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Research Article

# Evaluating the Readiness of Health Information Management Professionals for AI Integration in Healthcare Systems in Bayelsa State, Nigeria

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## Abstract

Artificial intelligence (AI) is revolutionizing healthcare delivery globally. But existing literature on the extent of AI computer literacy among respectively physicians in Nigeria as an evidence of its level of integration into healthcare is insufficient. This study was designed to evaluate the level of AI awareness and knowledge, digital competence, organizational readiness, professional development, and AI preparedness of healthcare provider (HIM professionals') towards healthcare integration in Bayelsa State. The study adopted a descriptive cross-sectional survey design. The study population comprised 332 members of AHRIMPN Bayelsa chapter WhattsApp platform. From which 205 turned out to be the respondents and were analyzed with the use of structured 36-item self-administered questionnaire. Data were analyzed by descriptive statistics, Cronbach's alpha reliability analysis, Spearman's rank correlation, Mann Whitney U test, exploratory factor analysis, relative importance analysis, and multivariable regression at 5% significance level. The results showed moderate AI knowledge and awareness (3.052 ±0.116), digital competence (2.923 ±0.100), organizational readiness (3.141 ±0.124), professional development (3.143 ± 0.158) and AI readiness for healthcare integration (3.115±0.101). The instrument possessed Cronbach's α of 0.760 0.887 while Kaiser–Meyer–Olkin of 0.820 and significant Bartlett's Test of 19.155, P value = 0.000 validated the data for factor analysis. There were strong positive relationships between AI knowledge, digital competence and organizational readiness. But multivariable regression analysis revealed none of the observed four explanatory variables individually and significantly predicted AI readiness ($p > 0.05$). Respondents who had previous AI/digital health training had significantly better reported knowledge, digital competence, organizational readiness and professional development than those who did not have such training. The study revealed moderate AI readiness among healthcare professionals into AI-enabled health systems, though lack of the requisite AI skills and lack of standardized, continuous and obligatory AI capacity building interventions as well as poor investment in digital technology, robustness of organization, and health institution-related variations in knowledge, digital competence, organizational readiness and professional development are impeding AI integration into healthcare. The study concludes that continuous AI capacity development programmes, digital infrastructure investment, organizational autonomy and investment, and well-articulated AI curriculum into practitioner education, healthcare professional professional development programmes and organization-related accreditation are indispensable to successful, affordable and sustainable AI-enabled health systems.

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## Keywords

Artificial Intelligence, AI Readiness, Digital Competence, Organizational Readiness, Professional Development, Health Information Management Professionals, Healthcare Integration, Nigeria

## 1. Introduction

Artificial intelligence is considered one of the most disruptive innovations in healthcare and has transformed the way health information is generated, collected, managed, analyzed, and utilized to improve healthcare services. In particular, progress in areas of machine learning, natural language processing, predictive analytics, clinical decision support, intelligent electronic health records and computer-assisted coding has improved healthcare efficiency, efficiency and quality in high-income, as well as, in low and middle-income countries [1]. Moreover, as a technological breakthrough, AI presents revolutionary opportunities to tackle fundamental healthcare challenges such as diagnostic errors, treatment errors, workflow inefficiency, soaring healthcare costs, unequal service access and the growing need for timely information for clinical decision making [2-4]. Despite these seemingly unparalleled opportunities, realizing the aspirations of AI-enabled healthcare depends not merely on the existence, but also on adequacy, appropriateness and accessibility of AI technologies and as much on the healthcare workforce capacity, competence, ownership and readiness for digital health transformation [5, 6]. As such, Health Information Management (HIM) professionals, as stewards of health data and information systems, need to be equipped with sufficient AI knowhow and awareness, digital literacy, organizational leadership and investment, health workers' staff development and quality improvement. AI adoption and integration within the health sector is gaining momentum across Nigeria and is increasingly being used for disease diagnosis, medical imaging, public health surveillance, predictive modeling, health information management among others [8-12]. However, its implementation continues to be limited by factors such as inadequate digital infrastructure, weak interoperability between health information systems, lack of funding and investment, poor regulation, dearth of digitally literate healthcare personnel, among others [8-12]. Parallel implementation barriers have also been identified in technologically advanced health systems where organisational readiness, governance, professional workforce readiness and responsible AI usage still affect its successful integration [5, 13]. In Nigeria, despite the increasing investments in electronic health records, telemedicine and other digital health interventions, the use of AI in routine health services is slow due to infrastructural challenges, poor power supply, poor internet connectivity, inadequate funding, weak institutional support, and limited capacity building opportunities for AI [14]. Moreover, little is known about the readiness of Nigerian health information management professional workforce for AI integration. This study therefore examines AI awareness and the knowledge of Bayelsa state health information management professionals on AI, with the aim of providing evidence-based data to inform the planning for AI workforce development, professional curriculum advancement, formulation of institutional policies and strategic investment needed to promote sustainable AI integration and use within the Nigerian health sector.

## 2. Materials and Methods

### 2.1. Study Area

The study will be conducted in Bayelsa State, located in the South-South geopolitical zone of Nigeria within the Niger Delta region. Bayelsa State was created on 1 October 1996 from the old Rivers State and has its capital in Yenagoa. The State comprises eight Local Government Areas: Brass, Ekeremor, Kolokuma/Opokuma, Nembe, Ogbia, Sagbama, Southern Ijaw, and Yenagoa. It is bounded by Delta State to the north, Rivers State to the west and the Atlantic Ocean to the south and east. The State is characterized by riverine communities, mangrove forests, and extensive creeks that influence healthcare accessibility and health information management practices.

The study population comprises Health Information Management professionals working in public and private healthcare institutions across Bayelsa State who are registered members of the Association of Health Records and Information Management Practitioners of Nigeria (AHRIMPN), Bayelsa State Chapter.

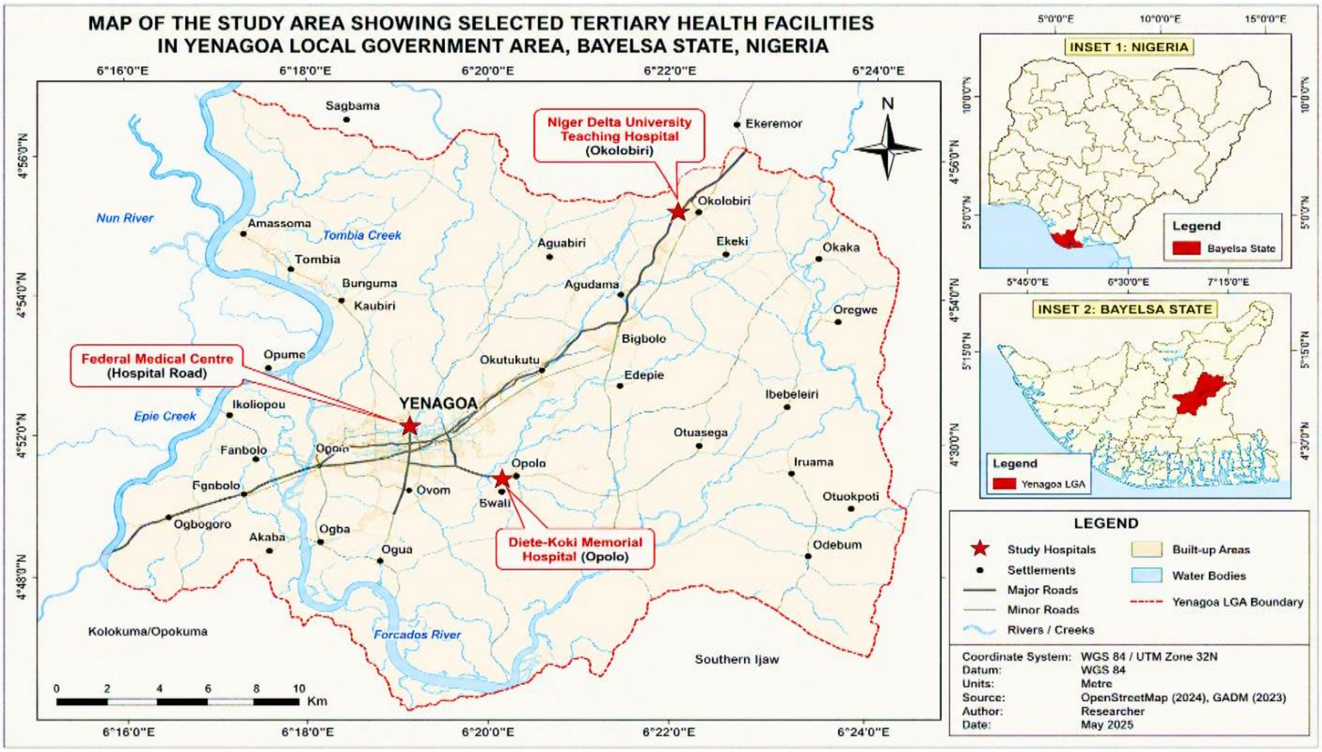


***Figure 1.*** *Map of Yenagoa Metropolis showing study locations.*

*Source*: Researcher's GPS survey (2026); administrative boundaries adapted from official geospatial datasets; cartographic design by the researcher

## 2.2. Study Design and Sample Collection

The study adopted a descriptive cross-sectional survey research design. The choice of the study design is to enable the collection information from Health Information Management (HIM) professionals at a single point in time regarding their readiness for Artificial Intelligence (AI) integration into healthcare systems. The design allow for the assessment AI readiness of Health Information Management professionals in terms of AI knowledge and awareness, digital competencies, organizational readiness, and professional development using a structured questionnaire.

## 2.3. Study Population

The target population comprises all 332 registered Health Information Management professionals in the official WhattsApp platform of the Association of Health Records and Information Management Practitioners of Nigeria (AHRIMPN) Bayelsa state Chapter as at (2026), whom belong to the association.

## 2.4. Sampling and Sample Size

The study adopt a total population sampling technique (census sampling), Due to the relatively small size of the target population that is appropriate, because all members are identifiable and accessible through the official Association WhatsApp platform and every registered professional has an equal opportunity to participate. Therefore the sample size is the entire population of 332 as the respondents, in order to eliminate sampling error, increases representativeness, enhances statistical power, and improves the generalizability of the findings within Bayelsa State.

## 2.5. Instrument for Data Collection

Data was collected using a structured self-administered questionnaire developed after extensive review of related literature on Artificial Intelligence readiness among healthcare professionals. The questionnaire consist of section A t0 F, with 43 items; Socio-demographic characteristics of respondents and Study variables (AI Knowledge and Awareness, Digital Competence, Organizational Readiness, Professional Development and AI Readiness for Healthcare Integration), responses was measured using five-point Likert scale such as strongly agree, agree, undecided, disagree and strongly disagree, the instrument was adopted from [15-19].

## 2.6. Data Collection and Analysis

Approval was obtained from the leadership of the association of Health Records and Information Management Practitioners of Nigeria (AHRIMPN), Bayelsa State Chapter. An electronic version of the questionnaire was created using Google Forms. The survey link, accompanied by an introductory letter explaining the purpose of the study, informed consent, confidentiality assurance, and voluntary participation, was posted on the Association's official WhatsApp platform. To improve the response rate, reminder messages was sent weekly for four weeks. Completed responses was automatically be stored in Google Forms and downloaded into Microsoft Excel before being exported to SPSS version 29 for analysis.

Data was analysed using IBM SPSS Statistics Version 29, descriptive statistics include: frequency, percentage, mean standard deviation and median, also exploratory factor analysis (EFA) was employed to examine the dimensionality of the adapted questionnaire and Cronbach's alpha to establish internal consistency reliability, Spearman's rank correlation, Mann Whitney U test, exploratory factor analysis, relative importance analysis, and multivariable regression at a 5% level of significance. Because the primary objective was to examine relationships among theoretically defined constructs using composite scores rather than to develop or validate a new measurement instrument, subsequent analyses were conducted using the validated composite variables, while confirmatory factor analysis (CFA) and structural equation modeling (SEM) are recommended as avenues for future research to further validate the measurement model in broader populations.

The mean concentration of each parameter was calculated as:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Where:

1) $\bar{x}$= sample mean
2) $x_i$= observed value
3) $n$= number of observations

Results were expressed as mean ± standard deviation.

The standard deviation was calculated using:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}} \tag{2}$$

Where:

1) $SD$= standard deviation
2) $x_i$= individual observation
3) $\bar{x}$= sample mean
4) $n$= sample size

For Multiple regression:

AI Readiness=β0 + β1 (AI Knowledge) + β2 (Digital Competence) + β3 (Organizational Readiness) + β4 (Professional Development)

### 2.7. Ethical Considerations

Ethical approval was obtained from the association leadership before commencement of the study. Participation will be voluntary, and respondents was provided with informed consent electronically before completing the questionnaire. No identifying information was collected, and all responses was treated with strict confidentiality, the obtained data was used solely for the research purposes and stored securely in password-protected electronic files.

## 3. Results

*Table 1. Socio-demographic Characteristics of the Respondents (N = 205).*

| Variable | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| Sex | Male | 101 | 49.3 |
| | Female | 104 | 50.7 |
| Age (years) | Below 30 | 65 | 31.7 |
| | 30–39 | 33 | 16.1 |
| | 40–49 | 85 | 41.5 |
| | 50–59 | 22 | 10.7 |
| Educational Qualification | Diploma | 90 | 43.9 |
| | HND | 103 | 50.2 |
| | B-HIM | 2 | 1.0 |
| | MSc | 10 | 4.9 |

| Variable | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| Professional Work Experience | <5 years | 28 | 13.7 |
| | 5–10 years | 25 | 12.2 |
| | 11–15 years | 82 | 40.0 |
| | 16–20 years | 49 | 23.9 |
| | Above 20 years | 21 | 10.2 |
| Current Professional Designation | Health Information Management Technician | 36 | 17.6 |
| | Health Information Management Officer | 74 | 36.1 |
| | Principal Health Information Manager | 63 | 30.7 |
| | Chief/Assistant Director | 32 | 15.6 |
| Previous Formal Training in Artificial Intelligence or Digital Health Technologies | Yes | 48 | 23.4 |
| | No | 157 | 76.6 |

Table 1, presents the socio-demographic characteristics of the 205 Health Information Management professionals who participated in the study. Artificial intelligence is considered one of the most disruptive innovations in healthcare and has transformed the way health information is generated, collected, managed, analyzed, and utilized to improve healthcare services. In particular, progress in areas of machine learning, natural language processing, predictive analytics, clinical decision support, intelligent electronic health records and computer-assisted coding has improved healthcare efficiency, efficiency and quality in high-income, as well as, in low and middle-income countries [1]. Moreover, as a technological breakthrough, AI presents revolutionary opportunities to tackle fundamental healthcare challenges such as diagnostic errors, treatment errors, workflow inefficiency, soaring healthcare costs, unequal service access and the growing need for timely information for clinical decision making [2-4]. Despite these seemingly unparalleled opportunities, realizing the aspirations of AI-enabled healthcare depends not merely on the existence, but also on adequacy, appropriateness and accessibility of AI technologies and as much on the healthcare workforce capacity, competence, ownership and readiness for digital health transformation [5, 6]. As such, Health Information Management (HIM) professionals, as stewards of health data and information systems, need to be equipped with sufficient AI knowhow and awareness, digital literacy, organizational leadership and investment, health workers' staff development and quality improvement.

AI adoption and integration within the health sector is gaining momentum across Nigeria and is increasingly being used for disease diagnosis, medical imaging, public health surveillance, predictive modeling, and health information management among others [8-12]. However, its implementation continues to be limited by factors such as inadequate digital infrastructure, weak interoperability between health information systems, lack of funding and investment, poor regulation, dearth of digitally literate healthcare personnel, among others [8-12]. Parallel implementation barriers have also been identified in technologically advanced health systems where organisational readiness, governance, professional workforce readiness and responsible AI usage still affect its successful integration [5, 13]. In Nigeria, despite the increasing investments in electronic health records, telemedicine and other digital health interventions, the use of AI in routine health services is slow due to infrastructural challenges, poor power supply, poor internet connectivity, inadequate funding, weak institutional support, and limited capacity building opportunities for AI [14]. Moreover, little is known about the readiness of Nigerian health information management professional workforce for AI integration. This study therefore examines AI awareness and the knowledge of Bayelsa state health information management professionals on AI, with the aim of providing evidence-based data to inform the planning for AI workforce development, professional curriculum advancement, formulation of institutional policies and strategic investment needed to promote sustainable AI integration and use within the Nigerian health sector.

*Table 2. Descriptive Statistics and Reliability of the Study Constructs (N = 205).*

| Construct | No. of Items | Mean | SD | Median | Cronbach's α | Interpretation |
|---|---|---|---|---|---|---|
| Artificial Intelligence Knowledge and Awareness | 8 | 3.052 | 0.936 | 3.000 | 0.887 | High internal consistency; moderate knowledge and awareness |
| Digital Competence | 7 | 2.923 | 0.883 | 2.857 | 0.839 | Good internal consistency; moderate digital competence |
| Organizational Readiness | 7 | 3.141 | 0.847 | 3.143 | 0.760 | Acceptable internal consistency; moderate organizational readiness |
| Professional Development | 7 | 3.143 | 0.911 | 3.143 | 0.848 | Good internal consistency; relatively higher professional development |
| AI Readiness for Healthcare Integration | 7 | 3.115 | 0.954 | 3.143 | 0.821 | Good internal consistency; moderate AI readiness |
| Overall | 36 | 3.075 | 0.906 | 3.057 | 0.831 | Overall moderate readiness with satisfactory reliability |

Table 2 shows that the descriptive statistics of the respondents suggest that they expressed a moderate opinion on all the five constructs involved of the study, with an overall mean value of 3.075 (SD=0.906), which indicated that the respondents held moderate opinion on the level of AI preparedness for the healthcare setting. The highest mean value was obtained for Professional Development (Mean=3.143; SD=0.911). Slightly below were the means of organization Readiness (Mean=3.141; SD=0.847) and AI Readiness for Healthcare Integration (Mean=3.115; SD=0.954). While the respondents scored the lowest mean value on Digital Competence (Mean= 2.923; SD=0.883). This meant that these respondents found their digital competencies were not as advanced as the other constructs in this study. The median score ranged from 2.857 to 3.143. It further evidenced that respondents were relatively balanced in the opinion about these concepts.

Reliability analysis revealed that all five constructs had considerable good to excellent internal reliability with Cronbach‘s alpha values within the range 0.760 to 0.887, above the general standard of 0.70 for a research instrument. For example, the construct of Artificial Intelligence Knowledge and Awareness has the highest reliability coefficient (α = 0.887), suggesting the reliability for all its measurement items to be very consistent, while Organizational Readiness has the lowest reliability coefficient, but acceptable values (α = 0.760). The overall reliability coefficient of 0.831 indicated that the questionnaire consistently measured the underlying constructs, and is appropriate for what turns out to be subsequent meaningful inferential tests. Though findings shows good reliable and moderate readiness for AI incorporation, the relatively insignificant mean score for Digital Competence has compelled Health Institutions, providers and practitioners to continue with incremental digital capacity strengthening schemes, informatics and practical AI-centric training programmes and intervention studies to further develop AI competences to realize successful implementation in the practice of Healthcare.

*Table 3. Inter-construct Spearman correlations Analysis.*

| Construct | Knowledge (p-value) | Digital (p-value) | Org. Readiness (p-value) | Prof. Development (p-value) | AI Readiness (p-value) |
|---|---|---|---|---|---|
| AI Knowledge & Awareness | 1.000 | 0.873 | 0.718 | -0.015 | 0.066 |
| Digital Competence | 0.873 | 1.000 | 0.734 | -0.092 | 0.070 |
| Organizational Readiness | 0.718 | 0.734 | 1.000 | -0.121 | 0.095 |
| Professional Development | -0.015 | -0.092 | -0.121 | 1.000 | -0.121 |
| AI Readiness | 0.066 | 0.070 | 0.095 | -0.121 | 1.000 |

Table 3 illustrates the correlations between Artificial Intelligence Knowledge and Awareness, Digital Competence, Organizational Readiness, Professional Development and AI Readiness for Healthcare Integration. Very strong positive correlations were found between Artificial Intelligence Knowledge and Awareness and Digital Competence (ρ = 0.873) (Artificial Intelligence Knowledge and Awareness and Digital Competence) positively correlated strongly with each other, as well as Central Artificial Intelligence Knowledge and Awareness and Digital Competence, with a (ρ = 0.873). Artificial Intelligence Knowledge and Awareness positively correlated strongly with Organizational Readiness (ρ = 0.718) (Central Artificial Intelligence Knowledge and Awareness and Organizational Readiness). Also, Digital Competence also positively correlated strongly with Organizational Readiness (ρ = 0.734). These positive correlations provide anecdotal evidence that Artificial Intelligence Knowledge and Awareness, Digital Competence and Organizational Readiness are strongly correlated and serving as foundations for AI integration in healthcare organizations.

In contrast, AI Knowledge and Awareness had weak negative associations with Professional Development (ρ =-0.015), Digital Competence (ρ =-0.092), and Organizational Readiness (ρ =-0.121) while weak positive associations were observed between AI Readiness for Healthcare Integration with AI Knowledge and Awareness (ρ =0.066), Digital Competence (ρ =0.070), Organizational Readiness (ρ =0.095), and a negative correlation with Professional Development (ρ =-0.121). These weak relationships imply that rising individual professional knowledge or training levels may not necessarily lead directly to higher AI readiness. Instead, various departmental, technological and policy context-related variables, all of which were outside the scope of this study, are also likely to shape perceived AI readiness. As such, Hospital administrators and policymakers should therefore formulate an integrative implementation plan with a combination of training initiatives and infrastructural investments, leadership engagement and positive workplace organisational policies to bolster AI readiness levels in H.I.M.

***Table 4**. Multivariable regression.*

| Predictor | B | t | p | Bootstrap 95% CI |
|---|---|---|---|---|
| AI Knowledge & Awareness | 0.036 | 0.226 | 0.821 | -0.279 to 0.343 |
| Digital Competence | -0.051 | -0.303 | 0.763 | -0.350 to 0.279 |
| Organizational Readiness | 0.118 | 0.967 | 0.335 | -0.126 to 0.352 |
| Professional Development | -0.124 | -1.682 | 0.094 | -0.263 to 0.018 |

Table 4 displays the results of a multivariable regression testing the independent effects of Artificial Intelligence Knowledge and Awareness, Digital Competence, Organizational Readiness and Professional Development on AI Readiness for Healthcare Integration. These predictor variables failed to significantly predict AI readiness at the 5% significance level. Whilst Artificial Intelligence Knowledge and Awareness delivered a negative but statistically insignificant B value (0.036) and t-value (0.226) and p-value (0.821), Digital Competence had a small but statistically insignificant B value (-0.051), t-value (-0.303) and p-value (0.763); the regression coefficient for Organizational Readiness was positive but statistically insignificant (B= 0.118, t= 0.967, and p= 0.335); the Professional Development predictor variable had the largest regression coefficient in absolute terms, was negative but statistically insignificant (0.124), (t= 1.682), (p= 0.094); and the bootstrap confidence intervals surrounding the predictors crossed zero, providing further evidence that none of these variables predicted AI readiness with independence.

Taken together, these results imply that the degree of health information management AI readiness is a complex construct that cannot be sufficiently articulated through only knowledge, digital competencies, organizational readiness or professional development alone. Lack of statistically valid predictors on the multiple regression analysis table does not mean these constructs are "vanishing" factors. Instead, it should be interpreted as each construct could have an indirect, synergist or moderator effect with other external factors, such as organizational leadership, existing AI infrastructure, institutional funding, policymaking support, regulation and prior AI project implementation experience. To build a more accurate model predicting health information management AI readiness, future researches should consider including broad, institutional and technological factors. Practically, healthcare institutions should avoid overly depending on training programs and adopt integrated implementation strategies which strengthen technological, leadership, regulatory and organizational aspects simultaneously.

***Table 5.*** *Relative importance analysis of professional Development Ranking.*

| Predictor | Average incremental $R^2$ | Relative contribution |
|---|---|---|
| AI Knowledge & Awareness | 0.0021 | 8.0% |
| Digital Competence | 0.0017 | 6.7% |
| Organizational Readiness | 0.0073 | 28.4% |
| Professional Development | 0.0147 | 57.0% |

Table 5 summarizes the relative importance analysis for the four predictor variables in explaining the variability in the dependent variable AI Readiness for Healthcare Integration. From the analysis, it can be observed that Professional Development contributes the highest proportion of variance explained, 57.0%, in the model with an average incremental R 2 0.0147. Next to this, Organizational Readiness accounted for about 28.4% (average incremental R 2 0.0073), with Artificial Intelligence Knowledge and Awareness and Digital Competence accounting for 8.0% and 6.7%. While the F ratios for the predictors were not statistically significant, their relative contribution to the explanation of the dependent variable by the regression model ranks the Professional Development and Organizational Readiness higher than the remaining two predictors.

It‘s important to note relative importance are meant to be read in conjunction with the regression analysis, as a higher relative importance does not equate to significance or even causality; a higher relative importance rates simply as a larger proportion of the model variance explained relative to the other of variables in the model. Hence, we regard Professional Development as the most prominent construct examined in this model, but it is insignificant in predicting AI readiness on its own, conferring that to improve healthcare workforce AI readiness, professional development can be strengthened with DPC or CPD as regular occurrence, and AI capacity building intervention within Digital skills, but its effect must be combined with improvements in the organizational structure (delivery), institutional policy, and leadership.

***Table 6.*** *Previous AI/digital-health training.*

| Construct | Training Yes | Training No | U | p | Rank-biserial r |
|---|---|---|---|---|---|
| AI Knowledge & Awareness | 3.737 | 2.843 | 6034.0 | 0.0000 | -0.601 |
| Digital Competence | 3.363 | 2.788 | 5205.5 | 0.0001 | -0.382 |
| Organizational Readiness | 3.506 | 3.029 | 5017.0 | 0.0005 | -0.331 |
| Professional Development | 3.640 | 2.991 | 5247.5 | 0.0000 | -0.393 |
| AI Readiness | 3.167 | 3.099 | 3922.5 | 0.6675 | -0.041 |

Table 6 presents a comparison of the study constructs by respondents' previous experience with formal training in AI or digital health. Highly significant differences between trained and untrained respondents were found in AI Knowledge and Awareness ($U = 6034.0$, $p < 0.001$), Digital Competence ($U = 5205.5$, $p = 0.0001$), Organisation Readiness ($U = 5017.0$, $p = 0.0005$) and Professional Development ($U = 5247.5$, $p < 0.001$). For each of these constructs the respondents who had previous formal training in AI or digital health scored higher than those who had not. The largest difference was in AI Knowledge and Awareness where respondents with prior formal training scored an average of 3.737 compared to 2.843 of those who had not had formal training, with a large rank-biserial effect size ($r = -0.601$).

However, the respondents' healthcare integration AI readiness did not significantly differ between the trained and untrained groups ($U = 3922.5$, $p = 0.6675$, $r = -0.041$), with the former showing only a slight increase in mean scores. This indicates that AI training by itself may not be enough for fostering organisation-wide AI integration readiness. Factors external to the individual that were relevant are acquired skills, realisation of the benefits of AI use, institutional policies, technological infrastructure, managerial support and resources. As such, healthcare organisation should couple staff training with organisation-wide support and reinforcement to facilitate clinical implementation. It is prognosticated that all round AI implementation readiness measures may yield even better results with a combined approach than with training alone.

***Table 7.*** *Sampling adequacy for factor analysis.*

| Diagnostic | Result | Interpretation |
|---|---|---|
| Kaiser–Meyer–Olkin (KMO) | 0.820 | Good sampling adequacy |
| Bartlett's test of sphericity | $\chi^2(630) = 5118.55$, $p < .001$ | Correlation matrix suitable for factor analysis |
| Sample size | N = 205 | Adequate for exploratory measurement assessment |
| Items | 36 | Five theoretically specified domains |

Diagnostic statistics, shown in Table 7, were assessed to confirm that the data was suitable for exploratory factor analysis. The KMO measure of sampling adequacy for the entire set of variables was 0.820 (≥ 0.60 for an adequate factor analysis) and Bartlett's Test of Sphericity was statistically significant (x 2(630) = 5118.55, p < 0.001). These results indicate that the variables shared some common variance and that the correlation matrix was appropriate for factor extraction. Additionally, the sample size of 205 participants was well above the minimum recommended sample size for exploratory measurement evaluation, providing sufficient power to examine the underlying structure of the questionnaire.

Together, the findings of the CFA indicate that the set of variables can be used for factor analytic procedures and strengthens confidence in the results for the construct level analyses contained within this report. The significant result of Bartlett's test indicates that there are meaningful relationships among the questionnaire items and the acceptable KMO value suggests that the variables are not overly interdependent. In turn, the results of the factor analysis from the instrument can be interpreted with comfort as an exploratory examination of the measure. Those conducting similar studies should continue to consider adequacy of sampling for factor analysis before interpreting latent construct analyses as naturally occurring rather than the product of spurious correlation.

***Table 8.*** *Eigenvalue assessment.*

| Component | Eigenvalue |
|---|---|
| Factor 1 | 9.814 |
| Factor 2 | 4.359 |
| Factor 3 | 3.595 |
| Factor 4 | 2.142 |
| Factor 5 | 1.586 |
| Factor 6 | 1.409 |
| Factor 7 | 1.280 |
| Factor 8 | 1.065 |
| Factor 9 | 1.004 |
| Factor 10 | 0.924 |

The eigenvalues produced from the exploratory factor analysis can be seen in Table 8. The first factor had the highest eigenvalue (9.814), with subsequent factors: 2, 3, 4 and 5 having eigenvalues of 4.359, 3.595, 2.142 and 1.586 respectively. Even factors 6 through to 9 had eigenvalues over 1, contrary to factor 10 which had an eigenvalue of only 0.924. The significant difference between the eigenvalue for the first factor and the remaining factors indicates that this particular factor accounts for a large proportion of the variance in the answers to the questionnaire and that the data was shaped by one primary conceptual underpinning along with other meaningful factors.

Although several of the factors presented with an eigenvalue above 1, it was conceptually developed to assess five factors: Artificial Intelligence Knowledge and Awareness, Digital Competence, Organizational Readiness, Professional Development, and AI Readiness for Healthcare Integration. Based on the constructivist approach of developing these questionnaires, the dimensional structure of the survey should be based on the a-priori theoretical framework than the eigenvalue 1 cutoff criterion. The eigenvalue pattern was consistency with the literature, and shows supportive evidence of a multifactor structure, and future validation studies might be better utilizing the confirmatory approach to test whether five factor model is the best fitting conceptual structure.

***Table 9.*** *Exploratory five-factor solution.*

| Theoretical construct | Items | Items sharing dominant rotated factor | Dominant factor |
|---|---|---|---|
| AI Knowledge & Awareness | Q1–Q8 | 4/8 (50.0%) | Factor 1 |
| Digital Competence | Q9–Q15 | 4/7 (57.1%) | Factor 5 |
| Organizational Readiness | Q16–Q22 | 3/7 (42.9%) | Factor 1 |
| Professional Development | Q23–Q29 | 7/7 (100.0%) | Factor 2 |
| AI Readiness | Q30–Q36 | 6/7 (85.7%) | Factor 3 |

Table 9 below also displays the proportion of items that had loaded onto their a priori construct via Principle Axis Factoring, following the EFA. Professional Development displayed the greatest structural consistency with 7 (100%) items clustering on the same dominant factor. AI Readiness for Healthcare Integration was also highly consistent with 6 (85.7%). In comparison, the other constructs showed a slightly lower consistency with 2 (42.9%), 4 (57.1%) and 3 (50%) items clustering as expected.

Although the clustering for AI Knowledge and Awareness, Digital Competence and Organisational Readiness was so comparatively weak, this may suggest that the respondents viewed those constructs as more interrelated than the distinct dimensions of AI readiness that they are supposedly to be. This is somewhat intuitive, as usually knowledge, digital competence and organisational support are concomitantly fostered in healthcare organisations experiencing a period of digital transformation. Yet, the relative success of Professional Development and AI Readiness as constructs indicates that those were better operationalised. Further revisions to the instrument should focus on modification and exactification of the items within the first three constructs, to reduce conceptual variance and separation of constructs, while ensuring the conceptual framework of the instrument remains intact.

***Table 10.*** *Item-level factor concerns requiring attention.*

| Item | Maximum absolute loading | Communality |
|---|---|---|
| I can effectively use Electronic Health Records? | 0.343 | 0.339 |
| There is reliable internet connectivity in my workplace? | 0.291 | 0.202 |
| Management is committed to adopting AI technologies? | 0.492 | 0.279 |
| My organization provides technical support for digital innovations? | 0.315 | 0.142 |
| I have attended workshops related to digital health technologies? | 0.344 | 0.239 |
| Overall, I consider myself ready for Artificial Intelligence integration into healthcare systems? | 0.200 | 0.049 |

Table 10 presents the questionnaire items which tended to have relatively low factor loadings or communalities in the exploratory factorial analysis. Of the 6 items present, the statement representing overall psychological preparedness for implementation of AI into the health system experienced the lowest psychometric properties, with the highest loading on a component being 0.200 and the communalities being a meager 0.049. In addition, the items describing consistent availability of high-speed internet access, technical expertise supporting digital health advancements, and participation in digital health intervention workshops had low communalities of between 0.142–0.239 meaning that at least 1 item in the set had weak representation with regards to the factors. The information technology implementation item stated that higher management supported AI technology had a stronger loading of 0.492 and a communalities of 0.279, yet failed to be in the desired range.

These results are not to be taken as an indication that the items need to be removed at this point. The particular items in question are the ones that should be examined and possibly revised through the process of instrument improvement in the future. The depression of communalities in these items is likely due to the idiosyncratic nature of some of these organisational factors (e.g., internet access, leadership support, and technical assistance) across healthcare setting and their contextual nature which is not fully captured using the broader constructs. While these items should be retained in the reference instrument, the wording should be revised to eliminate confusion, and improve the psychometric properties of the questionnaire while monitoring the same factors.

## 4. Discussions of Findings

This study assessed the AI knowledge and awareness of HIM professionals in AI integration in healthcare in Bayelsa state. The socio-demographic characteristics show study participants were relatively evenly distributed across gender lines, though females formed the majority (50.7%). The two respondent groups with the highest frequency distribution fell within the 40 49 age age group (34.5%) and the 11-15 year band of health Information management expertise (30.4%). These views provides a population of largely well-experienced practitioners actively practicing health information management, and hence well positioned to proffer informed opinions regarding the integration of AI into healthcare delivery in the state. More importantly, the observation that 76.6% of respondents reported never having received any formal training in either artificial intelligence or digital health technologies highlights the impressive scale of the nation-wide skilled healthcare human resource capacity gap, despite the general digitization of the sector and the seemingly inevitable digitization of healthcare services going forward. This view affirms the findings of other studies that have reported healthcare practitioners, especially in low and middle income nations, continued lack of formal artificial intelligence education irrespective of their increasing awareness of its potential to revolutionize healthcare delivery [6, 20-22]. Similar concerns have been stressed by other researchers [4], who assert that the key factor enabling the successful integration of AI into healthcare is the consistent education and reskilling of the workforce through digital literacy enhancement programs. Likewise, as noted by other researchers that he skillset of healthcare workers will have to be upgraded substantially to be able to work effectively within AI-enabled healthcare settings [7, 23]. All the same, the findings of the present study disagree with similar reported experiences of healthcare workers in advanced healthcare systems who report their having received more formalAI training and Institutional Digital transformation program educational exposure [24-26], respectively. The variance between the present report and existing literature from high-resource healthcare settings may be partly attributable to higher levels institutional investment, preparedness and digitized healthcare infrastructure as well as strategic national AI implementation programmes in those settings, and further illustrates the need for Indonesian-specific capacity-building AI interventions targeting the nation rather than state-level HM health professionals.

The descriptive statistics also revealed respondents had moderate levels of AI literacy and awareness, digital competence, organizational capacity, professional development and AI readiness, while the tool had an adequate internal reliability across all factors (Cronbach‘sα=0.760-0.887). The findings indicated that despite respondents having a basic level of understanding of AI and perceiving of their organizations to be relatively prepared, there were significant gaps in all five areas, with the lowest score being associated with digital competence. The significant and positive correlation between AI knowledge and awareness and digital competence and organizational readiness further inferred these factors are bi-directionally associated with each other, implying advances in one factor may catalyze improvement in the other. The results corroborate with the World Health Organization directions on artificial intelligence for health, which advocates that the development of the health workforce capacity, institutional preparedness and effective governance be carried out concurrently for better AI integration [6]. They also seem to align with the empirical evidence from other studies [27-32], which identified digital competence and organizational investment as critical requirements for AI success within healthcare systems. On the contrary, the minimal association between professional development and AI readiness, together with lack of statistically significant relationships between the covariates and AI readiness, are unlike the findings from other studies [4, 22, 33], where digital literacy and professional competence has been shown as significant influential factors for AI assimilation among healthcare professionals. The finding may suggest that readiness to integrate AI within the present context may go beyond individual skillsets and compromises on other factors related to digital infrastructure, organizational mission and strategic planning, which were not fully measured in the current study. This would signify that healthcare organizations should undertake hybrid modes of implementation that combine workforce capacity building with large-scale investment into digital architecture, leadership, governance and institutional commitment in order to facilitate successful integration of AI into routine health information management practices.

The multivariable regression and relative importance analyses on AI readiness for HIA has yielded some noteworthy findings among the HIMP in Bayelsa state. While total (Artificial Intelligence Knowledge and Awareness), unique (Digital Competence), organizational (Organizational Readiness) and individual professional (Professional Development) organizational factors all represent factors of theoretical importance to AI implementation, among the variables set, none of these factors independently predicted AI Readiness at the 0.05 alpha level of significance in the current study. Among these predictors, the bootstrap confidence intervals optimized at 0.05- alpha level of significance flanked zero for all four in the current study, further confirming lack of statistically reliable estimates of the direct effect was more than that of all four predictors taken together. Nevertheless, the dominance analysis showed that compared with the other variables, Professional Development accounted for the largest marginal contribution (57.0%) of the predicted variance, with Organizational Readiness alone (28.4%) lagging a little behind, while Artificial Intelligence Knowledge and Awareness (8.0%) and Digital Competence (6.7%) contributed very little to the prediction. These results imply that although Professional Development and Organizational Readiness seems to simply overarch all the other predictors in terms of contribution to AI readiness, their effects are still unable to explain AI readiness on their own. The results is consistent with the growing consensus that AI is not just about individual users' knowledge and skills, but a much more complex and multifaceted process, with Professional Development and Organizational Readiness playing relatively greater roles than what was observed in the current study [4]. Other reports [6, 22, 29, 31], have also reiterated this point of view, emphasizing that organizational leadership, governance, technology infrastructure, and effective organizational investment are essential conditions for the implementation and adoption of AI in healthcare. However, the findings of the current research contrast with some other studies [16, 33-34], as part of their affirmation that digital competence and AI knowledge and familiarity can either facilitate or hinder healthcare workers' willingness to embrace AI technologies. One possible reason for this is the relatively limited AI environment in the study setting, where institutional policies, digital infrastructure and organizational support systems are still witnessing minimal investment. Therefore, improving individual (healthcare workers) competence level alone, will not translate into meaningful impact unless the overall environment is also matured enough.

The comparison of those respondents who had received formal AI or digital health training in the past to those who had not highlighted further benefits of capacity building initiatives. Those with previous AI training had significantly higher levels of AI Knowledge and Awareness, Digital Competence, Organizational Readiness and Professional Development status, with the largest gap being in AI Knowledge and Awareness. This supports the argument that structured education and training can significantly enhance knowledge, digital literacy, employment preparedness and professional development amongst the health workforce. Similar results have been presented [20, 21, 23, 35, 36] for the effectiveness of AI training, who found that education improves health workers' confidence and digital competency and acceptance of new health technologies. The Organisation for Economic Co-operation and Development and others [5, 6] have also advocated for ongoing professional development to cultivate an AI ready health work force. In contrast to the other three indicators, AI Readiness for Healthcare Integration did not significantly differ across trained and untrained respondents. This is in contrast to findings in other studies [24-26], whereby AI training did facilitate integration into clinical practice. The inconsistency in results from the current study indicates that AI training cannot be used in isolation to achieve AI integration within health organizations. Instead, readiness depends not only on workforce expertise but a multitude of other factors including leadership, infrastructure, regulations, funding and organisational competencies. Accordingly, in order to translate capacity building into clinical practice, funding, policy and governance should also be provided.

Additional psychometric testing of the study tool enhances the validity of the findings. The Kaiser–Meyer–Olkin statistic of 0.820 and Bartlett's Test of Sphericity p-value of 0.000 confirmed the adequacy of factorability of the dataset, permitting the use of exploratory factor analysis. In addition, the eigenvalues supported the multidimensionality of the questionnaire with all first five factors accounting for large proportions of the observed variance. Two components, Professional Development and AI Readiness showed the greatest degree of structural consistency, while the third component, Artificial Intelligence Knowledge and Awareness was moderately overlapping with the fourth component, Digital Competence and Organizational Readiness. Patients' responses affirmed that knowledge, digital competence and organisational readiness appeared to be conceptually related within the context of the questionnaire, although all three were considered different constructs than AI Readiness. Similar findings have been described for the multidimensionality of healthcare provider AI experience [29, 31, 32], where insufficient organisational infrastructure, digital capability and scope of practice have consistently shown conceptual relationships. However, the extent of overlap observed among these components of AI readiness diminishes the predictive power of any one component and may lead to difficulties distinguishing between concepts [22, 34]. This is unlike the findings of others using confirmatory factor analysis to establish clear empiric separation of individual AI literacy, digital competence and organisational readiness components [16, 34]. The item-specific analysis identified the content concerning internet access and technical support, management commitment and overall AI readiness that loaded at low communalities, indicating that these concepts would benefit from further refinement, but not necessarily deletion from future items. Nonetheless, it remains true that infrastructural and organisational factors show heterogeneity across healthcare institutions and this dimension should remain part of any future appraisals of AI readiness while further psychometric investigation takes place.

## 5. Conclusion and Recommendation

The present study evaluated AI Knowledge and Awareness, Digital Competence, Organizational Readiness, Professional Development and AI Readiness for Healthcare Integration of Bayelsa state-based HIM professionals using quantitative method. Findings revealed that the study participants' individuals collectively attained moderately adequate levels in all the attributes examined except for AI awareness and competence of the respondents and their perceived organizations' digital readiness to effectively assimilate AI innovations and technologies into routine practice. The significant deficit in digital competence among the respondents in addition to the significant proportion of non-previous training in AI and digital health by the respondents might have accounted for the observed moderate organizational preparedness among the participants. Reliability and exploratory factor analysis showed the instrument used to be internally consistent and exhibited suitable level of construct validity.

The relationships found in the bivariate analysis imply that if organizations provide education and training to increase individual levels of AI knowledge and awareness, that efforts would also improve digital competence and organizational readiness. The multivariate regression analysis showed no significant relationships between the predictors and AI readiness for healthcare transformation. This result supports the hypothesis that AI readiness among HIM professionals is a multidimensional phenomenon that also arises from organizational, technological, leadership and policy-based factors that may fall outside the model limits. In addition, study participants who had previously undergone formal AI/digital health training had significant increases in levels of AI knowledge and awareness, digital competence, organizational readiness, and professional development, compared with those who were not trained suggesting the increasing need for a technologically capable workforce. However, those who had previously undergone formal AI training showed no significant differences in the levels of overall AI readiness compared with those who had not acquired formal AI training; again, this demonstrates that individual training alone may be insufficient for AI integration success.

Overall, the results show that while Health Information Management professionals do have an appropriate knowledge base to make use of AI, the level of readiness is still inadequate to support effective and sustainable adoption of AI in the healthcare systems. As such, the pathway to successful AI-enabled healthcare has to take into account an integrated approach that involves ongoing professional development, further enhancement of digital capabilities, increased organization readiness, inclusion of the digital infrastructure, institutional leadership, policies, governance and commitment, a synergy of all these forces will potentially elevate the capabilities of health information management professionals to take part in AI-enabled healthcare, foster health information management practices, support evidence based decision for better healthcare delivery and patient outcomes. Though satisfactory internal consistency reliability and exploratory construct validity was established using Cronbach‘s alpha, KMO test, Bartlett‘s Test and exploratory factor analysis, confirmatory factor analysis and structural equation modeling were not undertaken. Future researches may consider these methods to further assess the measurement model and structural relationships among the constructs.

Based on the findings of this study, the following recommendations are proposed:

1) Healthcare institutions should implement structured and continuous AI capacity-building programmes for Health Information Management professionals to improve AI knowledge, digital competence, and practical application of emerging digital technologies in routine healthcare practice.
2) Health facility management and policymakers should strengthen organizational readiness by investing in reliable digital infrastructure, electronic health information systems, internet connectivity, technical support services, and AI implementation frameworks that facilitate the adoption of AI technologies.
3) Professional regulatory bodies and academic institutions should integrate Artificial Intelligence, digital health, data analytics, and machine learning into Health Information Management curricula and continuing professional development programmes to ensure that graduates and practicing professionals acquire competencies required for contemporary healthcare systems.
4) Healthcare organizations should establish comprehensive AI governance structures, including institutional policies, ethical guidelines, leadership commitment, data governance mechanisms, and implementation strategies that support safe, responsible, and sustainable AI integration into healthcare delivery.
5) Future researchers should investigate additional determinants of AI readiness, including organizational culture, leadership support, digital infrastructure, financial resources, policy implementation, technology acceptance, and innovation climate, using larger and more diverse samples. Future studies may also employ confirmatory factor analysis (CFA) and structural equation modeling (SEM) to further validate the measurement model and examine the complex relationships among the study constructs.

## Abbreviations

| | |
|---|---|
| AHRIMPN | Association of Health Records and Information Management Practitioners of Nigeria |
| AI | Artificial Intelligence |
| HIM | Health Information Management |
| SPSS | Statistical Package for Social Science |
| EFA | Exploratory Factor Analysis |
| SEM | Structural Equation Modeling |
| CPD | Continuous Professional Development |
| KMO | Kaiser–Meyer–Olkin |
| HIA | Health Information Administration |

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## Author Contributions

**Kurokeyi Ebimene Japheth Teddy:** Conceptualization, Formal Analysis, Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing

**Victor Ayebanengimote:** Formal Analysis, Investigation, Methodology, Resources, Visualization, Writing – review & editing

## Data Availability Statement

The data used in this study is available from the corresponding author upon reasonable request. Also, the data supporting the outcome of this research work has been reported in this manuscript.

## Conflicts of Interest

The authors declare no conflicts of interest.

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