

From Automation to Augmentation: Artificial Intelligence, Competence Evolution, and Career Sustainability in the Accounting Profession

Opeyemi Tunmise Ajeigbe¹; Ododa Confidence²; Ogbe George Junior² & Samuel Bafanayaa³

¹Department of Management & Accounting, Obafemi Awolowo University, Ile-Ife, Nigeria

²Department of Social Sciences - Population and Development, National Research University Higher School of Economics

³Department of Economics and Management, National Research University Higher School of Economics

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*Corresponding author: Opeyemi Tunmise Ajeigbe

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Abstract

Original Research

Artificial intelligence (AI) is changing the content of accounting work, but the career consequences of that change remain less clear in emerging economies. Using field responses from 600 accounting and finance professionals in Nigeria, Ghana, and Kenya (200 per country), this paper examines whether intensive AI use is associated with professional role transformation, whether role transformation is associated with competence evolution, and whether those evolving competencies are linked to career sustainability. Learning and organizational support is considered both as a contextual resource and as a potential moderator. The analysis uses multi-item composite measures, HC3-robust path regressions, 5,000-resample bootstrapping, effect-size estimates, 10-fold cross-validation, and exploratory country comparisons. AI adoption was positively associated with role transformation ($\beta = .491, p < .001$). AI adoption ($\beta = .286, p < .001$) and role transformation ($\beta = .462, p < .001$) jointly explained 42.6% of the variance in competence evolution, while competence evolution was positively associated with career sustainability ($\beta = .414, p < .001$). The direct role-transformation effect on career sustainability was negligible ($\beta = .013, p = .764$), whereas the indirect effect through competence evolution was significant ($\beta = .192, 95\% \text{ bootstrap CI } [.146, .242]$). The serial pathway from AI adoption through role transformation and competence evolution to career sustainability was also significant ($\beta = .094, 95\% \text{ CI } [.069, .123]$). Learning and organizational support had a positive main effect but did not moderate the competence-sustainability relationship. The results suggest that the long-term value of AI-related role change depends less on the fact that work changes than on whether professionals acquire the digital, analytical, advisory, and ethical capabilities needed to succeed in the redesigned role.

Keywords: artificial intelligence; accounting profession; role transformation; competence evolution; career sustainability; emerging economies; Africa; human capital.

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1. Introduction

Artificial intelligence is rapidly reshaping accounting through machine learning, generative AI, robotic process automation, intelligent

analytics, and large language models. These technologies increasingly support reconciliation, anomaly detection, forecasting, document review, research, reporting, and assurance.



Earlier studies anticipated this transition by showing how big data and intelligent systems could transform accounting and audit processes (Vasarhelyi et al., 2015; Sutton et al., 2016; Kokina & Davenport, 2017). Generative AI has extended the debate to work design, governance, professional judgment, and skill development (Dong et al., 2024), while recent reviews portray AI and automation as forces restructuring accounting practice rather than merely supporting existing tasks (Kassar & Jizi, 2026; Abbas, 2026). The workforce implications are substantial. The World Economic Forum (2025) identifies AI and big data among the fastest-growing skill areas while noting employment pressure on accounting occupations. At the same time, accountants increasingly need analytical, strategic, technological, communication, ethical, and governance capabilities (ICAEW, 2024, 2025). This challenge is especially important in emerging economies, where digital transformation depends on infrastructure, organizational capability, education, regulation, and continuous learning. African evidence highlights growing demand for digital, data-management, critical-thinking, and problem-solving skills (Mbizi et al., 2022), while Ghanaian research emphasizes adaptability, readiness, leadership, and resistance to change (Anomah et al., 2024). ACCA (2025) further reports concerns about future skills and limited AI-training opportunities. Similar evidence from Nigeria, Kenya, Jordan, Saudi Arabia, and Bangladesh identifies persistent challenges involving skills, trust, governance, training, and implementation capacity (Olaoye, 2025; Toumeh, 2024; Mgamal, 2024; Rahman et al., 2025). Despite this growing literature, three gaps remain. First, accounting-AI studies still focus largely on adoption, readiness, benefits, and barriers (Kassar & Jizi, 2026), with less attention to professionals' longer-term outcomes. Second, the mechanism linking changing roles to career outcomes remains underexplored. Third, career consequences are often reduced to displacement or employability, whereas sustainable-career research emphasizes meaning, well-being, productivity, and employability over time and within context (De Vos et al., 2020; Van der Heijden et al., 2020; Russo et al., 2026).

This study addresses these gaps by testing a transformation-to-sustainability model using 600 accounting and finance professionals from Nigeria, Ghana, and Kenya. The results show that AI adoption is associated with professional role transformation and competence evolution, while competence evolution is positively related to career sustainability. The direct relationship between role transformation and career sustainability becomes negligible once competence is considered, indicating that transformed work supports sustainable careers mainly through capability development. Learning and organizational support also contributes positively to career sustainability, although its moderating effect is not supported. The study therefore positions competence evolution as the central mechanism through which AI-driven changes in accounting work can support sustainable careers.

2. Theoretical Background and Hypothesis Development

2.1 AI as an automation-augmentation force in accounting

AI changes professional work through two interdependent logics. Automation transfers tasks from humans to machines, while augmentation combines machine capabilities with human judgment to improve task performance. Raisch and Krakowski (2021) describe this as an automation-augmentation paradox: organizations cannot simply choose augmentation while ignoring automation because the two processes coexist and reshape one another. Jarrahi (2018) similarly argues that the future of knowledge work is likely to involve human-AI symbiosis, with machines contributing computational scale and humans contributing contextual understanding, judgment, social intelligence, and responsibility. Accounting illustrates this paradox clearly. Routine activities are unusually susceptible to codification, standardized data flows, pattern recognition, and automatic reconciliation. At the same time, the proliferation of automated outputs increases demand for interpretation, exception handling, model validation, governance, client communication, and professional skepticism. Kokina and Davenport (2017) documented how

cognitive technologies were beginning to automate audit tasks while changing the skills expected of auditors. Fedyk et al. (2022) later found that investment in AI could improve audit quality and efficiency while also producing labor displacement over time. Field evidence from large audit firms further shows that relatively simple AI applications are already common while more complex AI remains constrained by explainability, bias, privacy, reliability, overreliance, and guidance concerns (Kokina et al., 2025). Samiolo et al. (2024) add an important professional-learning caution: automating apparently low-level audit tasks can also remove opportunities through which early-career professionals acquire practical judgment. Thus, efficiency gains, role redesign, and occupational risk are simultaneous consequences of the same technological shift.

The broader digital-accounting literature points in the same direction. Moll and Yigitbasioglu (2019) show that cloud systems, big data, blockchain, and AI reshape the everyday work of accountants and can raise concerns about professional legitimacy even as they improve visibility and timeliness. Han et al. (2023) emphasize the capacity of AI to extract patterns from increasingly rich accounting information and augment decision-making. A systematic review of digitalization in accounting finds that routine activities are progressively automated while non-routine analytical and interactive activities, together with general digital competence, become more important (Pargmann et al., 2023). Abbas (2026), reviewing 91 studies in management accounting and AI, likewise concludes that digitalization and AI transform accounting information, organizational structures, and the relationship between the accounting function and other organizational functions. The professional role therefore becomes less bounded by transaction processing and more connected to data, strategy, technology, risk, and organizational decision-making.

2.2 AI adoption intensity and professional role transformation

Role transformation should become more pronounced as AI is used more frequently and

across a wider range of work processes. Professionals who rarely encounter AI may retain established task portfolios, whereas professionals who integrate AI into analysis, forecasting, research, drafting, decision support, and anomaly detection are more exposed to changes in workflow architecture. Automation reduces time spent on routine processing and documentation; augmentation shifts attention toward interpreting results, exercising judgment, advising stakeholders, and overseeing technology-generated outputs. Emerging empirical evidence supports this logic. Assidi et al. (2025), using a survey of 400 academics and professional accountants in Tunisia, found that AI adoption was associated with substantial changes in professional roles and responsibilities as well as digital workplace productivity and training requirements. Mgamal (2024) reports significant relationships between AI awareness, usage, engagement, and accounting procedures in Saudi Arabia. Studies in African contexts also describe a transition toward technology-enabled practice and the need for professionals to adapt their functions rather than merely acquire isolated software skills (Mbizi et al., 2022; Anomah et al., 2024; Olaoye, 2025). Related evidence also links digital-technology readiness and accountants' perceptions of digitization to changing professional expectations and future-role profiles (Faizal et al., 2022; Grosu et al., 2023). These arguments lead to the first hypothesis.

H1: AI adoption intensity is positively associated with professional role transformation.

2.3 AI adoption, role transformation, and competence evolution

Technological change creates value only when it is matched by human-capital renewal. Human capital theory treats education, knowledge, and skill development as investments that increase productive capacity and economic value (Schultz, 1961; Becker, 1964). In an AI-intensive profession, the relevant capital is broader than technical proficiency. Accountants must understand the capabilities and limitations of AI; work with data and analytics; recognize

hallucinations, unsupported claims, and poor data quality; apply judgment under ambiguity; communicate insights to non-specialists; collaborate with technology and risk functions; and govern privacy, bias, accountability, and professional skepticism. This multidimensional view is consistent with current accounting evidence. Mbizi et al. (2022) identify information-technology, data analytics, problem-solving, specialized software, and business-intelligence skills as important for African accountants in the Fourth Industrial Revolution. Pargmann et al. (2023) similarly show that digitalization increases the salience of non-routine analytical and interactive work alongside general digital competence. Tiron-Tudor et al. (2025) document a gap between labor-market demand for future-ready digital skills and accounting students' self-assessed competencies, emphasizing cyber, digital, and technological capability. ICAEW (2024, 2025) likewise highlights AI understanding, analytics, critical thinking, communication, adaptability, and business partnering. Ethical competence is equally important because AI-enabled accounting raises risks involving privacy, bias, accountability, transparency, and trust (Munoko et al., 2020; Zhang et al., 2023; Kokina et al., 2025). Two pathways should drive competence evolution. The first is direct exposure. Regular AI use provides practice, feedback, and problem-solving opportunities that can strengthen digital fluency and complementary capabilities. The second is role-induced learning. When work shifts from routine processing to interpretation, advice, validation, and cross-functional collaboration, professionals face new performance demands that motivate or require capability development. Role transformation is therefore not merely an outcome of AI adoption; it is also a learning pressure that can accelerate human-capital renewal.

H2: AI adoption intensity is positively associated with competence evolution.

H3: Professional role transformation is positively associated with competence evolution.

2.4 Competence evolution and career sustainability

The sustainable-careers perspective broadens career success beyond employment continuity. De Vos et al. (2020) conceptualize sustainable careers through person, context, and time, with happiness, health, and productivity as core indicators. Van der Heijden et al. (2020) further emphasize that sustainable careers unfold across the lifespan and multiple life domains. More recently, Russo et al. (2026) developed and validated a multidimensional sustainable-career scale encompassing happiness, health, productivity, and social empowerment. Competence evolution should strengthen each of these outcomes. Digital and analytical competence protects productivity by enabling professionals to work effectively with changing technologies and increasingly complex information. Human and advisory competence creates value in areas less easily commoditized by automation, such as stakeholder communication, collaboration, influence, and context-sensitive advice. Ethical and governance competence protects professional legitimacy and reduces the risk that AI use undermines trust. Together, these capabilities can increase employability and confidence while also reducing the strain created by technological change because professionals are better equipped to understand and manage new work demands.

This reasoning is consistent with evidence from graduates and professionals. Maulana et al. (2025) show that AI-based learning experiences can shape AI literacy, competence, self-efficacy, and commitment to an accounting career. Beyond accounting, time-lagged evidence indicates that perceived AI disruption can stimulate career adaptability partly through skill development, reinforcing the idea that human-capital renewal is a central response to technological uncertainty (Burhan, 2024). Studies of digitalization also suggest that professionals with roles oriented toward business partnering and broader value creation are better positioned to benefit from digital change, whereas narrower role identities may experience greater ambiguity or conflict (van Slooten et al., 2026). Competence evolution therefore represents the adaptive resource that makes a

technology-intensive accounting career sustainable rather than merely survivable.

H4: Competence evolution is positively associated with career sustainability.

2.5 Does role transformation directly sustain careers?

Role transformation may also have a direct positive relationship with career sustainability. Moving away from repetitive processing toward interpretation, strategic advice, cross-functional collaboration, and oversight can increase task variety, professional relevance, decision influence, and perceived future value. Such changes may improve career meaning and perceived employability even before competence gains are fully realized. However, the same role transformation can create strain, uncertainty, or role ambiguity if capability development does not keep pace. Van Slooten et al. (2026) describe digitalization as a double-edged sword: it can benefit professionals whose role orientation is aligned with emerging digital expectations while increasing ambiguity and conflict for others. The net direct effect of role transformation is therefore theoretically plausible but less certain than the competence-mediated pathway. We nevertheless test the conventional positive expectation.

H5: Professional role transformation is positively associated with career sustainability.

2.6 Competence evolution as the transmission mechanism

Combining the preceding arguments suggests that the central effect of role transformation may operate indirectly. When AI changes what accountants do, the career consequence depends on whether professionals develop the capacities required by the redesigned role. New responsibilities without new capabilities can generate overload or insecurity; new responsibilities accompanied by competence development can increase professional value and adaptability. Human capital theory therefore identifies competence evolution as the conversion mechanism between changed work and sustainable careers. The same logic produces

a longer serial pathway from technology use to career outcomes. AI adoption increases exposure to automation and augmentation; that exposure transforms the role; role transformation stimulates competence development; and competence development supports sustainable career indicators. This serial mechanism integrates the automation-augmentation paradox with human capital and sustainable-career theory and makes a stronger claim than a simple correlation between AI use and career optimism: it specifies how that relationship should occur.

H6: Competence evolution mediates the positive relationship between professional role transformation and career sustainability.

2.7 Learning and organizational support as a contextual resource

Competence does not develop or generate value in an institutional vacuum. Organizations influence access to approved tools, time for learning, training budgets, managerial encouragement, professional development opportunities, and guidance about responsible AI use. Professional bodies and training providers can also reduce uncertainty by translating technological change into standards, curricula, and continuing professional development pathways. These resources are especially salient in emerging economies, where access to infrastructure, high-quality training, and specialized expertise may be uneven. Learning support can affect career sustainability directly by signaling investment in employees, lowering the individual cost of reskilling, and increasing confidence that new capabilities will be recognized and used. It may also strengthen the payoff from competence evolution: a capable professional working in an environment that provides suitable tools, learning opportunities, and supportive leadership should be better able to convert capability into productivity, employability, meaning, and manageable work demands. This motivates a contextual moderation hypothesis.

H7: Learning and organizational support positively moderates the relationship between competence evolution and career sustainability, such that the relationship is

stronger when support is higher.

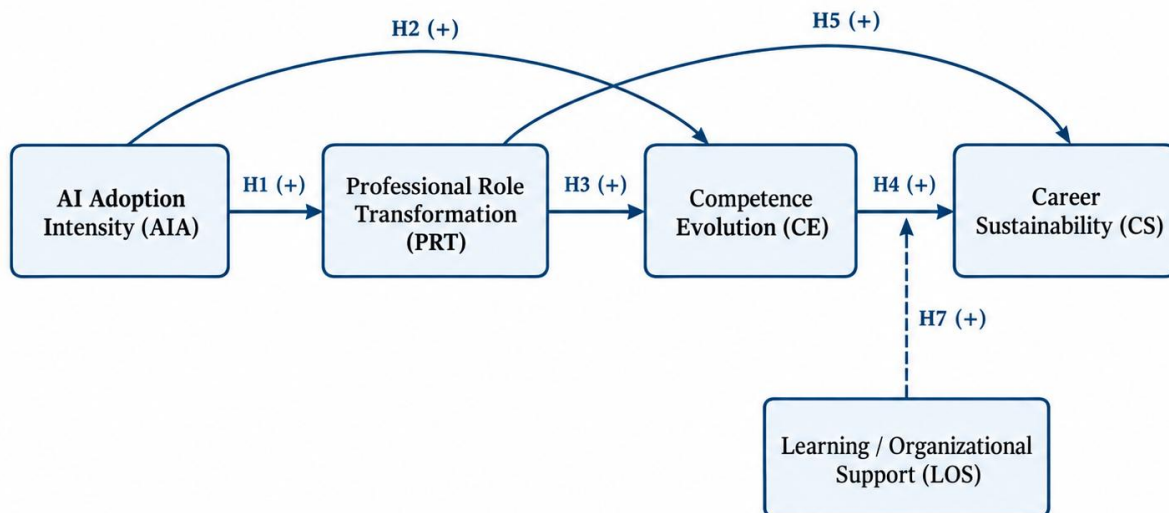


Figure 1. Conceptual framework and hypothesized relationships. *H6 represents the indirect PRT → CE → CS pathway; the serial indirect pathway extends from AIA through PRT and CE to CS. LOS is hypothesized to moderate the CE → CS relationship (H7).*

3. Methodology

3.1 Research design and analytical sample

The study used a quantitative multi-country field-survey design. The instrument was organized into two linked measurement waves using an anonymous respondent identifier. Wave 1 contained background variables, AI adoption intensity, professional role transformation, and learning/organizational support; Wave 2 contained the competence and career-sustainability measures. The linked analytical dataset contained 600 complete respondent records, with 200 professionals each from Nigeria, Ghana, and Kenya. The sample spans a broad cross-section of accounting and finance work. Financial accounting/reporting (18.2%), audit/assurance (18.0%), and management accounting/FP&A (17.3%) are the largest professional areas, followed by internal audit/risk (12.7%), banking/financial services (11.8%), tax (10.2%), public-sector finance

(8.5%), and other roles (3.3%). Career levels range from entry/junior (15.3%) to partner/CFO/finance executive (8.7%), with professional/specialist and supervisor/manager respondents each representing 27.5% of the sample. Experience is also distributed across career stages: 22.8% report 1-3 years, 25.8% 4-7 years, 21.8% 8-12 years, 18.7% 13-20 years, and 10.8% more than 20 years. Almost half of respondents (49.0%) report formal AI or generative-AI training within the previous 24 months. The data-quality audit found 600 unique respondent IDs, no duplicated IDs, no exact duplicate rows, and no missing responses across the focal Likert items. All focal items were within the intended seven-point range. The balanced country allocation allows country-level comparison without reweighting, although the country analyses are interpreted as exploratory structural comparisons rather than population-representative national estimates.

Table 1. Selected respondent characteristics (N = 600).

Characteristic	Category	n	%
Country	Nigeria	200	33.3
	Ghana	200	33.3
	Kenya	200	33.3
Professional area	Financial accounting/reporting	109	18.2
	Audit/assurance	108	18.0
	Management accounting/FP&A	104	17.3
	Internal audit/risk	76	12.7
	Banking/financial services	71	11.8
	Tax	61	10.2
	Public-sector finance	51	8.5
	Other	20	3.3
Career level	Entry/junior	92	15.3
	Professional/specialist	165	27.5
	Supervisor/manager	165	27.5
	Senior manager/director	126	21.0
	Partner/CFO/finance executive	52	8.7
Experience	1-3 years	137	22.8
	4-7 years	155	25.8
	8-12 years	131	21.8
	13-20 years	112	18.7
	>20 years	65	10.8
AI training, past 24 months	Yes	294	49.0
	No	306	51.0

Characteristic	Category	n	%
AI use frequency	Never	17	2.8
	Less than monthly	69	11.5
	Monthly	171	28.5
	Weekly	159	26.5
	Several times per week	128	21.3
	Daily	56	9.3

Percentages may not sum to exactly 100 because of rounding.

3.2 Measures

All focal constructs were measured on seven-point response scales ranging from 1 (strongly disagree) to 7 (strongly agree). AI adoption intensity (AIA; five items) captures regular AI use, use for analysis and decision support, generative-AI use for accounting information, incorporation of AI outputs into work processes, and growth in the breadth of AI use. Professional role transformation (PRT; five items) captures reduced routine processing, increased interpretation, advisory or business-partnering responsibilities, responsibility for validating technology-generated outputs, and cross-functional collaboration. Learning and organizational support (LOS; five items) assesses access to AI-related learning opportunities and approved tools, time/funding/encouragement for professional development, managerial support for responsible experimentation, and useful guidance from employers, professional bodies, or training providers. LOS is entered both as a main-effect contextual resource and, after standardization, in interaction with competence evolution. Competence evolution (CE) is modeled as a theory-driven multidimensional aggregate of four first-order dimensions. Digital and AI competence (DAC; four items) covers understanding AI capabilities and limitations, effective prompting, confidence with data and analytics tools, and detection of hallucinations or data-quality problems. Analytical and strategic

competence (ASC; four items) covers translating analysis into business insight, judgment under ambiguity, integrating financial and nonfinancial information, and evaluating scenarios and risks. Human and advisory competence (HAC; four items) covers communication, stakeholder advice, cross-functional collaboration, and adaptive learning. Ethical and governance competence (EGC; four items) covers confidentiality and security, bias and fairness, human accountability, and professional skepticism/documentation when evaluating AI-assisted outputs. CE is calculated as the mean of the four dimension scores so that each domain contributes equally.

Career sustainability (CS) is likewise treated as a multidimensional aggregate rather than a reflective single trait. Career happiness and meaning (CHM; three items) assesses satisfaction with career direction, professional meaning or accomplishment, and an attractive long-term future. Career health and well-being (CHW; three items) assesses adaptation without unsustainable strain, long-term well-being, and the ability to manage continuing learning demands. Career productivity and employability (CPE; three items) assesses the future value of current skills, confidence in adapting to AI-reshaped roles, and expected continued employability/productivity. CS is the equal-weight mean of CHM, CHW, and CPE, reflecting the happiness-health-productivity logic in the sustainable-career framework (De

Vos et al., 2020).

3.3 Measurement-quality assessment

First-order reflective dimensions were evaluated using Cronbach's alpha, standardized loadings on the first principal component, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). Alpha and CR values of approximately .70 or higher were treated as evidence of satisfactory internal consistency, while AVE values around .50 or higher and loadings around .70 or higher were used as convergent-validity guides (Cronbach, 1951; Fornell & Larcker, 1981). Discriminant validity was evaluated using HTMT, with .85 used as a conservative reference value (Henseler et al., 2015). Because CE and CS

deliberately combine complementary dimensions rather than interchangeable indicators, internal-consistency coefficients across the dimensions were not used to judge the validity of those higher-order aggregate indices. Potential common method bias was assessed using two statistical diagnostics. A single unrotated component extracted from all focal items accounted for 21.85% of variance, well below the level that would indicate one dominant common factor. Full-collinearity VIFs for AIA, PRT, LOS, CE, and CS ranged from 1.205 to 2.167, below the 3.3 diagnostic threshold proposed by Kock (2015). These diagnostics cannot eliminate the possibility of common method bias, but they provide no evidence of a dominant single-source factor or problematic full collinearity (Podsakoff et al., 2003).

Table 2. First-order measurement quality.

Construct	Items	α	CR	AVE	Loading range
AIA	5	0.840	0.887	0.611	0.753-0.810
PRT	5	0.854	0.895	0.631	0.781-0.811
LOS	5	0.844	0.889	0.615	0.756-0.815
DAC	4	0.802	0.871	0.628	0.781-0.810
ASC	4	0.817	0.879	0.646	0.781-0.821
HAC	4	0.800	0.870	0.626	0.768-0.802
EGC	4	0.765	0.850	0.587	0.748-0.802
CHM	3	0.764	0.864	0.679	0.820-0.829
CHW	3	0.771	0.868	0.686	0.826-0.833
CPE	3	0.731	0.848	0.650	0.787-0.823

AIA = AI adoption intensity; PRT = professional role transformation; LOS = learning/organizational support; DAC = digital/AI competence; ASC = analytical/strategic competence; HAC = human/advisory competence; EGC = ethical/governance competence; CHM = career happiness/meaning; CHW = career health/well-being; CPE = career productivity/employability. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Maximum HTMT = .579.

3.4 Structural analysis

Composite scores were standardized before structural estimation. H1 was estimated as PRT regressed on AIA. H2 and H3 were estimated jointly in a CE equation containing AIA and PRT. Career sustainability was regressed on CE, PRT, AIA, LOS, and the standardized CE $\times$ LOS product term, allowing H4, H5, and H7 to be evaluated in the same outcome equation. Ordinary least squares estimates were reported with HC3 heteroskedasticity-consistent standard errors, which provide improved finite-sample robustness to nonconstant error variance (MacKinnon & White, 1985). Indirect effects were evaluated using 5,000 nonparametric bootstrap resamples. The primary mediation test (H6) is the product of PRT $\rightarrow$ CE and CE $\rightarrow$ CS. The serial indirect effect multiplies AIA $\rightarrow$ PRT, PRT $\rightarrow$ CE, and CE $\rightarrow$ CS. A parallel AIA $\rightarrow$ CE $\rightarrow$ CS indirect effect and their combined total indirect effect were also estimated to clarify the mechanisms through which AI adoption relates to career sustainability. Bootstrap confidence intervals that excluded zero were treated as evidence of a statistically supported indirect relationship (Preacher & Hayes, 2008; Hayes, 2022). Effect sizes were calculated as Cohen's f^2 by comparing the full model with a reduced model omitting the focal predictor (Cohen, 1988). Predictive relevance was evaluated using 10-fold cross-validation and $Q^2 = 1 - \text{PRESS/SSO}$, where values above zero indicate that the model predicts held-out observations better than an intercept-only benchmark. Robustness models additionally controlled for professional experience, career level, organization size, formal AI training in the previous 24 months, and country. Finally, the structural equations were re-estimated separately

for Nigeria, Ghana, and Kenya. Pairwise coefficient differences were examined with 1,500 bootstrap resamples. These country comparisons are presented as exploratory evidence of structural stability rather than as a formal latent measurement-invariance test.

4. Results

4.1 Descriptive patterns and construct relationships

Mean scores were above the scale midpoint for all focal constructs. AI adoption intensity averaged 4.786 (SD = .837), professional role transformation 4.817 (SD = .872), learning support 4.804 (SD = .826), competence evolution 4.983 (SD = .543), and career sustainability 4.878 (SD = .590). The four competence dimensions were all relatively high, with ethical/governance competence having the highest mean ($M = 5.088$) and digital/AI competence the lowest ($M = 4.900$). Career productivity/employability ($M = 4.997$) exceeded career happiness/meaning ($M = 4.872$) and career health/well-being ($M = 4.767$), suggesting that respondents were somewhat more confident about future professional value than about the well-being implications of technological change. The correlation structure was consistent with the proposed mechanism. AIA correlated with PRT ($r = .491$) and CE ($r = .514$). PRT showed the strongest bivariate relationship with CE ($r = .603$). CE correlated .538 with CS, compared with .349 between PRT and CS. LOS correlated .350 with CS and .331 with CE. The AIA-LOS correlation was comparatively small ($r = .067$), indicating that individual AI adoption intensity and perceived learning support were empirically distinct.

Table 3. Descriptive statistics and correlations among focal constructs.

Construct	M	SD	1	2	3	4	5
1. AIA	4.786	.837	1				
2. PRT	4.817	.872	.491	1			

Construct	M	SD	1	2	3	4	5
3. LOS	4.804	.826	.067	.197	1		
4. CE	4.983	.543	.514	.603	.331	1	
5. CS	4.878	.590	.330	.349	.350	.538	1

N = 600. AIA = AI adoption intensity; PRT = professional role transformation; LOS = learning/organizational support; CE = competence evolution; CS = career sustainability. All correlations $\geq .197$ are $p < .001$; AIA-LOS is not statistically significant at .05.

4.2 Structural hypotheses

H1 was supported. AI adoption intensity was strongly associated with professional role transformation ($\beta = 0.491$, HC3 SE = 0.035, $t = 14.09$, $p < .001$, 95% CI [0.423, 0.560]). AIA alone explained 24.1% of the variance in PRT ($R^2 = 0.241$), and its f^2 effect size was .318, indicating a moderate-to-large contribution. The result supports the premise that professionals who integrate AI more intensively into accounting and finance work experience greater movement away from routine processing and toward interpretation, advisory work, cross-functional collaboration, and technology oversight. H2 and H3 were also supported. In the competence-evolution equation, AI adoption intensity retained a positive association with CE ($\beta = 0.286$, SE = .036, $t = 7.98$, $p < 0.001$, 95% CI [0.216, 0.357]), while professional role transformation had an even larger association ($\beta = 0.462$, SE = 0.035, $t = 13.32$, $p < 0.001$, 95% CI [.394, 0.530]). Together, AIA and PRT explained 42.6% of CE variance. The f^2 values were .108 for AIA and 0.283 for PRT, indicating that role transformation had the larger proximal association with competence development once AI use was taken into account. H4 was

supported. Competence evolution was positively related to career sustainability ($\beta = 0.414$, SE = 0.048, $t = 8.64$, $p < 0.001$, 95% CI [0.320, 0.508]) in the final model. Its f^2 value of .134 was the largest contributor in the career-sustainability equation. By contrast, H5 was not supported: the direct PRT $\rightarrow$ CS coefficient was $\beta = 0.013$ (SE = 0.042, $p = 0.764$), with a 95% CI spanning -0.069 to 0.094 and a negligible f^2 of approximately 0.000. This pattern shows that transformed roles were not independently associated with sustainable career outcomes after competence, AI adoption, and learning support were considered.

The final model explained 33.2% of career-sustainability variance. AIA retained a small positive direct association with CS ($\beta = 0.096$, $p = 0.018$; $f^2 = 0.009$), while LOS had a positive main association ($\beta = -0.206$, $p < 0.001$; $f^2 = 0.055$). H7, however, was not supported. The CE $\times$ LOS interaction was small and statistically nonsignificant ($\beta = 0.031$, SE = 0.030, $p = 0.304$, 95% CI $[-0.028, .091]$; $f^2 = 0.002$). Thus, support appears to contribute additively to career sustainability rather than systematically increasing the slope linking competence evolution to sustainability in the pooled sample.

Table 4. Structural path estimates.

Hyp.	Path	β	SE	t	p	95% CI	f^2	Decision
H1	AIA $\rightarrow$ PRT	0.491	0.035	14.09	<.001	[0.423, 0.560]	0.318	Supported

Hyp.	Path	β	SE	t	p	95% CI	f ²	Decision
H2	AIA $\rightarrow$ CE	0.286	0.036	7.98	<.001	[0.216, 0.357]	0.108	Supported
H3	PRT $\rightarrow$ CE	0.462	0.035	13.32	<.001	[0.394, 0.530]	0.283	Supported
H4	CE $\rightarrow$ CS	0.414	0.048	8.64	<.001	[0.320, 0.508]	0.134	Supported
H5	PRT $\rightarrow$ CS	0.013	0.042	0.30	0.764	[-0.069, 0.094]	0.000	Not supported
H7	CE $\times$ LOS $\rightarrow$ CS	0.031	0.030	1.03	0.304	[-0.028, 0.091]	0.002	Not supported

Standardized coefficients are reported with HC3 heteroskedasticity-consistent standard errors. The CE/CS outcome model also included AIA and LOS main effects. H7 is the CE $\times$ LOS interaction.

Figure 2
Structural Model Results with Standardized Path Coefficients

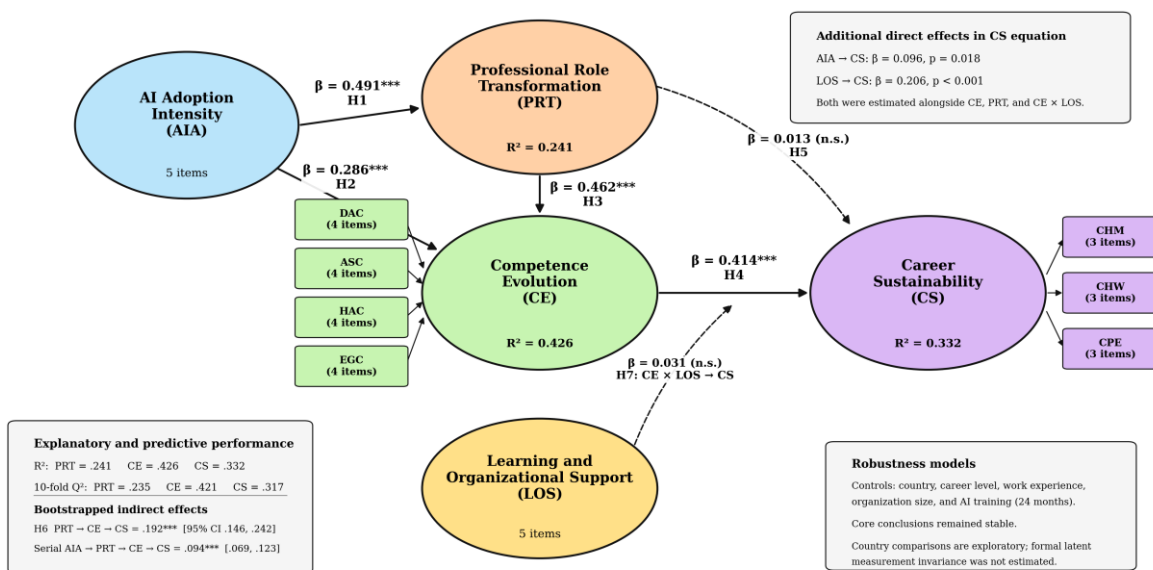


Figure 2. Structural model results with standardized path coefficients. Solid arrows denote supported hypothesized paths, while dashed arrows denote nonsignificant hypotheses. R² values indicate explained variance in the endogenous outcomes; Q² values are based on 10-fold cross-validation. CE and CS are multidimensional aggregate indices. Additional direct effects included in the career-

sustainability equation (AIA $\rightarrow$ CS and LOS $\rightarrow$ CS), the bootstrapped indirect effects, and robustness controls are summarized within the figure.

Figure 2 consolidates the structural results. AI adoption intensity was positively associated with professional role transformation ($\beta = 0.491$, $p < 0.001$) and competence evolution ($\beta = 0.286$, $p < .001$), while professional role transformation was

positively associated with competence evolution ($\beta = 0.462$, $p < 0.001$). Competence evolution was in turn positively associated with career sustainability ($\beta = 0.414$, $p < .001$). The near-zero direct PRT $\rightarrow$ CS path ($\beta = 0.013$, $p = .764$) contrasts with the supported indirect pathway through competence evolution ($\beta = 0.192$, 95% bootstrap CI [.146, 0.242]), reinforcing the interpretation that capability development, rather than role change alone, links AI-related transformation to sustainable career outcomes. In the career-sustainability equation, AIA retained a smaller positive direct association ($\beta = 0.096$, $p = .018$) and LOS had a positive main association ($\beta = 0.206$, $p < 0.001$), whereas the CE $\times$ LOS interaction was nonsignificant ($\beta = 0.031$, $p = 0.304$). The model explained 24.1% of the variance in PRT, 42.6% in CE, and 33.2% in CS; predictive Q^2 values were 0.235, 0.421, and 0.317, respectively.

4.3 Mediation, serial indirect effects, and predictive relevance

The mediation result provides the central empirical finding. The bootstrapped PRT $\rightarrow$ CE $\rightarrow$ CS indirect effect was 0.192, with a 95% bootstrap CI from .146 to .242. Because this interval excludes zero while the direct PRT $\rightarrow$ CS path is essentially zero, the data exhibit an

indirect-only mediation pattern: professional role transformation is related to career sustainability primarily through competence evolution rather than through an independent direct channel. H6 is therefore supported. The serial pathway from AI adoption through role transformation and competence evolution to career sustainability was also supported (indirect effect = .094, 95% bootstrap CI [.069, .123]). A second AI pathway operating directly through competence evolution was .119 (95% CI [.084, .158]). The combined AIA indirect effect through CE-related pathways was .213 (95% CI [.163, .265]). These effects indicate that a substantial share of the association between AI adoption and sustainable career outcomes is carried by capability development, both directly and through the changed professional role. Cross-validated predictive results were positive for all endogenous constructs. Ten-fold predictive Q^2 values were .235 for PRT, .421 for CE, and .317 for CS. The models therefore predicted held-out observations better than intercept-only benchmarks, with particularly strong predictive relevance for competence evolution. This reinforces the explanatory result that competence development is not merely statistically significant within the estimation sample; the transformation model retains useful predictive structure under repeated out-of-sample testing.

Table 5. Indirect effects and predictive relevance.

Effect / predictive metric	Estimate	95% bootstrap CI	p
H6: PRT $\rightarrow$ CE $\rightarrow$ CS	0.192	[0.146, 0.242]	<.001
Serial: AIA $\rightarrow$ PRT $\rightarrow$ CE $\rightarrow$ CS	0.094	[0.069, 0.123]	<.001
AIA $\rightarrow$ CE $\rightarrow$ CS	0.119	[0.084, 0.158]	<.001
AIA total CE-related indirect	0.213	[0.163, 0.265]	<.001
Predictive Q^2 : PRT	0.235	—	—
Predictive Q^2 : CE	0.421	—	—
Predictive Q^2 : CS	0.317	—	—

Indirect effects use 5,000 bootstrap resamples. Predictive Q^2 uses 10-fold cross-validation and $Q^2 = 1 - \text{PRESS}/\text{SSO}$.

4.4 AI-use intensity in practice

A descriptive segmentation by reported AI-use frequency provides an intuitive view of the model. Respondents who reported never using AI for work had mean AIA of 3.41, PRT of 4.20, CE of 4.57, and CS of 4.61. At the other end of the spectrum, daily users averaged 5.82 on AIA, 5.41 on PRT, 5.46 on CE, and 5.13 on CS. The steepest gradient is visible for AI adoption itself, as expected, but role transformation and competence evolution also rise steadily across use-frequency groups. Career sustainability increases more gradually, consistent with the structural result that technology use does not

translate one-for-one into career outcomes; competence is the more proximal link. Formal training shows a similar descriptive pattern. Respondents reporting AI/GenAI training in the previous 24 months had higher means for AIA (5.01 versus 4.57), PRT (4.98 versus 4.66), CE (5.12 versus 4.85), LOS (5.05 versus 4.57), and CS (4.99 versus 4.77) than those without such training. Because training was not randomized, these differences should not be interpreted causally. They nevertheless reinforce the practical importance of structured learning opportunities in a profession where the technology and associated standards are evolving quickly.

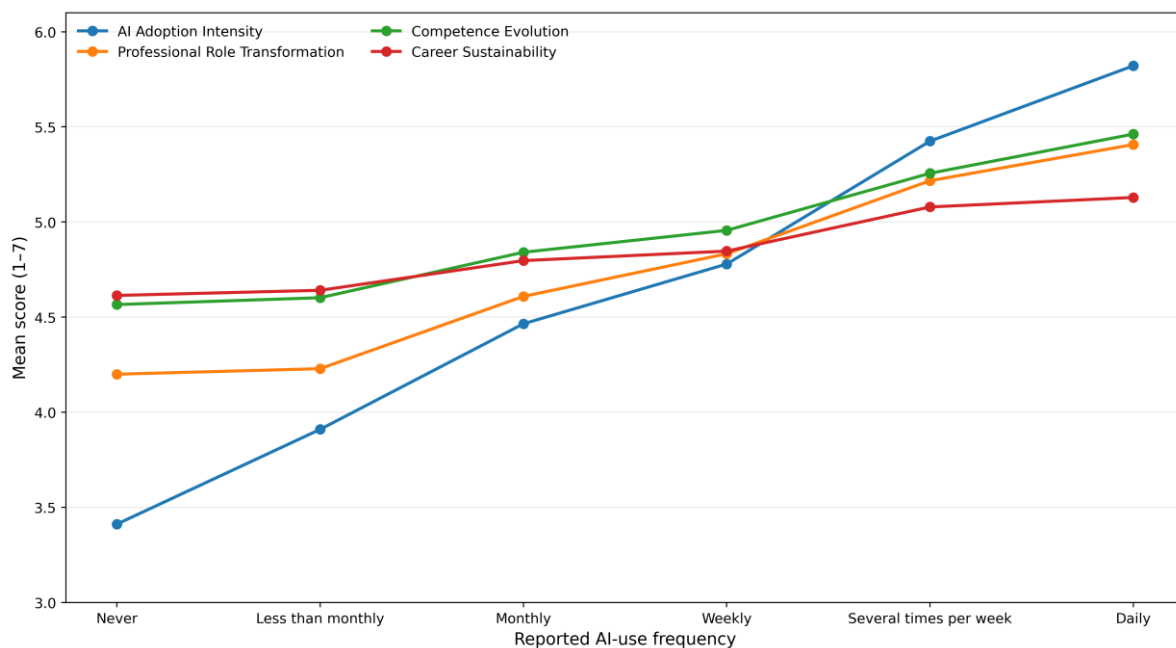


Figure 3. Mean construct scores by reported AI-use frequency (N = 600). The profile is descriptive; group differences are not interpreted as causal effects of use frequency.

4.5 Cross-country patterns and robustness

The focal construct means were highly similar across Nigeria, Ghana, and Kenya. Country ANOVAs did not reach statistical significance for AIA ($p = .674$), PRT ($p = .354$), LOS ($p = .994$), CE ($p = .826$), and CS ($p = .581$), with trivial eta-squared values. Of the seven first-order competence/career dimensions, only career

health/well-being showed a weak country difference ($p = 0.043$, $\eta^2 = 0.010$), indicating a very small share of variance attributable to country. The structural paths were also broadly stable. H1 ranged from .457 in Nigeria to 0.543 in Ghana; H2 ranged from 0.251 to 0.306; H3 ranged from 0.436 to 0.492; and H4 ranged from .341 to 0.456. Bootstrap pairwise comparisons found no statistically significant country

differences for H1-H5. The only pairwise difference below .05 involved the already nonsignificant H7 interaction (Kenya versus Nigeria, difference = -0.195 , bootstrap $p = 0.009$). Because the pooled moderation hypothesis was not supported and formal latent measurement invariance was not estimated, this isolated interaction difference is treated as exploratory rather than substantive evidence of country-specific moderation. Robustness models including experience, career level, organization size, AI training, and country dummies did not

change the principal conclusions. AIA remained associated with PRT ($\beta = 0.476$, $p < 0.001$). In the CE equation, AIA ($\beta = 0.268$, $p < 0.001$) and PRT ($\beta = 0.453$, $p < 0.001$) remained significant. In the CS equation, CE remained significant ($\beta = 0.411$, $p < 0.001$), PRT remained nonsignificant ($\beta = 0.017$, $p = 0.682$), LOS remained positive ($\beta = 0.206$, $p < 0.001$), and the $CE \times LOS$ interaction remained nonsignificant ($\beta = 0.036$, $p = 0.242$). The substantive pattern is therefore robust to several demographic and organizational controls.

Table 6. Exploratory country-specific standardized coefficients.

Path	Ghana	Kenya	Nigeria
H1	0.543	0.472	0.457
H2	0.306	0.299	0.251
H3	0.492	0.436	0.453
H4	0.445	0.341	0.456
H5	0.086	0.038	-0.026
H7	0.003	-0.064	0.131

H1 = AIA → PRT; H2 = AIA → CE; H3 = PRT → CE; H4 = CE → CS; H5 = PRT → CS; H7 = CE × LOS → CS. Bootstrap pairwise differences for H1-H5 were not significant.

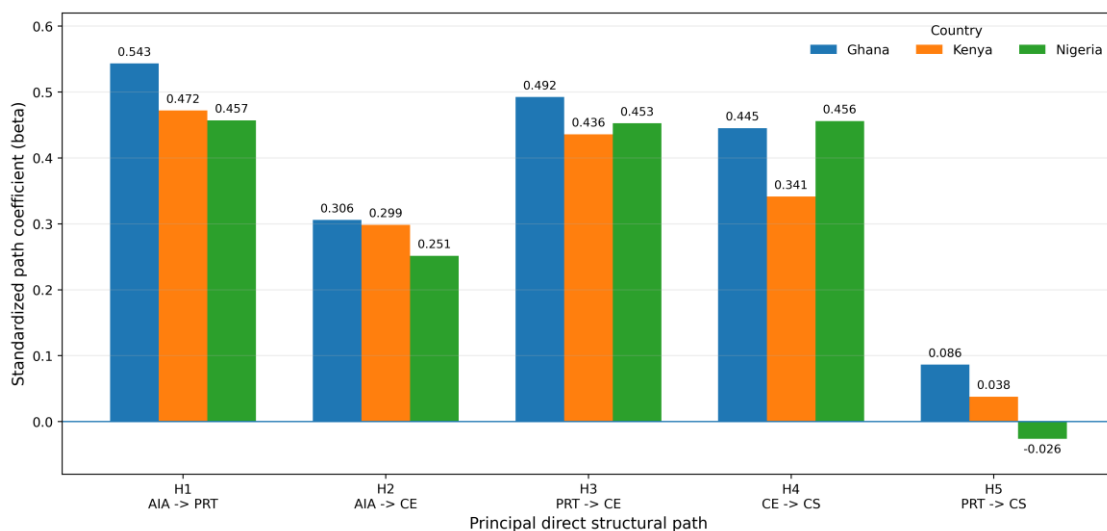


Figure 4. Country-specific standardized coefficients for the five principal direct structural paths. Pairwise bootstrap differences for H1-H5 were not statistically significant; cross-country comparisons are exploratory because formal measurement invariance was not tested.

5. Discussion, Contributions, and Implications

5.1 Discussion

The central question was how AI-related changes in accounting work become career outcomes that can be sustained over time. The evidence points to a capability-based mechanism. AI adoption is associated with transformed professional roles, transformed roles are strongly associated with competence evolution, and competence evolution is the strongest proximal predictor of career sustainability in the model. The contrast between H4 and H5 is particularly revealing. Competence evolution remains substantively important, whereas professional role transformation has almost no direct relationship with career sustainability after competence is included. Changed work, by itself, is therefore not a career resource; its value depends on whether professionals develop the capabilities needed to perform and govern that work effectively.

The AIA-PRT relationship is consistent with the automation-augmentation perspective. Professionals who use AI more intensively report less exclusive reliance on routine processing and greater involvement in interpretation, advisory responsibilities, validation of technology-generated outputs, and cross-functional collaboration. Comparable patterns have been reported in Tunisia (Assidi et al., 2025) and Saudi Arabia (Mgammal, 2024), while recent reviews describe AI and RPA as increasingly embedded across accounting and auditing despite unresolved governance and capability gaps (Kassar & Jizi, 2026). Audit-field evidence adds an important qualification: efficiency gains occur alongside concerns about explainability, bias, privacy, reliability, and overreliance (Kokina et al., 2025), and AI investment can improve audit quality while reducing some labor inputs (Fedyk et al., 2022). Automation and augmentation should therefore be understood as concurrent features of professional redesign rather than as mutually exclusive futures. The competence results sharpen that interpretation. AI adoption has a direct positive association with competence evolution, but the coefficient for role

transformation is larger when both predictors enter the model. Regular use of AI may build familiarity with the tools, yet capability formation appears to depend even more on the new demands created by redesigned work. Roles that require interpretation, advice, validation, and cross-functional collaboration create pressure for integrated digital, analytical, human, and governance capabilities. That pattern fits human capital theory, in which skill investment becomes more valuable when it is aligned with changing productive tasks (Becker, 1964), and it accords with evidence that digitalization shifts accounting away from routine activity toward analytical and interactive work (Pargmann et al., 2023). African competency research similarly shows that technology proficiency is only one part of the requirement; data management, critical thinking, problem solving, business intelligence, and professional capabilities remain essential (Mbizi et al., 2022).

The CE-CS relationship broadens the way career consequences of AI can be understood. Debate about AI in accounting often collapses into a choice between job loss and job survival. A sustainable-career perspective asks a more demanding question: can professionals remain productive and employable while preserving meaning, well-being, and the capacity to adapt? Respondents who reported stronger digital/AI, analytical/strategic, human/advisory, and ethical/governance capabilities also reported stronger career meaning, greater confidence in handling technological change, and better expectations of future employability. This pattern is consistent with wider career research showing that skill development can help convert perceived AI disruption into career adaptability (Burhan, 2024). H5 is informative precisely because it is not significant. Redesigning a role does not automatically produce a better or more sustainable career. Work may become more strategic and technology-enabled while also becoming difficult to perform if knowledge, judgment, confidence, or institutional support lag behind the new demands. This interpretation helps reconcile optimistic accounts of technology-enabled business partnering with evidence of role ambiguity and conflict during digitalization (van Slooten et al., 2026). It also

echoes Samiolo et al. (2024), who show that automation can remove some of the practical learning opportunities through which professional judgment develops. Once competence is treated as the transmission mechanism, the apparent contradiction is reduced: role change creates new possibilities, while capability determines whether those possibilities translate into professional value. The mediation estimates support this mechanism. The indirect PRT-CE-CS effect is statistically robust, as is the longer AIA-PRT-CE-CS sequence. These findings extend adoption-oriented studies in emerging economies. Rahman et al. (2025), for example, show how trust, perceived usefulness, perceived threat, and financial feasibility shape AI adoption among accountants in Bangladesh, while Toumeh (2024) examines the potential integration of large language models in Jordanian accounting practice. Such work helps explain why AI is adopted. The present evidence addresses the next stage by showing how post-adoption role change is connected to longer-term career outcomes through capability development.

The findings for learning and organizational support are more qualified. LOS is positively associated with career sustainability, but it does not significantly alter the slope between competence evolution and career sustainability in the pooled sample. Support therefore appears to operate mainly as an additive resource. Access to tools, time, training, encouragement, and professional guidance can reduce uncertainty and strengthen confidence in career continuity even when they do not amplify the return to competence. This distinction matters in the African context, where ACCA (2025) reports a gap between concern about future skills and satisfaction with AI training opportunities. Another possibility is measurement: the LOS construct captures a broad institutional climate, whereas moderation may depend on more specific resources. Future work should distinguish access to approved tools, supervisory support, training quality, protected learning time, and professional-body guidance.

Country-level results offer a useful check on the generality of the model. Nigeria, Ghana, and

Kenya differ in their institutional structures, sector composition, digital ecosystems, and professional accounting environments, yet the focal means and principal structural coefficients are remarkably similar. None of the H1-H5 paths differs significantly across the three samples. The evidence is therefore compatible with a common adaptation process in these settings: AI exposure changes the work, changed work raises capability requirements, and stronger capabilities are associated with more sustainable career outcomes. This should not be read as evidence that all emerging economies operate in the same way; rather, it shows that the proposed mechanism is not confined to a single national setting in the present sample. The descriptive AI-use profile makes the same point in a more intuitive way. Moving from non-use to daily use is accompanied by steep increases in AIA, PRT, and CE, whereas career sustainability rises more gradually. That divergence is consistent with the mediation results. Technology can alter work quickly, while career outcomes depend on slower processes involving learning, identity, opportunity, well-being, and employability. For organizations, this means that usage statistics alone are a poor measure of a successful AI program. Finance leaders also need to know whether employees are developing the complementary human capital required to make the redesigned work sustainable.

5.2 Theoretical Contributions

One contribution is to move accounting-AI research beyond adoption and into the post-adoption redesign of professional work. Technology-acceptance and diffusion models explain why organizations or individuals begin using AI, but they are less suited to explaining what happens once the technology becomes embedded in everyday practice. Treating professional role transformation as an outcome associated with AI adoption places technological change inside the actual structure of accounting work rather than treating use as the endpoint of analysis. A second contribution is the identification of competence evolution as the mechanism linking role change with career outcomes. This helps explain why optimistic and pessimistic accounts of AI can both contain part

of the truth. AI can automate familiar tasks and unsettle established roles while also opening higher-value forms of work. Whether that shift becomes professionally beneficial depends on human capital. The indirect-only PRT-CE-CS pattern provides empirical support for that argument.

The paper also links accounting digitalization with sustainable-career theory. Sustainable-career research evaluates happiness, health, and productivity across person, context, and time (De Vos et al., 2020), whereas accounting research has rarely used this broader career lens when examining AI. In the present model, career sustainability is represented through career meaning, well-being/adaptability, and productivity/employability. This framing moves the analysis beyond forecasts of job loss and asks whether accountants can remain both valuable and viable as technology changes their work. A further contribution is contextual. Much of the literature remains concentrated in single-country or developed-market settings. The balanced samples from Nigeria, Ghana, and Kenya make it possible to examine whether the central mechanism is highly context-bound. The broad similarity of the structural relationships across the three countries suggests that the transformation-to-competence-to-career process may travel across comparable emerging-economy settings, although the isolated country difference in the unsupported moderation path is a reminder that organizational contingencies should not be assumed to operate identically everywhere.

5.3 Practical, Professional, and Policy Implications

For accounting firms and finance leaders, AI implementation should be treated as a work-and-skill transformation program, not simply as software deployment. Counts of licenses, usage frequency, automated hours, or AI-enabled processes provide only a partial picture. Managers also need to identify which tasks are being automated, which responsibilities are being augmented, which controls are newly required, and which capabilities employees must develop. Role redesign and learning architecture are therefore best planned together. The training

implication is equally clear. Digital and AI literacy matters, including an understanding of model limitations, prompt design, data-quality risks, and hallucination detection, but it is not sufficient on its own. The model also points to analytical and strategic judgment, communication and advisory capability, cross-functional collaboration, and ethical/governance competence. A training strategy built mainly around prompt engineering would therefore be too narrow. The professional value of accountants in an AI-intensive environment rests on combining technology with judgment, interpretation, trust, and accountable advice.

Professional accountancy organizations can translate this evidence into more differentiated continuing professional development. Instead of generic digital-awareness courses, CPD can be linked to the tasks and responsibilities encountered at different career stages: foundational AI literacy for early-career professionals, analytics and model-governance capability for managers, and strategic AI oversight, risk governance, and business partnering for senior finance leaders. Ethical guidance should also make clear that professional accountability remains human when AI contributes to a work product, consistent with the concerns raised by Munoko et al. (2020) and Zhang et al. (2023). Accounting education faces the same challenge. Tiron-Tudor et al. (2025) show that labor-market demand for digital skills can move faster than students' perceptions of which capabilities matter. Programs therefore need integrated exposure to AI-assisted accounting cases, data analytics, professional skepticism, communication, ethics, and scenario-based decision-making rather than a small number of isolated technology electives. Maulana et al. (2025) also suggest that AI learning experiences can influence accounting career self-efficacy and commitment. Evidence from accounting education indicates that generative AI performs better on lower- to mid-order learning tasks than on higher-order work, which strengthens the case for curricula that preserve and develop judgment, evaluation, and professional reasoning rather than delegating them to AI (Tharapos et al., 2025).

For policymakers, the main issue is the pace and

distribution of reskilling. If AI adoption moves faster than skill formation, digital transformation may widen professional inequality between workers who have access to appropriate tools and structured learning and those who do not. Investment in digital infrastructure, continuing education, responsible-AI standards, cybersecurity, data governance, and partnerships among universities, employers, and professional bodies can lower the cost of human-capital renewal. This priority is consistent with African professional evidence showing concern about future skills and uneven satisfaction with AI training (ACCA, 2025), as well as the World Economic Forum's (2025) expectation that large-scale reskilling will accompany AI-driven changes in task structure. Career sustainability should also be monitored as an implementation outcome. Employee surveys and workforce analytics can examine whether AI-enabled redesign is improving meaning, manageable workload, confidence, employability, and productive contribution. Where role transformation advances but competence and career sustainability do not, organizations have evidence that work is changing faster than employees are being equipped to perform it successfully.

6. Limitations, Future Research, and Conclusion

6.1 Limitations and Future Research

The conclusions should be read within several limits. The design is observational. Although the linked-wave structure and hypothesized ordering separate the measurement blocks, they do not establish temporal or experimental causality. Reverse or reciprocal relationships remain possible: more capable professionals may adopt AI more intensively, and people with stronger career prospects may be given greater access to advanced work. Repeated longitudinal measurements, organizational adoption events, and quasi-experimental designs would provide stronger tests of temporal ordering. The evidence also relies on self-reported professional perceptions. The statistical diagnostics do not suggest severe common-method concentration, but no diagnostic can remove all same-source

bias. A useful next step would combine survey measures with system logs of AI use, training completion records, supervisor assessments, objective skill tests, promotion histories, performance indicators, and turnover or mobility data. CE and CS were deliberately specified as multidimensional aggregate indices. That choice is consistent with the argument that competence and sustainable careers depend on complementary domains, but it also means that the higher-order scores should not be interpreted as reflective latent factors with interchangeable dimensions. Future research could compare formative, hierarchical-component, bifactor, and profile-based specifications and test whether different competence configurations lead to similar career outcomes. The country comparison is exploratory rather than definitive. The balanced design supports useful structural comparisons, but formal latent measurement invariance was not estimated within the present composite framework. Replication using confirmatory multi-group SEM and explicit invariance testing would provide a firmer basis for comparing coefficient magnitudes. Extending the design to additional African, Asian, Latin American, and Middle Eastern economies would also show how far the observed mechanism travels beyond Nigeria, Ghana, and Kenya. Learning support was measured broadly, and the proposed interaction was not supported. More granular measures could separate formal AI-training quality, protected learning time, and access to approved enterprise tools, and psychological safety for experimentation, managerial coaching, peer learning, professional-body guidance, and infrastructure reliability. These resources may condition different stages of the transformation process rather than the CE-CS relationship specifically. AI itself is also a moving target. Generative models, agentic systems, enterprise controls, and professional standards are developing quickly, so competencies that are valuable today may change in content or relative importance. Longitudinal research should therefore treat AI competence as dynamic, track skill renewal and depreciation, and identify which human capabilities remain complementary as machine capability advances.

6.2 Conclusion

The evidence does not support a simple replacement story for accounting. Across 600 professionals in Nigeria, Ghana, and Kenya, more intensive AI adoption is associated with greater role transformation; AI adoption and role transformation are both associated with competence evolution; and competence evolution is strongly associated with career sustainability. Once competence is considered, the direct relationship between role transformation and career sustainability is effectively absent, whereas the indirect route through competence remains robust. That result shifts attention from whether accounting roles will change to whether the profession can convert change into capability quickly enough. Digital and AI capability, analytical judgment, advisory and communication skills, and ethical/governance competence form the bridge between technological disruption and sustainable professional value. Organizational learning support contributes positively to career sustainability, but it does not substitute for capability development. For emerging economies, the distinction matters. If AI adoption outpaces reskilling, professionals may experience rapidly changing roles without gaining durable career benefits. When adoption is accompanied by broad competence development, however, accountants can move away from routine production toward technology-enabled interpretation, governance, and strategic partnership. The more sustainable future is therefore not a choice between automation and human work, but a professionally governed form of augmentation in which human capabilities evolve alongside the technology.

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