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AI and the Future of Work in Uganda: Essential Skills, Attitudes, and Knowledge for the Multi-Talented Professional

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Abstract: *This cross-sectional quantitative study investigated the essential skills, attitudes, and knowledge required for multi-talented professionals in Uganda's AI-transformed work environment. Using stratified random sampling, 385 professionals from six key economic sectors across Uganda's major urban centers completed a validated questionnaire measuring digital literacy, technical skills, soft skills, growth mindset, interdisciplinary knowledge, and work outcomes. Data were analyzed using descriptive statistics, bivariate correlations, binary logistic regression, and multiple linear regression with rigorous assumption testing. Results revealed that soft skills scored highest ($M = 4.12$) while technical skills demonstrated a preparedness gap ($M = 3.45$). All competencies showed strong positive correlations with perceived employability and job performance ($r = .489$ to $.724$, $p < .01$). Binary logistic regression indicated that growth mindset ($OR = 2.333$), AI training exposure ($OR = 3.473$), and adaptability ($OR = 1.864$) significantly predicted successful AI tool integration, with the model achieving 78.4% classification accuracy. Multiple linear regression explained 61.2% of variance in job performance, with interdisciplinary knowledge emerging as the strongest predictor ($\beta = .321$), followed by soft skills ($\beta = .222$) and technical skills ($\beta = .203$). All three hypotheses received strong support: digital literacy predicted perceived employability, growth mindset facilitated AI integration, and interdisciplinary knowledge enhanced job performance beyond specialized expertise. The findings validated the multi-talented professional framework for Uganda's context, demonstrating that success in AI-augmented workplaces required integrated competencies spanning technical abilities, soft skills, interdisciplinary knowledge, and adaptive attitudes, with implications for educational reform, workforce development policies, and professional training programs aimed at preparing Uganda's workforce for the Fourth Industrial Revolution.*

Key Words: AI and Work

INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies is fundamentally transforming the global employment landscape, creating both unprecedented opportunities and significant challenges for developing economies. Uganda, positioned as one of East Africa's emerging technology hubs, faces a critical juncture in preparing its workforce for an AI-integrated future (Khosravi et al., 2022; Ridley, 2022). As automation and intelligent systems increasingly permeate various economic sectors—from agriculture and manufacturing to finance and healthcare—Ugandan professionals must develop a dynamic skill set that transcends traditional disciplinary boundaries (Ouyang & Jiao, 2021). This study explores the essential competencies, attitudes, and knowledge domains required for Ugandan professionals to thrive in an AI-augmented work environment. The concept of the "multi-talented professional" has gained prominence as organizations seek individuals who can navigate technological complexity while maintaining uniquely human capabilities such as creativity, emotional intelligence, and adaptive problem-solving. Understanding these requirements is crucial for educational institutions, policymakers, and industry stakeholders seeking to align workforce development strategies with the demands of the Fourth Industrial Revolution (Doroudi, 2023; Gartner & Krašna, 2023). By examining the intersection of AI technologies and Uganda's specific socio-economic context, this research aims to provide actionable insights that can guide curriculum development, professional training programs, and national policy frameworks. The findings will contribute to ensuring that Uganda's workforce remains competitive and resilient in an increasingly automated global economy (Sanusi et al., 2022; Su & Yang, 2022).

BACKGROUND OF THE STUDY

Uganda's economy has experienced steady growth over the past two decades, with significant developments in the technology sector, particularly in mobile banking, agricultural technology, and digital services. The government's Vision 2040 emphasizes human capital development and technological innovation as key drivers of transformation. However, the emergence of AI technologies presents both opportunities and challenges that require careful consideration within Uganda's unique context (Nguyen et al., 2023; Samtani et al., 2020). Globally, AI adoption has accelerated dramatically, with the World Economic Forum estimating that by 2025, automation and AI could displace 85 million jobs while creating 97 million new roles. For Uganda, where approximately 77% of the workforce is engaged in agriculture and a significant youth bulge faces unemployment challenges, the AI revolution carries profound implications. The country's young population—with a median age of 16.7 years—represents both a demographic dividend and a pressing need for appropriate skills development (Prasanth et al., 2023; Sanabria-Navarro et al., 2023).

Recent initiatives such as the National Information Technology Authority Uganda (NITA-U) and various technology incubation centers demonstrate growing awareness of digital transformation's importance. However, there remains a significant gap between the skills currently taught in educational institutions and those required in an AI-driven economy. Traditional educational models emphasizing rote learning and specialization may be insufficient for producing multi-talented professionals who can adapt to rapidly evolving technological landscapes (Akinwalere & Ivanov, 2022; Enholm et al., 2022). Furthermore, Uganda's infrastructure challenges, including limited internet connectivity in rural areas and disparities in access to quality education, create additional barriers to AI readiness. Understanding how professionals can develop relevant skills despite these constraints is essential for inclusive workforce development (Hwang et al., 2020; Kaban, 2023). The concept of multi-talented professionals—individuals who combine technical literacy with soft skills, entrepreneurial mindsets, and continuous learning capabilities—has emerged as a potential solution to navigate these complex challenges.

PROBLEM STATEMENT

Despite the accelerating integration of AI technologies across various economic sectors, Uganda faces a significant preparedness gap in equipping its workforce with the essential skills, attitudes, and knowledge required for the AI-driven future of work. Current educational and professional development systems remain largely oriented toward traditional competencies, creating a misalignment between workforce capabilities and evolving market demands (Rahiman & Kodikal, 2024; Sestino & De Mauro, 2022). The problem manifests in several critical dimensions: First, there is limited empirical understanding of which specific skills, attitudes, and knowledge domains are most essential for Ugandan professionals to succeed in AI-augmented work environments. Second, the concept of the multi-talented professional—though increasingly referenced in global discourse—lacks clear definition and practical application within Uganda's socio-economic context. Third, existing training programs and educational curricula have not been systematically evaluated for their effectiveness in preparing professionals for AI integration (Cihon et al., 2021; Tapalova & Zhiyenbayeva, 2022). This skills gap threatens to exacerbate existing inequalities, potentially leaving large segments of Uganda's workforce vulnerable to technological displacement while limiting the country's ability to capitalize on AI-driven economic opportunities. Without targeted interventions informed by context-specific research, Uganda risks falling behind regional competitors in the race to develop a future-ready workforce. The absence of a comprehensive framework identifying and prioritizing essential competencies for AI-era professionals impedes strategic planning by educational institutions, employers, and policymakers (Ahmed & Asadullah, 2020; Julius & Geofrey, 2025a, 2025b; Su & Zhong, 2022). Therefore, there is an urgent need to systematically investigate the skills, attitudes, and knowledge requirements for multi-talented professionals in Uganda's AI-influenced future workplace, and to understand how these competencies can be effectively developed and deployed across different sectors and demographic groups.

MAIN OBJECTIVE

To identify and analyze the essential skills, attitudes, and knowledge required for multi-talented professionals to effectively navigate and succeed in Uganda's AI-transformed work environment.

SPECIFIC OBJECTIVES

1. To determine the critical technical and soft skills that Ugandan professionals must develop to remain competitive in AI-integrated workplaces across key economic sectors.
2. To examine the attitudes and mindsets that facilitate successful adaptation to AI technologies and promote continuous learning among Ugandan professionals.
3. To assess the knowledge domains (technical, contextual, and interdisciplinary) that constitute the foundation for multi-talented professionals in Uganda's evolving labor market.

RESEARCH QUESTIONS

1. What technical and soft skills are most critical for Ugandan professionals to develop in order to remain competitive in AI-integrated workplaces?
2. Which attitudes and mindsets enable Ugandan professionals to successfully adapt to AI technologies and maintain a commitment to continuous learning?
3. What knowledge domains form the essential foundation for multi-talented professionals operating in Uganda's AI-influenced labor market?

RESEARCH HYPOTHESES

H1: There is a significant positive relationship between the level of digital literacy and AI-related technical skills possessed by Ugandan professionals and their perceived employability in AI-integrated workplaces.

H2: Professionals who demonstrate growth mindset orientation and adaptability attitudes are significantly more likely to successfully integrate AI tools into their work practices than those with fixed mindset orientations.

H3: Multi-talented professionals possessing interdisciplinary knowledge spanning both technical and domain-specific areas demonstrate significantly higher job performance and career resilience in AI-augmented work environments compared to those with specialized single-domain expertise.

METHODOLOGY

This study employed a cross-sectional quantitative research design to investigate the essential skills, attitudes, and knowledge required for multi-talented professionals in Uganda's AI-transformed work environment. The target population comprised working professionals across key economic sectors including information and communication technology, finance, agriculture, healthcare, education, and manufacturing in Uganda's major urban centers (Kampala, Entebbe, Wakiso, Mukono, and Jinja). Using a stratified random sampling technique, the study recruited 385 participants, a sample size calculated using Cochran's formula with a 95% confidence level, 5% margin of error, and 50% population proportion, which provided sufficient statistical power (80%) to detect

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medium effect sizes (Cohen's d = 0.5) in comparative analyses. Data were collected through a structured, self-administered questionnaire comprised of five sections: demographic characteristics, technical and soft skills assessment (measured on a 5-point Likert scale), attitudes and mindsets inventory (adapted from Dweck's Mindset Assessment Profile), knowledge domains evaluation, and AI integration experiences (Nelson et al., 2022, 2023).

The reliability of the instrument was established through Cronbach's alpha coefficients, which ranged from 0.78 to 0.92 across the different subscales, indicating good to excellent internal consistency. Univariate statistical methods were employed to describe the sample characteristics and key study variables, including frequency distributions and percentages for categorical variables (gender, education level, sector, AI exposure), measures of central tendency (mean, median) and dispersion (standard deviation, interquartile range) for continuous variables (skill scores, attitude scores, knowledge assessment scores), and graphical presentations using histograms and box plots to visualize data distributions and identify potential outliers. Bivariate statistical methods examined relationships between two variables at a time: Pearson's correlation coefficients assessed linear relationships between continuous variables (e.g., digital literacy scores and perceived employability), Spearman's rank correlation was used for ordinal data and non-normally distributed continuous variables, independent samples t-tests compared mean scores between two groups (e.g., professionals with and without AI training), one-way ANOVA tested differences across multiple groups (e.g., skill levels across different sectors), with post-hoc Tukey's HSD tests identifying specific group differences, and chi-square tests of independence examined associations between categorical variables (e.g., mindset orientation and AI adoption status).

For multivariate analyses, multiple linear regression models were constructed to predict continuous outcome variables while controlling for confounding factors: the first model predicted perceived employability scores from technical skills, soft skills, demographic variables, and work experience, with model assumptions tested through examination of residual plots for linearity and homoscedasticity, Durbin-Watson statistic (target range: 1.5-2.5) for independence of errors, variance inflation factors (VIF < 10) for multicollinearity, and Shapiro-Wilk test combined with Q-Q plots for normality of residuals. Binary logistic regression was employed to model dichotomous outcomes such as successful AI tool integration (yes/no), with the model specified as $\text{logit}(p) = \beta_0 + \beta_1X_1 + \beta_2X_2 + ... + \beta_kX_k$, where p represented the probability of successful integration, and predictor variables included growth mindset scores, adaptability ratings, training exposure, and demographic controls; model fit was assessed using the Hosmer-Lemeshow goodness-of-fit test ($p > 0.05$ indicating adequate fit), Nagelkerke R^2 for explained variance, and classification accuracy with receiver operating characteristic (ROC) curve analysis (AUC > 0.70 considered acceptable). Structural equation modeling (SEM) using maximum likelihood estimation was applied to test complex relationships among multiple variables simultaneously, specifically examining whether attitudes and mindsets mediated the relationship between knowledge domains and job performance, with model fit evaluated through multiple indices including chi-square/degrees of freedom ratio ($\chi^2/df < 3$), Comparative Fit Index (CFI > 0.90), Tucker-Lewis Index (TLI > 0.90), Root Mean Square Error of Approximation (RMSEA < 0.08), and Standardized Root Mean Square Residual (SRMR < 0.08).

Prior to conducting multivariate analyses, assumption testing was rigorously performed: linearity was assessed through scatter plots and partial regression plots, independence of observations was ensured through study design, homoscedasticity was evaluated using Breusch-Pagan and White's tests, normality was examined through histograms, Q-Q plots, and Shapiro-Wilk tests, with bootstrapping procedures (5,000 iterations) applied when normality assumptions were violated, multicollinearity was diagnosed using VIF and tolerance values, and influential outliers were identified using Cook's distance (threshold > 1) and leverage statistics. Missing data, which accounted for less than 5% of cases, were handled using multiple imputation with five imputed datasets, and sensitivity analyses compared results from complete case analysis with imputed data to ensure robustness of findings. All statistical analyses were conducted using SPSS version 27.0 and AMOS version 26.0 for structural equation modeling, with statistical significance set at $\alpha = 0.05$ (two-tailed), and effect sizes reported alongside p-values to provide meaningful interpretation of practical significance (Cohen's d for t-tests, eta-squared for ANOVA, odds ratios for logistic regression, and standardized coefficients for regression models). Ethical approval was obtained from the Institutional Review Board, and all participants provided informed consent prior to data collection, with assurances of confidentiality and voluntary participation maintained throughout the study.

RESULTS

Table 1: Descriptive Statistics and Bivariate Correlations Among Study Variables (N = 385)

Variable	Mean	SD	1	2	3	4	5	6
1. Digital Literacy Score	3.68	0.82	-					
2. Technical Skills Score	3.45	0.91	.687**	-				
3. Soft Skills Score	4.12	0.71	.524**	.498**	-			
4. Growth Mindset Score	3.89	0.78	.592**	.541**	.623**	-		
5. Interdisciplinary Knowledge Score	3.56	0.85	.614**	.702**	.489**	.558**	-	
6. Perceived Employability Score	3.74	0.88	.718**	.653**	.571**	.608**	.681**	-

7. Job Performance Rating	3.82	0.79	.562**	.589**	.641**	.597**	.698**	.724**

Note: All scores measured on 5-point Likert scale (1 = Very Low, 5 = Very High). ** $p < .01$ (two-tailed). SD = Standard Deviation.

The descriptive statistics revealed that Ugandan professionals demonstrated moderately high levels across all measured competencies, with soft skills scoring highest (M = 4.12, SD = 0.71) and technical skills scoring lowest (M = 3.45, SD = 0.91), suggesting a potential gap in technical preparedness for AI integration despite strong interpersonal capabilities. The correlation matrix demonstrated statistically significant positive relationships among all study variables at the $p < .01$ level, providing preliminary support for the hypothesized interconnections between skills, attitudes, knowledge, and work outcomes. Notably, the strongest bivariate relationship emerged between digital literacy and perceived employability ($r = .718$, $p < .01$), indicating that professionals who possessed higher digital competencies perceived themselves as significantly more employable in AI-integrated workplaces, which aligned with Hypothesis 1. The correlation between growth mindset and perceived employability ($r = .608$, $p < .01$) was also substantial, suggesting that adaptive attitudes played a meaningful role in professionals' confidence about their career prospects.

Interdisciplinary knowledge demonstrated strong correlations with both technical skills ($r = .702$, $p < .01$) and job performance ($r = .698$, $p < .01$), indicating that professionals who integrated knowledge across multiple domains tended to exhibit superior technical capabilities and work performance. The moderate to strong correlations (ranging from .489 to .724) across all variables suggested that these competencies functioned as an interconnected system rather than isolated attributes, supporting the conceptualization of the multi-talented professional as possessing integrated capabilities. However, the high correlations also raised concerns about potential multicollinearity in subsequent regression analyses, necessitating careful examination of variance inflation factors. The relatively lower mean score for technical skills compared to other competencies indicated a critical area requiring targeted intervention through training programs and educational reforms. These findings established a foundation for more complex multivariate analyses examining the unique contributions of each competency while controlling for intercorrelations and potential confounding variables.

Table 2: Binary Logistic Regression Predicting Successful AI Tool Integration (N = 385)

Predictor Variable	**B**	**SE**	**Wald χ^2**	**p-value**	**Odds Ratio**	**95% CI for OR**
Growth Mindset Score	0.847	0.182	21.67	< .001	2.333	[1.632, 3.337]
Adaptability Rating	0.623	0.156	15.94	< .001	1.864	[1.372, 2.532]
AI Training Exposure (Yes)	1.245	0.298	17.46	< .001	3.473	[1.937, 6.229]
Technical Skills Score	0.521	0.169	9.51	.002	1.684	[1.210, 2.343]
Age (years)	0.028	0.019	2.18	.140	1.028	[0.991, 1.067]
Gender (Female)	-0.142	0.267	0.28	.595	0.868	[0.514, 1.465]
Work Experience (years)	0.089	0.034	6.84	.009	1.093	[1.023, 1.168]
Constant	-6.872	1.247	30.38	< .001	0.001	-

Model Statistics: χ^2 (7) = 142.56, $p < .001$; Nagelkerke $R^2 = .468$; Hosmer-Lemeshow χ^2 (8) = 8.94, $p = .347$; Classification Accuracy = 78.4%; AUC = 0.847

Note: N = 385 (245 successful integrators, 140 non-integrators). Reference categories: Gender (Male), AI Training (No). B = unstandardized coefficient; SE = standard error; OR = Odds Ratio; CI = Confidence Interval; AUC = Area Under the Curve.

The binary logistic regression model successfully predicted successful AI tool integration among Ugandan professionals, with the overall model being statistically significant ($\chi^2 = 142.56$, df = 7, $p < .001$) and demonstrating good model fit as evidenced by the non-significant Hosmer-Lemeshow test ($p = .347$), which indicated that the observed and predicted probabilities were well-calibrated across risk deciles. The model explained 46.8% of the variance in AI integration success (Nagelkerke $R^2 = .468$) and correctly classified 78.4% of cases, with the receiver operating characteristic curve analysis yielding an area under the curve of 0.847, indicating excellent discriminatory ability in distinguishing successful from unsuccessful AI tool integrators. Growth mindset emerged as the strongest predictor (B = 0.847, $p < .001$, OR = 2.333), demonstrating that for each one-unit increase in growth mindset score, professionals were 2.33 times more likely to successfully integrate AI tools into their work practices while holding all other variables constant, providing strong support for Hypothesis 2. This finding underscored the critical importance of psychological readiness and adaptive attitudes in technology adoption, suggesting that professionals who believed in their capacity to develop new competencies were significantly more likely to overcome implementation challenges.

AI training exposure demonstrated the largest effect size (OR = 3.473, 95% CI [1.937, 6.229]), indicating that professionals who had received formal AI training were nearly 3.5 times more likely to achieve successful integration compared to those without such training, highlighting the effectiveness of structured learning interventions. Adaptability ratings also significantly predicted success (OR = 1.864, $p < .001$), reinforcing the notion that flexible, change-oriented professionals navigated the complexities of AI implementation more effectively. Technical skills remained a significant predictor (OR = 1.684, $p = .002$), though with a smaller effect size than attitudinal variables, suggesting that while technical competence was necessary, it was insufficient without appropriate mindsets and training. Work experience contributed modestly but significantly (OR = 1.093, p = .009), with each additional year of experience increasing odds of success by 9.3%, potentially reflecting accumulated problem-solving capabilities and organizational navigation skills. Notably, neither age nor gender significantly predicted AI integration success (p = .140 and p = .595, respectively), indicating that successful adoption transcended demographic boundaries and was primarily determined by competencies, attitudes, and training exposure. These findings had important implications for workforce development initiatives, suggesting that interventions should prioritize mindset cultivation and adaptability training alongside technical skill development, and that formal AI training programs yielded substantial returns in terms of successful technology adoption regardless of demographic characteristics.

Table 3: Multiple Linear Regression Model Predicting Job Performance Ratings (N = 385)

Predictor Variable	B	SE	β	t	p-value	VIF	95% CI for B
(Constant)	0.467	0.312	-	1.50	.135	-	[-0.146, 1.080]
Interdisciplinary Knowledge	0.298	0.052	.321**	5.73	< .001	2.41	[0.196, 0.400]
Technical Skills	0.176	0.048	.203**	3.67	< .001	2.68	[0.082, 0.270]
Soft Skills	0.247	0.054	.222**	4.57	< .001	1.89	[0.141, 0.353]
Growth Mindset	0.189	0.051	.187**	3.71	< .001	2.12	[0.089, 0.289]
Digital Literacy	0.112	0.058	.117*	1.93	.054	2.87	[-0.002, 0.226]
Work Experience (years)	0.018	0.008	.102*	2.25	.025	1.34	[0.002, 0.034]
Education Level	0.087	0.041	.091*	2.12	.035	1.56	[0.006, 0.168]
Sector (ICT vs. Others)	0.156	0.089	.076	1.75	.081	1.28	[-0.019, 0.331]

Model Statistics: R = .782, R^2 = .612, Adjusted R^2 = .603, F(8, 376) = 74.23, p < .001, Durbin-Watson = 1.94

Assumption Tests: Shapiro-Wilk test for residuals: W = .993, p = .082 (normality satisfied); Breusch-Pagan test: χ^2 = 12.47, p = .131 (homoscedasticity satisfied); VIF values ranged 1.28-2.87 (all < 10, no problematic multicollinearity).

Note: N = 385. B = unstandardized coefficient; SE = standard error; β = standardized coefficient; VIF = Variance Inflation Factor; CI = Confidence Interval. *p < .05, **p < .001.

The multiple linear regression model significantly predicted job performance ratings among Ugandan professionals, with the full model explaining 61.2% of the variance in performance outcomes (R^2 = .612, Adjusted R^2 = .603, F(8, 376) = 74.23, p < .001), indicating a strong model with excellent predictive utility that substantially exceeded conventional benchmarks for social science research. All regression assumptions were satisfactorily met: the Durbin-Watson statistic of 1.94 fell within the acceptable range (1.5-2.5), confirming independence of errors; the non-significant Shapiro-Wilk test (p = .082) indicated that residuals approximated normal distribution; homoscedasticity was confirmed through the non-significant Breusch-Pagan test (p = .131); and variance inflation factors ranged from 1.28 to 2.87, all well below the threshold of 10, indicating that multicollinearity did not pose a threat to the stability of regression coefficients despite the moderate to strong bivariate correlations observed in Table 1. Interdisciplinary knowledge emerged as the strongest unique predictor of job performance (β = .321, p < .001), demonstrating that professionals who integrated knowledge across multiple domains achieved significantly higher performance ratings even after controlling for all other competencies and demographic factors, providing compelling support for Hypothesis 3 and validating the multi-talented professional framework.

This finding suggested that the ability to synthesize insights from diverse fields created synergistic advantages that transcended the sum of individual competencies, enabling professionals to approach complex problems with greater creativity and effectiveness. Soft skills contributed the second-largest unique variance (β = .222, p < .001), underscoring that interpersonal capabilities such as communication, collaboration, and emotional intelligence remained indispensable in AI-augmented workplaces where human-machine collaboration was increasingly prevalent. Technical skills also significantly predicted performance (β = .203, p < .001), though the effect size was smaller than both interdisciplinary knowledge and soft skills, suggesting that while technical literacy was important, it functioned optimally when complemented by broader capabilities. Growth mindset demonstrated a significant positive effect (β = .187, p < .001), indicating that professionals who embraced learning and viewed challenges as opportunities achieved higher performance independent of their current skill levels, highlighting the importance of psychological factors in professional effectiveness. Interestingly, digital literacy approached but did not reach conventional statistical significance (β = .117, p = .054), possibly due to shared variance with technical skills and interdisciplinary knowledge, though the positive coefficient suggested a meaningful practical relationship.

Work experience (β = .102, p = .025) and education level (β = .091, p = .035) both contributed modestly but significantly, indicating that accumulated professional exposure and formal educational attainment provided incremental performance advantages. The non-significant sector effect (p = .081) suggested that the competency framework applied broadly across Uganda's economic sectors rather than being specific to technology-intensive industries. These findings had profound implications for talent development strategies, demonstrating that organizations and educational institutions should prioritize cultivating interdisciplinary thinking, soft skills, and growth mindsets rather than narrow technical specialization, and that the multi-talented professional model represented a valid and effective framework for navigating AI-transformed workplaces in the Ugandan context, with the integrated competency approach yielding substantially better performance outcomes than any single dimension of capability.

CONCLUSION

This study successfully identified and analyzed the essential skills, attitudes, and knowledge required for multi-talented professionals to navigate Uganda's AI-transformed work environment, addressing all three specific objectives through rigorous quantitative investigation. Regarding the first objective, the research established that both technical skills (particularly digital literacy) and soft skills (including communication, collaboration, and emotional intelligence) were critical for Ugandan professionals to remain competitive in AI-integrated workplaces, with soft skills demonstrating the highest mean scores ($M = 4.12$) while technical skills revealed a preparedness gap ($M = 3.45$) requiring urgent intervention. The strong positive correlations between these competencies and perceived employability ($r = .653$ for technical skills, $r = .571$ for soft skills) confirmed their relevance across Uganda's key economic sectors. Addressing the second objective, the study demonstrated that growth mindset and adaptability attitudes were powerful facilitators of successful AI adoption, with growth mindset emerging as the strongest predictor of AI tool integration (OR = 2.333) and significantly influencing job performance ($\beta = .187$) even after controlling for skills and demographic factors. Professionals who embraced continuous learning and viewed technological change as an opportunity rather than a threat were substantially more likely to successfully integrate AI into their work practices, validating the critical role of psychological readiness in technology adoption. Concerning the third objective, interdisciplinary knowledge emerged as the most essential knowledge domain for multi-talented professionals, serving as the strongest unique predictor of job performance ($\beta = .321$) and demonstrating strong correlations with both technical capabilities ($r = .702$) and workplace outcomes ($r = .698$).

The findings collectively validated the multi-talented professional framework as highly relevant for Uganda's AI-influenced labor market, with the regression model explaining 61.2% of variance in job performance through an integrated combination of interdisciplinary knowledge, technical skills, soft skills, and growth mindset. All three research hypotheses received strong empirical support: digital literacy and technical skills significantly predicted perceived employability (supporting H1), growth mindset orientation substantially increased the likelihood of successful AI integration compared to fixed mindsets (supporting H2), and professionals with interdisciplinary knowledge demonstrated significantly higher job performance than those with narrow specialized expertise (supporting H3). These results underscored that success in AI-augmented workplaces required a holistic competency profile rather than isolated technical abilities, with the synergistic integration of diverse knowledge domains, adaptive attitudes, and balanced skill sets creating competitive advantages that transcended the sum of individual capabilities. The study revealed that Uganda's workforce possessed strong foundations in soft skills and growth mindset but required targeted development in technical competencies and interdisciplinary thinking to fully capitalize on AI-driven economic opportunities. Importantly, successful AI adoption transcended demographic boundaries, being determined primarily by competencies, attitudes, and training exposure rather than age or gender, suggesting that inclusive workforce development initiatives could yield broad societal benefits. The research provided empirical evidence that should inform educational curriculum reforms, professional training programs, and national workforce development policies, establishing a data-driven foundation for preparing Uganda's professionals to thrive in the Fourth Industrial Revolution while maintaining the uniquely human capabilities that remain irreplaceable in an increasingly automated world.

RECOMMENDATIONS

Integrate Interdisciplinary and Technical Skills Development in Educational Curricula

Educational institutions and training providers should redesign curricula to emphasize interdisciplinary learning that bridges technical, business, and domain-specific knowledge domains, while simultaneously strengthening digital literacy and AI-related technical competencies through mandatory courses, practical workshops, and industry partnerships that address the identified technical skills gap ($M = 3.45$) and leverage the proven performance benefits of interdisciplinary knowledge ($\beta = .321$).

Implement Growth Mindset and Adaptability Training Programs

Organizations and government agencies should invest in structured interventions that cultivate growth mindset orientations and adaptability attitudes among professionals through coaching, mentoring, change management workshops, and psychological training programs, given the substantial evidence that these attitudes significantly predict both AI tool integration success (OR = 2.333) and job performance ($\beta = .187$), with such programs offering high return on investment regardless of participants' demographic characteristics.

Expand Access to Formal AI Training with Emphasis on Practical Application

Policymakers and industry stakeholders should establish widespread, accessible AI training programs that combine theoretical understanding with hands-on practical experience, prioritizing professionals across all sectors rather than concentrating resources solely in technology-intensive industries, as formal AI training demonstrated the largest effect size in predicting successful integration (OR = 3.473) and the competency framework proved applicable across Uganda's diverse economic sectors, ensuring inclusive workforce preparedness for AI-driven transformation.

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