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# Exploring the Role of Lecturers' Psychological Readiness, Teaching Expertise, and Perceptions in Advancing Digital Literacy Integration in Higher Education

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**Abstract**

Exploring the Integration of Digital Literacy (DL) in Higher Education (PT) is a complex and continuously developing relationship. This research aims–identify barriers and factors for effective integration and assesses their impact on learning. This research uses mixed methods to measure 93 lecturers from various academic backgrounds~~,~~ and teaching experiences to reveal the multifaceted dynamics of DL integration by examining experiences, perceptions, and institutional factors that influence lecturers. Correlation findings reveal distinct relationships, while regression and structural equation modeling highlight the explanatory power of selected predictors. The findings of this research have practical implications for lecturers, administrators, policymakers in higher education. Additionally, this research contributes to the scholarly discourse by capturing diverse narratives surrounding the integration of DL in HE. This increased understanding of research opens up opportunities for future research in the form of further investigation into the specific dynamics of peer influence and the impact of institutional policies. In conclusion, higher education institutions adapt to the digital era's demands, and collective research and practice efforts can form an inclusive and adaptive education system.

**Keywords:** Digital literacy integration; higher education; educational technology; pedagogical readiness

## 1.Introduction

In higher education, integrating literacy is very important. It is to bridge knowledge gaps and foster critical thinking (Haleem, Javaid, Qadri, & Suman, 2022). This research explores barriers to using digital tools, overcoming resistance to change, digital divide concerns, and the need for robust training programs (Gkrimpizi, 2023). This research applies the Diffusion of Innovation theory, and we will investigate how digital literacy spreads among lecturers and categorize it based on the user-innovator curve (Pinho, Franco, & Mendes, 2021; Rogers, 1983; Sasaki, 2018).

This research uses an integrated framework from the Technology Acceptance Model (TAM) and Diffusion of Innovation Theory, which captures the nuances in technology adoption (Emon, 2023; Hubert et al., 2019). Lecturers' beliefs about digital tools' ease of use (TAM) align with broader innovation contexts, shaping collective decisions within their professional community (Al-Rahmi et al., 2019; Awang et al., 2022).

Identifying research gaps, we address the limited application of TAM and the Diffusion of Innovation Theory during the pandemic (Vodă, Cautisanu, Grădinaru, Tănăsescu, & de Moraes, 2022). This research accelerates technology use, assessing factors influencing digital literacy accumulation. Going beyond Choe and Noh (2018), we explore individual perceptions and social influences, emphasizing psychological preparedness, teaching skills, and perceptions as key variables. The study recognizes institutional and peer dynamics' moderating influence on digital literacy integration, providing insights into the broader educational context.

Based on the context and gaps identified in the literature related to integrating digital literacy in higher education, this research can have the following objectives.

Research Objectives:

1. To investigate integration practices by assessing how lecturers integrate digital literacy tools into their teaching, focusing on their perceptions, psychological readiness, and expertise.

2. To understand the role of moderating variables by examining how institutional factors and peer influence moderate the relationship between lecturers' readiness, expertise, perceptions, and the integration of digital literacy tools.
3. To identify obstacles and supporting factors by determining the key facilitators and obstacles in integrating digital literacy tools, considering individual and contextual factors.
4. To assess the impact on teaching and learning by evaluating the effects of integrating digital literacy tools on teaching methodologies and student learning outcomes, with attention to how these effects might vary in different institutional and peer contexts.
5. To provide recommendation strategies by developing recommendations for educational institutions that address individual lecturer needs and the broader institutional and peer dynamics influencing digital literacy integration.

Research Questions:

1. How are lecturers integrating digital literacy tools in their teaching, and what roles do individual perceptions, psychological readiness, and teaching expertise play in this process?
2. How do institutional factors and peer influence moderate the relationship between lecturers' perceptions of digital literacy tools and their integration into teaching?
3. What are the primary barriers and enablers to integrating digital literacy tools in higher education, and how do these relate to individual and contextual factors?
4. How do integrating digital literacy tools influence teaching methodologies and student learning outcomes, and how do institutional and peer contexts influence this impact?
5. Based on the findings, what strategies and policy recommendations can be formulated to enhance the adoption and effective use of digital literacy tools in educational institutions?

Based on these research objectives and questions, hypotheses correspond to each area this research explores. These hypotheses are statements that this research aims to test and validate.

Hypothesis 1: Lecturers with positive perceptions of digital literacy tools (ease of use and usefulness), higher psychological readiness, and greater teaching expertise are more likely to integrate these tools effectively into their teaching practices.

Hypothesis 2: Institutional support positively moderates the relationship between lecturers' perceptions of digital literacy tools and their integration into teaching, such that stronger institutional support enhances this relationship.

Hypothesis 3: Peer influence positively moderates the relationship between lecturers' psychological readiness to adopt digital literacy tools and their integration into teaching.

Hypothesis 4: The primary barriers to integrating digital literacy tools in higher education (such as inadequate training and technological infrastructure) negatively influence lecturers' ability to integrate these tools. In contrast, enablers (such as institutional support and positive peer attitudes) have a positive influence.

Hypothesis 5: Integrating digital literacy tools in higher education impacts teaching methodologies and student learning outcomes, further enhanced in environments with strong institutional support and positive peer influence.

## 2.Method

### Research Design

This study employs a mixed methods approach to investigate the intricate dynamics of digital literacy integration in higher education. Guided by Creswell's methodology (Creswell & Clark, 2018), the research explores the direct impact of lecturers' psychological readiness, teaching skills, and perceptions of digital literacy integration. This comprehensive design allows for an in-depth analysis, considering the moderating effects of institutional factors and peer influence (Memon et al., 2019).

### Data Collection

Structured questionnaires, based on a thorough literature review and established frameworks (Aithal & Aithal, 2020), were electronically distributed to participants in Tangerang City. A ten-day window was provided for completion.

### Data Analysis

#### Quantitative Phase

We employ Structural Equation Modelling (SEM) with PLS statistical software to measure the quantitative phase and analyze the variables' relationships (Hair, Risher, Sarstedt, & Ringle, 2019). Reliability analysis using Cronbach's alpha ensured measurement consistency.

**Qualitative Phase**
Semi-structured interviews were conducted with six lecturers, and focus group discussions (FGDs) enriched perspectives. Atlas. ti, the software facilitated analysis, unveiling the nuances of lecturers' experiences with digital literacy tools (Friese, 2016; Rahmadani & Adityo, 2023). FGDs ensured diverse inputs from participants across disciplines, experience levels, and institution types.

**Ethical Consideration**
In maintaining ethical standards, this study prioritizes participant rights and well-being. Transparency, informed consent, and data confidentiality are integral to upholding the highest ethical principles (Kang, E. & Hwang, 2023; Manti & Licari, 2018; McCulloch, 2018). A demographic profile of the 93 lecturers enhances contextual understanding, demonstrating the researcher's commitment to responsible and considerate research (Fleming & Zegwaard, 2018; Stam & Kleiner, 2020).

## 3. Findings

**Table 1.** Demographic Profile (N=93)

| Information | F | % |
|---|---|---|
| **Gender** | | |
| Male | 49 | 52.7 |
| Female | 44 | 47.3 |
| | | |
| **Academic Discipline** | | |
| Civics | 34 | 36.5 |
| Economic Management | 38 | 40.9 |
| Indonesian | 21 | 22.6 |
| | | |
| **Teaching Experience** | | |
| 1-5 | 14 | 15.1 |
| 6-10 | 23 | 24.7 |
| 11-15 | 18 | 19.4 |
| 16-20 | 21 | 22.6 |
| 21-25 | 10 | 10.8 |
| 26> | 7 | 8 |

The analysis and results of this research focused on assessing the validity and reliability of questionnaire data using SEM PLS for key constructs. The results are presented in Table 2, showcasing discriminant validity and reliability statistics for each construct involved in the study.

**Table 2.** The results of the Discriminant Validity Assessment and Reliability

| | Intregrating DLin HE | Lecturers' Readiness | Peer Influence (Moderation) | Perception DL*Peer Influence | Perception DL | Psychological Readiness*Peer Influence | Teaching Expertise*Peer Influence | Teaching Expertise | Cronbach's Alpha |
|---|---|---|---|---|---|---|---|---|---|
| **Integrating DL in HE** | 0.757 | | | | | | | | 0.813 |
| **Lecturers' Readiness** | 0.727 | 0.738 | | | | | | | 0.729 |
| **Peer Influence (Moderation)** | 0.852 | 0.650 | 0.869 | | | | | | 0.777 |
| **Perception DL*Peer Influence** | -0.350 | -0.487 | -0.343 | 1.000 | | | | | 1.000 |
| **Perception DL** | 0.797 | 0.763 | 0.778 | -0.474 | 0.733 | | | | 0.784 |
| **Psychological Readiness*Peer Influence** | -0.345 | -0.522 | -0.328 | 0.960 | -0.488 | 1.000 | | | 1.000 |
| **Teaching Expertise*Peer Influence** | -0.352 | -0.476 | -0.365 | 0.978 | -0.466 | 0.922 | 1.000 | | 1.000 |
| **Teaching Expertise** | 0.696 | 0.682 | 0.744 | -0.431 | 0.922 | -0.441 | -0.410 | 0.871 | 0.918 |

*Interpretation of Table 2. The results of the Discriminant Validity Assessment and Reliability*
Table 2 presents the results of the discriminant validity assessment. In this table, this research calculated the correlation between various constructs. The goal was to determine whether the measurement items for one construct are

not highly correlated with the measurement items for another theoretically distinct construct (Henseler, Ringle, & Sarstedt, 2015).
The correlation between integrating DL in HE and other constructs, such as lecturer readiness and peer influence (moderation), is relatively low (0.57 and 0.852, respectively). This low correlation indicates that integrating DL into HE differs from other constructs.

The correlations between perceived DL peer influence and other constructs were very low, with values of -0.350, -0.487, -0.343, and 1.000. It strengthens the distinctiveness of the Influence of DL Peer Perception from other constructs because it shows low associations with these constructs. Some correlations are negative and significant. For example, the negative correlation between perceived DL and Psychological readiness*Peer influence (-0.474) indicates that these two constructs are inversely related, thus further supporting their distinctiveness. It is worth mentioning that a correlation of 1,000 represents the construct by itself, indicating perfect discriminant validity. Thus, the findings in Table 3 provide strong evidence of discriminant validity. According to Sürücü & Maslakçi (2020), the low correlation between constructs indicates that the constructs are different and do not measure the same basic concept. It supports the credibility and reliability of this research's measurement instruments, ensuring that this research accurately captures the various dimensions of research. For the reliability and validity statistics for each main construct involved in this research. In measuring reliability, the extent to which the items in each construct consistently measure the same basic construct is assessed (Taber, 2018). This study measured Cronbach's Alpha exceeding the widely accepted threshold of 0.7, indicating strong internal consistency reliability. It shows that the measurement items in each construct are very analytical and consistent. Construct validity assessment to validate further the research measurement instrument (Lia, Rusilowati, & Isnaeni, 2020; Mohajan, 2017). It examines the relationships between research measurement items and other established measurements (Dabbagh, Seens, Fraser, & MacDermid, 2023). The results demonstrated strong and expected correlations between this study's items and existing measures, providing strong evidence of construct validity.

Furthermore, the discriminant validity assessment and reliability results in Table 2 confirm the uniqueness of this research's constructs and strengthen the validity and reliability of this research's measurement instruments, thereby increasing the strength of this research's findings.

**Correlation Findings**

DL integration in HE vs. Other constructs, such as Lecturers' Readiness and Peer Influence (moderation), are relatively low, respectively, at 0.757 and 0.852. The low correlation indicates that integrating DL into HE differs from other constructs.

The influence of DL Peer perception and other constructs is very low, with values of -0.350, -0487, -0343, and 1.000. It reinforces the distinctiveness of the DL Peer Perceptual Influence from other constructs, as it shows low association with them.
Some correlations are negative and can be meaningful. For example, the negative correlation between Perceived DL and Psychological Readiness*Peer Influence (-0.474) indicates that these two constructs are inversely related, further supporting their distinctiveness.

In this research, there were findings of highly discriminant correlations, a correlation of 1,000 representing the construct with itself, indicating perfect discriminant validity.

Thus, the findings in Table 3 provide strong evidence of discriminant validity. According to Chiu & Lin (2022), the low correlation between constructs indicates that these constructs are indeed different and do not measure the same basic concept. It supports the credibility and reliability of this research's measurement instruments, ensuring that this research accurately captures the various dimensions of the research (SÜRÜCÜ & MASLAKÇI, 2020). Therefore, the results of the Discriminant Validity Assessment in Table 3 confirm the uniqueness of this research construct and strengthen the validity of the measurement instruments of this research, thereby increasing the strength of the findings from this research.
Next, this research will conduct a regression analysis, explained in Table 3.

**Table 3.** Regression Analysis

| | R Square | R Square Adjusted |
|---|---|---|
| **Integrating DL in HE** | 0.814 | 0.799 |

*Interpreting Regression Analysis*

The R-squared value of 0.814 indicates that the regression model of this research is quite capable of explaining variations in the dependent variable, integrating DL into HE. It means that the independent variables in this model collectively account for approximately 81.4% of the observed variation in this variable.

The adjusted R-squared value of 0.799, which is slightly lower than the unadjusted R-squared, indicates that including the independent variables in the research model is meaningful and contributes to explaining the variance in the variables. Thus, this R-squared value indicates that this research's regression model has a relatively good fit to the data, with a large portion of the variance in Integrating DL into HE explained by the predictors in this research's model.

In the regression analysis, we evaluate the overall model fit. It performs quite well, explaining most of the variance in Integrating Digital Literacy (DL) in Higher Education (HE). The adjusted R-squared value of 0.799 indicates that the predictors we selected are meaningful in explaining differences in integrating digital literacy tools. Thus, this research moves from a broader understanding to dissect the specific pathways and coefficients that govern these relationships.

## Path Coefficient

This research's SEM reveals a complex network of connections, each represented by a path coefficient, that measures the strength and direction of influence between variables (Hu, Li, Xi, Gu, & Zhang, 2019). Furthermore, it begins by exploring one pathway - the relationship between Lecturers' Readiness and Integrating DL in HE. Table 4 shows the path coefficient of this research.

**Table 4.** Path Coefficient

| | Integrating DL in HE | Peer Influence | Perception DL*Peer Influence | Perception in DL | Psychological Readiness*Peer Influence | Teaching Expertise*Peer Influence | Teaching Expertise |
|---|---|---|---|---|---|---|---|
| **Integrating DL in HE** | 0.215 | | | | | | |
| **Peer Influence** | 0.592 | | | | | | |
| **Perception DL*Peer Influence** | -0.268 | | | | | | |
| **Perception in DL** | 0.551 | | | | | | |
| **Psychological Readiness*Peer Influence** | 0.106 | | | | | | |
| **Teaching Expertise*Peer Influence** | 0.219 | | | | | | |
| **Teaching Expertise** | -0.374 | | | | | | |

*Interpretation of Path Coefficient*

This path coefficient, measured at 0.215, provides valuable insight. A positive sign of 0.215 indicates an important finding - increasing lecturers' readiness to use digital literacy tools is positively correlated with a greater likelihood of integrating these tools into teaching practices in higher education. Even though this relationship is statistically significant, the large coefficient indicates a relatively small influence. These findings partially support Hypothesis 1, which states that lecturers with higher psychological readiness will show a greater tendency to integrate digital literacy tools effectively.

The path coefficients offer a different perspective on the factors influencing the integration of digital literacy tools in higher education. In addition to statistical significance (Vijayalaxmi, Manohar Rao, Padmavatamma, & Siva Shankar, 2017), this research will explore these relationships' practical implications and relevance, considering how they align with existing literature and what they mean for educators and educational institutions.

## Total Effect

After analyzing the path coefficients in the Structural Equation Model (SEM), which represents the direct relationship between individual independent variables and the dependent variable, Integrating Digital Literacy (DL) in Higher Education (HE), this research will test the Total Effect (Hair et al., 2019). While Path Coefficients provide insight into the strength and direction of individual relationships, Total Effects provide a comprehensive view of the overall impact of each independent variable on the integration of digital literacy in higher education. The total effect considers all possible pathways, including direct and indirect influences, thereby providing a holistic understanding of the variable's contribution to the research.

**Table 5.** Total Effect

| | Integrating DL in HE | Peer Influence | Perception DL*Peer Influence | Perception in DL | Psychological Readiness*Peer Influence | Teaching Expertise*Peer Influence | Teaching Expertise |
|---|---|---|---|---|---|---|---|
| **Integrating DL in HE** | 0.215 | | | | | | |
| **Peer Influence** | 0.592 | | | | | | |
| **Perception DL*Peer Influence** | -0.268 | | | | | | |

| | |
|---|---|
| **Perception in DL** | 0.551 |
| **Psychological Readiness*Peer Influence** | 0.106 |
| **Teaching Expertise*Peer Influence** | 0.219 |
| **Teaching Expertise** | -0.374 |

*Interpretation of Total Effect*

Lecturer Readiness (Total Effect: 0.215). The total effect of lecturers' readiness to integrate DL in higher education (HE) is positive; this shows that increasing lecturers' readiness is associated with a positive increase in integrating digital literacy in higher education. Thus, a higher level of lecturer readiness is associated with higher digital literacy integration.

Peer Influence (Moderation) (Total Effect: 0.592). A moderating variable, peer influence, positively affects the integration of digital literacy in higher education. It shows that when considering peer influence as a moderator, stronger peer influence is associated with a more significant positive impact on digital literacy integration.

Perception in DL (Total Effect: 0.551). Perceptions of DL have a positive Total Effect, indicating that positive perceptions of digital literacy are associated with greater integration of digital literacy in higher education.

Psychology Readiness*Peer Influence (Total Effect: 0.106). The total effect of the interaction between Psychological Readiness and Peer Influence is positive but relatively smaller in magnitude. It shows that the combined effect of psychological readiness and peer influence has a manageable positive impact on integrated digital literacy.

Teaching Expertise*Peer Influence (Total Effect: 0.219). Similar to psychological readiness, the interaction between teaching skills and peer influence was positive, and it showed that when considering teaching skills and peer influence together, there was a positive effect on digital literacy integration.

Teaching Expertise (Total Effect: -0.374). Teaching expertise has a negative total effect indicating that higher levels of teaching expertise are associated with reduced integration of digital literacy in higher education.

The conclusion is that the Total Effect interpretation provides a broader perspective on the influence of each variable on this research topic and offers valuable insight into the multifaceted nature of digital literacy integration in higher education.

After carrying out the Total Effects test in the research structural equation model, which highlights the direct and indirect relationships between the variables studied, we will assess the suitability of this research model as a whole. Evaluating the suitability of the model provides a critical perspective on how aligned the theoretical framework of the study is with the empirical data collected (Ringle, Sarstedt, Sinkovics, & Sinkovics, 2023). To do this, we focus on various fit indices, including SRMR (Standardized Root Mean Square Residual) and rms Theta. These goodness-of-fit indices provide valuable insight into the adequacy of this research model in explaining the data patterns observed in our analysis, and we obtain specific values for SRMR and rms Theta (Pavlov, Maydeu-Olivares, & Shi, 2021). Table 6 shows Model Fit: Fit Summary, and Table 6 shows Model Fit: rms Theta.

**Table 6.** Model Fit: Fit Summary

| | Saturated Model | Estimated Model |
|---|---|---|
| **SRMR** | 0.140 | 0.140 |
| **d_ULS** | 4.940 | 0.4977 |
| **d_G** | n/a | n/a |
| **Chi-Square** | infinite | infinite |
| **NFI** | n/a | n/a |

*Interpretation of Model Fit: Fit Summary*

Examining the main fit indices, including SRMR and rms Theta, assesses the suitability of this research's structural equation model. SRMR measures the standardized difference between the observed and implied correlations in the model and provides valuable insight into how well the study's estimated model aligns with the data. In both the Saturated model and the Estimation Model, this research obtained an identical SRMR value of 0.140. Typically, SRMR values below 0.10 indicate a good fit. However, it is important to note that the appropriateness of these thresholds may vary depending on the complexity and context of the study. In this study, the SRMR value of 0.140 was slightly above the conventional threshold, thus indicating room for improvement in model fit.

Moreover, this study considers rms Theta, another measure of model fit. The obtained rms Theta value of 0.290 provides additional perspective regarding the model's suitability. These similarity indices collectively indicate that this research's structural equation model fits the data well. However, there is still potential for improvement, especially considering the slightly increased SRMR value—the complexity of the context of this study and the nature of the data when assessing model fit. In addition, a comprehensive evaluation of other fit indices is also recommended to better understand the fit model with the observation data of this research.

**Collinearity Statistics (VIF)**

In this section, we describe the Outer VIF Value for interpreting VIF Values, and The VIF values for individual variables (A1 to D5) ranged from 1.000 to 131.152 as shown in Table 7.

**Table 7.** Outer VIF Value

| | VIF | | VIF | | VIF | | VIF | | VIF |
|---|---|---|---|---|---|---|---|---|---|
| A1 | 1.943 | B1 | 68.894 | C1 | 1.770 | D1 | 2.693 | Lecturers Readiness * Peer Influence (Moderation) | 1.000 |
| A2 | 1.443 | B2 | 67.761 | C2 | 2.060 | D2 | 1.980 | M1 | 1.354 |
| A3 | 1.871 | B3 | 1.504 | C3 | 1.536 | D3 | 1.863 | M2 | 1.354 |
| A4 | 1.497 | B4 | 1.754 | C4 | 1.266 | D4 | 1.467 | Perception in DL * Peer Influence (Moderation) | 1.000 |
| A5 | 1.431 | B5 | 131.152 | C5 | 1.292 | D5 | 1.406 | Teaching Expertise * Peer Influence (Moderation) | 1.000 |

*Interpretation of Analysis VIF (Variance Inflation Factor) Value*

This research (A1 to D5) determines the specific analyzed variables. The VIF values ranged from 1,000 to 131,152, indicating the lowest and highest VIF values observed in this research, thus providing a clear understanding of the range of multicollinearity present in the analysis of this research.

Individual variables (A1 to D5) are the specific variables whose VIF values have been calculated. In this study, the variables are labelled as A1, A2, A3, A4, A5, B1, B2, B3, B4, B5, C1, C2, C3, C4, C5, D1, D2, D3, D4, and D5.

Variables with a VIF of 1,000 have no significant multicollinearity problems, which indicates that these variables can be interpreted safely without considering multicollinearity. The highest VIF value was 131.152 observed among the variables of this research. The highest VIF indicates a strong degree of multicollinearity, which can complicate the interpretation of the effect of individual variables.

Variables with VIF <2.5 are variables from A1 to D5, with VIF values below 2.5; this indicates low multicollinearity. It means that these variables do not have significant multicollinearity problems, and this research interprets their individual effects without worry.

Variables with a VIF between 2.5 and 5 (B1, B2, B3, B4, C1, C2, C3, C4, C5, D1, D2, D3, D4, and D5) have VIF values in the range of 2.5 to 5. Even though there is multicollinearity in certain levels, it is not severe enough to invalidate the interpretation of their individual effects; in addition, we must be careful when interpreting these variables and considering their multicollinearity.

The variable with a VIF >5 is variable B5, and its interaction terms in Lecturer Readiness*Peer Influence (Moderation), Perception in Digital Literacy*Peer Influence (Moderation), Teaching Skills*Peer Influence (Moderation) has a VIF value above 5, indicating high multicollinearity. High multicollinearity can affect the stability and interpretation of regression coefficients. For these variables, care must be taken when interpreting their individual effects. Thus, it is important to consider multicollinearity when interpreting and analyzing the influence of these variables in this research. Next, in Table 8, we describe and interpret Inner VIF Value.

**Table 8.** Analysis Inner VIF Value

| | **Integrating DL in HE** | **Peer Influence (Moderation)** | **Psychological Readiness*Peer Influence** | **Teaching Expertise*Peer Influence** | **Teaching Expertise** |
|---|---|---|---|---|---|
| **Integrating DL in HE** | | | | | |

| | |
|---|---|
| **Lecturers Readiness** | 2.730 |
| **Peer Influence (Moderation)** | 2.854 |
| **Psychological Readiness*Peer Influence** | 49.586 |
| **Teaching Expertise*Peer Influence** | 9.501 |
| **Teaching Expertise** | 14.892 |

Interpretation of Description of the Inner VIF Value.

Lecturer Readiness with VIF: 2.730 indicates that the VIF Value is 2.730, below the threshold of 2.5. Lecturer Readiness has low multicollinearity, showing that it does not have significant multicollinearity problems. Interpret the influence of Lecturer Readiness on the outcome variable Integrating Digital Literacy (DL) in Higher Education (HE) without paying attention to multicollinearity. Next, we discuss Peer Influence (Moderation) with a VIF Value 2.854.

The VIF value for Peer Influence (Moderation) of 2,854 is below 2.5. It shows that Peer Influence (Moderation) has low multicollinearity, and its influence on the outcome variables can be interpreted without major concerns regarding multicollinearity.

Perception of DL*Peer Influence (Moderation) with VIF 49.586 is very high. A high VIF like this indicates a strong degree of multicollinearity. Moreover, this suggests that the interaction between Perceived DL and Peer Influence (Moderation) may be problematic to interpret, and researchers should be careful when analyzing its influence. Next is Perception in DL, with a VIF value of 9.501.

The VIF value for Perception in DL is relatively high, namely 9.501. This VIF value does not fall into the very high multicollinearity range but shows a moderate multicollinearity level. To interpret the effects of Perception in DL, we were alert to moderate multicollinearity and considered it in the analysis of this study. Then Psychological Readiness*Peer Influence (Moderation) with a VIF Value of 14,892.

In assessing the VIF Psychological Readiness*Peer Influence (Moderation), it is quite high, namely 14.894. Like Perception in DL, it shows moderate multicollinearity. In interpreting the Psychological Readiness*Peer Influence (Moderation) interaction, you must be careful of this multicollinearity.

The VIF value for Psychological Readiness*Peer Influence (Moderation) is 14,892. It shows moderate multicollinearity. In interpreting the interaction of Psychological Readiness*Peer Influence (Moderation), one must be careful of multicollinearity.

The VIF Value of Teaching Expertise*Peer Influence (Moderation) is 27,044, and the VIF Value for Teaching Expertise*Peer Influence (Moderation) is relatively high, namely 27,044. It shows that the interaction between Teaching Expertise *Peer Influence (Moderation) is moderate to multicollinearity.

In the VIF, the value of teaching expertise is 7,160. The VIF value for Teaching Skills is relatively high, 7.160. The level of multicollinearity is not too high, but the level of multicollinearity is moderate.

Interpretation of VIF Values for Lecturer Readiness*Peer Influence (Moderation) interactions

The presence of an interaction term with a VIF of 1,000 indicates that this specific interaction does not contribute to multicollinearity in the model. In addition, these interaction terms do not substantially increase collinearity between predictors and can be interpreted independently without considering problems related to multicollinearity. In the statistical collinearity analysis of this research using the Variance Inflation Factor (VIF), this research examines potential multicollinearity problems among the variables included in the structural equation model of this research. Multicollinearity can cause unstable parameter estimates and challenges in interpreting relationships between variables.

Interpretation of VIF Values for Lecturer Readiness*Peer Influence (Moderation) interactions. The presence of an interaction term with a VIF of 1,000 indicates that this specific interaction does not contribute to multicollinearity in the model. In addition, these interaction terms do not substantially increase collinearity between predictors and can be interpreted independently without considering problems related to multicollinearity.

*Qualitative Phase*

In measuring the qualitative phase, this research uses Atlas.ti (Friese, 2016), the following are the results of the qualitative phase measurements:

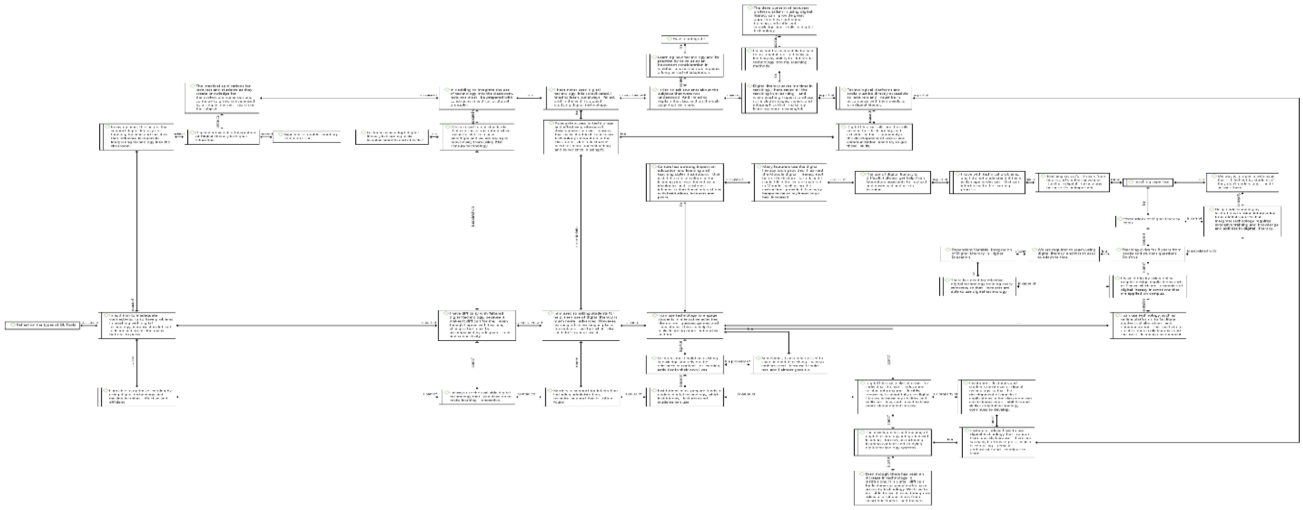

**Figure 1.** Diagram of Qualitative Phase

The Qualitative Phase of this research analyzed using Atlas. ti (Friese, 2016) unfolds in four key aspects:

1. Psychological Readiness of Lecturers
   - A. The Lowest: Resistance and low confidence in digital tools, preferring traditional methods.
   - B. Moderate: Recognition of the need for technology, albeit with slow progress.
   - C. The Highest: Proactive approach with early technology exposure and active utilization.
2. Teaching Expertise
   - A. The Lowest: Dependence on external help and resistance to technology.
   - B. Moderate: Recognition of the importance of technology but a need for institutional support.
   - C. The Highest: Seamless integration of technology into teaching methodologies, fostering engagement.
3. Perceptions of Digital Literacy Tools:
   - A. Lowest: Challenges in using tools, reluctance to seek help.
   - B. Moderate: Recognizing importance with practical limitations, highlighting the need for continuous learning.
   - C. Highest: Positive experiences with tools, emphasizing efficiency and time-saving benefits.

4. Institutional Factors (Moderating Variable)
   - A. Lowest: Resistance and frustration due to inadequate support.
   - B. Moderate: Recognition of the role of effective training and practicality in technology adoption.
   - C. Highest: Acknowledgment of cultural impact and the importance of funding, training, and facilities.

Dependent Variable: Integration of Digital Literacy in Higher Education
   - A. Lowest: Reluctance to learn, stagnation, and basic understanding.
   - B. Moderate: Striving to meet challenges, emphasizing the need for continuous learning.
   - C. Highest: Emphasis on professional development through training programs for effective integration.

The qualitative insights provide a rich understanding of lecturers' varied experiences, shedding light on the factors influencing their digital literacy integration. From resistance to proactive adoption, the findings contribute nuanced perspectives to the broader discourse on digital literacy in higher education.

## DISCUSSION

### 1. Demographic Profile:

In the demographics profile, we first discuss gender distribution. The observed gender imbalance (62.7% male, 47.3% female) prompts consideration of gender dynamics in shaping attitudes toward digital literacy. Gender-specific approaches, experiences, and challenges related to technology use may influence research findings significantly. Future analyses and interpretations should account for potential gender differences. Next, we discuss the multidisciplinary nature of participants (e.g., Civics, Economic Management, Indonesian), emphasizing diverse subject matter expertise. Acknowledging the influence of academic discipline on attitudes and digital literacy tools is crucial for a comprehensive understanding of findings. Moreover, we discuss teaching experience at various levels, introducing a spectrum of perspectives. Recognizing how experience impacts participants' comfort, familiarity, and openness to digital literacy tools adds contextual depth to the research.

**2. Reliability and Validity Results (Tables 2 and 3):**

In Reliability statistics, we start with a Cronbach's Alpha value that exceeds 0.7, indicating strong internal consistency reliability, thus instilling confidence in the reliability of the data collected. It strengthens the credibility of the research findings. Furthermore, this study addresses discriminant validity in which low correlations between constructs confirm effective differentiation, emphasizing the distinct nature of digital literacy integration. Negative correlations provide different insight into the relationship, contributing to discriminant validity evidence.

**3. Correlation Findings:**

In these findings, we will discuss the relatively low correlations with constructs such as Lecturer Readiness and Peer Influence that underscore the uniqueness of digital literacy integration. These specificities are important for understanding the factors that influence DL integration independently.

The negative correlation between Perceived DL and Psychological Readiness*Peer Influence (-0.474) highlights the potential trade-off or tension between these variables. Further exploration is needed to uncover the complex dynamics that influence perceptions of digital literacy.

**4. Regression Analysis (Table 4)**

The positive path coefficient (0.215) between Lecturer Readiness and DL Integration shows a moderate positive correlation. Although readiness contributes positively, other factors beyond readiness also play an important role, emphasizing the multidimensional nature of digital literacy integration.

**5. Total Effect Analysis (Table 5)**

The substantial positive total effect of Peer Influence (0.592) underscores its important role in positively shaping DL integration. It highlights the importance of peer dynamics and collaborative influence in creating an environment conducive to digital literacy in higher education.

**Teaching Skills**

The unexpected negative total effect of Teaching Skills (-0.374) suggests a counterintuitive relationship. Further exploration is needed to understand how teaching skills interact with or potentially hinder digital literacy integration.

**6. Model Fit Index (Table 6)**

SRMR is slightly above the conventional threshold, at which model fit indices should be interpreted collectively. Overall goodness-of-fit and other indices comprehensively understand how well theoretical models align with observational data.

**7. Collinearity Statistics (Table 7)**

In VIF analysis, a VIF below 2.5 indicates that a variable has a minimal correlation with others, making its contribution clear. However, a high VIF (132.152) suggests potential issues due to a strong correlation with other variables. High VIF suggests that the variable is highly correlated with other predictors in the model, making it challenging to interpret its unique contribution. Adjustments may be needed to maintain the model's reliability and interpretability, such as excluding or transforming the variable with high VIF.

**8. Qualitative Phase**

The qualitative investigation explored psychological readiness, teaching skills, perceptions of DL tools, and institutional factors. The diverse insights gained from individual experiences add depth to the overall analysis, recognizing the diversity of perspectives among faculty members.

**Practical Implications**

Qualitative findings offer practical implications for tailored interventions, professional development, and institutional policy. Recommendations can be derived from rich insights, contributing to effective educational practices and future research efforts.

Therefore, the discussion analyzes the research findings thoroughly, emphasizing the importance of demographic factors, reliability, validity, correlation findings, regression analysis, total effects, model fit indices, collinearity statistics, and insights from the qualitative phase. The different insights gained from this comprehensive analysis enrich the interpretation of the results and contribute to the robustness of the research findings.

## CONCLUSION

In conclusion, this mixed-method research has comprehensively explored integrating Digital Literacy (DL) in Higher Education Institutions (HEIs). The combination of quantitative and qualitative approaches has offered a nuanced understanding of the complex factors influencing faculty engagement with DL tools and practices.

The demographic profile highlighted participant diversity, emphasizing the necessity for varied approaches to DL integration. The reliability and validity analyses confirmed the reliability and validity of the research measurement instruments, ensuring the results' trustworthiness. Correlation findings illuminate the intricate network of influences on DL integration, emphasizing the need for a multifaceted approach.

Regression analysis underscored the model's explanatory power, indicating that the selected predictors play a substantial role in understanding the variance in DL integration. Structural equation modeling (SEM) provided insights into the interaction between lecturer readiness and DL integration, contributing to a deeper understanding of the relationships between constructs.

The practical implications of the findings are significant for both practice and research. Insights into faculty experiences, perceptions, and institutional factors lay the groundwork for tailored interventions, professional development initiatives, and informed decision-making at the institutional level. Identifying influential factors, such as peer influence and teaching expertise, provides actionable entry points for enhancing DL integration strategies.

**FUTURE RESEARCH**

While this research has expanded our understanding of DL integration, there are opportunities for future research to enrich the field further:

Specific Dynamics of Peer Influence, which digs deeper into the specific mechanisms and dynamics of peer influence, can provide insight into effective strategies for leveraging collaborative efforts in DL integration. Another opportunity is to investigate the impact of institutional policies on DL integration, which could provide a deeper understanding of how organizational structures shape faculty engagement in digital literacy practices. In addition, future research could explore the evolving landscape of digital tools, where the dynamic nature of technology follows emerging trends and challenges, so that the continuously developing digital tool landscape can provide input for strategies to adapt to technological advances.

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