

DIGITAL SKILL GAPS AND HUMAN RESOURCE DEVELOPMENT PRACTICES IN SELECTED LOCAL GOVERNMENT AREA COUNCILS OF IMO STATE, NIGERIA

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ABSTRACT

This study examined the effect of digital skill gaps on Human Resource Development practices in Local Government Area councils of Imo State, Nigeria. Guided by Contingency Theory and Human Capital Theory, the study adopted a cross-sectional survey design. Data were collected from employees of selected LGA Councils using structured questionnaires and analyzed using hierarchical regression. Findings revealed that data analytics and interpretation skill gap significantly predicts technical training. Artificial intelligence proficiency skill gap significantly predicts job rotation and labour mobility. Digital communication and collaboration skill gap significantly predicts mentoring and coaching. The results indicate that HRD responses are contingent on the specific type of digital skill gap identified. The study concludes that LGA Councils should strategically diagnose skill gaps and deploy targeted HRD interventions rather than ad-hoc approaches. This will enhance workforce digital competence and improve public service delivery.

Keywords: Digital Skill Gap, HRD Practices, Technical Training, Job Rotation, Mentoring, Local Government.

1. INTRODUCTION

The adoption of digital technologies in Nigerian local government administration has accelerated over the past decade. Digitalization is now considered vital for public sector efficiency, service delivery, and internal process streamlining (Anikeze, Abonyi, & Okafor, 2023). Technologies such as wireless communication, online

platforms, and database management systems are redefining personnel policies and transformation efforts across levels of government (Shukla, Mishra, & Agnihotri, 2023).

Despite this growth, a persistent challenge has in the Nigerian case emerged in digitalization process in Local Government Area Councils including those in Imo State. This is the challenge of the digital skill gaps among employees. Digital skills refer to the abilities to use digital devices, applications, and networks to access, manage, and create information (UNESCO, as cited in Sanz, 2025). In practice, this includes competencies in data analytics and interpretation, digital communication and collaboration, and proficiency in artificial intelligence (Ziqubu, 2026). On the other hand, digital skill gaps are defined as the differences between the digital skills employees possess and those required to perform effectively in modern work contexts (Schreiber-Shearer, 2025; Future Point of View, 2024). While some LGA Council workers in the Nigerian states, including Imo State to be precised have basic digital literacy, their skills often misalign with workplace demands in areas such as data analytics and interpretation, digital communication and collaboration, and AI proficiency.

As access gaps narrow, these digital skill gaps increasingly determine technology usage and outcomes (Van Dijk & Hacker, 2003). Given that LGA Councils are constitutionally mandated to deliver grassroots services (Ukwu et al., 2023), these skill deficiencies existing in them risk constraining operational efficiency and service quality. Consequently, Human Resource Development practices have become the key organizational responses to bridging the gap. HRD practices refer to deliberate activities aimed at improving employee capacity, including technical training, job rotation and labour mobility, and mentoring and coaching (Noorollahi et al., 2019; Dahiya, Warne, & Arora, 2023). Evidence suggests the LGA Councils in Nigeria including those in Imo State are deploying these practices specifically to bridge emerging digital skill deficits (Ogba-Amaugo, 2024).

This paper argues that the nature of the digital skill gaps shapes the type of HRD practices adopted. Specifically, it examines the effect of three digital skill gaps: data analytics and interpretation, digital communication and collaboration, and AI proficiency, on three HRD practices: technical training, job rotation and labour mobility, and mentoring and coaching in selected LGA Councils of Imo State, Nigeria, from 2017 to 2025.

1.1 Statement of the Problem

Digital technology adoption in Ngor-Okpala, Obowo, and Orlu LGA Councils of Imo State is seriously growing. However, a widening gap exists between digital skills possessed by workers in these Councils and those required for effective operations and service delivery in areas like data analytics and interpretation, digital communication and collaboration, and AI application.

If not decisively dealt with, these gaps may constrain work processes and deepen operational inefficiency. This study therefore, examines how the need to address these gaps shapes HRD practices in the selected councils.

1.2 Objectives of the Study

The general objective of the study is to analyze the effect of digital skill gaps among employees on HRD practices in selected LGA Councils of Imo State. Specifically, the study seeks to:

1. Assess the effect of data analytics & interpretation skill gap on technical training
2. Examine the effect of artificial intelligence proficiency skill gap on job rotation & labour mobility
3. Analyze the effect of digital communication & collaboration skill gap on mentoring & coaching

1.3 Significance of the Study

Theoretically, the study utilizes Human Capital Theory and Contingency Theory to offer explanation of how specific digital skill gaps trigger specific HRD responses in LGA Councils administration (Becker, 1964;

Lawrence & Lorsch, 1967). It also substantiates Van Dijk and Hacker's argument that skills are the new digital divide.

Empirically, the findings of the study provide guidance for LGA Council administrators and policymakers in Imo State on targeted HRD interventions to close digital skill gaps for improved digital governance.

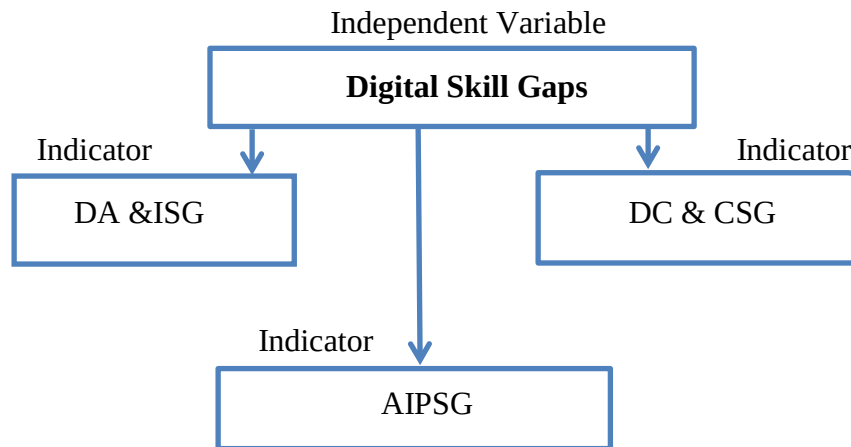
2. LITERATURE REVIEW

2.1 Conceptual Review

This covers digital skill gaps, human resource development practices, local government council, and the conceptual framework.

2.1.1 Digital Skill Gaps

Digital skill gaps is conceptualized as a multidimensional construct comprising: data analytics and interpretation skill gap; digital communication and collaboration skill gap; and artificial intelligence proficiency skill gap. This is as captured in figure 1 below.



Keys:

Data Analytics and Interpretation Skill Gap = **DA & ISG**

Digital Communication and Collaboration Skill Gap = **DC & CSG**

Artificial Intelligence Proficiency Skill Gap = **AIPSG**

Fig 1: Conceptual breakdown of the independent variable (digital skill gaps)

Source: Authors drawing, 2026.

Data Analytics and Interpretation Skill Gap refers to the inability to inspect, model, and derive meaning from organizational data for decision-making. On the other hand, Digital Communication and Collaboration Skill Gap is inability to effectively exchange information and work with others through digital channels to achieve shared goals. Artificial Intelligence Proficiency Skill Gap involves limited ability to use AI and automation tools relevant to job tasks, including generative AI and work-flow automation.

2.1.2 Human Resource Development Practices

HRD practices refers to organizational undertakings aimed at building employee skills and capacity (Dahiya, Warne, & Arora, 2023). Three practices are examined as represented in figure 2 below.

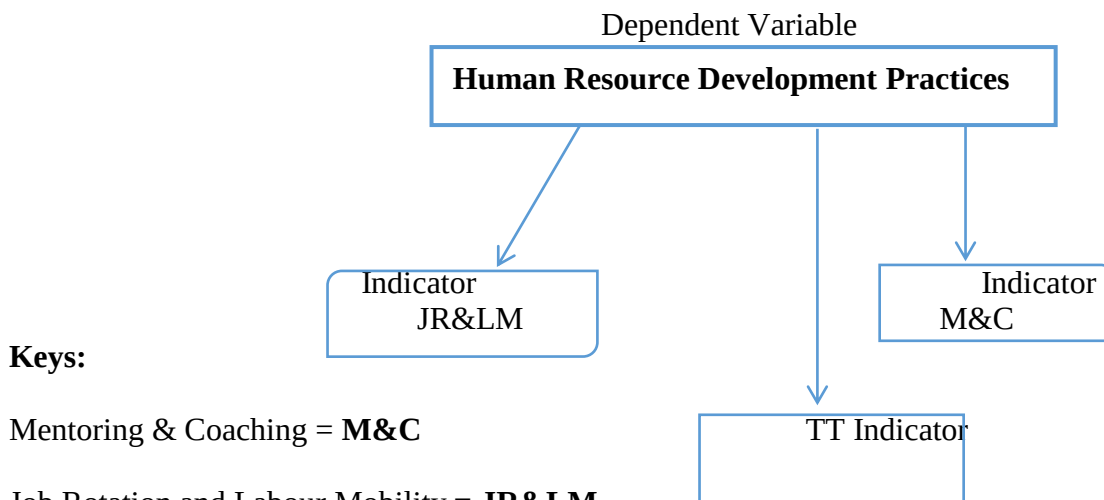


Fig 2: Conceptual Model of the Dependent Variable (Human Resource Development Practices)

Source: Author's construction, 2026.

Technical Training is a structured process for teaching employees the technological aspects of their jobs (University of Wisconsin, 2024; Chand, 2026). Job Rotation and Labour Mobility involve moving employees across jobs or departments to develop diverse skills and organizational agility (Keka, 2025; Jackson & Sund, 2023; Ingram, 2024). Mentoring and Coaching provide personalized guidance to improve employees specific skills and support their long-term professional growth (Amacus, 2024).

2.1.3 Local Government Council

In Nigeria, Local Government is the third tier level of government and a political sub-division of a State which has the responsibility of bringing development to the people at the grassroots (Ola, 1984). This level of government is established to perform some salient constitutional functions order than bringing development. For this reason, governments with this nomenclature have organizational structure and employees that are permanently hired to carryout these functions. These employees work in the local government council. A local government council represents administrative and political unit of grassroots governance in Nigeria.

2.1.4 Conceptual Framework

The study proposes that even though human resource development practices are reliable measures to address digital skill gaps deficits, digital skill gaps however are the main drivers of HRD responses, especially as the specific HRD practice to be implemented depends on the nature of the gap itself. This is duly represented in figure 3 below.

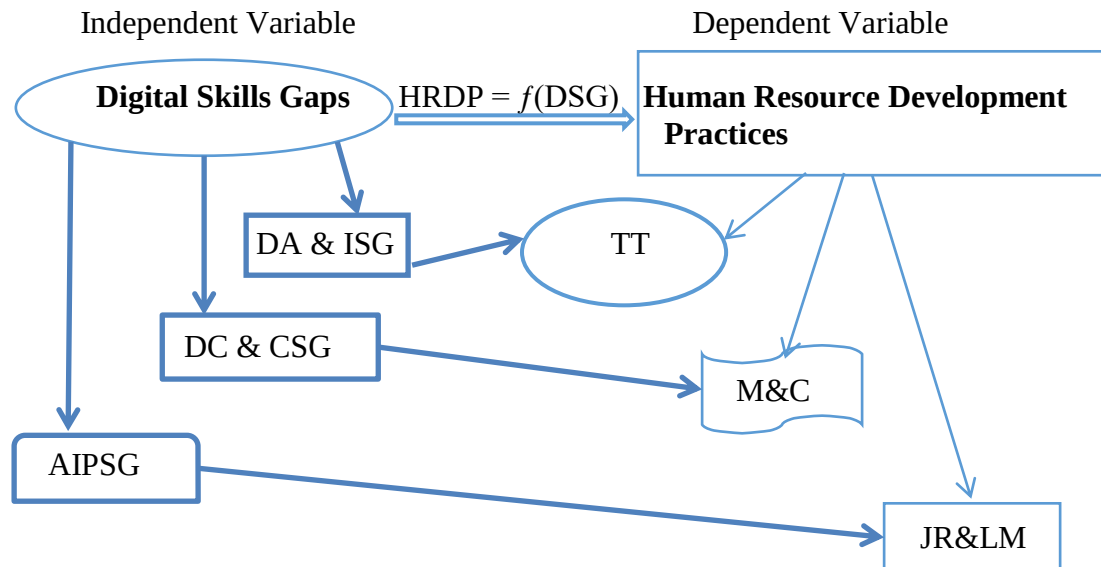


Fig 3: Diagram of the Conceptual Framework of the Independent Variable (Digital Skill Gaps Among Employees) and Dependent Variable (Human Resource Development Practices)

Source: Author's construction, 2026.

This conceptual logic is grounded in Human Capital Theory, which posits that skill deficits trigger investment in human capacity building (Becker, 1964; Wuttaphan, 2017), and Contingency Theory, which argues that effective HRD depends on fit between problem and intervention (Lawrence & Lorsch, 1967). Thus: technical gaps require technical training; communication and collaboration gaps (behavioural) require mentoring and coaching; emergent gaps- artificial intelligence proficiency skill gap require job rotation and labour mobility. The analyzed relationship is: ' $HRDP = f(DSG)$ '.

2.2 Theoretical Framework

This study adopts Human Capital Theory and Contingency Theory (Becker, 1964; Lawrence & Lorsch, 1967). Human Capital Theory predicts that skill gaps increase organizational investment in HRD (Wuttaphan, 2017). Contingency Theory suggest there is no one best HRD practice; rather, effectiveness depends on matching the practice to the specific skill gap (Mark & Erude, 2023). Therefore, the selected LGA Councils administration effectiveness in closing digital skill gaps depends on their aligning of technical gaps with technical training, behavioural gaps with mentoring and coaching, and emergent gaps with job rotation and labour mobility.

2.3 Empirical Review and Research Gap

Ramos et al. (2025) found that Artificial Intelligence proficiency predicts graduate employability and productivity. Tusquellas, Palau and Santiago (2024) found that Artificial Intelligence is being used to enhance recruitment processes, to identify individual training and development skills and needs etc. Alim and Nestia (2025) reported that digital communication tools improve team collaboration. BhuvaneshwarI and Vincent (2025), and Sikdar and Chandra (2022) linked technical training to efficiency and data analytics skills demand. Mung'ala, Aluvale, and Momanyi (2024) showed job rotation significantly enhances employee performance. While Mark, Davis and Luke (2018) found that mentoring culture supports digital work.

However, no prior study within Nigerian LGA Councils administration has tested the specific predictive relationships between: AI proficiency gap and job rotation & labour mobility; digital communication and collaboration gap and mentoring & coaching; and data analytics and interpretation gap, and technical training. This study closes that gap.

2.4 Hypotheses

H1: Data analytics & interpretation skill gap has a significant positive effect on technical training

H2: Artificial intelligence proficiency skill gap has a significant positive effect on job rotation & labour mobility

H3: Digital communication & collaboration skill gap has a significant positive effect on mentoring & coaching

3. METHODOLOGY

3.1 Study Area, Design and Population

The study was conducted in Ngor-Okpala, Obowo and Orlu Local Government Areas of Imo State, Nigeria. Imo state is one of the 36 states of the Nigerian federation. It is specifically located in the Southeastern part of the country. The three local government areas studied are mostly dominated by farmers, public servants and artisans. Their economy is mostly agrarian with a minor combination of manufacturing and construction activities. A quantitative survey design was adopted. The target population comprised of employees of the selected three LGA Councils: Ngor-Okpala, Obowo, and Orlu. Total accessible population is 2,620.

3.2 Sample Size and Sampling Technique

A sample size of 347 was determined using Taro Yamane formula. Multistage sampling was used. First was purposive selection of three LGA Councils, one each from the three senatorial districts into which Imo state is divided. The choice of the three LGAs is due to the increasing digital transformation ongoing in them. And last was proportionate sampling within each LGA Council to draw research respondents.

3.3 Instrument and Data Collection

Primary data was collected using a structured questionnaire on a 5-point Likert scale. Section A of the questionnaire captured demographics/covariates. Section B measured digital skill gaps. Section C measured HRD practices.

3.4 Validity and Reliability of Instrument

Validity was established through expert review. Reliability was tested via pilot study. The Cronbach's Alpha values ranged from 0.932 to 0.957, indicating excellent internal consistency and reliability of the research instrument.

To reduce recall bias, respondents reported current perceptions of practices and gaps experienced over 2017-2025, rather than year-specific data. Also, common method bias was tested using Harman's single-factor test based on Principal Component Analysis. All 30 items were loaded into one factor. The result showed that a single factor explained 84.75% of the total variance, which is above the 50% threshold recommended by Podsakoff et al. (2003). This suggests the presence of common method variance. However, procedural remedies such as anonymity of respondents and different scale anchors were employed during data collection to minimize the effect. The table 1 displaying the result is in Appendix A.

3.5 Variables and Measurement

Independent Variable: Digital Skill Gaps — DA&ISG, DC&CSG, AIPSG.

Dependent Variable: HRD Practices — TT, JR&LM, M&C.

Covariates: Age, Education Level, Staff Category, and Gender. The measurement and dummy coding of all covariates are presented in table 2 below.

Table 2: Measurement and Dummy Coding of Covariates

Variable	Measurement	Categories	Coding for Regression
Age	Categorical	18-30, 31-43, 44+	2 Dummies: D1= 18-30, D2 = 31-43. Ref = 44+
Education	Categorical	O'level, HND, BSc, MSc, Professional	4 Dummies: D1= O'level, D2 = HND, D3 = BSc, D4 = MSc. Ref = Professional
Staff_Category	Categorical	Junior, Senior, Management	2 Dummies: D1= Junior, D2 = Senior. Ref = Management
Gender	Dichotomous	Male, Female	1= Male, 0 = Female

Source: Authors construction, 2026.

As shown in Table 2, the categorical covariates with k levels were dummy coded into k-1 variables to aid regression. Reference categories were selected as the highest qualification, rank, and age group.

3.5 Method of Data Analysis

Data were analyzed using descriptive statistics, and Hierarchical Multiple Regression analysis. This was carried out on SPSS v20. Descriptive statistics summarized demographics. Any single item statement with mean of 3.0 and above is accepted. While general decision rule for composite item statements rating is: **1.00- 2.33 = Low, 2.34-3.66 = Moderate, 3.67-5.00 = High**. To test hypotheses, hierarchical regression analysis were conducted to determine the effect of digital skill gaps on HRD practices, with 9 dummy-coded covariates to control for confounding effects:

1. **'TT** = $\beta_0 + \beta_1(\text{DA\&ISG}) + \beta_2(\text{Age}_{18-30}) + \beta_3(\text{Age}_{31-43}) + \beta_4(\text{Edu}_{0\text{level}}) + \beta_5(\text{Edu}_{\text{HND}}) + \beta_6(\text{Edu}_{\text{BSc}}) + \beta_7(\text{Edu}_{\text{MSc}}) + \beta_8(\text{Staff}_{\text{Junior}}) + \beta_9(\text{Staff}_{\text{Senior}}) + \beta_{10}(\text{Gender}) + \epsilon$

2. **'JR&LM** = $\beta_0 + \beta_1(\text{AIPSG}) + \beta_2(\text{Age}_{18-30}) + \beta_3(\text{Age}_{31-43}) + \beta_4(\text{Edu}_{0\text{level}}) + \beta_5(\text{Edu}_{\text{HND}}) + \beta_6(\text{Edu}_{\text{BSc}}) + \beta_7(\text{Edu}_{\text{MSc}}) + \beta_8(\text{Staff}_{\text{Junior}}) + \beta_9(\text{Staff}_{\text{Senior}}) + \beta_{10}(\text{Gender}) + \epsilon$

3. **M&C** = $\beta_0 + \beta_1(\text{DC\&CSG}) + \beta_2(\text{Age}_{18-30}) + \beta_3(\text{Age}_{31-43}) + \beta_4(\text{Edu}_{0\text{level}}) + \beta_5(\text{Edu}_{\text{HND}}) + \beta_6(\text{Edu}_{\text{BSc}}) + \beta_7(\text{Edu}_{\text{MSc}}) + \beta_8(\text{Staff}_{\text{Junior}}) + \beta_9(\text{Staff}_{\text{Senior}}) + \beta_{10}(\text{Gender}) + \epsilon$.

Directional one-tailed tests were used. Decision rule: accept H if $p \leq .05$ and relationship is in the predicted direction. The analysis was conducted at 0.05 level of significance.

4. Data Presentation, Analysis and Results, and Discussion of Findings

4.1 Demographic/Control Variables

Table 3 in Appendix A shows that three hundred and forty-seven (347) copies of questionnaire were distributed to research respondents. Out of the 347 copies distributed, 312 (89.9%) were completed and returned valid while 35 (10%) were not returned and some were invalid. Therefore, 89.9 percent respondents were good fit of representation. Furthermore, the table revealed respondents' profile in frequency and percentage distribution of educational qualification: O' Level 98 (31.4%), HND 80 (25.6%), BSc 55 (17.6%), MSc 54 (17.3%), and Professional 25 (8%); staff category: junior staff 100 (32%), senior staff 123 (39.4%), management staff 89 (28.5%); age bracket: 18-30 (37.2%), 31-43 (32.4%), and 44 and above (31.4%); and gender male 185 (59.3%), female 127 (40.7%).

4.1.1 Descriptive Statistics of Study Main Variables

The descriptive statistics for the six constructs of the study are presented in table 3. The constructs were measured on a 5-point Likert scale with 312 respondents. Overall construct mean was calculated by averaging the 5 item means for each construct.

Table 3: Summary of Descriptive Statistics for Study Constructs as obtained from Respondents from Ngor-Okpala, Obowo, and Orlu LGA Council, 2017-2025

S/N	Construct	N	No. of Items	Overall Mean	Decision
1	Data Analytics & Interpretation Skill Gap	312	5	4.02	High skill gap
2	Technical Training	312	5	4.07	High
3	Artificial Intelligence Proficiency Skill Gap	312	5	4.08	High skill gap
4	Job Rotation & Labour Mobility	312	5	3.76	High
5	Digital Communication & Collaboration Skill Gap	312	5	3.81	High skill gap
6	Mentoring & Coaching	312	5	3.98	High

Source: Field Survey, 2026 & SPSS v20.

As shown in Table 3, all six constructs recorded high mean scores above 3.67. This indicates that respondents reported high levels of skill gaps in data analytics and interpretation, artificial intelligence proficiency, and digital communication & collaboration. Similarly, high levels of technical training, job rotation & labour mobility, and mentoring & coaching were reported within the three LGA Councils during the period of 2017-2025. However, the detailed item-by-item breakdown for each construct is presented in Appendix A.

After establishing the pattern of responses, this next section tested the three stated hypotheses of the study.

4.2 Data Analysis and Results

Test of Hypothesis One

H1: Data analytics & interpretation skill gap has a significant positive effect on technical training

Table 6: Summary of Hierarchical Regression Results for the Effect of Data Analytics and Interpretation on Technical Training

Variable	R ² Change	R Square	Partial r	β	t	Sig.	VIF	Decision
Model 2: Controls + DA_ISG	.021	.984	.756	.621	20.05	.000	18.51	Supported

Control: Gender, Age, Education, Staff Category.

Source: SPSS v20.

Results in Table 6 show that the full model including controls and DA_ISG explained 98.4% of the variance in Technical Training, $R^2 = .984$. The addition of DA_ISG to the controls resulted in a significant increase in explained variance, $R^2 = .021$, $p < .001$. DA_ISG had a significant positive effect on Technical Training, $\beta = .621$, $t = 20.05$, $p < .001$. The partial correlation of .756 indicates that DA_ISG uniquely accounts for 57.1% of the variance in Technical Training after accounting for control variables.

The VIF value of 18.51 indicates the presence of multicollinearity. However, this is theoretically meaningful and suggests that technical training provision directly mirrors and directly targets the closure of data analytics and interpretation skill gaps within the Councils. This tight coupling aligns with a reactive HRD approach, where training interventions are deployed in direct response to identified skill deficiencies. Given the significance of the effect and its theoretical relevance, it is supported that data analytics & interpretation skill gap has a significant positive effect on technical training across the LGA Councils.

Test of Hypothesis Two

H2: Artificial intelligence proficiency skill gap has a significant positive effect on job rotation & labour mobility

Table 9: Summary of Hierarchical Regression Results for the Effect of Artificial Intelligence Proficiency Skill Gap on Job Rotation & Labour Mobility

Variable	R ² Change	R Square	Partial r	β	t	Sig.	VIF	Decision
Model 2: Controls + AIPSG	.019	.991	.825	1.00	25.35	.000	53.54	Supported

Control: Gender, Age, Education, Staff Category.

Source: SPSS v20.

Results in Table 9 show that the full model explained 99.1% of the variance in Job Rotation and Labour Mobility, $R^2 = .991$. The addition of AI Proficiency Skill Gap after controlling for demographics significantly improved the model, $R^2 = .019$, $p < .001$. AI Proficiency Skill Gap had a significant positive effect on Job Rotation and Labour Mobility, $\beta = 1.001$, $t = 25.35$, $p < .001$. The standardized beta of 1.0 and the high partial correlation of .825, indicates that AI Proficiency Skill Gap uniquely explains 68.1% of the variance in Job Rotation and Labour Mobility after accounting for controls, suggesting a very strong direct relationship.

The VIF value of 53.54 indicates high multicollinearity. This reflects an extremely tight coupling between the perceived AI proficiency skill gap and the deployment of Job Rotation and Labour Mobility. Theoretically, this is consistent with a reactive HRD approach where job rotation and labour mobility are used almost exclusively as direct responses to identified deficiencies in AI proficiency. Organizations rotate staff and move labour to units adopting AI tools in order to close the proficiency gap through on-the-job exposure. While multicollinearity is present, the effect remains statistically significant and theoretically expected, thus it is supported that artificial intelligence proficiency skill gap has a significant positive effect on job rotation & labour mobility across the LGA Councils.

Test of Hypothesis Three

H3: Digital communication & collaboration skill gap has a significant positive effect on mentoring & coaching

Table 12: Summary of Hierarchical Regression Results for the Effect of Digital Communication and Collaboration on Mentoring & Coaching

Variable	R ² Change	R Square	Partial r	β	t	Sig.	VIF	Decision
Model 2: Controls + DC_CSG	.011	.984	.634	.769	14.24	.000	54.30	Supported

Control: Gender, Age, Education, Staff Category.

Source: SPSS v20.

Results in Table 12 show that the full model explained 98.4% of the variance in Mentoring and Coaching, $R^2 = .984$. The addition of Digital Communication and Collaboration Skill Gap after controlling for demographics significantly improved the model, $R^2 = .011$, $p < .001$. Digital Communication and Collaboration Skill Gap had a significant positive effect on Mentoring and Coaching, $\beta = .769$, $t = 14.24$, $p < .001$. The partial correlation of .634 indicates that Digital Communication and Collaboration Skill Gap uniquely explains 40.2% of the variance in Mentoring and Coaching after accounting for control variables.

The VIF value of 54.30 indicates high multicollinearity. This suggests a strong coupling between the perceived digital communication skill gap and the use of Mentoring and Coaching as an HRD response. Theoretically, this also aligns with a reactive HRD approach where mentoring and coaching are deployed specifically to address gaps in employees' ability to use digital tools for communication and collaboration. As staff struggle with virtual platforms, collaboration software, and digital communication etiquette, organizations respond by pairing them with mentors or coaches to facilitate learning and adaptation. Despite the presence of multicollinearity, the effect is statistically significant and theoretically consistent, thus it is supported that digital communication & collaboration skill gap has a significant positive effect on mentoring & coaching across the LGA Councils.

4.3 Discussion of Findings

The findings provide support for all three hypotheses and demonstrate that perceived digital skill gaps are key drivers of HRD practices in Imo State LGA councils, after controlling for demographics. First, Data Analytics and Interpretation Skill Gap had a significant positive effect on Technical Training, $\beta = .621$, $p < .001$. The full model explained 98.4% of the variance, $R^2 = .984$, with DA_ISG accounting for an additional 2.1%, $R^2 = .021$. This indicates that when councils perceive deficits in data handling and interpretation, they respond with increased technical training.

Second, Artificial Intelligence Proficiency Skill Gap had a significant positive effect on Job Rotation and Labour Mobility, $\beta = 1.001$, $p < .001$. The model explained 99.1% of the variance, $R^2 = .991$, with AI Skill Gap contributing $R^2 = .019$. The very high VIF of 53.54 suggest a tight coupling consistent with a reactive HRD approach, where staff are rotated into AI-using units specifically to close proficiency gaps through on-the-job exposure. Third, Digital Communication and Collaboration Skill Gap had a significant positive effect on Mentoring and Coaching, $\beta = .769$, $p < .001$. The model explained 98.4% of the variance, $R^2 = .984$, with $R^2 = .011$. The high VIF of 54.30 similarly reflects that mentoring and coaching are deployed as direct responses to gaps in digital communication and collaboration.

Collectively, these results advance Contingency Theory and Human Capital Theory by showing that the nature of a specific skill gap determines the HRD strategy used to address it. Rather than generic training, councils adopt targeted responses: technical training for analytics and interpretation gaps, job rotation and labour mobility for AI gaps, and mentoring and coaching for communication and collaboration gaps. The higher the perceived gap, the more intensive the corresponding HRD practice.

4.4 Implication for Practice

Local Government Area Councils should formalize mentoring and coaching, job rotation and labour mobility, and technical training as deliberate digital upskilling strategies rather than ad-hoc responses. Policy should allocate funding to structured peer-learning programmes alongside technical training to maximize reach. Furthermore, LGA authorities should sensitize employees to positively perceive digital technologies required for their official duties, as improved perception can help bridge digital skill gaps and increase uptake of HRD interventions.

4.5 Limitations and Future Research

This study has several limitations. First, the cross-sectional design and focus on LGAs in one state restrict causal claims and generalizability. Second, reliance on perceptual, self-report data from a single instrument over a multi-year period introduced common method bias and recall bias. Harman's single-factor test indicated CMB was present > 50%. To mitigate this, procedural remedies such as respondent anonymity and different scale anchors were used, and items were worded to elicit general perceptions. Third, the study could not directly account for contextual factors such as funding, infrastructure, and leadership support, which may also influence HRD practices alongside digital skill gaps. Finally, the absence of secondary data, such as LGA training records or budget allocations, limits triangulation with objective evidence.

Future studies should use longitudinal designs, include multiple states, and incorporate secondary records or objective performance data to complement employee perceptions and reduce method bias.

4.6 Conclusion

The ongoing digital transformation in Local Government Area councils in Imo State, Nigeria has created urgent capacity building demands that personnel departments in the Councils must address to realize the benefits of digitalization. This study concludes that perceived digital skill gaps are the primary drivers of HRD practices within the Councils. The evidence shows that Councils do not deploy HRD interventions generically. Rather, the specific type of digital skill gap determines the specific HRD response adopted. This pattern of targeted response provides empirical support for both Contingency Theory and Human Capital Theory in the public sector context. Given these findings, HRD practices in LGAs must be strategically and deliberately planned to close identified digital skill gaps, rather than being based solely on cost effectiveness, convenience, or available instruments. By systematically diagnosing skill gaps and matching them with appropriate HRD strategies such as technical training, job rotation and labour mobility, and mentoring and coaching, LGAs can enhance workforce digital competence. Ultimately, this will improve the quality and efficiency of public service delivery at the grassroots level.

REFERENCES

- Adegboyega, O., Aderemi, A., Oadimeji, A., Bolaji, H., & Adebayo, W. (2022). Analysis of the impact of information and communication technology on Nigeria Bottling Company's organizational performance. *ACTA Universitatis Donubius*, 18(1), 22-31.
- Agoda Careers. (2024). The benefits of job rotation and internal mobility. <https://careersatagoda.com/blog/tech/the-benefits-of-job-rotation-and..>

- Alim, J., & Nestia, L. (2025). The role of digital communication in enhancing collaboration in the information technology industry. *International Journal of Linguistics Communication and Broadcasting*, 3(1), 24-28. DOI: 10.46336/ijlcb.v3i1.199.
- Amacus. (2024). The importance of coaching and mentoring in the workplace. <https://www.linkedin.com/pulse/importance-coaching-mentoring-wo..>
- Ankeze, H., Abonyi, U., & Okafor, C. (2023). Information communication technology and organizational decision-making of federal parastatals in Nigeria. *World Journal of Advanced Research d Review*, 18(1), 1061-1071.
- Becker, J. (1964). Human capital: A theoretical and empirical analysis with special reference to education (1st Ed.). NBER.
- Bhuvaneshwari, C., & Vincent, S. (2025). A study on the impact of technical training on employees efficiency. *International Journal of Creative Research Thoughts*, 13(5), 801- 808.
- Chand, S. (2026). Training: Meaning, definition and types of training. <https://www.yourarticlelibrary.com/human-resource-development/training...>
- Dahiya, M., Warne, D., & Arora, S. (2023). Theory and concept of human resources development. <https://doi.org/10.4018/978-1-6684-7494-5.ch012>
- Digital Hill. (2026). Importance of digital skill in today' workplace. <https://www.digitalhill.com/blog/importance-of-digtal-skills-in-todays--->
- Fiedler, F. (1964). A contingency model of leadership effectiveness. <https://www.scirp.org/reference/referencespapers?referenceid=2456>.
- Future Point of View. (2024). What is the digital skills gap and how much is it costing enterprises? <https://fpov.com/2024/02/27/what-is-the-digital-skill-gap-and-how-much..>
- Ingram, A. (2024). Internal investment: The rewards of a job rotation program. <https://worldatwork.org/publications/workplan-daily/internal-investment-->
- Jackson, J., & Sund, M. (2023). Assessing the efficacy of a job rotation for improving occupational physical and psychosocial work environment, musculoskeletal health, social equality, production quality and resilience at a commercial laundromat: Protocol for a longitudinal case study. *BMJ Open Journal*, 13(5), e06733. <https://pmc.ncbi.nlm.nih.gov/articles/PMC10186472/>
- Keka, V. (2025). Job rotation and employees productivity in private organizations in Mali. *African Journal of Human Resource*, 13(6), 13-23.

- Lawrence, P., & Lorsch, J. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 12(1), 1-30. <https://doi.org/10.2307/2391211>.
- Mark, W., Davis, L., & Luke, N. (2018). The impact of remote work on coaching and mentoring relationships. *Journal of Organizational Growth*, 17(1), 50-62.
- Mark, T., & Erude, S. (2023). Contingency theory: An assessment. *American Journal of Research in Business and Social Sciences*, 3(2), 1-12. DOI: 10.58314/WT2023.
- Mung'ala, M., Aluvale, V., & Momanyi, N. (2022). the role of job rotation in enhancing employee performance in cement manufacturing firms in Kenya. *International Journal of Academic & Research*, 7(1), 36-47.
- National Institute of Information Technology. (2024). The importance of technical training for today's workforce. <https://www.niit.com/en/learning-outsourcing/technical-training/>
- Ng'ang'a, D. (2014). The impact of ICT in service delivery: A case study of the ministry of planning and devolution. KDI School of Public Policy and Management.
- Noorollahi, Y., Shabbir, S., Siddiqi, A., Ilyashenko, L., & Ahmadi, E. (2019). Review of two decade geothermal energy development in Iran, benefits, challenges, and future policy. *Geothermics*, 77(1), 257-266.
- Ogba-Amaugo, I. (2024). The use of technology in human resources management: Opportunities and challenges for organizations. <https://rsisinternational.org>
- Ola, R. (1984). *Local administration in Nigeria*. Kegan and Paul International.
- Podsakoff, P., MacKenzie, S., Lee, J., & Podsakoff, N. (2003). Common method biases in behavioural research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903. DOI: 10.1037/0021-9010.88.5.879.
- Ramos, H., et al., (2025). Artificial intelligence skills and their impact on the employability of university graduates. *Front. Artif. Intell.* 8:1629320. <https://doi.org/10.3389/frai.2025.1629320>.
- Rodriguez, A., & Barrero, L. (2017). Job rotation: Effects on muscular activity variability. *Applied Ergonomics*, 60(1), 83-92.
- Schreiber-Shearer, N. (2025). Digital skill gaps: What they are and how to bridge them. <https://gloat.com/blog/what-are-digital-skill-gas/>

- Shukla, F., Mishra, L., & Agnihotri, A. (2023). A comprehensive review of the effects of digital technology on human resource management. *Technology, Management and Business, Advanced Series in Management*, 31(1), 7-19.
- Sikdar, R., & Chandra, S. (2022). Data analytics: An emerging skill gap. *International Journal of Creative Research Thoughts*, 10(10), 1-13.
- Tusquellas, N., Palau, R., & Santiago, R. (2024). Analysis of the potential of artificial intelligence for professional development and talent management: A systematic literature review. *International Journal of Information Management Data Insights*, 4(2), 10-23. <https://doi.org/10.1016/j.jjime.2024.100288>.
- Ukwu, F., Manasseh, C., Logan, C., Okanya, O., Eze-Dike, F., & Ejim, E. (2023). ICT and social service delivery in the local government councils in Enugu state Nigeria. *International Journal of Business and Economics Research*, 12(3), 123-128.
- Universities of Wisconsin. (2024). Types of training.
<https://wisconsin.pressbooks.pub/introhrm/chapter/8-2-types-of-training..>
- Van Dijk, J., & Hacker, K. (2003). The digital divide as a complex and dynamic phenomenon. *The Information Society*, 19(1), 315-326.
- Woodward, J. (1965). *Industrial organizations theory and practice*. Oxford University Press.
- Wuttaphan, N. (2017). Human capital theory: The theory of human resource development, implications, and future. *Life Sciences and Environmental Journal*, 18(1), 240-253.
- Ziqubu, S. (2026). Bridging digital divide in human resource functions: Information and communication technology usage within Kwazulu-Natal's public sector. *South African Journal of Human Resource Management*, 24(1), 17-25.

APPENDIX A

Table 1: Single Factor Test

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	25.033	83.442	83.442	25.033	83.442	83.442
2	2.349	7.832	91.274			
3	.997	3.322	94.596			
4	.635	2.116	96.711			
5	.287	.958	97.669			
6	.272	.907	98.576			
7	.211	.705	99.281			
8	.076	.255	99.535			
9	.060	.200	99.735			
10	.038	.128	99.863			
11	.032	.106	99.969			
12	.009	.029	99.998			
13	.001	.002	100.000			
14	6.867E-016	2.289E-015	100.000			
15	1.354E-016	4.514E-016	100.000			
16	3.136E-017	1.045E-016	100.000			
17	2.075E-017	6.917E-017	100.000			
18	1.408E-017	4.695E-017	100.000			
19	1.098E-017	3.661E-017	100.000			
20	7.158E-018	2.386E-017	100.000			
21	6.535E-018	2.178E-017	100.000			
22	-1.079E-018	-3.598E-018	100.000			
23	-4.164E-018	-1.388E-017	100.000			

24	-7.140E-018	-2.380E-017	100.000			
25	-7.473E-018	-2.491E-017	100.000			
26	-1.503E-017	-5.008E-017	100.000			
27	-2.753E-017	-9.177E-017	100.000			
28	-2.857E-017	-9.523E-017	100.000			
29	-8.209E-017	-2.736E-016	100.000			
30	-1.709E-016	-5.695E-016	100.000			

Extraction Method: Principal Component Analysis.

Source: SPSS v20.

Table 2: Comprehensive demographic distribution of respondents/ Control Variables

Description	Frequency	Percentage
Questionnaire Distribution:		
Questionnaires Distributed	347	100%
Questionnaires Retrieved	312	89.9%
Educational Qualification:		
O'Level	98	31.4%
HND	80	25.6%
BSc	55	17.6%
M. Sc	54	17.3%
Ph.D	25	8%
Staff Category:		
Management	89	28.5%
Senior Staff	123	39.4%
Junior Staff	100	32%
Age Bracket:		
18-30	116	37.2%
31-43	98	31.4%
44 and above	98	31.4%
Gender:		
Male	185	59.3%

Female	127	40.7%
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Source: Field Survey, 2026 & SPSS v20.

Table 4: The mean responses of respondents on data analytics & interpretation skill gap

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
5	The best I can recall around 2017 to 2025 while working in this council, I found it difficult to analyze large datasets using tools like Excel, PowerBI, and SPSS	164 820 (53)	93 372 (30)	- - (-)	33 66 (11)	22 22 (7)	312 1280 100%	4.10	Accept
6	From what I observed over the past 8 years in this council, there were times I struggled to interpret data visualizations and dashboards to make official decisions	100 500 (32)	64 256 (21)	- - (-)	109 218 (35)	39 39 (13)	312 1013 100%	3.25	Accept
7	Considering my cumulative experience of this period, I lacked skills to clean, organize, and validate data before analysis	190 950 (61)	84 336 (27)	10 30 (3)	28 56 (9)	- - (-)	312 1372 100%	4.39	Accept
8	Within the period, I had difficulty translating data insights into actionable recommendations	211 1055 (68)	25 100 (8)	- - (-)	57 114 (18)	19 19 (6)	312 1288 100%	4.13	Accept
9	I was not very confident in using statistical techniques to identify patterns and solve work problems	170 850 (54)	90 360 (29)	10 30 (3)	39 78 (13)	3 3 (1)	312 1321 100%	4.23	Accept

Source: Field Survey, 2026 & SPSS Version 20.

Table 5: The mean responses of respondents on technical training

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
20	Over the period of 2017 to 2025 this council provided regular technical training to me on my job	239 1195 (76)	71 284 (23)	- - (-)	- - (-)	2 2 (1)	312 1481 100%	4.75	Accept
21	From what I have observed over the past 8 years, technical training programmes in this council are adequate for my job requirements	98 490 (31)	88 352 (28)	- - (-)	100 200 (32)	26 26 (8.3)	312 1068 100%	3.42	Accept
22	Considering my cumulative experience of this period, technical training received has improved my ability to perform my job effectively	158 790 (51)	79 316 (25)	35 105 (11)	40 80 (13)	- - (-)	312 1291 100%	4.14	Accept
23	Within the period, I can very well say the council provided regular technical training relevant to staff jobs generally	198 990 (63)	49 196 (16)	- - (-)	34 68 (11)	31 31 (10)	312 1285 100%	4.12	Accept
24	Funds were made available for staff to attend technical training and certification programmes	151 755 (48)	87 348 (28)	- - (-)	44 88 (14)	30 30 (10)	312 1221 100%	3.9	Accept

Source: Field Survey, 2026 & SPSS v20.

Table 7: The mean responses of respondents on artificial intelligence proficiency skill gap

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
10	Looking back over 2017-2025 as a whole, I had no	189 945	39 156	- -	47 94	37 37	312 1232	3.95	Accept

	understanding of how to apply AI tools like ChatGPT, Copilot, or ML models to my work	(60)	(13)	(-)	(15)	(12)	100%		
11	To the best of my current knowledge of this period, I did not understand the ethical and data privacy issues involved in using AI at work	163 815 (52)	17 68 (5)	13 39 (4)	85 170 (27)	34 34 (11)	312 1126	3.61	Accept
12	As of now, reflecting on 2017-2025, I am unable to evaluate the outputs and limitations of AI-generated content that relates to my job	179 895 (57)	95 380 (30)	10 30 (3)	28 56 (9)	- - -	312 1361 100%	4.36	Accept
13	In my present assessment of the period, I had limited skills in prompting AI tools to get accurate and relevant results at work	98 490 (31)	121 484 (39)	- - (-)	93 186 (30)	- - (-)	312 1160 100%	3.72	Accept
14	To the best of my current knowledge of this period, I lacked knowledge of how AI can be used to automate routine tasks in my department	238 1190 (76)	72 288 (23)	- - (-)	- - (-)	2 2 (1)	312 1480 100%	4.74	Accept

Source: Field Survey, 2026 & SPSS v20.

Table 8: The mean responses of respondents on job rotation & labour mobility

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
25	Looking back over 2017-2025 as a whole, in this council, staff were rotated into where AI/digital tools are	150 750 (48)	30 120 (10)	8 24 ()	65 130 (21)	59 59 (19)	312 1083	3.47	Accept

	used for them to gain new experiences								
26	To the best of my current knowledge of this period, I was given opportunities to work in cross-functional teams to learn new digital skills	130 650 (42)	115 230 37)	7 21 (2)	60 60 (19)	- - -	312 961 100%	3.08	Accept
27	As of now, reflecting on 2017-2025, job rotation in this council exposed employees to emerging technologies like AI	211 1055 (68)	25 100 (8)	- - (-)	57 114 (18)	19 19 (6)	312 1288 100%	4.13	Accept
28	In my present assessment of the period, this council encouraged movement across departments to build digital competence	200 1000 (64)	98 392 (31)	- - (-)	12 24 (4)	2 2 (1)	312 1418 100%	4.54	Accept
29	To the best of my current knowledge of this period, learning by doing through job rotation was actively promoted in in this council	115 575 (37)	103 412 (33)	- - (-)	57 114 (18)	19 19 (6)	312 1120 100%	3.59	Accept

Source: Field Survey, 2026 & SPSS v20.

Table 10: The mean responses of respondents on digital communication & collaboration skill gap

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
15	Looking back over 2017-2025, I used to find it difficult to collaborate effectively using tools like Teams, Zoom, Slack, or Google Workspace	111 555 (36)	76 304 (24)	- - (-)	98 196 (31)	27 27 (9)	312 1082 100%	3.46	Accept
16	In general over this	228	72	-	-	12	312		

	period, I was not proficient in sharing, co-editing, and managing documents on cloud platforms	1140 (73)	288 (23)	- (-)	- (-)	12 (4)	1440 100%	4.62	Accept
17	As it has typically been from 2017 to around 2025, I struggled with digital etiquette and professional communication in virtual meetings	98 490 (31)	121 484 (39)	- - (-)	93 186 (30)	- - (-)	312 1160 100%	3.72	Accept
18	Since 2017 to about 2025, I lacked skills in managing digital work-flows and project collaboration online	153 765 (49)	7 28 (2)	13 39 (4)	95 190 (30)	44 44 (15)	312 1066 100%	3.42	Accept
19	From what I observed over the years, I had difficulty building rapport and engaging team members in virtual settings	211 1055 (68)	25 100 (8)	- - (-)	57 11 (18)	19 19 (6)	312 1185 100%	3.81	Accept

Source: Field Survey, 2026 & SPSS v20.

Table 11: The mean responses of respondents on mentoring & coaching

S/N	ITEMS	SA 5 (%)	A 4 (%)	U 3 (%)	D 2 (%)	SD 1 (%)	SUM	MEAN	DEC
30	Looking back over 2017-2025, senior staff in this council mentor junior staff on digital communication and collaboration	188 940 (60)	84 336 (27)	- - (-)	23 46 (7.4)	17 17 (5)	312 1339 100%	4.29	Accept
31	In general over this period, I received regular feedback and coaching on how to use digital collaboration tools	238 1190 (76)	72 288 (23)	- - (-)	- - (-)	2 2 (6)	312 1480 100%	4.74	Accept
32	As it has typically	108	100	-	85	19	312		

	been from 2017 to around 2025, this council paired employees with mentors to improve virtual work skills	540 (35)	400 (32)	- (-)	170 (27)	19 (6)	1129 100%	3.62	Accept
33	Since 2017, in my experience, managers in this council provide one-on-one guidance on digital etiquette and online teamwork	163 815 (52)	17 68 (5)	13 39 (4)	85 170 (27)	34 34 (11)	312 1126 100%	3.61	Accept
34	From what I observed over the period, role modeling by experienced staff helped me improve my digital communication skills	111 555 (36)	108 432 (35)	- - (-)	48 96 (15)	45 45 (14)	312 1128 100%	3.62	Accept

Source: Field Survey, 2026 & SPSS v20.