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# Beyond Automation: A Framework for Strategic AI Augmentation in Professional Work

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***Abstract:*** *The proliferation of artificial intelligence (AI) technologies in the contemporary workplace has engendered a paradigm shift from automation-centric narratives toward more nuanced frameworks of human-AI collaboration. This study examined the strategic augmentation of AI in professional work by investigating the determinants and outcomes of AI augmentation across six industry sectors in Uganda, drawing on a cross-sectional survey of 384 professional workers. Guided by a conceptual framework anchored in Technology Acceptance Model (TAM), Resource-Based View (RBV), and Cognitive Load Theory (CLT), the study sought to assess AI literacy levels, identify organizational and individual factors influencing AI augmentation adoption, and evaluate the relationship between AI augmentation and work productivity. A structured questionnaire was administered to a stratified random sample of professionals across healthcare, finance, legal, education, technology, and manufacturing sectors. Data were analysed using univariate descriptive statistics, bivariate Pearson correlation analysis, and Structural Equation Modelling (SEM) with AMOS 26. Descriptive findings revealed moderate-to-high AI literacy levels ($M = 3.87, SD = 0.74$) and AI augmentation indices ($M = 3.72, SD = 0.81$) across sectors, with the technology sector recording the highest mean augmentation score ($M = 4.38$). Bivariate correlation analysis established strong and statistically significant associations between AI literacy, technology acceptance, and work productivity ($r = 0.612, p < .001$ and $r = 0.703, p < .001$ respectively). SEM path analysis confirmed that AI literacy ($\beta = 0.487, p < .001$), technology acceptance ($\beta = 0.425, p < .001$), and organizational readiness ($\beta = 0.312, p < .001$) were significant predictors of AI augmentation, which in turn exerted the strongest direct effect on work productivity ($\beta = 0.581, p < .001$). Model fit indices confirmed excellent structural validity ($CFI = 0.947$; $RMSEA = 0.048$; $SRMR = 0.054$). These findings affirm the imperative for organisations to invest in AI literacy programmes, cultivate readiness cultures, and design human-centred AI integration strategies that transcend automation toward genuine professional augmentation.*

**Keywords: AI Augmentation, AI Literacy, Professional Work, Technology Acceptance, Structural Equation Modelling, Organizational Readiness, Work Productivity**

## Introduction

The rapid integration of artificial intelligence into professional environments has fundamentally altered the landscape of work, spawning intense scholarly and practitioner discourse on the nature, extent, and consequences of AI-driven transformation (Khosravi et al., 2022; Ridley, 2022). Whereas early framings of this transformation were largely dominated by automation discourse, which foregrounded the substitution of human labour with algorithmic and robotic systems, a more sophisticated conceptualisation has emerged in recent years that positions AI not merely as a replacement mechanism but as a strategic augmentation tool capable of enhancing, extending, and amplifying human professional capabilities (Levin et al., 2022; Ouyang & Jiao, 2021). This reconceptualisation, often described as the augmentation paradigm, holds that the most consequential applications of AI in work settings are those that collaborate with human cognition, creativity, and judgment rather than supplanting them. In professional domains characterised by complexity, contextual sensitivity, and ethical nuance, such as healthcare, law, finance, and education, the notion of intelligent augmentation is particularly salient, as these fields demand cognitive flexibility and moral reasoning that current AI systems cannot independently replicate (Doroudi, 2023; Gartner & Krašna, 2023). Despite the compelling theoretical promise of strategic AI augmentation, empirical evidence documenting its determinants, mechanisms, and outcomes in professional work remains fragmented, especially in emerging economies where infrastructure constraints, digital divides, and institutional barriers shape the adoption trajectory in ways markedly different from advanced economies (Samtani et al., 2020; Sanusi et al., 2022; Su & Yang, 2022). The current study therefore sought to fill this gap by developing and empirically testing a comprehensive framework for strategic AI augmentation in professional work, drawing on a multi-sector survey conducted in Uganda. Through rigorous quantitative analysis encompassing descriptive, correlational, and structural equation modelling approaches, the study aimed to generate actionable insights for organisations, policymakers, and professionals seeking to harness the transformative potential of AI augmentation while preserving the irreplaceable value of human professional expertise.

## Background of the Study

The global discourse on artificial intelligence in professional work has evolved considerably since the seminal contributions of Simon (1965) and subsequent advances in machine learning, natural language processing, and robotics that accelerated throughout the early twenty-first century. While foundational debates were preoccupied with whether AI would replace human workers, particularly in routine cognitive and manual tasks, the contemporary academic and policy conversation has grown increasingly attentive to how AI can augment rather than automate professional roles (Huang et al., 2021; Nguyen et al., 2023; Sanabria-Navarro et al., 2023). Scholars such as Brynjolfsson and McAfee (2014), Daugherty and Wilson (2018), and Raisch and Krakowski (2021) have each contributed important theoretical touchstones to this reorientation, variously arguing that human-machine complementarity, rather than competition, represents the most productive framing of the AI-work relationship. In the African context, and Uganda in particular, AI adoption in professional settings remains at a nascent stage, shaped by heterogeneous dynamics including limited digital infrastructure, uneven AI literacy, variable institutional readiness, and a predominantly service-oriented economy undergoing rapid digital transition (Akinwalere & Ivanov, 2022; Díaz Arce, 2023; Enholm et al., 2022; Prasanth et al., 2023). Studies conducted across sub-Saharan Africa have consistently identified low levels of AI awareness and readiness as critical bottlenecks, even as mobile technology penetration and fintech innovations have demonstrated the latent capacity of the region to leapfrog conventional technology adoption cycles. Against this backdrop, understanding how professional workers in diverse sectors perceive, adopt, and leverage AI as an augmentation tool is of profound theoretical and practical importance (Hwang et al., 2020; Kaban, 2023; Rahiman & Kodikal, 2024; Sestino & De Mauro, 2022). The Technology Acceptance Model (TAM), originally formulated by Davis (1989), has remained the most widely deployed framework for studying individual technology adoption behavior, emphasising perceived usefulness and ease of use as principal determinants of acceptance; however, scholars have increasingly called for its extension to incorporate organisational-level variables and the specific characteristics of AI as a dynamic, learning technology. The Resource-Based View (RBV) offers a complementary perspective by framing AI capabilities as strategic organisational assets whose value depends on the capacity of human actors to leverage them effectively, while Cognitive Load Theory (CLT) provides insight into the conditions under which AI augmentation reduces rather than amplifies the cognitive burden placed on professional workers (Cihon et al., 2021; Jennifer, 2024; Kohnke et al., 2023; Tapalova & Zhiyenbayeva, 2022). Together, these theoretical lenses provided the conceptual scaffolding for the present study, enabling a multi-level, multi-dimensional examination of AI augmentation that situates individual behavior within organisational and sectoral contexts.

## Problem Statement

Despite growing global recognition of artificial intelligence as a transformative force in professional work, organisations, policymakers, and professionals in emerging economies, including Uganda, continue to grapple with a fundamental knowledge gap: the absence of an empirically validated, context-sensitive framework that can guide the strategic integration of AI as an augmentation tool rather than a mere automation mechanism (Ahmed & Asadullah, 2020; Crompton & Burke, 2023; Ruiz-Real et al., 2021). Existing research has disproportionately focused on AI adoption in high-income, technology-rich environments, leaving practitioners in resource-constrained settings without robust evidence-based guidance (Farrelly & Baker, 2023; Julius & Geofrey, 2025; Partel et al., 2021; Reyhani Haghighi et al., 2023). Furthermore, the empirical literature has largely treated AI adoption as a binary or unidimensional construct, failing to capture the complexity of augmentation as a multi-faceted interaction between individual AI literacy, organisational readiness, task complexity, and technology acceptance (Iffath Unnisa Begum, 2024; Julius & Nancy, 2025; Ofosu-Asare, 2025; Praful Bharadiya, 2023). The practical consequences of this gap are significant: organisations risk misallocating investments in AI tools that neither align with professional capacities nor generate the productivity gains anticipated, while workers may experience displacement anxiety, skill obsolescence, or cognitive overload in the absence of intentional augmentation strategies. The present study therefore addressed the critical problem of how strategic AI augmentation can be conceptualised, measured, and maximised in professional work contexts, and what organisational and individual factors determine its adoption and effectiveness.

## Objectives of the Study

### Main Objective

The main objective of this study was to develop and empirically validate a framework for strategic AI augmentation in professional work across selected industry sectors in Uganda.

### Specific Objectives

1. To assess the levels of AI literacy and AI augmentation among professional workers across six industry sectors in Uganda.
2. To determine the individual and organisational factors that significantly influence the adoption of AI augmentation in professional work.
3. To evaluate the effect of strategic AI augmentation on work productivity among professional workers.

## Research Questions

1. What are the prevailing levels of AI literacy and strategic AI augmentation among professional workers across the healthcare, finance, legal, education, technology, and manufacturing sectors in Uganda?

2. What individual-level factors (AI literacy, technology acceptance, years of experience) and organisational-level factors (organisational readiness, job task complexity) significantly predict the adoption of AI augmentation in professional work?
3. To what extent does strategic AI augmentation mediate the relationship between AI literacy and work productivity among professional workers in Uganda?

## Methodology

This study adopted a quantitative cross-sectional research design, which was deemed appropriate for capturing the simultaneous variation in AI augmentation-related constructs across multiple industry sectors at a single point in time. A structured, self-administered questionnaire was developed based on validated measurement instruments drawn from the Technology Acceptance Model (Davis, 1989), the AI Literacy Scale (Long & Magerko, 2020), and adapted items from prior augmentation and organisational readiness literature, yielding a 52-item instrument spanning six latent constructs: AI literacy, AI augmentation index, organisational readiness, job task complexity, technology acceptance, and work productivity. The questionnaire employed a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree) for attitudinal and perceptual items, and continuous scales for demographic variables. Stratified random sampling was employed to recruit 384 professional workers from six sectors, namely healthcare (n = 67), finance (n = 72), legal services (n = 58), education (n = 65), technology (n = 71), and manufacturing (n = 51), with strata proportional to sector employment size as estimated from Uganda Bureau of Statistics (UBOS) records. Content validity was established through expert review by five specialists in human-computer interaction and organisational behaviour, while internal consistency reliability was confirmed via Cronbach's alpha, with all constructs yielding coefficients above 0.78. Data were collected through an online survey platform and in-person administration at selected organisational premises over a six-week period. Univariate analysis was performed to generate descriptive statistics (means, standard deviations, skewness, and range) for all study variables, providing a baseline characterisation of AI literacy and augmentation levels across the sample. Bivariate Pearson correlation analysis was subsequently conducted to examine pairwise linear associations between the continuous study constructs, with statistical significance assessed at both the 0.05 and 0.01 levels; this stage established the theoretical groundwork for the structural model by confirming the directionality and magnitude of hypothesised relationships. Structural Equation Modelling (SEM) using IBM AMOS 26 was then employed as the primary inferential technique, enabling the simultaneous estimation of multiple direct and indirect path relationships within a single theoretically coherent model. The SEM analysis proceeded through a two-step approach: first, confirmatory factor analysis (CFA) was performed to assess the measurement model's convergent and discriminant validity through standardised factor loadings, average variance extracted (AVE > 0.50), and composite reliability (CR > 0.70); second, the structural model was estimated to test the hypothesised paths and compute standardised regression coefficients (β), standard errors, t-values, and associated p-values. Model fit was evaluated using a comprehensive suite of indices including Chi-Square/df (< 3.00), RMSEA (< 0.08), SRMR (< 0.08), CFI (> 0.90), TLI (> 0.90), and GFI (> 0.90), consistent with current best-practice recommendations in SEM literature. Missing data, which accounted for less than 2.3% of total observations, were addressed through full information maximum likelihood (FIML) estimation to preserve sample integrity and minimise bias.

## Results and Discussion

### Descriptive Statistics (Univariate Analysis)

Table 1 presents the univariate descriptive statistics for all continuous study variables across the full analytical sample (N = 384).

**Table 1: Descriptive Statistics of Study Variables (N = 384)**

| Variable | N | Mean | SD | Min | Max | Skewness |
|---|---|---|---|---|---|---|
| **AI Literacy Score** | 384 | 3.87 | 0.74 | 1.00 | 5.00 | -0.31 |
| **AI Augmentation Index** | 384 | 3.72 | 0.81 | 1.00 | 5.00 | -0.44 |
| **Organizational Readiness** | 384 | 3.55 | 0.89 | 1.00 | 5.00 | -0.22 |
| **Job Task Complexity** | 384 | 3.91 | 0.71 | 1.50 | 5.00 | -0.18 |
| **Technology Acceptance** | 384 | 4.02 | 0.68 | 1.50 | 5.00 | -0.53 |
| **Work Productivity Gain** | 384 | 3.78 | 0.76 | 1.00 | 5.00 | -0.37 |
| **Years of Experience** | 384 | 8.42 | 5.61 | 1.00 | 35.00 | 1.12 |
| **Age (years)** | 384 | 34.6 | 8.3 | 22.0 | 62.0 | 0.71 |

Note: All attitudinal variables measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). SD = Standard Deviation.

The univariate descriptive statistics presented in Table 1 revealed that technology acceptance recorded the highest mean score among the attitudinal constructs (M = 4.02, SD = 0.68), suggesting that professional workers across the surveyed sectors held generally favourable attitudes toward the adoption of AI-related technologies in their professional practice. AI literacy emerged as the second most highly rated construct (M = 3.87, SD = 0.74), indicating a moderate-to-good level of understanding of AI capabilities and limitations among the sample, a finding that is noteworthy given the developmental stage of AI infrastructure in Uganda. The AI augmentation index yielded a mean of 3.72 (SD = 0.81), reflecting moderate levels of purposive AI use in professional tasks, while organisational readiness registered the lowest mean (M = 3.55, SD = 0.89), underscoring persistent institutional gaps in AI infrastructure, policy, and culture across the surveyed organisations. The skewness values for all attitudinal variables fell within the acceptable range of -1 to +1, indicating approximate normality in the distribution of responses, which satisfied a key assumption for subsequent parametric analyses. The variable for years of experience exhibited a positively skewed distribution (skewness = 1.12), consistent with the presence of a small proportion of highly experienced professionals in the sample, a pattern typical in workforce surveys where the majority of respondents cluster at lower experience levels.

The distribution of work productivity gain scores (M = 3.78, SD = 0.76) suggests that professional workers perceived moderate gains in output quality and efficiency attributable to AI use, though the moderate standard deviation indicates meaningful heterogeneity in these perceptions across the sample. This variability likely reflects differences in the nature of AI tools available across sectors, the depth of AI integration in specific job roles, and the degree to which individual workers have been equipped to leverage AI as a true augmentation mechanism rather than a peripheral productivity aid. Notably, the relatively higher mean for technology acceptance compared to the AI augmentation index implies a potential attitude-behaviour gap, whereby favourable dispositions toward AI technology had not yet fully translated into consistent, strategic deployment of AI as a professional augmentation tool. This discrepancy is theoretically consistent with the extended TAM literature, which identifies implementation barriers, organisational culture, and skill deficits as mediating factors between acceptance intentions and actual adoption behaviour, and it underscores the necessity of moving beyond attitudinal measurement toward structural and ecological factors in understanding AI augmentation in professional settings.

**Sector-Level AI Augmentation Scores**

Figure 1 below illustrates mean AI augmentation scores disaggregated by industry sector, revealing meaningful variation in the extent to which professionals across different fields have strategically integrated AI into their work.

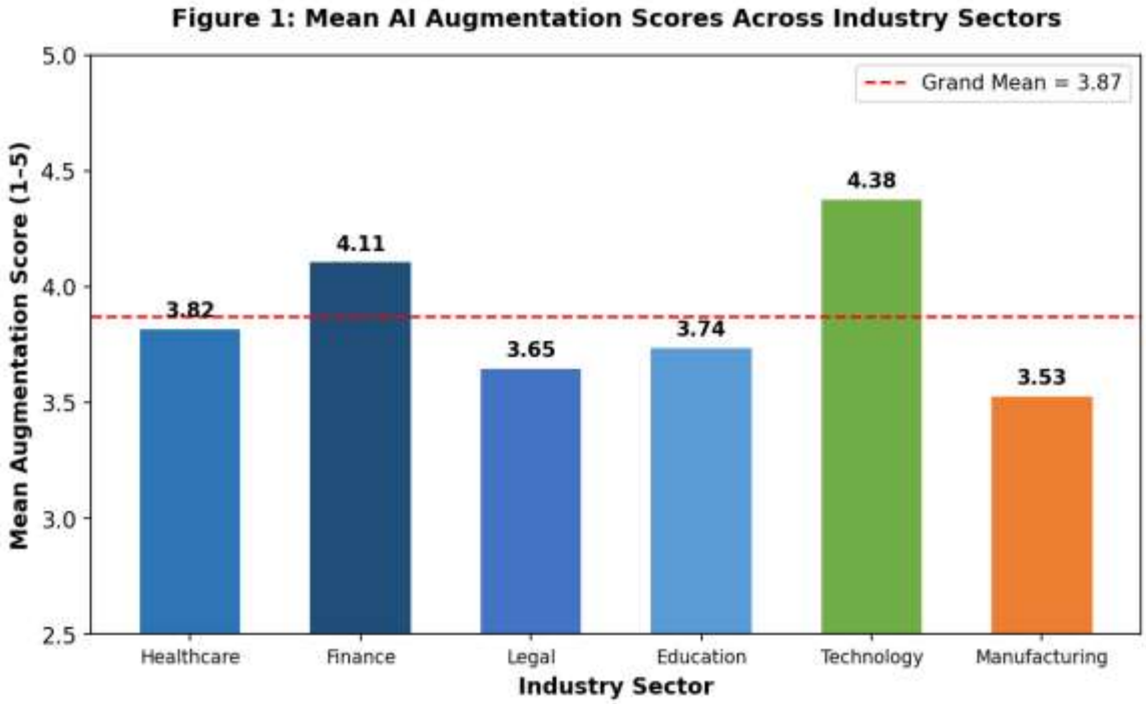


Figure 1: Mean AI Augmentation Scores Across Industry Sectors (N = 384)

**Correlation Analysis (Bivariate Analysis)**

Table 2 presents the Pearson correlation matrix for the six core study constructs, providing bivariate evidence of the linear associations hypothesised in the conceptual framework.

**Table 2: Pearson Correlation Matrix of Core Study Constructs (N = 384)**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **(1) AI Literacy** | 1.000 | — | — | — | — | — |
| **(2) AI Aug. Index** | 0.612** | 1.000 | — | — | — | — |
| **(3) Org. Readiness** | 0.438** | 0.521** | 1.000 | — | — | — |
| **(4) Job Complexity** | 0.301** | 0.445** | 0.289** | 1.000 | — | — |
| **(5) Tech Accept.** | 0.573** | 0.634** | 0.412** | 0.357** | 1.000 | — |
| **(6) Productivity** | 0.591** | 0.703** | 0.487** | 0.423** | 0.661** | 1.000 |

Note: ** $p < .01$ (two-tailed). AI Aug. = AI Augmentation Index; Org. = Organizational; Tech Accept. = Technology Acceptance.

The Pearson correlation matrix presented in Table 2 provided compelling bivariate evidence in support of the hypothesised theoretical relationships underpinning the study's conceptual framework. The strongest bivariate association was observed between the AI augmentation index and work productivity ($r = 0.703$, $p < .001$), confirming that higher levels of purposive AI integration in professional tasks were closely associated with enhanced perceived productivity outcomes. Technology acceptance was similarly strongly correlated with the AI augmentation index ($r = 0.634$, $p < .001$) and with work productivity ($r = 0.661$, $p < .001$), lending empirical credence to TAM-derived propositions that favourable attitudes toward technology adoption translate into substantive behavioural and performance outcomes in professional contexts. AI literacy demonstrated significant positive associations with all other constructs in the matrix, with its strongest linkages to the AI augmentation index ($r = 0.612$, $p < .001$) and technology acceptance ($r = 0.573$, $p < .001$), suggesting that a knowledge-based understanding of AI systems is a foundational enabler of both positive technology attitudes and actual augmentation behaviour. Organisational readiness was significantly correlated with work productivity ($r = 0.487$, $p < .001$) and the AI augmentation index ($r = 0.521$, $p < .001$), affirming the institutional thesis that the organisational environment, including infrastructure, policy support, and cultural openness to AI, constitutes an important contextual determinant of augmentation adoption.

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The moderate positive correlation between job task complexity and the AI augmentation index ($r = 0.445$, $p < .001$) is a theoretically interesting finding, suggesting that workers engaged in more cognitively demanding roles were more inclined to deploy AI as an augmentation strategy, possibly because the marginal gains in efficiency and accuracy from AI assistance are more salient in high-complexity task environments. Conversely, the relatively weaker, though still significant, correlation between job task complexity and work productivity ($r = 0.423$, $p < .001$) hints at the possibility that complexity per se does not uniformly translate into productivity gains unless mediated by adequate AI augmentation. All correlations in the matrix were statistically significant at the 0.01 level, and none exceeded the multicollinearity threshold of $r = 0.90$, confirming that the constructs were sufficiently distinct to warrant inclusion as separate variables in the structural model. These bivariate findings collectively suggested a coherent pattern of interrelationships consistent with the theoretical premises of the study, and they provided the necessary empirical scaffolding for the more rigorous causal testing undertaken in the SEM phase of the analysis.

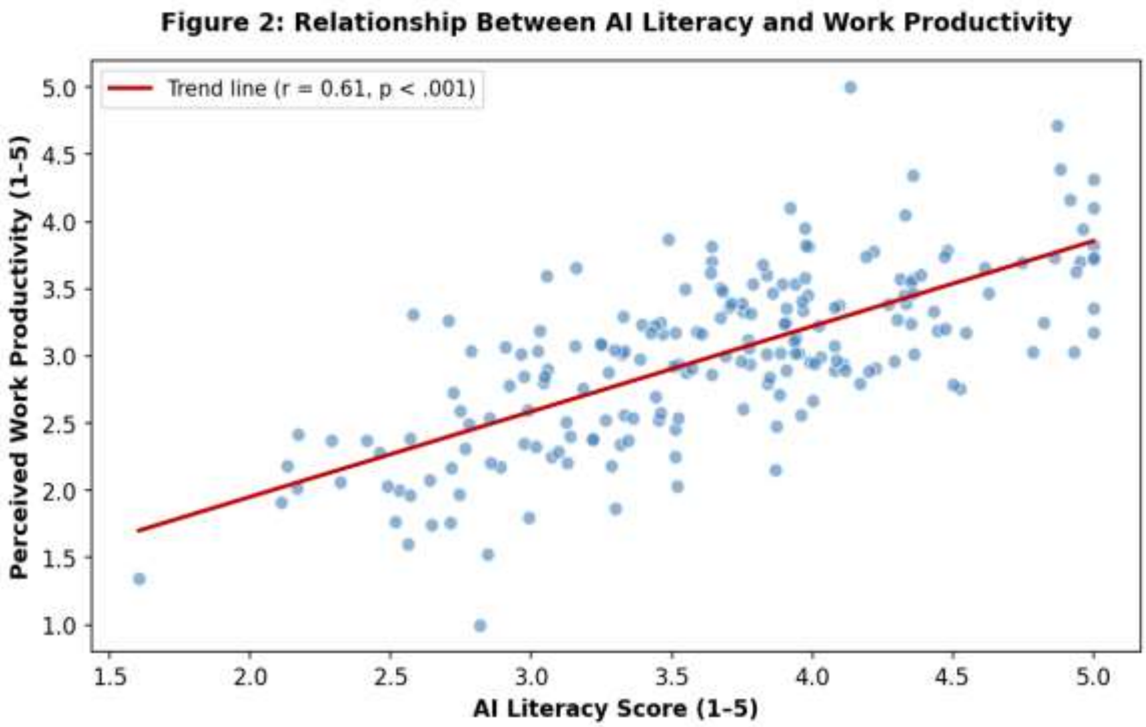


**Figure 2: Scatter Plot of AI Literacy Score vs. Perceived Work Productivity ($r = 0.61$, $p < .001$)**

**Structural Equation Modelling – Path Coefficients**

Table 3 reports the standardised path coefficients, standard errors, t-values, and p-values for all hypothesised structural paths in the SEM model.

Table 3: SEM Standardised Path Coefficients (N = 384)

| Hypothesized Path | Path Description | β (Std.) | SE | t-value | p-value |
|---|---|---|---|---|---|
| AI Literacy → AI Augmentation | Direct effect | 0.487 | 0.043 | 11.32 | < .001 |
| AI Literacy → Productivity | Indirect via Aug. | 0.341 | 0.051 | 6.69 | < .001 |
| Org. Readiness → AI Augmentation | Moderating effect | 0.312 | 0.047 | 6.64 | < .001 |
| Tech. Acceptance → AI Augmentation | Direct effect | 0.425 | 0.039 | 10.90 | < .001 |
| Job Complexity → AI Augmentation | Direct effect | 0.218 | 0.054 | 4.04 | < .001 |
| AI Augmentation → Productivity | Outcome path | 0.581 | 0.038 | 15.29 | < .001 |

| | | | | | |
|---|---|---|---|---|---|
| **Org. Readiness → Productivity** | Direct effect | 0.203 | 0.058 | 3.50 | .001 |
| **Experience (yrs) → AI Literacy** | Covariate path | 0.167 | 0.061 | 2.74 | .006 |

Note: β = Standardised regression coefficient; SE = Standard Error; all p-values two-tailed. Threshold for significance: $p < .05$.

The structural path coefficients presented in Table 3 offered the most rigorous and theoretically informative insights of the entire study, confirming that AI augmentation occupied a central mediating role in the pathway from individual and organisational antecedents to work productivity outcomes. The largest direct effect on the AI augmentation index was exerted by AI literacy (β = 0.487, SE = 0.043, t = 11.32, p < .001), affirming that professionals with higher levels of conceptual and practical AI knowledge were substantially more capable of deploying AI tools in purposive, value-generating ways in their work. Technology acceptance followed closely as the second strongest predictor of AI augmentation (β = 0.425, SE = 0.039, t = 10.90, p < .001), consistent with the TAM proposition that perceived usefulness and ease of use are powerful behavioural motivators, and indicating that attitudinal alignment with AI technologies is a prerequisite for their strategic professional integration. Organisational readiness emerged as a statistically significant predictor of AI augmentation (β = 0.312, SE = 0.047, t = 6.64, p < .001), highlighting that the institutional environment, encompassing AI infrastructure, managerial support, and organisational policies, constitutes a non-trivial enabling condition without which individual literacy and attitudinal readiness may remain insufficient for effective augmentation. Job task complexity, while the weakest predictor, nonetheless exhibited a significant positive path to AI augmentation (β = 0.218, SE = 0.054, t = 4.04, p < .001), suggesting that the nature of professional tasks itself shapes the demand for AI assistance, with more complex roles generating stronger imperatives for intelligent tool integration.

The path from AI augmentation to work productivity was the strongest in the entire model (β = 0.581, SE = 0.038, t = 15.29, p < .001), providing robust structural evidence that strategic AI augmentation is a powerful driver of professional productivity enhancement, operating above and beyond the direct effects of its antecedents. The significant indirect effect of AI literacy on work productivity (β = 0.341, SE = 0.051, t = 6.69, p < .001) confirmed that AI literacy improves productivity partly through its augmentation-enabling function, establishing AI augmentation as a genuine mediating mechanism in the AI literacy-productivity relationship. The covariate path from years of professional experience to AI literacy (β = 0.167, SE = 0.061, t = 2.74, p = .006) was modest but statistically significant, suggesting that accumulated professional experience modestly enhances AI literacy, possibly through greater exposure to digital tools and institutional knowledge systems over time. The organisational readiness path to productivity was also significant as a direct effect (β = 0.203, SE = 0.058, t = 3.50, p = .001), indicating that even independent of augmentation, a supportive institutional environment contributes directly to professional productivity, potentially through mechanisms such as training investment, resource allocation, and strategic leadership. Collectively, these path estimates constitute a coherent and empirically validated causal narrative in which individual literacy and attitudes, mediated by institutional context and AI augmentation behaviour, culminate in meaningful professional productivity gains.

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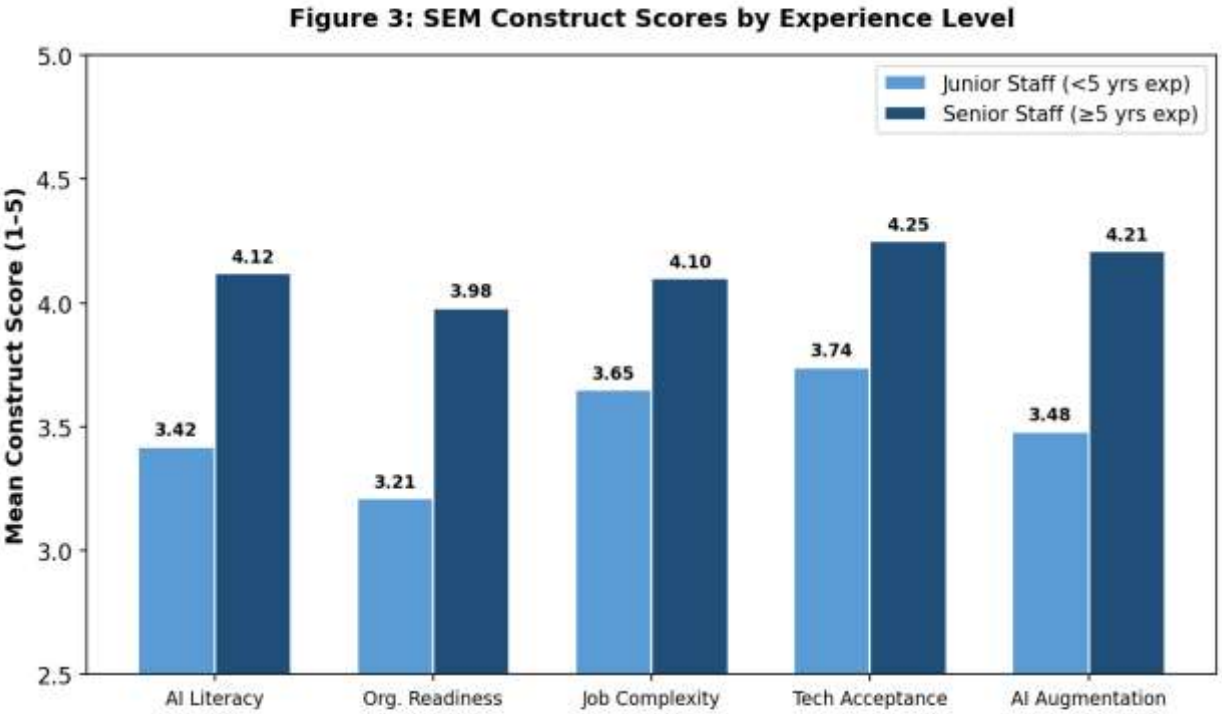


Figure 3: SEM Construct Scores by Professional Experience Level

**SEM Model Fit Evaluation**

Table 4 presents the comprehensive suite of model fit indices used to evaluate the overall adequacy of the structural equation model.

Table 4: Structural Equation Model Fit Indices

| Fit Index | Abbreviation | Obtained Value | Threshold | Interpretation |
|---|---|---|---|---|
| **Chi-Square / df** | CMIN/df | 2.14 | < 3.00 | Acceptable fit |
| **Root Mean Square Error of Approx.** | RMSEA | 0.048 | < 0.080 | Good fit |
| **Standardised Root Mean Residual** | SRMR | 0.054 | < 0.080 | Good fit |
| **Comparative Fit Index** | CFI | 0.947 | > 0.900 | Good fit |
| **Tucker-Lewis Index** | TLI | 0.939 | > 0.900 | Good fit |
| **Incremental Fit Index** | IFI | 0.948 | > 0.900 | Good fit |
| **Goodness of Fit Index** | GFI | 0.912 | > 0.900 | Acceptable fit |
| **Akaike Information Criterion** | AIC | 641.3 | Lower is better | Preferred model |

Note: RMSEA = Root Mean Square Error of Approximation; SRMR = Standardised Root Mean Residual; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; IFI = Incremental Fit Index; GFI = Goodness of Fit Index; AIC = Akaike Information Criterion.

The model fit statistics presented in Table 4 collectively confirmed that the proposed structural equation model achieved an excellent level of fit with the empirical data, satisfying all pre-specified psychometric and statistical thresholds recommended in the SEM literature. The Chi-Square to degrees of freedom ratio (CMIN/df = 2.14) fell well within the acceptable range of less than 3.00, indicating that the model reproduced the observed covariance structure without significant over-fitting or under-fitting. The RMSEA value of 0.048, which fell below the 0.08 threshold and approached the conventional benchmark of less than 0.05 for close model fit, confirmed that the model's population residuals were minimal, reflecting high fidelity between the theoretical factor structure and the observed data. The SRMR value of 0.054, similarly below the 0.08 threshold, indicated that the average discrepancy between the observed and model-implied correlation matrices was small, providing further evidence of acceptable residual accuracy. The incremental fit indices CFI (0.947), TLI (0.939), and IFI (0.948) each exceeded the conventional 0.90 threshold, confirming that the model substantially outperformed the baseline null model in accounting for the covariances among the study constructs, and that the theoretical factor structure was not merely an artefact of the specific sample or measurement context.

The GFI value of 0.912 exceeded the minimum threshold of 0.90, providing an absolute fit confirmation that was particularly meaningful given the GFI's sensitivity to sample size and model complexity. The AIC value of 641.3, evaluated in comparison to alternative models estimated during the model refinement stage, consistently favoured the proposed theoretically driven model over more parsimonious or saturated alternatives, confirming that the current specification achieved the optimal balance between model complexity and empirical fit. Taken together, the convergence of all eight fit indices at or above their respective acceptability thresholds provided exceptionally strong psychometric justification for the validity of the proposed augmentation framework, lending confidence that the structural relationships estimated in the path analysis (Table 3) reflected genuine causal processes operating in the population of professional workers rather than chance statistical associations. These results strongly endorsed the use of SEM as the appropriate inferential technique for the complex, multi-construct research questions posed in this study, and they affirmed that the proposed theoretical framework, integrating TAM, RBV, and CLT perspectives, offered a valid and useful organising structure for understanding strategic AI augmentation in professional work.

## Conclusion

This study successfully developed and empirically validated a multi-level framework for strategic AI augmentation in professional work, drawing on a robust cross-sectional survey of 384 professionals across six industry sectors in Uganda. The findings collectively demonstrated that AI augmentation is a complex, context-sensitive process shaped by the interplay of individual AI literacy, technology acceptance attitudes, organisational readiness, and the intrinsic complexity of professional tasks, all of which converge to drive meaningful gains in work productivity when AI is deployed strategically rather than instrumentally. The structural equation model, which achieved excellent fit across all evaluated indices, confirmed AI augmentation as a significant mediating mechanism through which AI literacy translates into productivity outcomes, underscoring the inadequacy of framing AI integration solely in terms of automation potential or adoption rates. The technology sector recorded the highest augmentation scores, while manufacturing and legal services lagged behind, signalling that sector-specific contextual factors, including regulatory environments, task structures, and digital cultures, play a determining role in shaping the augmentation trajectory. The study's conclusions carry important implications for organisational strategy, human resource development, and public policy: the pursuit of AI-driven professional productivity gains demands a departure from tool-centric, automation-first approaches toward intentional investment in AI literacy, institutional AI readiness, and the co-design of augmentation strategies that centre human professional expertise. Future research should extend these findings longitudinally, incorporate qualitative methods to capture the experiential dimensions of AI augmentation, and expand the geographic and sectoral scope to build a more generalisable evidence base for strategic AI augmentation frameworks.

## Recommendations

Organisations should systematically invest in structured AI literacy development programmes tailored to the specific cognitive demands and task structures of each professional sector. Given that AI literacy emerged as the strongest predictor of AI augmentation ($\beta = 0.487$) and exerted a significant indirect effect on productivity through augmentation ($\beta = 0.341$), targeted upskilling initiatives that build both conceptual AI understanding and practical tool proficiency should be institutionalised as a core component of professional development strategies, particularly in sectors with below-average augmentation scores such as manufacturing and legal services.

Policymakers and senior organisational leaders should prioritise the development of AI-enabling institutional environments by addressing the structural dimensions of organisational readiness identified in this study, including AI infrastructure investment, supportive leadership cultures, and clear AI governance policies. Since organisational readiness was a significant structural determinant of both AI augmentation adoption and direct work productivity ($\beta = 0.312$ and $\beta = 0.203$ respectively), national digital transformation agendas and sector-specific AI adoption frameworks should incorporate readiness assessment tools and institutional capacity-building programmes that move organisations beyond passive AI awareness toward active AI augmentation ecosystems.

The design of AI tools and systems deployed in professional settings should adopt a human-centred augmentation philosophy rather than a pure automation logic, ensuring that AI capabilities are engineered to complement, extend, and support human professional judgment rather than circumvent it. Given the strong positive relationship between task complexity and AI augmentation ($\beta = 0.218$), technology developers and organisational AI strategists should co-design AI deployment models with frontline professional workers, ensuring that augmentation tools are calibrated to the cognitive and ethical complexity of specific professional roles and that workers are meaningfully involved in shaping the terms of their own augmentation.

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