. https://myrobin.id/untuk-pekerja/literasikomputer/
- 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
- Ybema, J. F., Van Vuuren, T., & Van Dam, K. (2017). HR practices for enhancing sustainable employability: Implementation, use, and outcomes. *The International Journal of Human Resource Management*, 37, 886-907.
- Yu, T. K., Lin, M. L., & Liao, Y. K. (2017). Understanding factors influencing information communication technology adoption behaviour: the moderators of information literacy and digital skills. *Computers in Human Behavior*, 71, 196-208.
- 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.



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