Participatory Educational Research (PER)
Vol.13(1), pp. 191-212, January 2026
Available online at http://www.perjournal.com
ISSN: 2148-6123
http://dx.doi.org/10.17275/per.1724328

Id: 1724328

How Demographic Factors Shape the Effectiveness of Digital Literacy Training among Higher Education Lecturers

Novi Trilisiana*
Universitas Negeri Yogyakarta, Sleman, Indonesia
ORCID: 0000-0001-7985-4516

Herman Dwi Surjono
Universitas Negeri Yogyakarta, Sleman, Indonesia
ORCID: 000-0002-2720-2206

Rukiyati Rukiyati
Universitas Negeri Yogyakarta, Sleman, Indonesia
ORCID: 0000-0002-8073-1430

Kwarta Adimphrana
Center for Human Resources Training of Education and Culture, Jawa Barat, Indonesia
ORCID: 0009-0007-6855-6485

Article history
Received:
21.06.2025

Received in revised form:
01.09.2025

Accepted:
20.10.2025

Key words:
digital literacy training; demographic factors; lecturer performance; permanova; Indonesia

Digital literacy is vital for higher education lecturers, yet the effectiveness of training may differ across demographic and contextual factors. This study examines how gender, age, academic rank, and geographic location shape digital literacy training outcomes in Indonesia. Survey data from 1,144 lecturers were analyzed across seven digital literacy modules. Due to non-normal distributions (Kolmogorov-Smirnov, $p < 0.001$), nonparametric tests (Mann-Whitney U, Kruskal-Wallis H) and PERMANOVA were employed. Gender showed no significant differences in any module ($p > 0.05$). Age influenced Digital Space, Core Values, Digital Sexual Violence Prevention, and Digital Transformation ($p = 0.000 – 0.048$), with Millennials performing better in technology-based content. Academic rank significantly affected Digital Space, Digital Sexual Violence Prevention, and Digital Transformation ($p = 0.004 – 0.048$), where early-career lecturers outperformed senior faculty. Island of residence produced the strongest disparities in multiple modules ($p = 0.000 – 0.006$). PERMANOVA confirmed the global model as significant (pseudo-F = 1.41, $R^2 = 0.088$, $p = 0.001$), with island ($R^2 = 0.0119$) showing the largest effect. Training effectiveness is shaped more by structural and contextual inequalities than by biological demographics. Addressing digital divides requires infrastructure investment, targeted support, and alignment of training design with adult learning principles.

* Correspondency: novitri@uny.ac.id

Introduction

Information technology enables educational institutions to broaden their scope and enhance the effectiveness of training organizations for instructors. In Indonesia, where institutions are distributed across multiple islands with varying geographical challenges, online training serves as a strategic solution to enhance instructor competencies throughout the area. Information technology, particularly through Learning Management Systems (LMS), is essential for creating accessible and engaging learning environments. LMS platforms allow institutions to share training materials, monitor progress, and encourage collaboration among participants regardless of the participants' geographic location. The Center for Employee Education and Training, Secretariat General, Ministry of Education, Culture, Research, and Technology of Indonesia organizes the higher education service information management training in this context, utilizing LMS.

Information technology has been a driving force behind the expansion of online education, which enables institutions to offer flexible and accessible learning opportunities (Eom et al., 2012). The integration of technology in education through online platforms has transformed how knowledge is constructed. Online training has become increasingly relevant since the COVID-19 pandemic, forcing many educational institutions to switch from face-to-face to online learning. Lecturers must develop new skills and adapt to technology to manage distance learning effectively. Studies have proven that continuous training and technical assistance are crucial in equipping educators for the design and execution of online learning activities (Cutri et al., 2020; Mantashe, 2023; Mokoena-de Beer & Moloko, 2022). Lecturers face significant challenges in how to use digital devices in the classroom as well as digital skills (Abdul Razak et al., 2022; Singh-Pillay & Naidoo, 2020). These challenges show the urgent need for training to improve lecturers' digital skills in adapting to new activity modes.

Despite the widespread implementation of online training for lecturers, there remains a gap in understanding the impact of demographic factors on lecturers' performance in this training. The lecturers in Indonesia are spread across different regions with varying access to technological infrastructure, so variations in online training performance are an important issue to be researched. The age, job title, and geographic location can affect the outcome of lecturer training, but empirical evidence is still limited (Cutri et al., 2020). A more in-depth analysis of the influence of demographic factors on online training performance is needed.

Several studies have highlighted the relationship between online learning outcomes and demographic characteristics that are important for the online learning process. These studies include gender (Cai et al., 2017; Kelly et al., 2014; McAdams et al., 2022; Salles et al., 2019; Webster, 2024), age (Boyte-Eckis et al., 2018; Ke & Kwak, 2013), academic rank (Abramo et al., 2018; Faris, 2020; Krsmanovic & Foster, 2025), and region (Liu et al., 2016; Rizvi et al., 2019). These demographic attributes can contribute to better retention predictions. However, each factor has a different influence.

Despite the numerous studies on digital literacy training, a review of the existing literature reveals a need for further research into the impact of demographic factors on the performance of lecturers in online training. Many studies focus more on the technical effectiveness of training without considering variations caused by differences in age, job title, and geographic location. Some studies, such as those conducted by Adnan et al. (2017) and Zamani et al. (2016) show that cultural and infrastructure barriers are still a significant challenge in developing countries. This study aims to fill this gap by focusing on the influence of age, position, and geographical location on lecturer performance in online training.

The problem addressed by this study is that variations in their demographic factors, such as gender, age, job position, and geographical location, have not been explored simultaneously in the literature. Demographic factors can influence training outcomes (Cutri et al., 2020), but in the Indonesian context, empirical evidence regarding their specific impact is still limited. This study has aimed to fill this gap, thus providing valuable insights into how training programs can be optimized to meet the diverse needs of educators across the country.

Purpose of The Study

This study analyzed demographic factors (gender, age group, academic rank, and geographical island) that may influence lecturers' performance in online digital literacy training in Indonesia. This study investigated the following questions: (1) How does gender, (2) age group, (3) academic rank, (4) geographical location influence lecturers' performance in online digital literacy training in Indonesia?

Theoretical Framework

The rapid expansion of online training for higher education lecturers has raised questions about how demographic characteristics shape training performance. In Indonesia, where lecturers are dispersed across regions with uneven technological infrastructure, understanding the role of age, academic rank, and island of residence is particularly relevant (Adnan et al., 2017; Cutri et al., 2020). Existing studies highlight these factors but remain fragmented, emphasizing technical aspects while overlooking demographic and contextual disparities (Zamani et al., 2016). This gap underscores the need for a framework that combines individual adoption perspectives with structural explanations of inequality.

Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a comprehensive model to explain digital adoption. Its core constructs consist of performance expectancy, effort expectancy, social influence, and enabling conditions as predictors of intention and behavioral use (Dwivedi, Hughes, et al., 2020). Performance and effort expectancy reflect perceived usefulness and ease of use, social influence reflects organizational norms, and enabling conditions emphasize institutional support (Dwivedi, Hughes, et al., 2020; Magsamen-Conrad et al., 2015). Demographic factors such as gender, age, and experience moderate the relationships in UTAUT (Magsamen-Conrad et al., 2015).

Digital Divide Theory

Digital divide theory highlights the structural barriers that hinder adoption. This theory distinguishes between access to infrastructure, digital literacy, and usage, each of which influences how technology is adopted (Afrina et al., 2024; Mariane et al., 2023). Limited connectivity, device availability, and technical support create uneven adoption pathways across regions (Isabella et al., 2024). The digital literacy gap determines whether these intentions translate into effective use, and the sociocultural context shapes engagement in online training (Adnan et al., 2017; Mulyana et al., 2024). These barriers remain crucial in developing and island countries with unequal infrastructure (Zamani et al., 2016).

An integrated framework links adoption processes to structural conditions. UTAUT clarifies how perceptions of usefulness, ease of use, social influence, and institutional support shape intentions, while digital divide theory demonstrates how access, literacy, and usage patterns determine whether these intentions are realized (Afrina et al., 2024; Dwivedi, Rana, et al., 2020). Facilitating conditions are directly related to the availability of infrastructure and technical support (Mulyana et al., 2024). The moderating role of age or academic standing is shaped by disparities in literacy and access (Magsamen-Conrad et al., 2015; Mannheim et al., 2023). This framework also recognizes the importance of organizational culture and pedagogical competence in sustaining adoption (Mantashe, 2023; Puspitawati et al., 2023).

Method

This study employed a quantitative, cross-sectional design to examine how demographic characteristics (gender, age group, academic rank, and geographical island) influence the effectiveness of digital literacy training among higher education lecturers in Indonesia (consists of 7 modules). The design allows data collection at a single point in time (Cronk, 2016). The intervention was conducted fully online through a combination of synchronous webinars and asynchronous activities delivered via the LMS. Each training wave lasted two months, providing structured modules and interactive sessions to ensure comprehensive engagement with the content. The LMS assesses each participant's proficiency through quiz scores and assignments. This study was conducted in full compliance with the ethical guidelines of the Directorate of Research and Community Service, Universitas Negeri Yogyakarta.

Variable

This study included four independent variables, namely gender (X1), age group (X2), academic rank (X3), and island of residence (X4). The dependent variables were training performance scores measured across seven training modules: Digital Space (Y1), Core Values of Civil Servants (Y2), Digital Sexual Violence Prevention and Response (Y3), Digital Transformation (Y4), Indonesian Higher Education Information System (Y5), Electronic-Based Government System (Y6), and Electronic Official Document System (Y7). The operational definitions of the variables are presented in Table 1 and Table 2 outlines the training modules and corresponding objectives that participants were required to follow.

Table 1. Research variables

Variable	Type	Symbol	Operational Definition	Scale
Gender	Independent	G	Respondents' gender: Female and Male	Nominal
Age Group	Independent	AG	Respondents' age group: Millennial, Gen X, and Baby Boomer	Nominal
Academic rank	Independent	AR	Respondents' academic rank: Expert Assistant, Lector, Head Lector, and Professor	Nominal
Island	Independent	I	Island of residence: Java, Kalimantan, Sumatra, Sulawesi, and Papua	Nominal
Digital Space	Dependent	DS	Performance score on DC module	Interval (0-100)
Core Values of Civil Servants	Dependent	CV	Performance score on CV module	Interval (0-100)
Digital Sexual Violence Prevention and Response	Dependent	DSV	Performance score on DSV module	Interval (0-100)
Digital Transformation	Dependent	DT	Performance score on DT module	Interval (0-100)
Indonesian Higher Education Information	Dependent	IHEIS	Performance score on IHEIS module	Interval (0-100)

Variable	Type	Symbol	Operational Definition	Scale
System				
Electronic Based Government System	Dependent	EBG	Performance score on EBG module	Interval (0-100)
Electronic Official Document System	Dependent	EODS	Performance score on EODS module	Interval (0-100)

Table 2. Training modules

Module	Learning Objectives
DS	Understand the legal aspects of the use of digital space.
CV	Understand values: trustworthiness, competence, harmonious, adaptive, and collaborative.
DSV	Improving understanding of the protection and prevention of violence in digital space.
DT	Understand the implementation of digital transformation
IHEIS	Understanding the digital management of higher education data.
EBG	Mastering the concept and application of the electronic-based government system
EODS	Understand the management of official documents electronically.

Participants

The initial dataset comprised 2,014 lecturers from the Ministry of Education, Culture, Research, and Technology, representing diverse geographical and demographic characteristics of the lecturer population in Indonesia. Outlier detection led to the exclusion of a portion of cases; however, further data removal would have resulted in inadequate demographic variation. Consequently, the final analytic sample consisted of 1,144 lecturers. Although the retained data did not follow a normal distribution, this decision preserved sufficient representativeness across gender, age group, academic rank, and island of residence. The study population encompassed 74,888 lecturers nationwide, based on internal records provided by the Ministry of Education, Culture, Research, and Technology. Participation in this study was voluntary, and participants were informed that they could withdraw at any time without consequence. Participants were awarded a certificate of participation as a recognition of their involvement after completing the training sessions. This certificate serves only as recognition of their participation and does not include any financial or material incentives from external awards.

The sample size for this study was determined using Cochran's Sample Size Formula (Cochran, 1963). This formula ensures that the sample size is both statistically valid and reliable. This formula considers the margin of error and the desired confidence level. The below is used to calculate the sample size in Formula 1.

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{E^2} \quad (1)$$

Where n_0 is required sample size. Z is Z-value (based on the desired confidence level), which for 95% confidence, $Z = 1.96$ and $Z = 2.576$ for 99% confidence. p is estimated proportion of the population. E is desired margin of error (5%).

$$n_0 = \frac{1.96^2 \cdot 0.5 \cdot (1 - 0.5)}{0.05^2} = 384.16 \approx 384$$

In accordance with Cochran's sample size calculation, the minimum required sample size for this study was 384 lecturers (95% confidence). However, to ensure greater statistical power, better representation of demographic and geographical diversity, and to account for potential missing data, a sample size of 1144 lecturers was chosen for analysis. This larger sample size enhances the robustness of the study's findings and ensures that the results are more representative of the broader lecturer population in Indonesia.

This sample is enough for a statistical representation of the population. The number of female participants surpasses that of male participants, with women constituting the majority. The predominant age group is Millennials, comprising 53.8%, followed by Generation X at 35.1%, and Baby Boomers at 11.2% (see Table 3 to delineate the age categories by generation). The role of Expert Assistant constitutes 51.7%, Lector, Head Lector, and Professor represent a lesser fraction. The bulk of participants were from Java (44.2%), followed by Kalimantan (22.6%) and Sumatra (22.6%). Table 4 presents the demographic details of the trainees.

Table 3. Demographic information of research subjects

Age Group	**Year of Birth**
Millennial	1981 - 1996
Generation X	1965 - 1980
Baby Boomer	1946 - 1964

Table 4. Demographic Information of Research Subjects

	Demographics	**N**	**%**
Gender	Woman	596	52.1 %
	Man	548	47.9 %
Age Group	Millennial Gen	615	53.8 %
	Gen X	401	35.1 %
	Baby Boomer	128	11.2 %
Academic rank	Expert Assistant	592	51.7 %
	Lector	337	29.5 %
	Head Lector	198	17.3 %
	Professors	17	1.5 %
Island	Java	506	44.2 %
	Kalimantan	259	22.6 %
	Sumatra	259	22.6 %
	Sulawesi	69	6.0 %
	Papua	51	4.5 %
Total		**1144**	**100 %**

Data Collection and Analysis

The Center for Employee Education and Training manages the LMS through which we collected performance data from online training participants for this research. The data collected included the training material score and each participant's graduation status, which was used as a dependent variable in the analysis.

The data collection process involved gathering demographic information of participants, such as gender, age, position, and geographical location, sourced from the training management system and employee database of the Ministry of Education and Culture. Participant performance was assessed through material scores derived from evaluations of quizzes and assignments in online training. Performance data is combined with demographic information resulting in a cohesive data set that links participant demographics to training outcomes. Data processing includes cleaning the data set by removing conflicts, removing missing scores, and addressing inconsistencies, including incomplete records or misclassified demographics. Data validation guarantees accuracy by the cross-referencing of source files then anonymization techniques are implemented as necessary to safeguard participant privacy in compliance with ethical research standards.

The data were analyzed using multivariate techniques, which evaluate group differences based on multiple variables simultaneously. The approach is PERMANOVA (Permutational Multivariate Analysis of Variance). PERMANOVA enables the examination of differences in group dispersion while accounting for variance in the data (Ellis et al., 2017). This method is particularly useful in studies involving multivariate datasets and the assumption of normal distribution is not required (testing with nonparametric data). In this study, the approach was applied to identify whether specific factors influence group differences within a broader context.

The validity of the data was guaranteed through standard evaluation instruments in the LMS, which has been adjusted to the training guidelines from the Indonesian Ministry of Education and Culture. Meanwhile, the reliability of the data was examined using Cronbach's Alpha coefficient, with a score of 0.978, which indicates the internal consistency of the measurements used to measure the participants' performance scores.

Results

Normality Test Results

The collected data were tested for normality using the Kolmogorov–Smirnov test for each variable. The results indicated that all variables deviated from a normal distribution, with p-values equal to 0.000 (see Table 5). Subsequent analyses employed nonparametric methods to avoid violations of the normality assumption.

Table 5. Results of the kolmogorov–smirnov test for each variable

Variable	Test Statistic	p-value
G	0.352	0.000
AG	0.337	0.000
AR	0.320	0.000
I	0.260	0.000
DS	0.246	0.000
CV	0.208	0.000
DSV	0.234	0.000
DT	0.184	0.000
IHEIS	0.259	0.000
EBG	0.240	0.000
EODS	0.185	0.000

Nonparametric ANOVA Results

To assess differences in training performance among demographic groups, nonparametric ANOVA tests were conducted using the Kruskal-Wallis H test and the Mann-Whitney U test. The Kruskal-Wallis H test was applied to compare more than two independent groups on a single dependent variable, such as training performance by age group, academic rank, or island of residence. The Mann-Whitney U test was employed to examine differences between two groups on a single dependent variable, specifically comparing the performance of male and female participants in each training module. Table 6 presents the influence of each demographic group on performance across the training modules.

Table 6. Results of nonparametric test of the effect of independent variables on each dependent variable

Independent Variable	Dependent Variable	Test Statistics	Asymp. Sig. (p-value)	Z	df	Significant or No
Gender	DS	Mann-Whitney U	0.426	-0.797		No
	CV		0.082	-1.737		No
	DSV		0.105	-1.621		No
	DT		0.552	-0.595		No
	IHEIS		0.663	-0.435		No
	EBG		0.055	-1.921		No
	EODS		0.603	-0.521		No
Age Group	DS	Kruskal-Wallis H	0.000		2	Significant
	CV		0.048		2	Significant
	DSV		0.000		2	Significant
	DT		0.006		2	Significant
	IHEIS		0.250		2	No
	EBG		0.127		2	No
	EODS		0.682		2	No
Academic Rank	DS	Kruskal-Wallis H	0.004		3	Significant
	CV		0.209		3	No
	DSV		0.037		3	Significant
	DT		0.048		3	Significant
	IHEIS		0.970		3	No
	EBG		0.974		3	No
	EODS		0.530		3	No
Island	DS	Kruskal-Wallis H	0.000		4	Significant
	CV		0.006		4	Significant
	DSV		0.130		4	No
	DT		0.208		4	No
	IHEIS		0.342		4	No
	EBG		0.000		4	Significant
	EODS		0.000		4	Significant

Based on the Asymp. Sig. (2-tailed) values in Table 6, a p-value < 0.05 indicates a significant difference between groups. The groups within the gender variable ($p > 0.05$) did not show differences in performance across any of the training modules. Gender did not produce significant differences in training outcomes for the DS module (0.426), CV (0.082), DSV (0.105), DT (0.552), IHEIS (0.663), EBG (0.055), and EODS (0.603). The age group exerted a significant influence on training performance in DS (0.000), CV (0.048), DSV (0.000), and DT (0.006). No significant differences were found across age groups for CV and the IHEIS.

The Kruskal-Wallis H test further indicated significant differences for DS (0.004), DSV (0.037), and DT (0.048), but not for CV (0.209), EBG (0.970), and EODS (0.530). Academic rank significantly influenced outcomes in DS, DSV, and DT, while no significant differences were observed for CV, EBG, and EODS. Island of residence also contributed significantly to training performance in several modules. The Kruskal-Wallis H test revealed significant differences for DS (0.000), CV (0.006), and EODS (0.000), but not for DSV (0.130), DT (0.208), or EBG (0.342).

The Mann-Whitney U and Kruskal-Wallis H analyses demonstrated significant differences in training outcomes for age group, academic rank, and island, whereas gender did not show significant effects across any module. Specifically, age-related differences were evident in Digital Space, Core Values of Civil Servants, Digital Sexual Violence Prevention and Response, and Digital Transformation. Aacademic rank significantly affected several modules, although no differences were observed for Core Values of Civil Servants, Electronic-Based Government System, and Electronic Official Document System.

PERMANOVA Results

PERMANOVA was conducted to assess the influence of gender, age group, academic rank, and island of residence on the multivariate response variables derived from the training modules. Prior to conducting PERMANOVA, homogeneity of variance was tested using the betadisper method. The results in Table 7 showed that variance across groups was not significant ($p > 0.05$). Gender (0.256), age group (0.5017), academic rank (0.1516), and island (0.4688) all indicated that the assumption of homogeneity of variance was satisfied, suggesting no significant differences in variance among the groups.

Table 7. Results of the homogeneity of variance test

		Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Gender	Groups	1	65	65.389	1.2917	0.256
	Residual	1142	57809	50.621		
Age Group	Groups	2	70	34.764	0.6901	0.5017
	Residual	1141	57476	50.373		
Academic Rank	Groups	3	267	89.036	1.7676	0.1516
	Residual	1140	57423	50.371		
Island	Groups	4	185	46.297	0.8907	0.4688
	Residual	1139	59206	51.981		

After assuming equal variance across groups for each factor, PERMANOVA was conducted to examine the effects of gender, age group, academic rank, and island of residence (including their interactions) on performance scores across the seven training modules. In the global model, the total degrees of freedom for all factors and their interactions amounted to 73, with the model explaining a total variation of 74,068. The global results indicated significant differences (pseudo-F = 1.414; $R^2 = 0.088$; $p = 0.001$), meaning that the combination of these factors accounted for 8.8% of the variance in the data (Table 8). The remaining 91.2% of the variance was attributed to residual factors not captured by the model. The PERMANOVA analysis revealed significant group differences based on gender, age group, academic rank, and island, with $p = 0.001$, in relation to performance scores across the seven training modules.

To further determine the effect of each factor, separate tests or factor-specific PERMANOVA analyses were conducted. In Table 8, *df* (degrees of freedom) represents the number of categories or levels of each factor minus one, along with the residual degrees of freedom associated with unexplained variation. *Sum of Squares* reflects the total variation in the data that can be partitioned into variation explained by the model (factors) and residual variation. *R^2* (coefficient of determination) indicates the proportion of total variance explained by a given factor or by the overall model, with higher values reflecting greater influence. *Pseudo-F* is the ratio between among-group variation explained by the model and within-group residual variation, used to assess whether group differences are sufficiently large compared to variation within groups.

Table 8. Results of permanova on training performance (999 permutations, euclidean distance)

Factor	**df**	**Sum of Squares**	**R²**	**Pseudo-F**	**p-value**
Gender	1	1210	0.0014	1.6438	0.127
Age Group	1	1676	0.0043	2.2664	0.047
Academic Rank	3	3742	0.0045	1.6967	0.036
Island	4	9996	0.0119	3.4224	0.001
Overall Model	73	74068	0.0880	1.4143	0.001
Residual	1070	767651	0.9120	-	-
Total	1143	841720	1.0000	-	-

Variation by Gender

Based on the gender factor (see Table 8), no significant differences were found between male and female participants ($p = 0.127$). Gender accounted for only 0.14% of the variance ($R^2 = 0.0014$), indicating that most of the variation in training outcomes could not be explained by gender differences. The F value (1.6438) was relatively small, further suggesting that the influence of gender on training performance was minimal. As illustrated in Figure 1, the distribution of training scores between male and female participants was nearly identical across all modules. In the CV, DSV, DT, EODS, and IHEIS modules, both male and female participants achieved the same median scores, with interquartile ranges consistently between 70 and 90. In the DS and EBG modules, the median scores were also equal across genders, although male participants displayed a wider score distribution at the upper end. These differences were not statistically significant, consistent with the PERMANOVA results ($p = 0.127$).

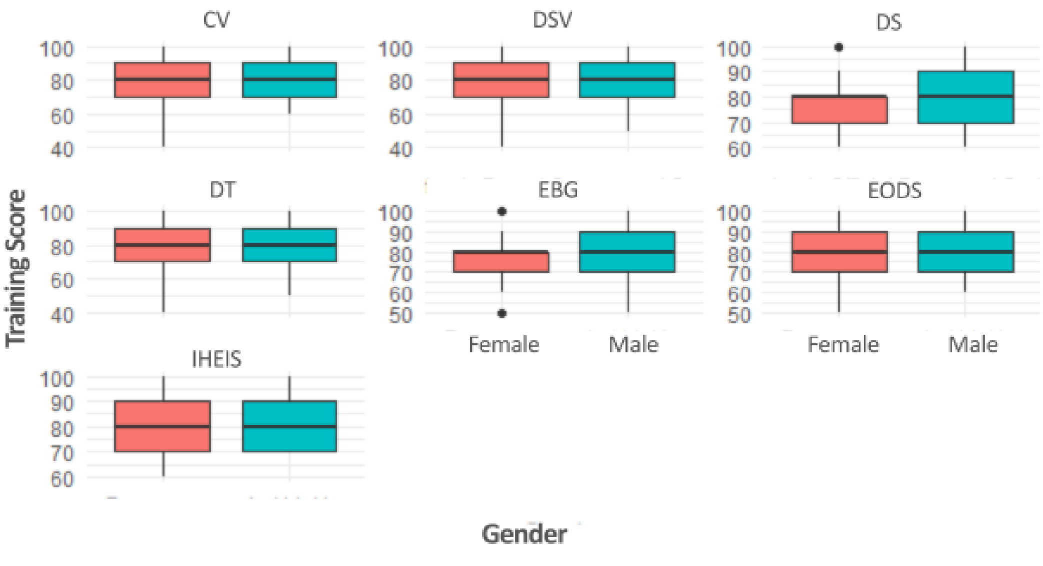

Figure 1. Training scores by gender

Variation by Age Group

Based on the age group factor (see Table 8), significant differences were observed among Millennial, Gen X, and Baby Boomer groups (pseudo-F = 2.2664; $R^2 = 0.0043$; $p = 0.047$), although the effect size was relatively small (0.43%). Figure 2 illustrates the distribution of scores across age groups, where the CV and DT modules showed identical medians (80) with consistent interquartile ranges (Q1–Q3) between 70 and 90. Similarly, the IHEIS, EBG, and EODS modules maintained a stable median of 80 with only slight variations in Q1–Q3 ranges, indicating relatively stable perceptions and outcomes across generations in these modules.

In the DS module, Millennials achieved a median of 80 with a higher interquartile range (75–90), while Gen X and Baby Boomers retained a median of 80 but exhibited lower Q1–Q3 ranges (70–80). This suggests that Millennials were more consistent and attained higher scores in the DS module compared to other age groups. The median in the DSV module indicated that Baby Boomers tended to achieve slightly lower outcomes. Millennials consistently demonstrated higher and more stable performance in technology-oriented modules, whereas Baby Boomers appeared less optimal in modules involving sensitive or emerging content, such as Digital Sexual Violence Prevention and Response.

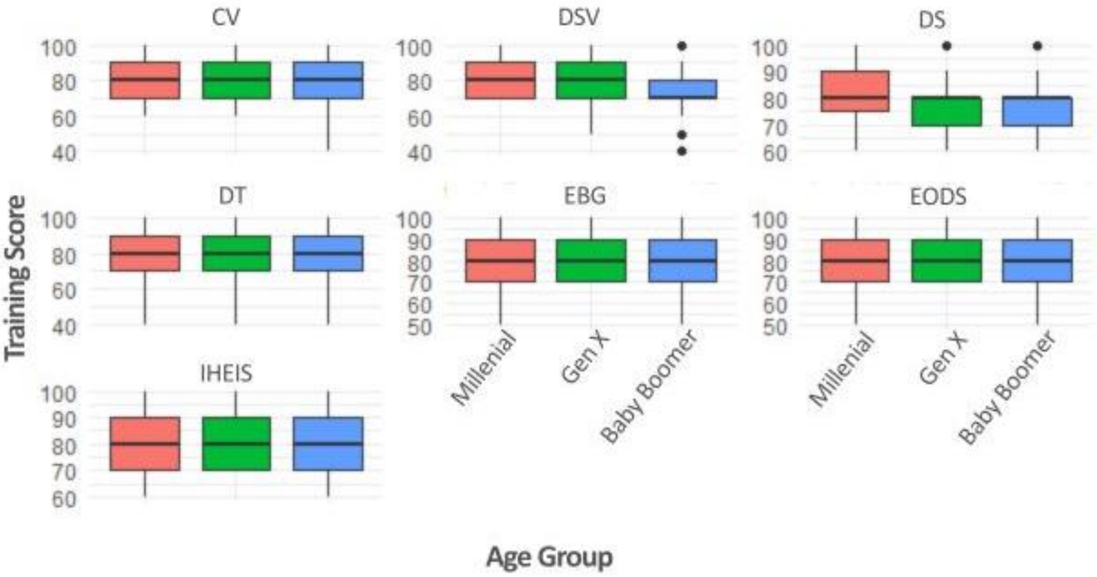

Figure 2. Training scores by age group

Variation by Academic Rank

Significant differences were found across academic ranks (p = 0.036), although the proportion of explained variance remained low (R^2 = 0.45%). The median scores for the CV and EBG modules were 80 across all academic ranks (Expert Assistant, Lector, Head Lector, Professors), with consistent interquartile ranges (Q1–Q3) between 70 and 90. Figure 3 illustrates that there were no notable differences among academic ranks for the CV and EBG modules.

In the DSV module, Expert Assistants and Lectors both recorded a median of 80 (Q1–Q3 = 70–90), while Head Lectors and Professors maintained a median of 80 but with a lower Q3 of 80. Among Professors, the median further declined to 70 (Q1–Q3 = 70–80), suggesting slightly lower outcomes at the professor level for the DSV module.

There is also evidence that early-career participants (Expert Assistants) exhibited slightly more variation but still relatively high performance in the DS module. Expert Assistants sustained a median of 80 with a wider range (70–90). Lectors and Head Lectors had a median of 80 but a narrower Q3 of only 80, while Professors were relatively consistent with a median of 80 (70–90). In the DT and IHEIS modules, all academic ranks achieved the same median, although Professors displayed a narrower score range and the presence of outliers. Conversely, in the EODS module, Professors demonstrated the highest distribution, with a median of 80 and a score range of 80–100.

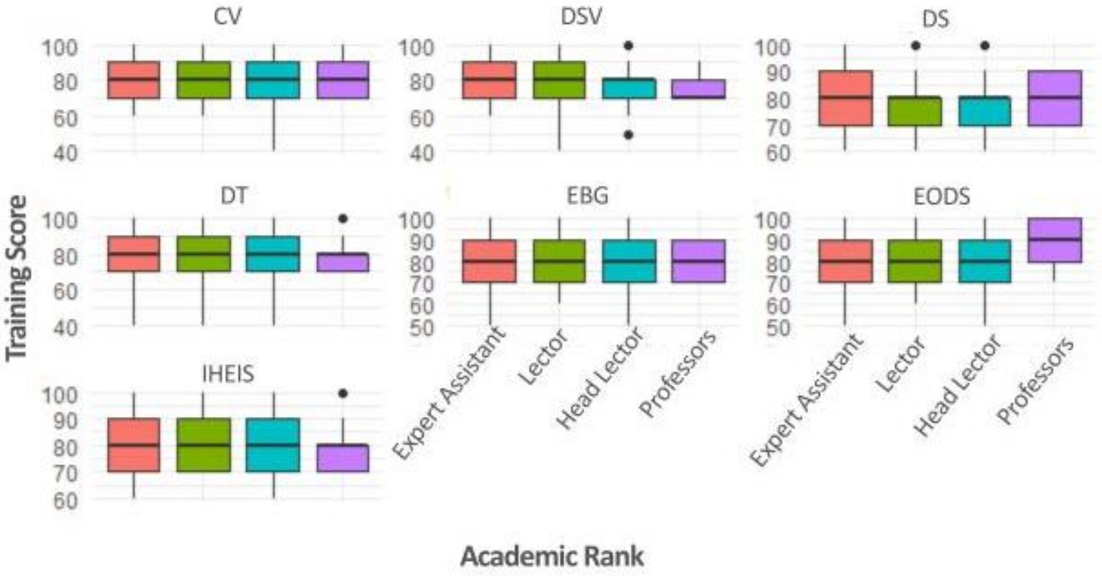

Figure 3. Training scores by academic rank

Variation by Island

Participants from the five major islands exhibited significant differences (p = 0.001), although the effect size accounted for only 1.19% of the variance ($R^2 = 0.0119$). Figure 4 presents the median scores for each island in the CV, DT, and IHEIS modules. In the CV module, a slight variation was observed, with Sumatra showing a higher interquartile range (Q1–Q3 = 75–90) compared to other islands, while Papua tended to be slightly lower, with Q3 limited to 85. Minor variation in the DT module was also observed for Papua. For the IHEIS module, the distribution differed in that Sumatra scored lower, while Papua scored higher relative to the other islands.

In the DSV module, the median score was 80 across nearly all islands. However, Papua recorded the lowest distribution with a median of 70, while Sulawesi maintained both a median and Q3 of 80. The highest median score in the EODS module was achieved by Sumatra (90), compared to 80 for other islands. For the DS module, the most common pattern was a consistent median of 80, but with varying interquartile ranges across islands. The lowest median in the DS module was found in Papua.

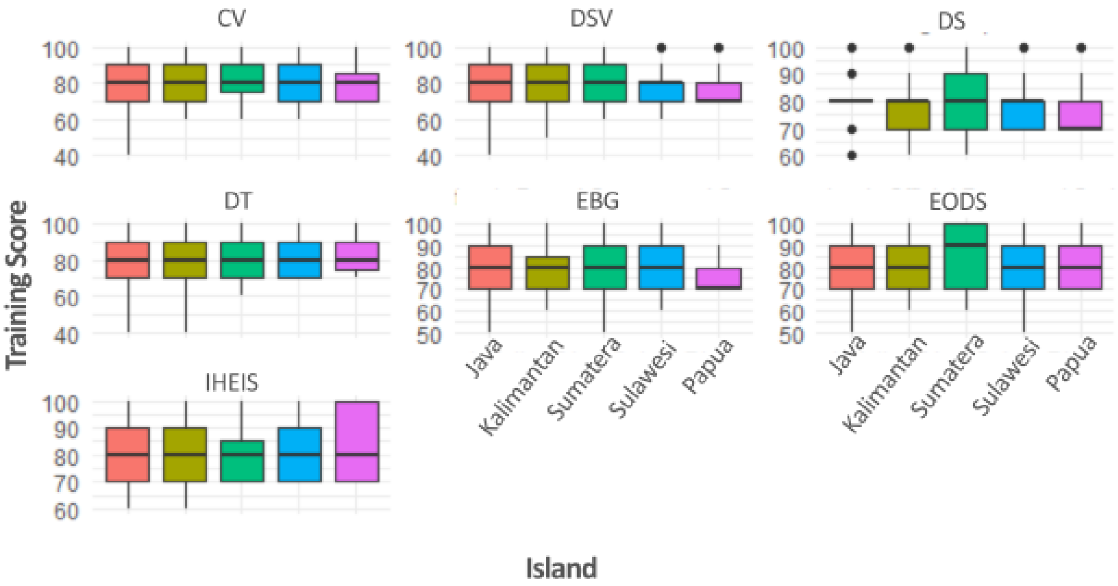

Figure 4. Training scores by island

The PERMANOVA results indicate that the overall model was significant; however, each factor individually contributed only marginally to the variance in training outcomes. The factor with the greatest contribution was island of residence ($R^2 = 0.0119$), followed by academic rank and age group, whereas gender did not exert a significant effect.

Discussion

This study examined how demographic factors shape the effectiveness of digital literacy training among higher education lecturers. The findings indicate that demographic characteristics collectively explained a modest proportion of variance in training outcomes. The overall multivariate model was significant, yet the explanatory power remained limited, with only 8.8 percent of the variance accounted for by gender, age group, academic rank, and island of residence. Among these, structural and contextual factors, particularly geographic location and academic rank, exerted greater influence than biological attributes such as gender. Gender did not significantly affect any training module, whereas age and academic rank demonstrated small but meaningful effects in specific modules. Island of residence emerged as the strongest predictor, revealing disparities in training outcomes across regions. These results highlight that while individual demographic factors matter to some extent, broader contextual inequalities (differences in digital infrastructure between regions or differences in access to academic career opportunities) play a more decisive role in shaping lecturers' digital literacy performance.

Gender and Training Effectiveness

The study found no significant differences in training performance between male and female lecturers across all modules. This result aligns with prior research indicating that gender is not necessarily a decisive factor in training outcomes. McAdams et al. (2022) emphasized that the effectiveness of training is shaped primarily by program quality rather than participants' gender. Salles et al. (2019) also highlighted that structured training interventions and transparent institutional policies can mitigate gender bias, suggesting that differences in outcomes are attributable to methodological design rather than inherent gender disparities. Kelly et al. (2014) demonstrated the application of standardized assessment methods reduces gender-based differences in training outcomes. The consistent quality improvement in training delivery and evaluation processes helps ensure equitable outcomes. The findings of Webster (2024) further reinforce this perspective, showing that gender was not significantly associated with variations in academic performance trajectories among students who had previously struggled.

Nevertheless, contrasting evidence exists. Some studies have documented nuanced or context-dependent gender differences. Gender-specific effects depending on training type and learning environment. Bausch et al. (2014) found that older women tended to achieve greater training success than older men, even though younger participants did not exhibit such differences. Tziner & Falbe (1993) observed that men often report stronger motivation to transfer training compared to women, which may affect long-term application of skills. Schwartz et al. (2022) noted that gender dynamics in mentor–trainee pairings can shape training effectiveness, particularly in academic career development. Kang et al. (2018) reported that mindfulness training yielded stronger emotional well-being benefits for female participants, while St-Jean et al. (2022) showed that training programs can enhance entrepreneurial self-efficacy particularly among women, contributing to long-term confidence and professional capability. Van Wyk et al. (2016) observed that women in academia increasingly outperform men in some training contexts, suggesting that gender effects may shift over time and across disciplines.

He et al. (2022) found that gender, along with school level and location, significantly influenced students' intention to continue online learning. Onwuegbuzie et al. (2020) and Onwuegbuzie & Ojo (2021) showed that female students were significantly more likely to report mental health challenges, suggesting that gender differences may be more pronounced in psychosocial outcomes than in in-person training performance. Al-Swidi & Al Yahya (2017) further documented that learning style and supervisor support are important determinants of training effectiveness across genders, although men and women may perceive these influences differently.

These studies suggest that while gender did not emerge as a significant factor in the present research, the broader literature indicates that its role in training effectiveness is highly context-dependent. Factors such as training design, assessment methods, psychosocial conditions, and institutional structures may either amplify or minimize gender-related differences. These factors have not been explored in this study.

In the context of the present study, training modules all showed comparable outcomes between male and female lecturers. The lack of gender differences across these diverse thematic areas suggests that training content, whether related to digital skills, civil service values, or prevention of digital-based misconduct, was equally accessible and effective for both groups.

Age-related Differences in Digital Literacy Training

The present study revealed significant differences in training performance across age categories, particularly in 4 modules. Millennial participants generally performed better on technology-intensive modules compared to Gen X and Baby Boomer groups, while older participants demonstrated relatively lower outcomes in modules requiring rapid adaptation to digital platforms. Within the UTAUT framework and variations of public technology adoption models, younger age groups are more responsive to perceived benefits and ease of use in a rapidly changing digital environment, while older age groups face cognitive barriers or lack basic digital skills (Magsamen-Conrad et al., 2015).

Modules related to system-based learning showed stable outcomes across age groups, with no substantial variance. These patterns highlight that age-related differences contribute meaningfully to technology-oriented and sensitive-content modules, whereas institutional and procedural modules appear less affected by generational variation. These findings confirm that modules that demand digital skills and technology-based interactions will show a performance advantage for younger generations, while modules that focus more on institutional benefits may show smaller variations between generations, if supported by a conducive work environment (Sudirman et al., 2019).

This finding is consistent with research by Islam et al. (2011), which state that age, study program, and level of education are factors that have a significant influence on the effectiveness of online learning among university students. Sherimon et al. (2022) show that age significantly influences engagement in online learning, with younger generations adapting more quickly to digital technology than older generations. Bennett et al. (2008) and Thinyane (2010) similarly argued that individuals aged 18–24 are considered “digital natives” who are more familiar with and easily navigate digital systems, while those aged 24 and above are more likely to be “digital immigrants.”

Age alone does not fully explain training outcomes. The influence of age becomes less significant when combined with other factors such as education and professional experience (Mahyuddin et al., 2018). Mintawati et al. (2023) further highlight that other factors substantially influence training success besides age, namely motivation, adaptability, and experience. This suggests that the role of age in training effectiveness should be considered within a broader and interacting framework of variables.

Age group exerts a significant but moderate influence on training performance. Younger lecturers appear to benefit more from modules requiring digital adaptation, while older lecturers require additional scaffolding to achieve comparable results. However, as demonstrated in previous studies, age should not be viewed as the sole determinant of training success, but rather as a factor interacting with education, motivation, and institutional context. This implies that training programs need to be tailored to age-related needs. Avelia and Esita (2020) suggest that training for older lecturers should emphasize gradual technological adaptation, while younger lecturers may benefit from more technologically advanced approaches. This differentiation accommodates generational differences in digital fluency and supports more inclusive training design.

Academic Rank and Training Effectiveness

The academic rank was significantly associated with differences in digital literacy training outcomes, particularly in three modules. Early-career lecturers, such as Expert Assistants, tended to show greater variation in performance yet displayed relatively higher adaptability in technology-based modules. In contrast, professors exhibited more stable but sometimes lower outcomes in modules requiring sensitivity to emerging issues. Senior academics maintain stronger performance in institutional and procedural content. These results highlight that academic rank contributes to variations in training effectiveness, although the effect size remains modest.

This pattern is broadly consistent with prior studies suggesting that academic rank influences lecturers' capacity to manage online learning and employ digital technologies effectively (Faris, 2020). Angervall et al. (2018) emphasized that higher-position lecturers have better access to institutional resources and professional training. Professors have extensive experience and their leadership roles provide valuable perspectives, but competing administrative and strategic demands may limit their engagement with the technical aspects of training (Abramo et al., 2018). The early-career academics, who are more focused on developing expertise in their core disciplines, may demonstrate greater concentration and consistency in training performance (Abramo et al., 2018; Krsmanovic & Foster, 2025). Vicianti and Hanifah (2021) noted that not all senior academics possess adequate digital skills. Inadequate digital skills can limit their ability to fully utilize digital training opportunities. Academic rank alone does not guarantee digital competence, as professional experience and exposure to technology training must also be considered.

Ekhsan and Nurlita (2020) argued that building an academic culture that encourages regular participation in technology training is essential for maintaining performance across lecturers' career paths. For senior lecturers to demonstrate strong performance on technical modules, they require further support. The literature suggests that while academic rank shapes having access to resources and opportunities, it interacts with other factors such as technological skills, institutional culture, and ongoing training. Training programs, therefore, need to address these disparities by ensuring that lecturers at all ranks receive adequate exposure to emerging digital competencies to sustain effective teaching and learning practices. The emphasis on leadership, resource allocation, and IT governance may explain why procedural modules tend to be more resilient to job variations despite differences in digital competencies among lecturers (Chetty, 2023; Sánchez, 2020).

Island and Training Effectiveness

The findings of this study revealed that the island of residence significantly influenced lecturers' performance in several training modules. Participants from major islands such as Java and Sumatra tended to achieve higher and more consistent outcomes compared to those from remote islands, particularly Papua, where median scores were lower in modules requiring advanced digital engagement. These differences highlight the structural disparities in training performance attributable to geographic location.

The findings are consistent with earlier research showing that geography plays a crucial role in shaping both the quality and accessibility of education, including online training (Heryati, 2022). Prior studies note that learners in remote islands often struggle with limited educational infrastructure and poor ICT access, which directly hampers training effectiveness. Maharani (2022) similarly highlighted that participants from larger islands benefit from greater access to quality training resources, reflecting wider geographical inequalities in Indonesian higher education. These structural gaps highlight the urgency of developing inclusive and region-sensitive policies to address disparities in digital training outcomes.

Afrina et al. (2024), Isabella et al. (2024), and Mariane et al. (2023) documented that differences in internet access contribute significantly to digital literacy gaps. The urban centers consistently outperform rural and peripheral regions. Regional studies further reveal that cultural practices, community support, and training design also influence outcomes, particularly in settings where infrastructure is weak (Andiyansari & Juwono, 2024; Mariane et al., 2023; Rizvi et al., 2019). The present findings reinforce the argument that island-based disparities are both technical and socio-cultural.

The relationship between training modules and geographical variation provides further insights. Modules demanding higher levels of digital literacy and adaptability demonstrated greater variability across islands, consistent with research emphasizing the importance of infrastructure in shaping digital competence (Afrina et al., 2024; Mariane et al., 2023). Modules rooted in institutional procedures showed more stable outcomes across regions, resonating with the view that standardized policy-driven content is less sensitive to geographic disparities (Fathoni et al., 2023; Isabella et al., 2024). This differentiation illustrates that geography exerts the strongest influence on innovation-oriented and digitally intensive modules, while its effect diminishes in procedural or policy-oriented content.

Limitations of the Study

This study has several limitations that should be acknowledged. The analysis was restricted to four demographic and contextual variables, namely gender, age, academic rank, and island of residence, while other relevant factors such as digital experience, institutional support, and motivation were not examined. The data relied on reported training performance through short-term training assessment mechanisms, which may be subject to response bias and do not fully capture long-term skill application in academic practice. The cross-sectional design also limits causal inference, as the findings reflect a single training period rather than longitudinal patterns of competence development. The study was conducted within the Indonesian higher education context, which may limit the generalizability of results to other national or regional settings with different educational and infrastructural characteristics.

Conclusion

This study examined how demographic and contextual factors shape the effectiveness of digital literacy training for higher education lecturers in Indonesia. The findings revealed that while the overall explanatory power of demographic factors was modest (8.8%), significant differences emerged across age, academic rank, and island of residence, with geographic disparities showing the strongest effect. Gender did not significantly influence training performance. Structural and contextual inequalities shape training effectiveness more strongly than individual demographic attributes. This study contributes to the literature by reinforcing the view that structural and institutional demographic conditions are more decisive than individual demographics in explaining digital literacy outcomes

Several recommendations can be drawn for policymakers and higher education institutions. Training programs should incorporate adaptive modules that can be tailored to participants' technological readiness. Institutions in remote areas require enhanced infrastructural investments. Senior academic lecturer in such regions would benefit from targeted support to strengthen their digital competencies. Professional development initiatives should ensure inclusivity across all academic ranks, integrating digital skills to close gaps between early career lecturers and senior academics.

Future research should extend beyond the demographic variables analyzed by examining the roles of digital experience, institutional support, and motivational factors in shaping training outcomes. Longitudinal approaches are needed to capture whether skills acquired in training are sustained and applied in academic practice over time. Comparative studies across countries or regions with different educational and infrastructural contexts could also provide broader insights into the global relevance of these findings. The mixed-methods designs may reveal deeper contextual mechanisms influencing digital literacy development.

Declarations

Acknowledgments: *The author would like to thank the Ministry of Education, Culture, Research, and Technology and the Directorate General of Higher Education, Research, and Technology for the financial support and sponsorship provided during this research's implementation. The valuable assistance and contributions from these parties are very important in the success of this research and in realizing useful results for developing digital literacy among lecturers in Indonesia. We are also grateful to all lecturers who have participated in this training and provided data to support this research.*

Funding: *Funding source is reported for this study.*

Ethics Statements: *Author/s declare presence of Ethics Statements that needed for ethical conduct of research using human subjects. This study was conducted in full compliance with the ethical guidelines of Directorate of Research and Community Service, Universitas Negeri Yogyakarta (No.T/51.2/UN34.9/KP.06.07/2024)*

Conflict of Interest: *The author(s) reported no potential conflict of interest.*

Informed Consent: *The data that support the findings of this study are available from the corresponding author upon reasonable request.*

References

Abdul Razak, A. N., Noordin, M. K., & Abdul Khanan, M. F. (2022). Digital learning in technical and vocational education and training (tvet) in public university, Malaysia. *Journal of Technical Education and Training*, *14*(3). https://doi.org/10.30880/jtet.2022.14.03.005

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2018). The effects of gender, age and academic rank on research diversification. *Scientometrics*, *114*(2), 373–387. https://doi.org/10.1007/s11192-017-2529-1

Adnan, M., Kalelioglu, F., & Gulbahar, Y. (2017). Assessment of a multinational online faculty development program on online teaching: reflections of candidate e-tutors. *Turkish Online Journal of Distance Education*, *18*(1), 22–22. https://doi.org/10.17718/tojde.285708

Afrina, C., Zulaikha, S. R., & Jumila, J. (2024). The low level of digital literacy in Indonesia: An analysis of online media content. *Record and Library Journal*, *10*(2), 374–387. https://doi.org/10.20473/rlj.v10-i2.2024.374-387

Al-Swidi, A., & Al Yahya, M. (2017). Training transfer intention and training effectiveness: Assessing the gender differences using multi-group structural equation modelling approach. *International Journal of Organizational Analysis*, *25*(5), 839–860. http://dx.doi.org/10.1108/IJOA-07-2016-1043

Andiyansari, P., & Juwono, A. P. (2024). Kecakapan literasi digital para penyintas online gender-based violence [Digital literacy skills of survivors of online gender-based violence]. *Jurnal Komunikasi*, *18*(2), 229–248. https://doi.org/10.20885/komunikasi.vol18.iss2.art7

Angervall, P., Gustafsson, J., & Silfver, E. (2018). Academic career: on institutions, social capital and gender. *Higher Education Research \& Development*, *37*(6), 1095-1108. https://doi.org/10.1080/07294360.2018.1477743

Avelia, T. E., & Esita, P. (2020). Pengaruh corporate governance dan umur perusahaan terhadap kinerja perusahaan [The influence of corporate governance and company age on company performance]. *Jurnal EBI*, *2*(2). https://doi.org/10.52061/ebi.v2i2.21

Bausch, S., Michel, A., & Sonntag, K. (2014). How gender influences the effect of age on self-efficacy and training success. *International Journal of Training and Development*, *18*(3), 171–187. https://doi.org/10.1111/ijtd.12027

Bennett, S., Maton, K., & Kervin, L. (2008). The 'digital natives' debate: A critical review of the evidence. *British Journal of Educational Technology*, *39*(5), 775–786. https://doi.org/10.1111/j.1467-8535.2007.00793.x

Boyte-Eckis, L., Minadeo, D. F., Bailey, S. S., & Bailey, W. C. (2018). Age, gender, and race as predictors of opting for a midterm retest: A statistical analysis of online economics students. *Journal of Business Diversity*, *18*(1). https://www.proquest.com/scholarly-journals/age-gender-race-as-predictors-opting-midterm/docview/2055193982/se-2

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education*, *105*, 1–13. https://doi.org/10.1016/j.compedu.2016.11.003

Chetty, K. (2023). Ai literacy for an ageing workforce: Leveraging the experience of older workers. *Obm Geriatrics*, *07*(03), 1–17. https://doi.org/10.21926/obm.geriatr.2303243

Cochran, W. G. (1963). *Sampling techniques* (2nd Ed.). John Wiley and Sons, Inc.

Cronk, B. C. (2016). *How to use IBM SPSS statistics: A step-by-step guide to analysis and interpretation*. Routledge.

Cutri, R. M., Mena, J., & Whiting, E. F. (2020). Faculty readiness for online crisis teaching: Transitioning to online teaching during the COVID-19 pandemic. *European Journal of Teacher Education*, *43*(4), 523–541. https://doi.org/10.1080/02619768.2020.1815702

Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management*, *55*, 102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211

Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-utaut): A review of emerging literature. *Current Opinion in Psychology*, *36*, 13–18. https://doi.org/10.1016/j.copsyc.2020.03.008

Ekhsan, M., & Nurlita, D. (2020). Pengaruh gaya kepemimpinan, pelatihan dan promosi jabatan terhadap kinerja karyawan [The influence of leadership style, training and job promotion on employee performance]. *Jurnal Pengembangan Wiraswasta*, *22*(02), 113. https://doi.org/10.33370/jpw.v22i02.418

Ellis, A. R., Burchett, W. W., Harrar, S. W., & Bathke, A. C. (2017). Nonparametric inference for multivariate data: The R package npmv. *Journal of Statistical Software*, *76*(1). https://doi.org/10.18637/jss.v076.i04

Eom, S., Ashill, N. J., Arbaugh, J. B., & Stapleton, J. L. (2012). The role of information technology in e-learning systems success. *Human Systems Management*, *31*(3–4), 147–163. https://doi.org/10.3233/HSM-2012-0767

Faris, S. (2020). Pengaruh kompetensi, pelatihan dan motivasi terhadap kinerja dosen tetap pada Universitas Prima Indonesia [The influence of competence, training and motivation on the performance of permanent lecturers at Universitas Prima Indonesia]. *Agriprimatech*, *4*(1), 16–24. https://doi.org/10.34012/agriprimatech.v4i1.1317

Fathoni, S., Nabella, N., Nurmala, V. F., & Prayoga, M. R. B. (2023). Application of technology in mitigation of forest and peatland fires in Riau Province to support national security. *Riau Journal of Empowerment*, *6*(1), 53–71. https://doi.org/10.31258/raje.6.1.53-71

He, J., Zhao, H., & Jiang, F. (2022). Analysis of the status and influencing factors of online learning. *Canadian Journal of Learning and Technology*, *48*(4), 1–19. https://doi.org/10.21432/cjlt28246

Heryati, N. (2022). Tata kelola kompetensi guru [Teacher competency management]. *Journal of Governance and Administrative Reform*, *3*(2), 123–141. https://doi.org/10.20473/jgar.v3i2.41756

Isabella, I., Alfitri, A., Saptawan, A., Nengyanti, N., & Baharuddin, T. (2024). Empowering digital citizenship in Indonesia: Navigating urgent digital literacy challenges for effective digital governance. *Journal of Governance and Public Policy*, *11*(2), 142–155. https://doi.org/10.18196/jgpp.v11i2.19258

Islam, M. A., Abdul Rahim, A., Tan, C. L., & Momtaz, H. (2011). Effect of demographic factors on e-learning effectiveness in a higher learning institution in Malaysia. *International Education Studies*, *4*(1), 112–121. https://doi.org/10.5539/ies.v4n1p112

Kang, Y., Rahrig, H., Eichel, K., Niles, H. F., Rocha, T., Lepp, N. E., Gold, J., & Britton, W. B. (2018). Gender differences in response to a school-based mindfulness training intervention for early adolescents. *Journal of School Psychology*, *68*, 163–176. https://doi.org/10.1016/j.jsp.2018.03.004

Ke, F., & Kwak, D. (2013). Online learning across ethnicity and age: A study on learning interaction participation, perception, and learning satisfaction. *Computers & Education*, *61*, 43–51. https://doi.org/10.1016/j.compedu.2012.09.003

Kelly, M. E., Dowell, J., Husbands, A., Newell, J., O'Flynn, S., Kropmans, T., Dunne, F. P., & Murphy, A. W. (2014). The fairness, predictive validity and acceptability of multiple mini interview in an internationally diverse student population- a mixed methods study. *BMC Medical Education*, *14*(1), 267. https://doi.org/10.1186/s12909-014-0267-0

Krsmanovic, M., & Foster, H. A. (2025). Sustainability of fully online and rapidly growing edd programs: Using student demographics to improve program outcomes. *The Journal of Continuing Higher Education*, *73*(1), 48–63. https://doi.org/10.1080/07377363.2024.2330118

Liu, Z., Brown, R., Lynch, C. F., Barnes, T., Baker, R., Bergner, Y., & McNamara, D. (2016). MOOC learner behaviors by country and culture: an exploratory analysis. *International Educational Data Mining Society*. https://eric.ed.gov/?id=ED592695

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015b). Bridging the Divide: Using UTAUT to Predict Multigenerational Tablet Adoption Practices. *Computers in Human Behavior*, *50*, 186–196. https://doi.org/10.1016/j.chb.2015.03.032

Maharani, K. (2022). Standar kompetensi kelulusan [Graduate competency standards]. *Borneo Journal of Islamic Education*, *2*(1), 57–72. https://doi.org/10.21093/bjie.v2i1.5928

Mahyuddin, T., Hanisah, H., & Rahmi, C. L. (2018). Faktor-faktor yang mempengaruhi kinerja penyuluh pertanian di kabupaten Aceh Timur [Factors influencing the performance of agricultural extension workers in East Aceh district]. *Jurnal Penelitian Agrisamudra*, *5*(1), 22–29. https://doi.org/10.33059/jpas.v5i1.838

Mannheim, I., Varlamova, M., Zaalen, Y. van, & Wouters, E. (2023). The role of ageism in the acceptance and use of digital technology. *Journal of Applied Gerontology*, *42*(6), 1283–1294. https://doi.org/10.1177/07334648231163426

Mantashe, L. X. (2023). Online pedagogy: A changing higher education pedagogy and an emerging lecturer habitus. *The Independent Journal of Teaching and Learning*, *18*(2), 29–41. https://doi.org/10.17159/ijtl.v18i2.17293

Mariane, I., Sariningsih, Y., Buanawaty, R. A., & Azis, H. A. (2023). Improving Digital literacy skills for youth karang taruna, Cigadung Village, Cibeunying Kaler District, Bandung City. *Kaibon Abhinaya Jurnal Pengabdian Masyarakat*, *5*(1), 91–99. https://doi.org/10.30656/ka.v5i1.5301

McAdams, E., Tingey, B., & Ose, D. (2022). Train the trainer: Improving health education for children and adolescents in Eswatini. *African Health Sciences*, *22*(1), 657–663.

https://doi.org/10.4314/ahs.v22i1.76

Mintawati, H., Rahayu, A. S., Puspita, D., Fauzan, F., & Safhira, F. (2023). Pengaruh pelatihan dan pengembangan terhadap kinerja karyawan di perusahaan pelayanan jasa [The influence of training and development on employee performance in service companies]. *Jurnal Ilmiah IPS Dan Humaniora (JIIH)*, *1*(1), 28–33. https://doi.org/10.61116/jiih.v1i1.38

Mokoena-de Beer, A. G., & Moloko, S. M. (2022). Nurse lecturers' experiences with online teaching during the pandemic at a public university in Gauteng, South Africa. *Curationis*, *45*(1). https://doi.org/10.4102/curationis.v45i1.2371

Mulyana, R., Pramadya, H., & Vindiazhari, N. R. (2024). Pelatihan literasi digital lembaga untuk lanjut usia indonesia (lli) Kota Bandung [Digital literacy training for the Indonesian elderly institution in Bandung City]. *SolusiBersama*, *1*(2), 1–17. https://doi.org/10.62951/solusibersama.v1i2.147

Onwuegbuzie, A. J., & Ojo, E. O. (2021). University students' experiences of learning in an online environment in COVID-19 pandemic : A meta-methods research study of perceptions and attitudes of South African students. *Journal of Pedagogical Research, 5*(4), 1–18. https://doi.org/10.33902/JPR.2021472164

Onwuegbuzie, A. J., Ojo, E. O., Burger, A., Crowley, T., Adams, S. P., & Bergsteedt, B. J. (2020). Challenges experienced by students at stellenbosch university that hinder their ability successfully to learn online during the covid-19 era: A demographic and spatial analysis. *International Journal of Multiple Research Approaches*, *12*(3), 240–281. https://doi.org/10.29034/ijmra.v12n3editorial2

Puspitawati, N. M. D., Andika, A. W., & Paramita, I. A. P. U. (2023). The impact of self-paced online training on self-efficacy and work engagement in private universities, Bali, Indonesia. *Jurnal Aplikasi Bisnis Dan Manajemen*. https://doi.org/10.17358/jabm.9.3.795

Rizvi, S., Rienties, B., & Khoja, S. A. (2019). The role of demographics in online learning; A decision tree based approach. *Computers and Education*, *137*(January), 32–47. https://doi.org/10.1016/j.compedu.2019.04.001

Salles, A., Awad, M., Goldin, L., Krus, K., Lee, J. V., Schwabe, M. T., & Lai, C. K. (2019). Estimating implicit and explicit gender bias among health care professionals and surgeons. *JAMA Network Open*, *2*(7), e196545. https://doi.org/10.1001/jamanetworkopen.2019.6545

Sánchez, M. A. (2020). University e-readiness for the digital transformation: The case of Universidad Nacional Del Sur. *Revista Gestão & Tecnologia*, *20*(2), 75–97. https://doi.org/10.20397/2177-6652/2020.v20i2.1848

Schwartz, L. P., Liénard, J. F., & David, S. V. (2022). Impact of gender on the formation and outcome of formal mentoring relationships in the life sciences. *PLoS Biology*, *20*(9), e3001771. https://doi.org/10.1371/journal.pbio.3001771

Sherimon, V., Leena Francis, Sherimon P.C., Disha Devassy, & Walid Aboraya. (2022). Exploring the impact of learners' demographic characteristics on course completion and dropout in massive open online courses. *International Journal of Research - GRANTHAALAYAH*, *10*(1), 149–160. https://doi.org/10.29121/granthaalayah.v10.i1.2022.4469

Singh-Pillay, A., & Naidoo, J. (2020). Context matters: Science, technology and mathematics education lecturers' reflections on online teaching and learning during the covid-19 pandemic. *Journal of Baltic Science Education*, *19*(6A), 1125–1136. https://doi.org/10.33225/jbse/20.19.1125

St-Jean, É., Tremblay, M., Fonrouge, C., & Chouchane, R. (2022). Gendered impact of training on entrepreneurial self-efficacy: A longitudinal study of nascent entrepreneurs.

Journal of Small Business & Entrepreneurship, *34*(5), 524–547. https://doi.org/10.1080/08276331.2021.1981731

Thinyane, H. (2010). Are digital natives a world-wide phenomenon? An investigation into South African first year students' use and experience with technology. *Computers & Education*, *55*(1), 406–414. https://doi.org/https://doi.org/10.1016/j.compedu.2010.02.005

Tziner, A., & Falbe, C. M. (1993). Training-related variables, gender and training outcomes: a field investigation. *International Journal of Psychology*, *28*(2), 203–221. https://doi.org/10.1080/00207599308247185

Van Wyk, J., Naidoo, S., Moodley, K., & Higgins-Opitz, S. (2016). Perceptions of final-year medical students towards the impact of gender on their training and future practice. *Advances in Medical Education and Practice*, *Volume 7*, 541–550. https://doi.org/10.2147/AMEP.S107304

Vicianti, A. P., & Hanifah, H. (2021). Penyesuaian diri dosen senior dalam pembelajaran jarak jauh di masa covid-19 [Senior lecturers' adjustments to distance learning during the Covid-19 pandemic]. *Jurnal Muara Ilmu Sosial, Humaniora, Dan Seni*, *5*(2), 425. https://doi.org/10.24912/jmishumsen.v5i2.11121.2021

Webster, K. (2024). The impact of online learning during the covid-19 pandemic on academic outcomes for newly-struggling high school students. *Online Learning*, *28*(3). https://doi.org/10.24059/olj.v28i3.3680

Zamani, B. E., Esfijani, A., & Abdellahi Damaneh, S. M. (2016). Major barriers for participating in online teaching in developing countries from Iranian faculty members' perspectives. *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.2678