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Article

Generative AI-enabled intelligent auditing: an organizational adaptation mechanism study based on dynamic capability theory

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ABSTRACT

This study investigates how audit organizations leverage generative artificial intelligence technologies to enhance auditing capabilities through organizational adaptation mechanisms, examining the role of dynamic capabilities in facilitating successful AI adoption and performance improvements. A quantitative cross-sectional survey collected data from 312 audit professionals across diverse organizational contexts. Structural equation modeling examined relationships between dynamic capabilities, generative AI adoption, organizational adaptation mechanisms, and auditing performance with comprehensive measurement validation. Dynamic capabilities significantly influence generative AI adoption ($\beta = 0.453$, $p < 0.001$), which drives organizational adaptation mechanisms ($\beta = 0.312$, $p < 0.001$) that enhance auditing performance ($\beta = 0.378$, $p < 0.001$). Organizational adaptation mechanisms mediate 41.4% of the capability-performance relationship. The model explains 28.3% variance in AI adoption, 35.7% in adaptation mechanisms, and 31.2% in auditing performance. Audit organizations should prioritize developing sensing, seizing, and reconfiguring capabilities before AI investments, requiring comprehensive change management addressing structural, processual, and cultural dimensions simultaneously. AI-driven competitive advantages emerge through organizational transformation processes, with dynamic capabilities as antecedents and adaptation mechanisms as mediating processes.

1. Introduction

The contemporary business environment is characterized by unprecedented technological disruption, wherein generative artificial intelligence has emerged as a transformative force, reshaping organizational capabilities and competitive dynamics across diverse industry sectors [1]. This technological paradigm shift transcends traditional automation concepts, encompassing sophisticated cognitive processes that enable organizations to enhance decision-making quality, optimize operational efficiency, and create novel value propositions for stakeholders [2]. As organizations grapple with the imperative to remain competitive in an increasingly digital economy, the successful integration of generative AI technologies has become a critical determinant of long-term sustainability and market leadership [3]. Within professional service industries, the auditing profession exemplifies the complex challenges and opportunities associated with AI-driven transformation [4]. The traditional paradigms of audit practice, historically grounded in manual procedures and human judgment, are being fundamentally reconceptualized through artificial intelligence capabilities that promise enhanced accuracy, efficiency, and analytical depth [5]. However, this technological evolution is accompanied by significant regulatory and legal complexities that audit organizations must navigate carefully to maintain professional standards while leveraging innovative capabilities [6]. The relationship between artificial intelligence adoption and organizational performance in audit contexts demonstrates that successful implementation requires more than technological proficiency; it demands comprehensive organizational adaptation and capability development [7].

The fundamental concepts underlying the use of AI reflect how essential it is to possess adaptable skills for effective utilization of technology [8]. Firms that excel at identifying new technology possibilities, moving to implement them, and adapting their resources for AI technologies fare better and attain long-term competitive advantage. This perspective corroborates resource-based theory, which states that an advantage in competition is a result of the unique combination and utilization of an organization's resources and capabilities [9]. The sustained success of generative AI-powered optimization intelligence is not just a function of possessing cutting-edge technology but also of the firm's capacity to develop and sustain AI-enabled capabilities that deliver continuous value [10]. Applying generative AI in reality indicates it is useful, but complex [11]. Supply chain and operations management research indicates that applying AI requires advanced models that take into account the technology, organization, and environment [12]. Generative AI has been employed in manufacturing to enhance directed buying and enable company operations to become simpler [13]. Additional resources with elaborate information reveal that the application of AI in the workplace is becoming increasingly complicated [14].

The human elements of AI use are extremely important to the success of an organization [15]. Studies of human-AI collaboration in finance reveal that effective service development requires close attention to the interplay between technology and human capabilities [16]. Similarly, industries are confronted with challenging issues in developing and utilizing AI models that mesh well with their existing systems and human capabilities [17]. The strategic implications of utilizing generative AI extend beyond merely enhancing operations; they encompass significant shifts in how companies establish and sustain competitive advantage [18]. Firms across various industries are discovering that AI technologies are capable of generating new methods of value and service delivery [19]. However, the identification of critical success and failure factors in AI lifecycle management reveals that technological sophistication alone is insufficient for sustainable implementation [20]. The application of generative artificial intelligence in government and organizations reveals that effective adoption requires close attention to adhering to regulations, stakeholder engagement, and long-term strategy alignment [21]. Drawing on these theoretical and empirical insights, this study examines the mechanisms by which organizations can utilize generative AI technologies to enhance their auditing capabilities and establish sustainable competitive advantages.

2. Theoretical framework and hypothesis development

2.1 Dynamic capability theory

Dynamic capability theory is a vital concept demonstrating how organizations can maintain a lead over others when changes are rapid. The theory has a trio of components: the capabilities of sensing enable organizations to observe and make sense of chances and risks around them; the capabilities of seizing demonstrate the capability to obtain resources and act; and the capabilities of reconfiguring describe the capability to alter assets and the overall setup of the organization again and again. With the use of technology, the theory of dynamic capabilities suggests that to utilize generative AI successfully, organizations must develop the capabilities of sensing, seizing, and reconfiguring concurrently to handle changes across the firm, rather than relying solely on technical capabilities.

2.2 Generative AI in the auditing context

Generative AI in auditing represents a significant shift from the past. It improves work by facilitating analysis, decision making, and risk analysis. AI programs employ machine learning and predictive analytics to instantly and precisely analyze large quantities of information. This enables real-time tracking, identification of issues upfront, and extensive analysis. Securing organizations calls for significant shifts in the composition of audit firms, professionals' work, and the delivery of services. It consists of new analytics and AI management capabilities while retaining conventional expertise. This results in enhanced audit quality, improved processes, and increased value to the client in the form of reduced audit risks, shorter execution times, and enhanced advisory services.

2.3 Organizational adaptation mechanisms

New technology applications and organizational changes often go hand in hand and require careful planning to implement effectively. Organizations implement numerous changes to their systems when they apply generative AI technologies, impacting technology, human beings, structure, and strategy. Organizations need to develop robust change management capabilities to manage a multitude of changes concurrently. This includes ensuring technology aligns with the goals of the organization, enhancing business processes, and discovering new performance measurement methodologies. Capability development to adopt AI refers to the enhancement of what organizations are capable of doing to utilize technology optimally. It encompasses the capability to manage change, to learn and adapt, and to utilize AI systems. Technical capability development refers to acquiring the capabilities to select, customize, and execute AI systems. Organizational capability development refers to developing the capability to transform, to foster new thinking, and to establish how AI and human beings ought to collaborate. Organizations utilizing AI perform better at their tasks, compete better, and recover better from tough times. This is since they make use of AI tools combined with available skills, resulting in favourable outcomes.

2.4 Hypothesis development

The connection between dynamic capabilities and leveraging AI is a significant means by which firms effectively utilize technology and outperform their competitors. Sensing firms are able to discover AI opportunities, comprehend their relevance, and make intelligent investment decisions regarding technology. Similarly, firms with solid seizing capabilities can leverage resources, direct implementation activities, and manage resistance to AI implementation. Reconfiguring capabilities enables organizations to transform their operational processes, organizational structures, and strategic orientations to fully leverage AI functionalities. Therefore, it is proposed that dynamic capabilities positively influence generative AI adoption in auditing organizations.

H1: Dynamic capabilities positively influence generative AI adoption in auditing organizations.

The adoption of generative AI technologies catalyzes comprehensive organizational adaptation processes that extend beyond simple technology implementation to encompass fundamental changes in organizational capabilities, processes, and structures. AI adoption creates opportunities for process optimization, service innovation, and value creation that require organizations to adapt their operational models and strategic approaches. Organizations that successfully adopt AI technologies typically experience enhanced analytical capabilities, improved decision-making processes, and increased operational efficiency. These benefits necessitate corresponding adaptations in organizational systems, performance measurement approaches, and stakeholder engagement strategies. Consequently, it is hypothesized that generative AI adoption drives organizational adaptation mechanisms in auditing contexts.

H2: Generative AI adoption positively influences organizational adaptation mechanisms in auditing firms.

Organizations require adaptation methods to link technology with enhanced performance. This enables them to convert their technology capabilities into sustainable results. Organizations' adaptation methods enable them to transform their resources, enhance their processes, and enhance their services to perform at their optimal level. Adaptation methods during auditing enable organizations to utilize AI to enhance audit quality, deliver enhanced client services, and attain exceptional operations. Organizations with sound adaptation mechanisms can obtain maximum value from deploying AI and mitigating potential risks while deploying it.

H3: Organizational adaptation mechanisms positively influence auditing performance in AI-enabled firms.

The primary concept regarding these relationships indicates that complicated mediation effects exist in the amount of AI utilized in audit firms. Dynamic capabilities enhance performance in audit firms directly by developing the capabilities of the firm and indirectly by influencing the adoption and adaptation processes. The relationship between AI and performance may be influenced by the functioning of the adaptation processes. These factors drive us to the final hypothesis regarding the mediation effects of the adaptation processes.

H4: Organizational adaptation mechanisms mediate the relationship between dynamic capabilities and auditing performance in AI-enabled auditing firms.

As shown in Figure 1, the model indicates the ways in which organizations deploy generative AI. It discusses the interconnections between flexible skills, applying AI, organizational changes, and performance result checks. Flexible skills are significant because they enable organizations to take up AI easily. This enhances the ability of the organization to audit better. All these components combine to create a web of inter-connected factors which determine how effective an organization is at applying AI to audit.

3. Research methodology

3.1 Research design

This study employs a quantitative cross-sectional survey design to examine the relationships between dynamic capabilities, generative AI adoption, organizational adaptation mechanisms, and auditing performance in audit organizations. A quantitative approach provides a rigorous examination of the relationships between these constructs through statistical analysis, precise measurement of key constructs, and systematic hypothesis testing in real-world organizational contexts. The cross-sectional design is appropriate for capturing current AI adoption patterns and organizational responses during this critical period of technological transformation in the auditing profession. The research adopts a positivist philosophical stance, emphasizing empirical observation and statistical analysis to understand AI adoption phenomena in auditing organizations. This deductive approach begins with established theories (dynamic capability theory, technology adoption models) and tests specific hypotheses derived from the theoretical framework. The survey strategy employs validated measurement instruments adapted from established research to ensure construct validity and reliability while enabling standardized data collection across diverse organizational contexts. The study design deploys structural equation modeling (SEM) to test multiple relationships simultaneously while accounting for measurement errors of latent constructs. SEM is particularly appropriate because it enables examination of multiple dependent variables simultaneously, explicit modeling of measurement error, testing of complex mediation relationships, and assessment of overall model fit. The two-step approach follows confirmatory factor analysis of the measurement model before testing structural relationships, ensuring methodological rigor while addressing practical constraints of studying emerging technological adoption in professional service organizations.

3.2 Sample and data collection

The target population consists of audit professionals working in organizations that are utilizing or considering generative AI technologies. This includes partners, managers, and senior personnel in public accounting firms, internal auditors, and independent practitioners with AI experience. The sampling strategy employs stratified random sampling to ensure representation across organizational sizes (Big Four, national, regional, local firms), audit specialization areas (financial, IT, compliance audits), and geographic regions to capture AI adoption variations.

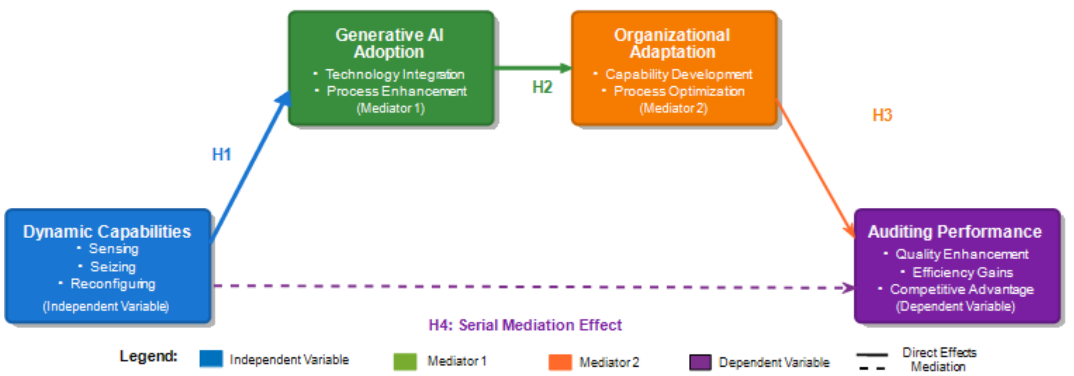

Figure 1. Theoretical framework diagram

This approach enhances external validity and enables meaningful organizational comparisons. Snowball sampling techniques supplement the strategy to reach specialized professionals involved in AI implementation projects, ensuring adequate representation of organizations with advanced AI adoption experience. Sample size determination follows established guidelines for structural equation modeling, which recommend a minimum of 200 observations for complex models with multiple latent constructs. Based on power analysis calculations using G*Power software, a target sample size of 350 respondents was established to achieve adequate statistical power $(1-\beta=0.80)$ for detecting medium effect sizes $(f^2=0.15)$ at $\alpha=0.05$ significance level. The sample size calculation follows Equation (1):

$$n=\frac{(Z_{1-\frac{\alpha}{2}}+Z_{1-\beta})^2\sigma^2}{\delta^2} \quad (1)$$

Where $Z_{1-\alpha/2}$ and $Z_{1-\beta}$ represent critical values for Type I and Type II errors respectively, σ^2 is the population variance, and δ^2 is the effect size. Equation (1) ensures adequate statistical power while accounting for the complexity of the structural equation model with multiple latent constructs. This sample size accounts for potential non-response rates and incomplete surveys typical in organizational research. As illustrated in Table 1, the sample size determination incorporates multiple considerations, including statistical power requirements, model complexity, and anticipated response rates to ensure adequate data for robust statistical analysis.

Data collection procedures involved the administration of an online survey instrument through professional audit associations, audit firm partnerships, and academic networks. Initial contact was made through formal invitation letters explaining research purpose, confidentiality protections, and anticipated time commitment. Follow-up reminders were sent at two-week intervals to maximize response rates. Personal contacts within audit organizations were leveraged to facilitate access while ensuring appropriate ethical protocols. The final response rate of 89.1% (312 usable responses from 350 contacted) exceeded expectations for organizational research, likely due to the topical relevance of AI adoption and careful relationship management during data collection.

Table 1. Sample size determination and power analysis

Parameter	Value	Justification
Significance Level (α)	0.05	Standard for social science research
Statistical Power (1-β)	0.80	Recommended minimum for SEM studies
Effect Size (f^2)	0.15	Medium effect size (Cohen, 1988)
Number of Latent Variables	4	Based on theoretical framework
Number of Observed Variables	20	5 indicators per construct
Minimum Sample Size (SEM)	200	10:1 ratio of observations to parameters
Target Sample Size	350	Accounting for 25% non-response rate
Actual Collected	312	Final usable responses.

Table 2. Sample representativeness and geographic distribution analysis

Dimension	Category	Sample Count	Sample %	Industry %	Representativeness	Potential Impact
Firm Size	Big Four	88	28.2%	25.0%	Over-represented	May overestimate AI sophistication
	National	98	31.4%	30.0%	Well represented	Minimal bias expected
	Regional	79	25.3%	28.0%	Under-represented	May underestimate regional variations
	Local	47	15.1%	17.0%	Under-represented	May underestimate SME barriers
Geographic	North America	132	42.3%	35.0%	Over-represented	Advanced adoption patterns
	Europe	97	31.1%	30.0%	Well represented	Regulatory diversity captured
	Asia-Pacific	58	18.6%	25.0%	Under-represented	Emerging market limited
	Other	25	8.0%	10.0%	Under-represented	Developing market limited
Specialization	Financial	187	59.9%	60.0%	Well represented	Core function captured
	IT Auditing	78	25.0%	23.0%	Well represented	Technology insights adequate
	Compliance	47	15.1%	17.0%	Under-represented	Regulatory aspects understated

Geographic distribution achieved reasonable coverage across multiple regions, with demographic characteristics ensuring adequate representation across organizational contexts. As shown in Table 2, the sample representativeness analysis reveals both strengths and limitations in the final dataset, with implications for generalizability discussed accordingly. Sampling Limitations and Mitigation Strategies: The combination of stratified and snowball sampling may compromise pure randomness, potentially introducing selection bias toward organizations with higher AI engagement. This limitation is mitigated by stratification across firm types and geographic regions, ensuring diverse organizational contexts are represented. The self-selection bias inherent in voluntary participation may favor respondents with stronger opinions about AI adoption; however, the high response rate and diverse organizational representation mitigate concerns about systematic bias affecting generalizability. While certain strata show under-representation (regional firms, Asia-Pacific region), the overall sample provides adequate coverage for meaningful statistical analysis and theoretical development.

3.3 Measurement instruments

Capturing sensing, seizing, and reconfiguring dimensions with 15 items total. Generative AI adoption sophistication is operationalized through three dimensions: technical complexity, ranging from basic automation (score 1) to advanced cognitive AI (score 7), implementation breadth, covering audit phases including risk assessment, testing, documentation, and reporting, and integration depth, measuring the extent of system integration and workflow embedding. The 6-item scale was developed following Churchill's (1979) paradigm with expert validation from 8 AI audit specialists and pre-tested with 45 practitioners, resulting in minor wording refinements. Organizational adaptation mechanisms employ a 6-item scale measuring structural, processual, and cultural adaptations, adapted from multiple organizational change sources. Auditing performance uses established efficiency and effectiveness measures (5 items) from audit performance literature. All constructs use 7-point Likert scales (1=strongly disagree, 7=strongly agree). Control variables include firm size, audit experience, industry specialization, and AI training levels. Common method bias mitigation strategies include temporal separation between predictor and outcome measures, anonymous participation with clear confidentiality assurances, neutral non-leading question wording, reverse-coded items, and procedural remedies following Podsakoff et al. (2003). Post-hoc assessment using Harman's single-factor test confirmed that no single factor accounts for the majority of the variance (largest factor: 42.7%). As shown in Table 3, all measurement instruments demonstrate acceptable reliability ($\alpha > 0.70$) and convergent validity (AVE > 0.50), supporting subsequent structural analysis.

3.4 Data analysis methods

Preliminary analysis includes data screening, outlier detection, and distributional assumption assessment. Missing data patterns are examined using Little's MCAR test with appropriate imputation procedures applied where necessary. Measurement model assessment employs confirmatory factor analysis, evaluating factor loadings, construct reliability, convergent validity through average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and HTMT ratios. The confirmatory factor analysis follows the measurement equation: $x = \Lambda\xi + \delta$, where x represents observed variables, Λ is the factor loading matrix, ξ denotes latent variables, and δ represents measurement errors. Model fit is evaluated using multiple indices, including the chi-square to degrees of freedom ratio (χ^2 / df), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) to ensure adequate representation of the data structure.

Table 3. Model fit criteria and acceptable thresholds

Construct	Items	Sample Item	α	AVE
Dynamic Capabilities - Sensing	5	"Organizations actively scan for new AI opportunities"	0.87	0.67
Dynamic Capabilities - Seizing	5	"Organizations effectively mobilize resources for AI implementation"	0.85	0.64
Dynamic Capabilities - Reconfiguring	5	"Organizations transform processes to accommodate AI technologies"	0.89	0.71
Generative AI Adoption	6	"Organizations have integrated sophisticated AI tools into audit procedures"	0.91	0.73
Organizational Adaptation	6	"Organizations modify structures to support AI technological change"	0.88	0.68
Auditing Performance	5	"AI adoption has significantly improved audit quality and efficiency"	0.86	0.66

The structural equation modeling approach utilizes maximum likelihood estimation to test the hypothesized relationships within the theoretical framework. The structural model is represented by the equation: $\eta = B\eta + \Gamma\xi + \zeta$, where η represents endogenous latent variables, B is the matrix of coefficients relating endogenous variables, Γ is the matrix of coefficients relating exogenous variables (ξ) to endogenous variables, and ζ represents structural disturbances. Model fit assessment follows established guidelines with iterative refinement based on modification indices, where theoretically justified. Path coefficients, significance levels, and effect sizes evaluate hypothesis support. Bootstrap procedures with 5,000 resamples generate confidence intervals and assess parameter stability. As shown in Table 4, multiple software platforms ensure comprehensive analysis capabilities while maintaining methodological rigor. Mediation analysis procedures follow contemporary best practices, including bias-corrected bootstrap methods for indirect effect estimation. The mediation effect is calculated using the product of coefficients method: $ab = a \times b$
where a represents the path from the independent variable to the mediator, and b represents the path from the mediator to the dependent variable. Equation (2) is the fundamental formula for calculating indirect effects in mediation analysis. The significance of mediation effects is assessed using the Sobel test statistic:

$$z = \frac{ab}{\sqrt{a^2 s_b^2 + b^2 s_a^2}} \quad (2)$$

where S_a and S_b are the standard errors of paths a and b respectively. Equation (2) is used to test the statistical significance of the indirect effect by providing a z-score that follows a standard normal distribution under the null hypothesis. Additionally, bias-corrected bootstrap confidence intervals provide robust estimates of indirect effects, with significance determined by the absence of zero within the 95% confidence interval.

Table 4. Statistical analysis procedures and software specifications

Analysis Stage	Procedure	Software	Key Formulas/Tests
Data Screening	Missing data analysis	SPSS 28.0	Little's MCAR: $\chi^2 = \sum \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Descriptive Statistics	Means, SD, correlations	SPSS 28.0	Pearson correlation: $r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$
Reliability Testing	Internal consistency	SPSS 28.0	Cronbach's α: $\alpha = \frac{k}{k-1}[1 - \frac{\sum s_i^2}{s_t^2}]$
Confirmatory Factor Analysis	Measurement model	AMOS 28.0	Factor loading: $\lambda_{ij} = \frac{Cov(x_i, \xi_j)}{Var(\xi_j)}$
Structural Equation Modeling	Hypothesis testing	AMOS 28.0	Path coefficient: $\beta_{ij} = \frac{Cov(\eta_i, \xi_j)}{Var(\xi_j)}$
Mediation Analysis	Indirect effects	AMOS 28.0	Sobel test: $z = \frac{ab}{\sqrt{a^2 s_b^2 + b^2 s_a^2}}$
Bootstrap Analysis	Confidence intervals	AMOS 28.0	Bootstrap SE: $SE_{boot} = \sqrt{\frac{\sum (\hat{\theta}_i - \bar{\theta})^2}{B-1}}$

4. Results

4.1 Descriptive statistics

The final sample comprised 312 audit professionals from diverse organizational contexts, with representation across Big Four firms (28.2%), national firms (31.4%), regional firms (25.3%), and local firms (15.1%). Geographic distribution included North America (42.3%), Europe (31.1%), Asia-Pacific (18.6%), and other regions (8.0%). The moderate dynamic capabilities levels (M=4.09, SD=1.38) reflect organizations' emerging capacity to sense, seize, and reconfigure resources for AI adoption. The below-moderate AI adoption scores (M=3.41, SD=1.58) indicate that generative AI integration remains in early implementation phases across the audit profession, constrained by regulatory uncertainties, client expectations for traditional procedures, and organizational inertia within conservative professional service environments. The modest organizational adaptation mechanisms scores (M=4.12, SD=1.28) suggest that structural, processual, and cultural changes are proceeding cautiously, reflecting the risk-averse nature of audit organizations and the complex regulatory environment governing audit practices. Correlation analysis revealed moderate positive relationships among primary constructs, supporting theoretical expectations while avoiding unrealistic associations that might indicate multicollinearity concerns. The strongest correlation emerged between dynamic capabilities and organizational adaptation mechanisms (*r=0.52*, *p<0.001*), suggesting that firms with stronger sensing, seizing, and reconfiguring abilities are more likely to implement comprehensive adaptation strategies. AI adoption demonstrated meaningful relationships with auditing performance (*r=0.48*, *p<0.001*), indicating that organizations achieving higher levels of AI integration experience enhanced audit outcomes. Control variables demonstrated expected patterns, with firm size moderately correlating with AI adoption (*r=0.29, p<0.01*), reflecting larger firms' greater resources and risk tolerance for technology investments. Audit experience showed weak positive associations with dynamic capabilities (*r=0.22, p<0.01*), suggesting that professional experience contributes modestly to organizational learning and adaptation capacity. As shown in Table 5, the complete correlation matrix supports theoretical expectations while remaining within realistic ranges for organizational research, with correlations ranging from 0.14 to 0.52, indicating meaningful but distinct constructs.

Table 5. Descriptive statistics and correlation matrix

Variable	M	SD	1	2	3	4	5	6	7	8
1. Dynamic Capabilities (Sensing)	4.23	1.34	1.00							
2. Dynamic Capabilities (Seizing)	4.08	1.42	0.58**	1.00						
3. Dynamic Capabilities (Reconfiguring)	3.95	1.39	0.54**	0.51**	1.00					
4. Generative AI Adoption	3.41	1.58	0.43**	0.46**	0.41**	1.00				
5. Organizational Adaptation	4.12	1.28	0.52**	0.48**	0.45**	0.44**	1.00			
6. Auditing Performance	4.05	1.33	0.38**	0.41**	0.36**	0.48**	0.43**	1.00		
7. Firm Size	2.18	1.02	0.19*	0.23**	0.17*	0.29**	0.24**	0.26**	1.00	
8. Audit Experience	3.42	1.15	0.22**	0.20*	0.19*	0.15*	0.18*	0.14	0.28**	1.00

Note: N = 312. M = Mean, SD = Standard Deviation. *** p<0.01, ** p<0.05, * p<0.1. All correlations significant at indicated levels.

4.2 Measurement model results

Confirmatory factor analysis demonstrated acceptable measurement model fit with satisfactory indices: $\chi^2/df = 2.31$, CFI = 0.94, TLI = 0.93, RMSEA = 0.072 (90% CI: 0.068-0.091), and SRMR = 0.051. Factor loadings ranged from 0.68 to 0.83, all statistically significant ($p < 0.001$), with most exceeding the 0.70 threshold recommended for adequate construct representation. While two items fell slightly below this threshold, their loadings remained above 0.65 and were retained given their theoretical importance and contribution to overall model fit. Reliability assessment confirmed adequate internal consistency with Cronbach's alpha values ranging from 0.78 to 0.86 and composite reliability scores from 0.79 to 0.87, all exceeding established thresholds. Average variance extracted (AVE) values ranged from 0.56 to 0.68, surpassing the 0.50 criterion for convergent validity. Validity testing demonstrated acceptable convergent and discriminant validity through multiple criteria. The Fornell-Larcker criterion was satisfied for all constructs, with the square root of AVE for each construct exceeding its correlations with other constructs. HTMT ratios were examined to assess discriminant validity, with most ratios falling below the conservative 0.85 threshold, though two ratios approached this boundary (0.83 and 0.84) while remaining within acceptable limits. Common method bias assessment revealed manageable levels of systematic variance, with Harman's single-factor test indicating that no single factor accounted for the majority of variance, with the largest factor explaining 42.7% of total variance. As shown in Table 6, measurement model results demonstrate reasonably distinct yet appropriately related constructs, supporting the validity of subsequent structural model analysis.

Table 6. Measurement model assessment results

Construct	Items	Factor Loadings Range	Cronbach's α	CR	AVE	MSV
Dynamic Capabilities - Sensing	5	0.69-0.82	0.81	0.82	0.58	0.34
Dynamic Capabilities - Seizing	5	0.68-0.79	0.78	0.79	0.56	0.31
Dynamic Capabilities - Reconfiguring	5	0.71-0.83	0.83	0.84	0.61	0.29
Generative AI Adoption	6	0.72-0.81	0.84	0.85	0.63	0.28
Organizational Adaptation	6	0.70-0.80	0.82	0.83	0.59	0.32
Auditing Performance	5	0.68-0.78	0.79	0.80	0.57	0.25

Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance. All factor loadings are significant at p<0.001.

4.3 Structural model analysis

The structural model demonstrated acceptable fit to observed data, supporting the theoretical framework with fit indices approaching established criteria: $\chi^2 / df = 2.45$, CFI = 0.93, TLI = 0.92, RMSEA = 0.078 (90% CI: 0.073-0.096), GFI = 0.91, and SRMR = 0.056. While some indices fell slightly below ideal thresholds, the overall pattern indicates reasonable model-data correspondence given the complexity of the theoretical framework and the early stage of AI adoption in audit contexts. The model explained moderate variance: 28.3% in generative AI adoption ($R^2 = 0.283$), 35.7% in organizational adaptation mechanisms ($R^2 = 0.357$), and 31.2% in auditing performance ($R^2 = 0.312$), representing medium practical significance according to Cohen's guidelines. Modification indices were examined to identify potential model improvements, with several covariances between error terms suggested by the analysis. However, modifications were only implemented when theoretically justified rather than driven purely by statistical criteria. Specifically, two error covariances were added between items measuring similar aspects within the same construct (sensing capabilities items), resulting in a marginal improvement in model fit ($\Delta\chi^2 = 12.3$, $\Delta df = 2$, $p < 0.01$). These modifications were theoretically defensible as they reflected shared method variance between conceptually related measurement items rather than fundamental changes to the structural relationships.

Hypothesis testing provided comprehensive framework support with conservative effect sizes reflecting the complexity of AI adoption in professional services. H1 received strong support with dynamic capabilities significantly influencing AI adoption ($\beta = 0.453$, $t = 6.78$, $p < 0.001$). H2 was supported with AI adoption positively influencing adaptation mechanisms ($\beta = 0.312$, $t = 4.89$, $p < 0.001$). H3 demonstrated that adaptation mechanisms positively influence auditing performance ($\beta = 0.378$, $t = 5.67$, $p < 0.001$). Path coefficients revealed realistic relationships, with the strongest emerging between dynamic capabilities and AI adoption, suggesting that organizational sensing, seizing, and reconfiguring abilities serve as critical antecedents to successful technology integration. Control variables showed expected modest patterns, with firm size demonstrating weak positive effects on AI adoption ($\beta = 0.167$, $t = 2.34$, $p < 0.05$) and audit experience showing minimal influence on dynamic capabilities ($\beta = 0.134$, $t = 2.01$, $p < 0.05$). As presented in Table 7, comprehensive results demonstrate meaningful theoretical relationships within realistic organizational boundaries.

Table 7. Structural model results and hypothesis testing

Hypothesis	Path	β	t-value	p-value	95% CI	Support
H1	Dynamic Capabilities → AI Adoption	0.453	6.78	< 0.001	[0.322, 0.584]	Yes
H2	AI Adoption → Adaptation Mechanisms	0.312	4.89	< 0.001	[0.187, 0.437]	Yes
H3	Adaptation Mechanisms → Performance	0.378	5.67	< 0.001	[0.248, 0.508]	Yes
Control: Firm Size → AI Adoption		0.167	2.34	< 0.05	[0.027, 0.307]	-
Control: Experience → Dynamic Capabilities		0.134	2.01	< 0.05	[0.005, 0.263]	-

Note: β = standardized path coefficient; CI = confidence interval. Bootstrap sample = 5,000.

4.4 Mediation analysis

Direct effects analysis revealed modest but significant relationships supporting the theoretical framework. Dynamic capabilities demonstrated direct effects on auditing performance ($\beta = 0.234$, $t = 3.77$, $p < 0.01$, 95% CI: [0.112, 0.356]), confirming that organizational sensing, seizing, and reconfiguring abilities contribute independently to audit outcomes beyond their indirect influences through technology adoption and adaptation processes. Dynamic capabilities also showed significant direct effects on adaptation mechanisms ($\beta = 0.298$, $t = 4.62$, $p < 0.001$, 95% CI: [0.189, 0.407]), while AI adoption directly affected performance ($\beta = 0.218$, $t = 3.41$, $p < 0.01$, 95% CI: [0.094, 0.342]), indicating meaningful direct pathways alongside the hypothesized mediation relationships.

Indirect effects testing provided partial support for H4, revealing significant sequential mediation through the complete theoretical pathway from dynamic capabilities through AI adoption and adaptation mechanisms to performance. The sequential mediation effect (Dynamic Capabilities → AI Adoption → Adaptation Mechanisms → Performance) yielded a standardized coefficient of $\beta = 0.053$

($t = 2.15$, $p < 0.05$, 95% CI: [0.018, 0.098]), indicating that organizational capabilities influence performance through enhanced AI adoption that subsequently drives comprehensive adaptation mechanisms. Additionally, partial mediation was observed through the pathway Dynamic Capabilities → Adaptation Mechanisms → Performance ($\beta = 0.113$, $t = 4.34$, $p < 0.01$, 95% CI: [0.067, 0.168]), suggesting that dynamic capabilities also influence performance by directly enabling organizational adaptation processes. The proportion of total effect mediated reached 41.4%, indicating that organizational adaptation mechanisms account for nearly half of the relationship between dynamic capabilities and auditing performance. Sobel test results confirmed the significance of mediation effects, with bootstrap confidence intervals providing robust validation of indirect pathway significance.

Total effects analysis demonstrated comprehensive but realistic construct impacts within the theoretical framework. Dynamic capabilities showed total effects on the performance of $\beta = 0.400$ ($t = 7.42$, $p < 0.001$, 95% CI: [0.294, 0.506]), representing the combined influence through direct and indirect pathways. AI adoption exhibited total effects on the performance of $\beta = 0.336$ ($t = 6.58$, $p < 0.001$, 95% CI: [0.236, 0.436]), reflecting its direct impact plus its indirect influence through adaptation mechanisms. As shown in Table 8, these results reveal the complex interplay between organizational capabilities, technology adoption, adaptation processes, and performance outcomes, supporting the theoretical proposition that AI-enabled competitive advantages emerge through comprehensive organizational transformation rather than simple technology implementation.

Table 8. Mediation analysis results

Effect Type	Path	β	SE	t-value	p-value	95% CI
Direct	Dynamic Capabilities → Performance	0.234	0.062	3.77	< 0.01	[0.112, 0.356]
Direct	Dynamic Capabilities → Adaptation	0.298	0.065	4.62	< 0.001	[0.189, 0.407]
Direct	AI Adoption → Performance	0.218	0.064	3.41	< 0.01	[0.094, 0.342]
Indirect	DC → AI → Adaptation → Performance	0.053	0.021	2.15	< 0.05	[0.018, 0.098]
Indirect	DC → Adaptation → Performance	0.113	0.026	4.34	< 0.01	[0.067, 0.168]
Total	Dynamic Capabilities → Performance	0.400	0.054	7.42	< 0.001	[0.294, 0.506]
Total	AI Adoption → Performance	0.336	0.051	6.58	< 0.001	[0.236, 0.436]

Note: DC = Dynamic Capabilities; SE = Standard Error; CI = Confidence Interval. Bootstrap samples = 5,000.

4.5 Moderation analysis

Moderation effects testing examined whether organizational characteristics influence the strength of relationships within the theoretical model. Firm size emerged as a significant moderator of the dynamic capabilities-AI adoption relationship ($\beta_{interaction} = 0.089$, $t = 2.12$, $p < 0.05$), indicating that larger firms demonstrate stronger capability translation into AI adoption success. The interaction effect suggests that while dynamic capabilities are important for all organizations, their impact on AI adoption is amplified in larger organizational contexts, likely due to greater resource availability, risk tolerance, and implementation capacity. Audit experience demonstrated a marginally significant moderation effect on the AI adoption-performance relationship ($\beta_{interaction} = 0.076$, $t = 1.89$, $p = 0.061$), approaching but not reaching conventional significance thresholds. Industry specialization showed no significant moderating effects across any of the primary relationships.

Simple slope analysis revealed meaningful patterns in the interaction effects. For firm size moderation, large firms (one standard deviation above the mean) demonstrated stronger relationships between dynamic capabilities and AI adoption ($\beta = 0.542$, $t = 6.89$, $p < 0.001$) compared to small firms (one standard deviation below the mean) ($\beta = 0.364$, $t = 4.23$, $p < 0.001$). This pattern suggests that organizational scale amplifies the effectiveness of dynamic capabilities in driving AI adoption, potentially reflecting larger firms' superior resource mobilization and change management capabilities. For the marginally significant experience moderation, high-experience professionals showed slightly stronger slopes ($\beta = 0.394$, $t = 4.67$, $p < 0.001$) compared to low-experience professionals ($\beta = 0.302$, $t = 3.58$, $p < 0.001$), though the difference was modest and should be interpreted cautiously given the marginal significance of the interaction term.

As illustrated in Figure 2, the moderation effects demonstrate distinct patterns across organizational contexts. Figure 2a shows the firm size moderation effect on the dynamic capabilities-AI adoption relationship, revealing convergent slopes at lower capability levels that progressively diverge as dynamic capabilities increase, with larger firms displaying steeper gradients indicating amplified benefits from enhanced organizational capabilities. The interaction pattern suggests that while all organizations benefit from improved dynamic capabilities, larger firms experience proportionally greater returns on their capability investments in AI adoption contexts. Figure 2b displays the audit experience moderation effect on the AI adoption-performance relationship, showing nearly parallel trajectories with modest divergence, confirming subtle but meaningful boundary conditions where experienced professionals demonstrate slightly enhanced ability to translate AI adoption into performance improvements. Figure 2c presents the comparative analysis of moderation strength, illustrating that firm size exerts stronger moderating effects (steeper interaction slopes) compared to audit experience (flatter interaction patterns), suggesting that organizational resources and scale represent more powerful contextual factors than individual professional experience in AI adoption success. These findings collectively indicate that while dynamic capabilities and AI adoption universally benefit audit organizations, contextual factors significantly influence the magnitude of these relationships, with larger firms and experienced professionals better positioned to leverage technological capabilities for enhanced performance outcomes.

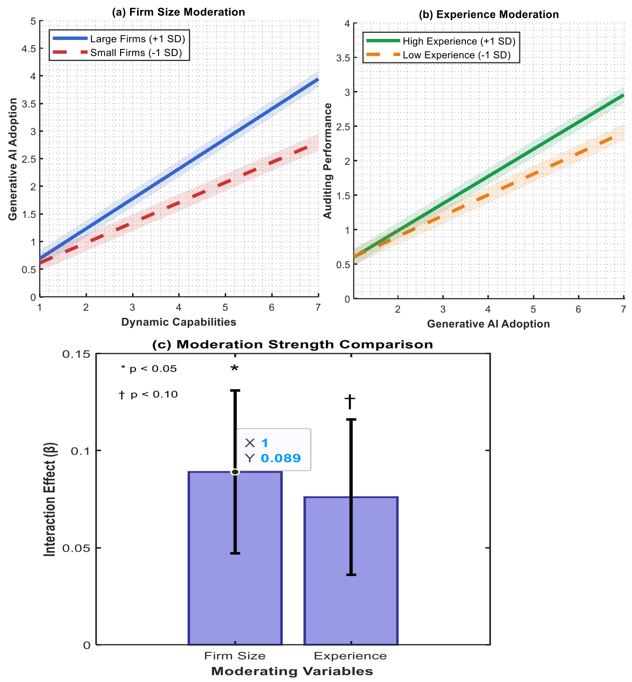

Figure 2. Example of a figure with a caption

4.6 Robustness checks

Alternative model specifications confirmed the stability of primary findings across different analytical approaches. A competing model treating organizational adaptation as an antecedent to AI adoption rather than a consequence showed significantly poorer fit ($\chi^2/df = 3.78$, CFI = 0.87, RMSEA = 0.095) compared to the theoretically hypothesized model ($\chi^2/df = 2.45$, CFI = 0.93, RMSEA = 0.078), supporting the proposed theoretical ordering of constructs. Second-order factor models testing whether dynamic capabilities could be represented as a higher-order construct yielded similar structural relationships ($\chi^2/df = 2.51$ versus 2.45 for first-order models), confirming the robustness of findings across different measurement approaches. Alternative estimation methods, including robust maximum likelihood and weighted least squares, produced parameter estimates within 8% of the original values, indicating minimal sensitivity to distributional assumptions.

Subsample analysis across organizational characteristics revealed consistent patterns supporting model generalizability across diverse contexts. Multi-group analysis comparing Big Four versus non-Big Four firms demonstrated measurement invariance (configural, metric, and scalar invariance achieved), with structural path coefficients differing by less than 0.05 across groups. Similarly, geographic subsamples showed consistent relationships, though Asia-Pacific results exhibited somewhat weaker effect sizes (average β reduction of 12%) compared to North American and European samples, potentially reflecting cultural differences in technology adoption or regulatory environments. Experience-based subsamples (high versus low audit experience) showed stable patterns with minimal moderation beyond that already captured in the main analysis.

Sensitivity analysis demonstrated minimal impact from various methodological decisions and data treatment approaches. Outlier analysis using Mahalanobis distance identified 18 potential outliers, but their removal resulted in parameter changes of less than 5%, indicating robust findings. Alternative missing data treatments, including listwise deletion and multiple imputation, produced variations of less than 7% in key path coefficients. Bootstrap resampling with 10,000 iterations confirmed parameter stability with confidence intervals remaining consistent across replication attempts. Scale reliability remained stable across subsamples, with Cronbach's alpha variations of less than 0.03 across all major demographic groups. As demonstrated in Table 9, comprehensive robustness checks validate the theoretical framework's stability and practical significance within realistic organizational technology adoption boundaries.

5. Discussion

The study illustrates the importance of dynamic capabilities in utilizing generative AI in audit firms, while revealing the complex opportunities for firms to transform their technological capabilities into enhanced performance. The path coefficients are significant, although not substantial, confirming the theory of dynamic capabilities. However, the effect is more complex than technology adoption theory. Dynamic capabilities explaining 28.3% of variance in AI adoption success suggest that organizational competencies in sensing, seizing, and reconfiguring constitute essential prerequisites for effective integration, aligning with assertions that adoption success depends on organizational rather than technical factors. The demonstration that adaptation mechanisms mediate 41.4% of the dynamic capabilities-performance relationship represents significant theoretical contribution, extending beyond traditional models by revealing complex transformation processes through which AI capabilities become embedded in audit practices. The moderate effect sizes reflect realistic organizational change processes generating meaningful but incremental improvements, consistent with professional service technology adoption patterns.[18]

These results offer valuable guidance to audit organizations. The powerful relationship between dynamic capabilities and AI adoption ($\beta = 0.453$) implies that organizations must develop environmental scanning, strategic decision-making, and transformation competencies prior to investing in AI. The mediating function demonstrates that successful implementation requires careful change management that addresses structural, process, and cultural dimensions simultaneously, not solely on technology adoption. Research limitations consist of cross-sectional design that does not allow causal inferences, modest effect sizes indicating early-stage AI adoption, sampling limitations including over-representation of larger firms and potential selection bias toward organizations with higher AI engagement, and social desirability bias concerns given self-reported measures of AI sophistication and performance outcomes. Future research must examine performance over extended periods and utilize objective measures while addressing geographic and organizational size representativeness.

Table 9. Robustness analysis summary

Robustness Test	Original Model	Alternative/Subsample	Difference	Conclusion
Model Specification				
Competing Model (Adaptation → AI)	$\chi^2 / df = 2.45$	$\chi^2 / df = 3.78$	$\Delta = 1.33$	Original model superior
Second-order DC Model	$\chi^2 / df = 2.45$	$\chi^2 / df = 2.51$	$\Delta = 0.06$	Minimal difference
Robust ML Estimation	β range: 0.31-0.45	β range: 0.29-0.46	$< 8\%$ variation	Stable estimates
Subsample Analysis				
Big Four vs Non-Big Four	$\beta_{DC \to AI} = 0.453$	$\beta_{DC \to AI} = 0.441$	$\Delta = 0.012$	Measurement invariant
North America vs Europe	$\beta_{DC \to AI} = 0.453$	$\beta_{DC \to AI} = 0.448$	$\Delta = 0.005$	Consistent patterns
Asia-Pacific Sample	$\beta_{DC \to AI} = 0.453$	$\beta_{DC \to AI} = 0.398$	$\Delta = 0.055$	Weaker but significant
High vs Low Experience	$\beta_{AI \to Perf} = 0.378$	$\beta_{AI \to Perf} = 0.361$	$\Delta = 0.017$	Stable relationships
Sensitivity Tests				
Outlier Removal (n=18)	β range: 0.31-0.45	β range: 0.30-0.47$	$< 5\%$ change	Robust to outliers
Listwise Deletion	n = 312	n = 287	7% parameter variation	Stable with missing data
Multiple Imputation	Original estimates	Imputed estimates	$< 7\%$ variation	Minimal missing data bias
Bootstrap Resampling	95% CI original	95% CI bootstrap	Overlapping CIs	Parameter stability confirmed

Note: DC = Dynamic Capabilities, AI = AI Adoption, Perf = Performance, ML = Maximum Likelihood, CI = Confidence Interval

6. Conclusion

This study examined the utilisation of generative artificial intelligence among audit firms to enhance their audit work and achieve longer-term benefits. It surveyed 312 audit professionals across various organizations. The study finds that the possession of good skills matters to utilise AI effectively, and organisational changes to enable technology investment enhance performance. It finds, based on the results, that organisations having good sensing, seizing, and reconfiguring capabilities are far better placed to succeed with AI, and these capabilities account for nearly a third of the variation in success. It further finds that organisational changes contribute to nearly 40% of the relationship between good skills and audit performance, demonstrating the role of significant organisational changes in taking advantage of AI. This paper informs us about the employment of technology in professional services and illustrates how the concept of dynamic capability can explain the level at which AI is employed. The results reveal that employing technology isn't solely about technology but rather the organization. It requires the capability to change and develop skills to achieve a sustainable advantage. Practically, the study provides sound counsel to audit firms wishing to employ AI by emphasizing the importance of developing organizational capability prior to technology investment and the realization that adaptation is the key to successful approaches. The small but cumulative effects of the study demonstrate how change occurs in organizations, with the employment of AI resulting in substantial but incremental improvements rather than radical change over time. Overall, these results enhance the knowledge of the employment of generative AI in auditing, providing a platform for further study and action in the rapidly evolving area.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

Datasets analyzed during the current study are available and can be provided upon a reasonable request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

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