Future Technology
Open Access Journal
ISSN 2832-0379

May 2026| Volume 05 | Issue 02 | Pages 25-37

Journal homepage: https://fupubco.com/futech

https://doi.org/10.55670/fpll.futech.5.2.3

Future Publishing LLC

Article

AI-enabled ESG consultancy capability building in small audit firms: a strategic transformation pathway analysis

Cheng Hu*, Rafidah Binti Othman
Azman Hashim International Business School, Universiti Teknologi Malaysia (UTM), Jalan Sultan Yahya Petra (Jalan Semarak), 54100 Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 25 September 2025
Received in revised form
25 November 2025
Accepted 07 January 2026

Keywords:
Artificial intelligence adoption,
ESG consulting capabilities, Small audit firms,
Digital transformation pathways,
Dynamic capabilities

*Corresponding author
Email address:
hucheng@graduate.utm.my

DOI: 10.55670/fpll.futech.5.2.3

ABSTRACT

This study investigates how small audit firms develop artificial intelligence-enabled environmental, social, and governance (ESG) consulting capabilities through strategic transformation pathways. Drawing upon dynamic capabilities theory and employing a mixed-methods research design, the research integrates qualitative interviews with 28 practitioners across 18 small audit firms and quantitative surveys from 156 respondents representing 87 organizations, supplemented by six in-depth case studies. The empirical analysis reveals substantial capability heterogeneity, with only 12.2% of firms deploying advanced AI applications and merely 11.5% achieving established ESG service maturity levels. A significant positive correlation between AI Intensity Index and Capability Maturity Index ($r=0.68$, $p<0.01$) demonstrates mutually reinforcing dynamics between technological adoption and domain expertise development. Cluster analysis identifies three transformation pathway archetypes—Technology-Led, Knowledge-Led, and Balanced—with Knowledge-Led approaches achieving marginally higher success rates (72.3%) compared with Technology-Led pathways (67.5%). The research develops a four-stage transformation pathway model spanning 30-36 months, delineating critical activities, resource requirements, and success indicators across foundation, development, integration, and optimization phases. AI-enabled resource optimization yields average efficiency improvements of 46.2% across operational functions, with report generation achieving 61.7% gains. The findings extend dynamic capabilities theory to resource-constrained professional services contexts and provide evidence-based guidance for practitioners navigating digital transformation in expanding ESG advisory markets.

1. Introduction

There has been a paradigm shift in the professional services industry, driven by technological change and regulatory shifts. The application of artificial intelligence has created an opportune environment for improving the effectiveness of audit work by automating verification processes [1]. There have been significant expenditures on machine learning algorithms and anomaly identification by large corporations [2]. Together with the development of technology, there has also been a significant evolution in the regulation of corporate sustainability reporting. There have been systematic reviews of the relevant literature suggesting an increase in scholarly work focusing on environmental, social, and ethical business practices, largely due to requirements such as the Corporate Sustainability Reporting Directive and the International Sustainability Standards Board [3]. The upsurge in regulation requires a significant dependence on professional ESG consulting advice. Training and capacity-building programs have had to evolve for the development of skills in ESG consulting, incorporating accounting, sustainability science, and regulation frameworks [4]. The use of artificial intelligence technology in the field of professional services creates complex ethical issues. The use of algorithmic decision-making raises questions about transparency, accountability, and professional skepticism [5]. The internal audit function faces challenges driven by the capabilities that involve real-time control assessment through the use of technology [6]. Although success is evident in the AI field, as well as an increasing number of prospects in ESG settings, a number of challenges are also faced by smaller auditing companies. A lack of technological and expertise resources is one of the major challenges, since it is a known fact that smaller companies tend to have limited manpower and capital. Costs of large-scale adoption are often a hindrance to smaller companies. AI applications within large audits and the development of ESG capabilities among established firms have been widely explored previously. However, there are considerable gaps in the existing knowledge regarding the simultaneous application of the two notions in a resource-constrained setting. Innovative strategies for developing ESG capabilities enabled by AI in small firms remain largely uncharted. In light of findings from the existing literature indicating the need to examine the transformative process by which small audit firms can leverage AI to develop ESG consulting capabilities, this paper proposes a transformative process model based on a mixed-methods design. This paper also contributes to the dynamics capability theory by investigating accelerators that enable the emergence of ESG consulting capabilities through AI technology.

2. Literature review and theoretical framework

2.1 Theoretical foundation and prior research

Dynamic capabilities theory is the basic framework for analyzing the malleability of organizations in dynamic environments [7]. Digital transition activities imply the necessity of dynamic capabilities for constant strategic renewal in the fields of sensing opportunities, seizing opportunities, and reconfiguring [8]. In the scenario of large organizations facing the digital transition, there are intense difficulties in performance measurement, leadership paradigms, and organizational structure [9]. Systematic literature research has designated five core areas of digital transformation capabilities, which are named as follows: Digital Dynamic Capability, Digital Leadership, Employee Digital Capability, Digital Strategy, and Digital Investment [10]. The Resource-Based View represents a conceptual foundation for dynamic capabilities, but recent studies emphasize digital platforms, data resources, and knowledge-intensive services provided through digital transformation processes [11]. Comparison studies between open innovation and dynamic capabilities emphasize resource access, especially during resource deficiency conditions by firms [12].

ESG consulting requires unique skill sets that include various bodies of knowledge. Emerging trends indicate increased regulation, evolving reporting frameworks, and growing demands for disclosures on ESG matters [13]. Several international frameworks are being widely adopted, signaling market maturity and growing demand for specialized consulting skills [14]. The theoretical framework of dynamic capabilities is imperative in analyzing change processes within businesses. On the other hand, the ESG consulting industry offers excellent growth opportunities. Surprisingly little research has examined the nexus between digital transformation and the development of ESG in small businesses. The specific difficulties that small auditing practices face when they do not depend on scale economies remain understudied. This research responds to this issue.

2.2 Capability gaps in small audit firms

Small auditing firms face complex capability gaps that limit their ability to compete effectively in the dynamic market for professional services. Studies on competitive approaches have clearly indicated that small practitioners face natural disadvantages in resource utilization, technological infrastructure, and specialized knowledge relative to larger players [15]. Such firms typically operate locally as small- to medium-sized enterprises in their surroundings. Technology-induced transformations in auditing, driven by the adoption of cloud computing, highlight the challenges posed by digital capabilities in small firms [16]. ESG consulting calls for the use of sophisticated data analytics for carbon footprint, materiality, and scenario analyses. Small firms lack the infrastructure to use artificial intelligence for such analyses. Service delivery capabilities are the outcomes of the interaction of the aforementioned shortcomings. There is empirical proof that the impact of the business unit's sustainability performance and ESG disclosure quality plays a crucial role in organizational outcomes [17]. This highlighted shortfall in capabilities places small firms at a competitive disadvantage in the ESG consulting market.

2.3 Transformation barriers

Small audit firms face numerous obstacles in their digital transformation. Strategic-level problems begin to manifest from inherent uncertainties in the expression of the value narrative for ESG consulting services. Digital transformation of external audit capabilities calls for a radical redesign of governance structures, risk management processes, and engagement strategies [18]. Management in small firms is often unclear about the best course of the proposed transformative process. A review of the literature on digital transformation in audits reveals key obstacles [19]: resistance to change among senior professionals, low digital literacy among the workforce, and the lack of training resources. Technology-specific barriers represent both cost and ability limitations. New technologies such as artificial intelligence, blockchain, and analytics have the potential for dramatic improvement but require advanced technological capabilities for implementation [20]. Market dynamics intensify pressure for transformative change while constraining the range of responses. Competition from larger accounting firms that already possess ESG methodologies undermines clients' confidence in smaller firms' ability to provide advice. Clients increasingly expect proven abilities, methods, and track records that smaller firms cannot provide without initial market access.

3. Data and methodology

3.1 Research design

In terms of research methodology, the paper adopts a mixed-methods approach that combines qualitative and quantitative methods. This approach enables comprehensive exploration of both the dynamics within the context and the broader observable tendencies for addressing research questions that involve interpreting organizational context transformations, as well as validating the organizational processes for developing capabilities. Through the case study research approach, the study gains specific benefits for theory-building in organizational contexts by allowing scrutiny of how firms respond to complex issues in organizational transformations, yielding organizational-level collective wisdom applicable to similar context parameters [21]. The research approach is represented in Figure 1. The research employed a concurrent triangulation design, in which qualitative interviews (March–August 2024) and quantitative surveys (April–September 2024) were conducted simultaneously. Integration occurred through instrument refinement, whereby preliminary interview themes informed survey question development, and through interpretive triangulation, whereby quantitative patterns were contextualized by qualitative narratives.

Cases for the study were selected according to the criteria for purposive sampling. The aim was to understand small-sized audit firms having 10-100 employees undergoing different levels of digital transformation processes for ESG-related services. Criteria for selecting small firms included maximizing variation across firm-related aspects, such as location, client base, technology use levels, and ESG market-entry timing. Finally, the selection resulted in 18 small firms being selected for in-depth interviews, 156 respondents for survey research, and 6 firms for in-depth analysis based on their varied experiences with digital transformations. Specific selection criteria included: 10-100 full-time employees, professional accounting body membership, minimum two years of operation, and documented AI usage or digital transformation interest. Firms were identified through professional association directories across North America, Europe, and Asia-Pacific, with initial contact made via managing partners. The six case study firms were selected from the 18 interview firms to represent early-stage (n=2), mid-stage (n=2), and advanced-stage (n=2) transformation categories, while the 87 survey firms were drawn from a separate sampling frame to enable independent triangulation. Ethical issues surrounded all research activities. Prior permission was sought from institutional review boards. Participants in the research were thoroughly informed about the research aims, data handling procedures, and confidentiality measures. Responses to the survey were anonymized. Firm-level identity was concealed to aggregate research results.

Voluntary participation was also adopted in the research. Sensitive competitive information was given special confidentiality measures. Research data were stored on encrypted institutional servers with access restricted to the research team. Interview recordings were assigned alphanumeric codes with linking keys stored separately. Survey responses were collected via SSL-encrypted platforms without recording IP addresses. For participants in GDPR-covered jurisdictions, additional consent procedures addressed data subject rights. The authors declare no conflicts of interest with the professional bodies through which the survey was distributed. To quantify ESG capability maturity and AI adoption intensity, this research develops two composite indices. The Capability Maturity Index (CMI) aggregates scores across multiple dimensions:

$$CMI = \frac{\sum_{i=1}^{n} w_i \times S_i}{n} \quad (1)$$

where w_i represents the weight of dimension i, S_i denotes the score for dimension i on a 1-5 scale, and n indicates the total number of dimensions. The AI Intensity Index (AII) captures technology adoption breadth and depth:

$$AII = (\alpha \times T_1 + \beta \times T_2 + \gamma \times T_3) \times U \quad (2)$$

Where T_1, T_2, T_3 represent counts of basic automation tools, AI analytics tools, and advanced AI applications, respectively, with weights $\alpha = 0.2$, $\beta = 0.3$, $\gamma = 0.5$, and U denoting usage frequency (0-1 scale). The weights were derived through expert panel consultation involving five academic researchers and three industry practitioners, representing mean importance assessments. Sensitivity analyses using equal weights (α=β=γ=0.33) produced correlation coefficients exceeding 0.91 with the original index, confirming robustness across weighting specifications. Psychometric validation of the composite indices was conducted using survey data. Exploratory factor analysis confirmed a unidimensional structure for both CMI and AII, with factor loadings exceeding 0.55 for all component items. Internal consistency was acceptable, with Cronbach's alpha values of 0.78 for CMI and 0.81 for AII.

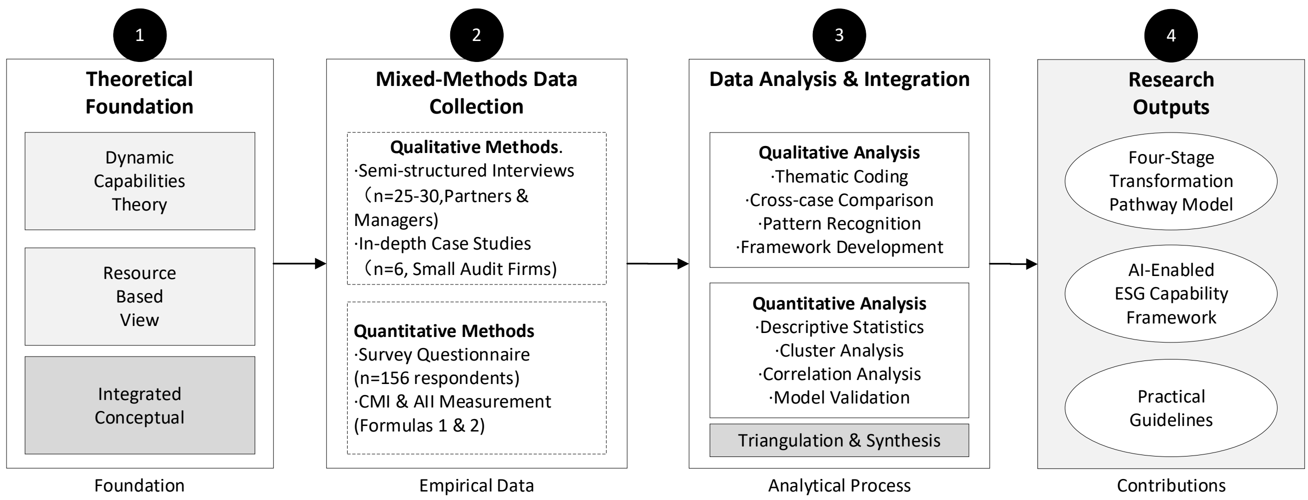

Figure 1. Research design and analytical framework

3.2 Data collection

To collect primary data on AI-enabled ESG capability building in small audit firms, various methods are employed to elicit diverse perspectives. Only semi-structured interviews are used as the primary qualitative approach for the initial extraction process. These interviews were conducted with 28 people from 18 small audit firms between March and August 2024. Participants in the interviews include senior partners, ESG leaders, technology managers, and audit directors from the firms. Participants are carefully selected through the process of purposive sampling. The average length of these interviews was 60-90 minutes. Research on digital transformation in small and medium-sized enterprises highlights the importance of examining perspectives on leadership and qualitative methods for building capabilities [22]. Audio recordings of all interviews were made after obtaining participants' consent. These transcriptions were imported into the software named NVivo 14.

To complement the interview findings, the authors developed a structured research questionnaire. This was used to survey 156 professionals in 87 small audit firms. There were 45 research questions assessing respondents' levels of AI adoption, the maturity of their ESG consulting offerings, their organizational capabilities, the degree of barriers to their transformations, and demographic details, all measured on five-point Likert scales. Scales for the research questions were developed based on prior research on technology adoption. Distribution was conducted through professional accounting bodies, and the survey response rate was 62%. Mixed-methods research techniques that combine in-depth analysis with broad quantitative data offer substantial benefits for ESG research in the emerging market and professional services sectors [23]. The 62% response rate was calculated as the number of completed surveys (n=156) divided by the number of successfully delivered invitations (n=252). Nonresponse bias assessment comparing early (n=89) and late (n=67) respondents revealed no significant differences on AI Intensity Index (t=1.23, p=0.22) or Capability Maturity Index (t=0.87, p=0.39). The 156 respondents represented 87 firms, with larger firms averaging 2.1 respondents and smaller firms 1.4 respondents.

Secondary research involved gathering data from multiple sources. Industry reports from prominent consulting firms and bodies provided data on trends and adoption rates, as well as the latest developments in ESG regulations. The firms' websites and other promotional materials provided insights into their services, marketing, and competitiveness.

Academic writing and government publications offered insights into the development of the framework. The list detailing the sample descriptions and the data collection process for the subject is provided in Table 1. The recruitment process and final sample composition are illustrated in Figure 2. From the flowchart, it is evident that individual samples for the interviews and the survey were drawn independently from different sampling frames, with minimal overlap, thereby enabling methodological triangulation. This means that the method of recruiting participants for the study enabled independent analysis of the interview and survey findings.

3.3 Data analysis

The qualitative data were analyzed using systematic and thematic coding. This was conducted after the initial stage of open coding, yielding first-order codes corresponding to the appropriate theme. It was followed by the application of axial coding, which aimed to condense the first-order codes into themes corresponding to factors such as capability, staged processes, and enabling factors. Additionally, the study employed the selective coding technique. The NVivo 14 tool facilitated systematic data management and efficient integration and visualization of the coded extracts. Two trained coders independently analyzed 29% of transcripts (n=8) to establish inter-coder reliability. The codebook combined deductive codes from dynamic capabilities theory with inductive codes from initial open coding. Following independent coding, Cohen's kappa reached 0.84 after codebook refinement, exceeding the 0.80 threshold for good reliability.

Cross-case analysis was conducted to compare experiences across the in-depth studies and, consequently, the findings. The pattern-matching method was employed to assess the extent to which the empirical evidence supported or conflicted with the assumptions derived from the framework analysis. Explanations were progressively developed to clarify the causal links between AI integration and the development of dynamic capabilities within an organization or firm. Research on the digital transformation of companies and the emerging economy suggests that robust frameworks can provide evidence of the development of dynamic capabilities [24].

In this study, the survey results were analyzed using various models to identify broad patterns. Descriptive statistics were used to characterize the distribution, central tendency, and variability of the key variables—AI intensity, ESG development, and readiness to change.

Table 1. Sample characteristics and data collection overview

Data Source	Sample Size	Key Characteristics	Collection Method	Time Period
Semi-structured Interviews	n=28 participants 18 firms	Senior Partners 35.7%, ESG Leaders 28.6%, Tech Managers 21.4%, Audit Directors 14.3%; Firm size: 10-30 emp. 50.0%, 31-60 emp. 33.3%, 61-100 emp. 16.7%	In-person/Virtual 60-90 minutes Audio recorded Professionally transcribed	March-August 2024
Survey Questionnaire	n=156 respondents 87 firms	Response rate 62%; Region: North America 42%, Europe 35%, Asia-Pacific 23%; Position: Partners 48%, Senior Managers 31%, Managers 21%	Online platform 45-item instrument 5-point Likert scales Anonymous responses	April-September 2024
In-depth Case Studies	n=6 firms	Maximum variation sampling; Stage: Early 2, Mid 2, Advanced 2; Avg. size 42 emp.; Years in operation 15-45	Multiple site visits Document review Observation Follow-up interviews	May-October 2024
Secondary Data	Multiple sources	Industry reports 15, Firm websites 87, ESG reports 23, Academic literature 60+, Regulatory documents 12	Desk research Archival analysis Public databases	January-October 2024

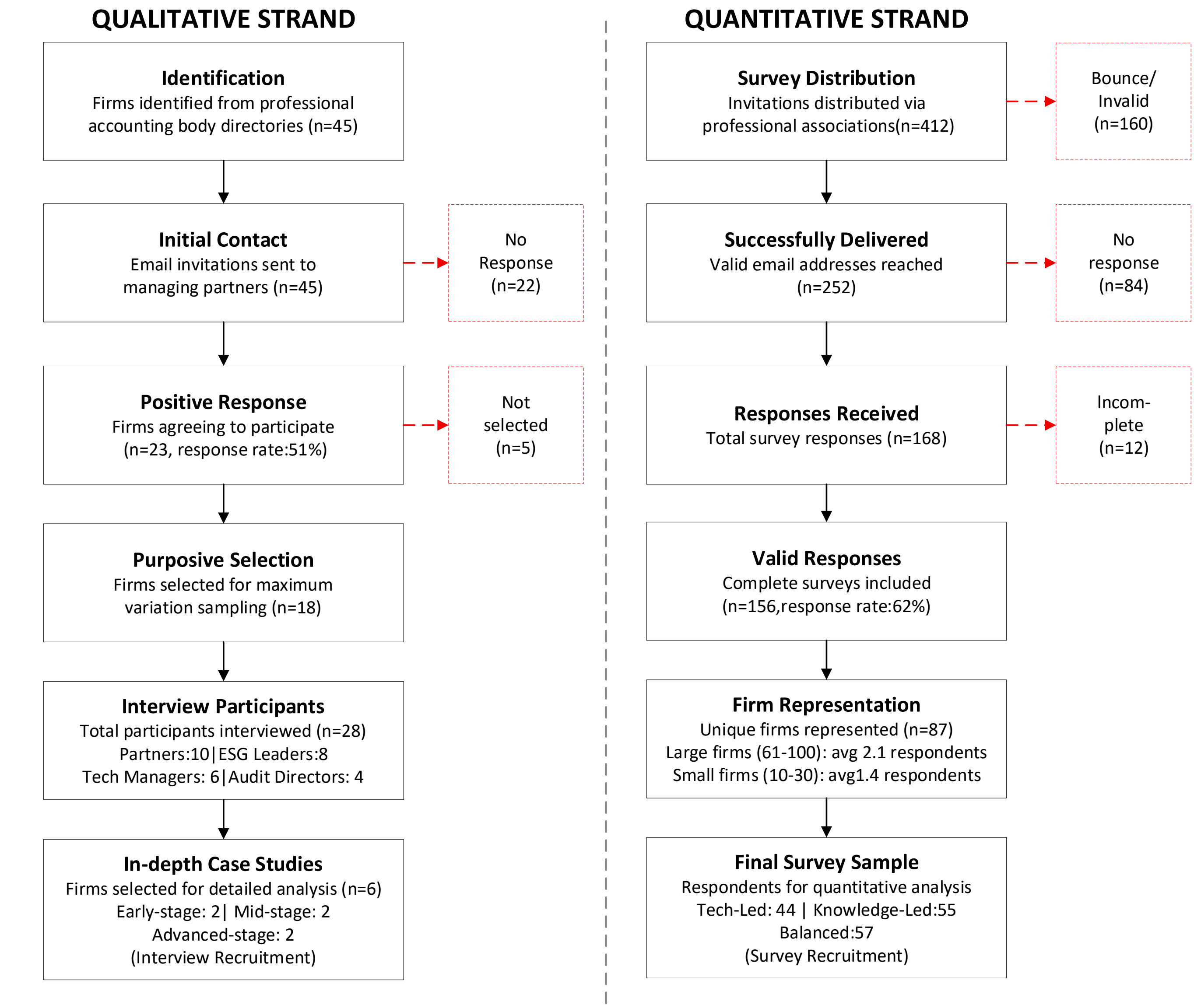

Figure 2. Participant recruitment flowchart

Table 2. Joint display of qualitative-quantitative integration

Finding	Quantitative Evidence	Qualitative Evidence	Meta-Inference
AI-ESG association	r=0.68, p<0.01	"AI tools changed how we approach ESG" (Partner, F12)	Technology enables capability development
Three pathways	Silhouette=0.58; T:28.2%, K:35.3%, B:36.5%	"We built ESG expertise first" (ESG Lead, F7)	Pathway contingent on existing capabilities
Resource optimization	Mean EOI=46.2%	"What took two weeks now takes three days" (Mgr, F3)	AI benefits documentation-intensive tasks
Stage progression	78.5% Foundation; 52.3% Optimization	"You cannot skip steps" (Director, F15)	Sequential building with cumulative effects

Note: Quantitative data from survey (n=156); qualitative evidence from interviews (n=28). F=Firm number.

Cluster analysis helped group companies based on capability profiles, and the results supported the hypothesis of three typical transformation patterns. In hierarchical clustering for cluster analysis using Ward's method, the number of clusters was determined, and validity tests were conducted through discriminant analysis and silhouette values. Lastly, correlation studies were conducted between AI intensity and ESG development through models that included the relevant variables as specified. All variables were standardized based on z-scores before analysis. Euclidean distance and Ward's criterion were used. With three clusters, the silhouette index of 0.58 and Calinski and Harabasz of 47.3 were achieved; this was better than the results of two and four clusters with silhouettes of 0.42 and 0.51 respectively. ANOVA analysis revealed significant differences between the clusters based on all the discriminant variables (p<0.001).

The process of development of the framework included the integration of findings from both qualitative and quantitative analyses. The preliminary frameworks based on case studies were tested using survey findings, and any inconsistencies were further probed. An expert panel to review the frameworks comprised three academics and five industry experts. This panel reviewed the theoretical consistency, applicability, and contribution to the existing literature of the frameworks. The integration of findings from qualitative and quantitative analyses is presented in Table 2 to demonstrate how interview narratives and survey statistics support the meta-narrative inferences drawn in this study. The panel members used structured instruments to assess the frameworks independently, with an interrater reliability of 0.79. The joint display demonstrates convergent findings across methodological strands, with quantitative correlations and efficiency metrics consistently corroborated by practitioner narratives from the interview data. The alignment between statistical patterns and qualitative themes provides evidence of construct validity, while minor discrepancies prompted additional investigation during the integration phase to reconcile different methodological perspectives.

4. Results

4.1 Current state assessment

The empirical findings demonstrate a high degree of heterogeneity in the use of AI and in the state of ESG service development among small auditing companies, as shown in Figure 3. Simple automation tools have achieved high penetration (67.3%), whereas the use of more sophisticated AI tools remains limited (12.2%). The intermediate stage of use, employing AI-aided data analytics tools, is 32.7%. ESG service maturity presents higher development challenges. Using the Capability Maturity Model framework, 38.5% of firms remain at Level 1 (Awareness), with only 11.5% achieving Level 4 (Established) or Level 5 (Optimized). Cross-tabulation reveals a strong positive association between AI adoption and ESG service maturity ($r=0.68$, $p<0.01$). Partial correlation analysis controlling for firm size, geographic region, and years of operation yielded a coefficient of 0.61 ($p<0.01$), confirming robustness after accounting for confounding variables. Given the cross-sectional design, these findings indicate association rather than causation. Detailed statistics are presented in Table 3.

4.2 AI enablement mechanisms

The empirical evidence from the research indicates that AI technology enables the development of ESG competencies across three interconnected functional dimensions, as shown in Figure 4. The findings and insights from the interviews and the case study make it clear that the use and integration of AI in auditing can help small auditing firms across the dimensions of the ESG delivery process. Figure 4(a) illustrates the adoption levels achieved by AI technologies in the three functional tiers, where the highest adoption of AI technology has been recorded in the data management application at 72.4%, followed by automatic reporting at 54.5%, and then analytical intelligence at 48.7%. AI technology in the data management functional tier enables the efficient collection, validation, and organization of ESG information. The survey revealed the use of additional AI tools throughout the process.

The analytical intelligence layer comprises AI tools that enable the interpretation, benchmarking, and development of insights from ESG information. Figure 4(b) above shows the efficiencies across various functions, with the highest value of 61.7% in report writing and the second-highest in data collection at 52.3%. The output component of this architecture comprises the automatic report function, which leverages various AI tools and technologies to generate an efficient and compliant ESG report based on GRI, TCFD, and SASB guidelines. Resource optimization effects were quantified using the Efficiency Optimization Index:

$$EOI = \frac{T_0 - T_1}{T_0} \times 100\% \quad (3)$$

Where T_0 represents time or cost under traditional approaches, and T_1 denotes requirements with AI assistance. As can be seen in Table 4, there is a detailed measurement of resource optimization using AI, indicating an average improvement in efficiency of 46.2% for all functions, an average reduction in operating expenditures of 38.6% each year, as well as an improvement in quality as measured by a reduction in errors of 43.7%.

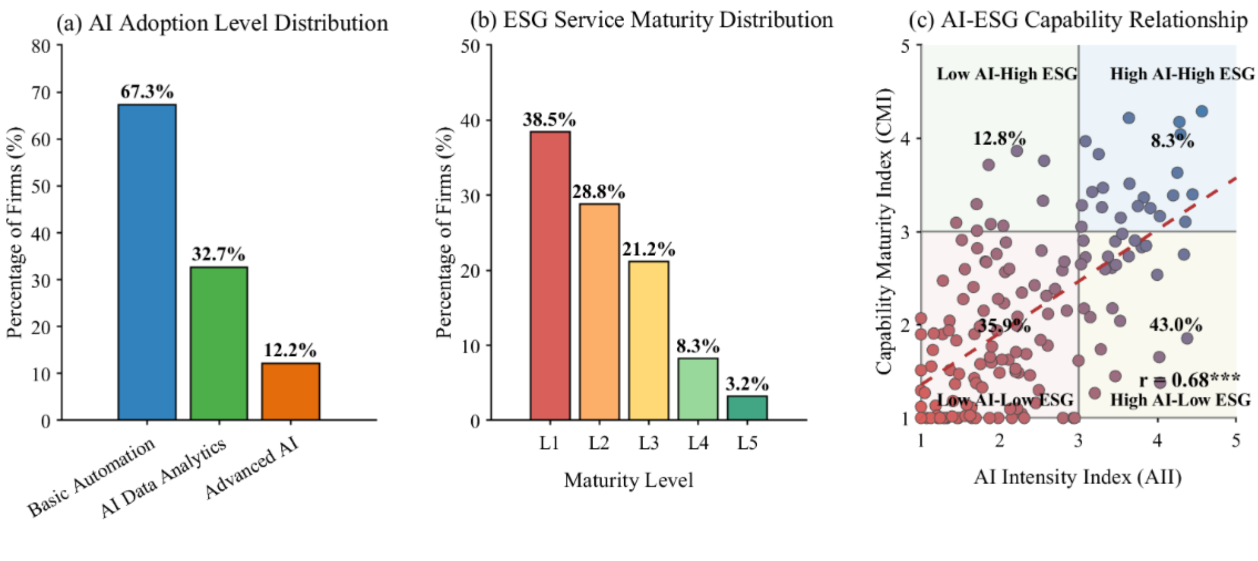

Figure 3. Dual-dimension assessment of AI adoption and ESG service maturity

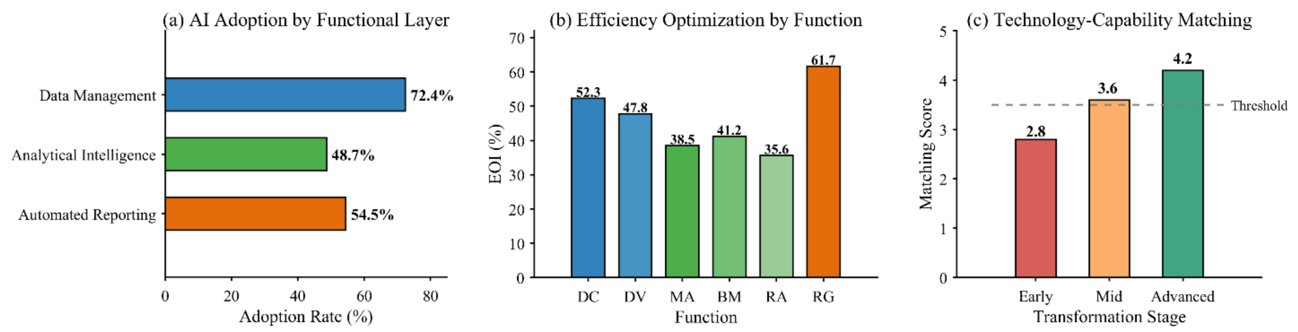

Figure 4. AI application framework for ESG consulting capability building

Table 3. Statistical analysis of current AI and ESG capabilities

Variable	Category/Dimension	Frequency (n)	Percentage (%)	Mean	SD
AI Adoption Level					
	Basic Automation Tools	105	67.3	—	—
	AI Data Analytics Tools	51	32.7	—	—
	Advanced AI Applications	19	12.2	—	—
AI Intensity Index (AII)	Overall Score (1-5)	156	100.0	2.34	1.12
ESG Service Maturity					
	Level 1 (Awareness)	60	38.5	—	—
	Level 2 (Initial Services)	45	28.8	—	—
	Level 3 (Developing)	33	21.2	—	—
	Level 4 (Established)	13	8.3	—	—
	Level 5 (Optimized)	5	3.2	—	—
Capability Maturity Index (CMI)	Overall Score (1-5)	156	100.0	2.08	0.94
Capability Gap Analysis					
	Knowledge Gap	156	—	2.65	0.87
	Technology Gap	156	—	2.87	0.95
	Organizational Gap	156	—	2.41	0.82
	Market Access Gap	156	—	2.53	0.91
AI-ESG Correlation	Pearson's r	—	—	0.68***	—

Note: Gap scores measured on 1-5 scale (1=minimal gap, 5=severe gap). ***p<0.01. SD=standard deviation

Table 4. Quantitative effects of AI-enabled resource optimization

Category	Dimension	Indicator	Before AI	After AI	Change
Efficiency	Data Management	Data Collection Time (hrs)	24.5	11.7	-52.3%
Efficiency	Analytical Intelligence	Materiality Assessment (hrs)	18.2	11.2	-38.5%
Efficiency	Automated Reporting	Report Generation (hrs)	32.5	12.4	-61.7%
Cost	Labor	Cost per Project (USD)	8,450	5,240	-38.0%
Cost	Operations	Annual Cost (USD)	142,000	87,200	-38.6%
Quality	Accuracy	Error Rate (%)	8.7	4.9	-43.7%
Quality	Completeness	Data Coverage (%)	72.4	91.6	+26.5%
Scalability	Capacity	Projects per Staff (Annual)	8.2	12.6	+53.7%

Note: Efficiency optimization index. Data based on survey responses (n=156) and case studies (n=6). Average efficiency gain across functions: 46.2%.

Table 5 summarizes the use of various tools in the surveyed companies, revealing that robotic process automation tools lead in deployment, while predictive analytics remain in the early adopter stage. Analysis of technology capability matching reveals the differentiating trends in AI adoption across the stages. Figure 4(c) shows an increase in matching scores from 2.8 in the early stages to 4.2 in the advanced stages, with the threshold fixed at 3.5. While early-stage companies use basic automation technologies to address pressing issues, advanced companies use advanced analytical tools to differentiate their services. The alignment between technology investment and development goals becomes a critical factor.

Table 5. Primary AI tools in the ESG consulting practice

AI Category	Representative Tools	Adoption Rate
Large Language Models	GPT-4, Claude, Gemini	23.7%
RPA + AI	UiPath, Power Automate	52.8%
ESG Data Platforms	Refinitiv, MSCI, Sustainalytics	31.4%
NLP/Text Analytics	BERT-based models, Azure AI	18.5%
Visualization + AI	Power BI Copilot, Tableau	41.2%
Document Intelligence	Azure Document AI, ABBYY	34.6%

4.3 Strategic transformation pathways

Cluster analysis and cross-case synthesis of the survey data identify that there are three distinct transformation pathway types that small auditing firms use in developing their ESG consulting services using AI, led on the Technology-Led pathway, illustrated in Figure 5. The Technology-Led approach perceives the adoption and development of AI technology and the resulting technical capability as vital preconditions that need to be achieved before the development of ESG knowledge. Figure 5(a) describes the radar chart comparison. The Knowledge-Led approach builds up ESG knowledge and credentialed accumulation before the integration of AI technology. The Balanced approach aims at balancing the development of technology and knowledge aspects. Statistical comparison of the three pathway clusters is provided in Table 6, presenting mean differences with ANOVA results.

The ANOVA results confirm statistically significant differences among the three pathway clusters across all capability-related variables, with Technology-Led firms exhibiting higher AI intensity and technology readiness, while Knowledge-Led firms demonstrated superior ESG knowledge depth. The success rate variable showed marginally non-significant variation across clusters, suggesting that multiple pathways can achieve comparable transformation outcomes. The four-stage model of transformation includes a development horizon of 30 to 36 months, as shown in Figure 6.

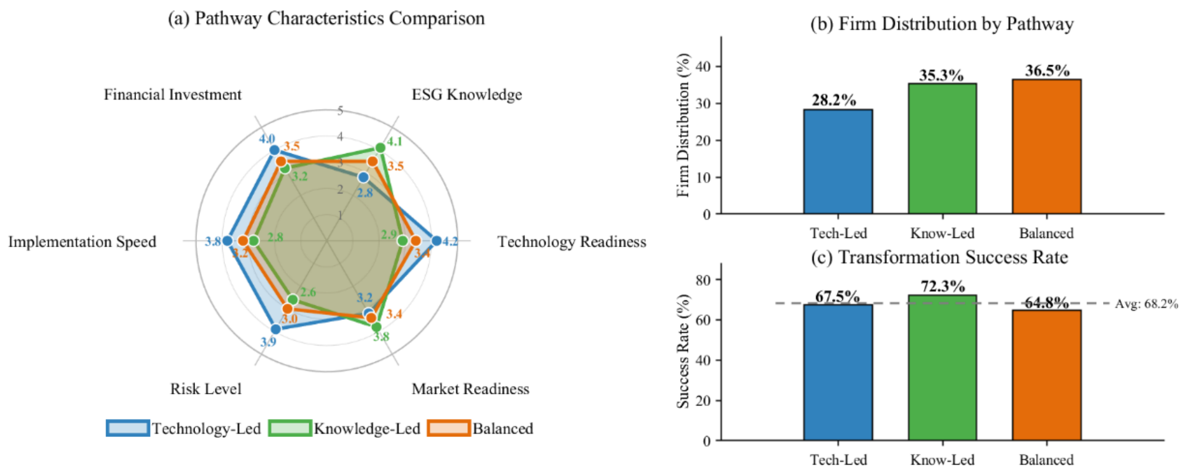

Figure 5. Comparison of three transformation pathway archetypes

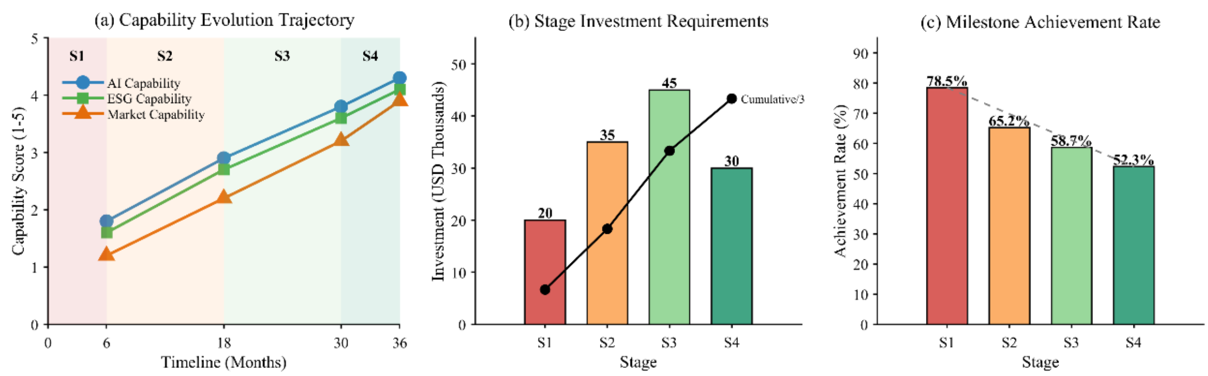

Figure 6. Four-stage transformation pathway model for AI-driven ESG capability building

Table 6. Statistical comparison of transformation pathway clusters

Variable	Tech-Led (n=44)	Know-Led (n=55)	Balanced (n=57)	F	p
AI Intensity Index	3.82 (0.71)	2.43 (0.68)	3.15 (0.59)	47.3	<0.001
ESG Knowledge Depth	2.76 (0.84)	4.12 (0.62)	3.48 (0.73)	38.9	<0.001
Technology Readiness	4.21 (0.58)	2.89 (0.77)	3.42 (0.65)	41.2	<0.001
Implementation Speed (months)	24.3 (5.2)	31.8 (6.7)	28.4 (5.9)	15.4	<0.001
Success Rate (%)	67.5 (18.3)	72.3 (15.6)	64.8 (17.1)	2.8	0.064

Table 7. Key elements matrix of the four-stage transformation pathway

Element	Stage 1: Foundation (0-6 months)	Stage 2: Development (6-18 months)	Stage 3: Integration (18-30 months)	Stage 4: Optimization (30-36+ months)
Strategic Objective	Establish transformation readiness and organizational commitment	Build systematic capabilities and initial market presence	Achieve technology-expertise convergence and service maturity	Pursue continuous improvement and market leadership
Key Activities	Leadership alignment, tool selection, training initiation, pilot testing	Team formation, process standardization, pilot client engagement, quality systems	Service portfolio expansion, client acquisition, capability integration, brand building	Innovation programs, partnership development, market expansion, knowledge sharing
Resource Investment	USD 15-25K; 1-2	USD 30-40K; 3-5 staff;	USD 40-50K; 5-8 staff;	USD 25-35K; 8+ staff;
Critical Success Factors	Leadership commitment, clear vision, adequate seed funding	Talent acquisition, client relationship, methodology rigor	Technology-expertise alignment, market positioning, service quality	Innovation culture, adaptive capacity, industry recognition
Achievement Rate	78.5%	65.2%	58.7%	52.3%

Note: Investment figures represent incremental stage requirements. Achievement rate indicates the percentage of firms successfully completing all stage milestones. Staff counts represent full-time equivalents dedicated to ESG services.

The Foundation Stage (0-6 months) lays the basic infrastructure. The Development Stage (6-18 months) focuses on the development of capabilities. The Integration Stage (18-30 months) integrates technological capabilities and knowledge of the domain area. The Optimization Stage (30-36+ months) focuses on constant improvement and seeks a leadership position in the marketplace. The major elements are defined in Table 7. Table 7 is the Key Elements Matrix that outlines the strategic aims and activities, as well as the resource commitments and attainment levels of the transformational stages. Issues of priority pertaining to capabilities were already discussed earlier. It is observable that there is an ascending order of complexity and resource requirements from stage to stage. The range of investment from the Foundation stage is projected at USD 15,000-25,000. Cumulatively from the Optimization stage, the investment required is between USD 80,000-120,000. The key elements of success shift from input to output-oriented criteria that stand at the accomplishment of training sessions, the application of tools, and the acquisition of clients to revenue enhancement and recognition within the marketplace. The matching threshold of 3.5 was determined through analysis of empirical distributions, with all corporations above this level demonstrating integrated capabilities in their interview accounts.

The time windows for stage duration were determined through case study observation and compared to data obtained in surveys. Investment estimates are median self-reports valued in USD, with exchange rates provided in June 2024. Pathway selection analysis identifies various factors that determine the best approach to transformation, as shown in Figure 7. Figure 7(a) shows the ranking of the importance of selection factors. It shows that existing capability profile (average score 4.3) and availability of financial resources (4.1) are the chief determinants, followed by market positioning objectives (3.8) and risk tolerance (3.6). Figure 7(b) shows the matching conditions between the characteristics of a firm and the pathway recommended through a decision logic visualization: firms with strong technology backgrounds and sufficient capital endowments have the highest success rates with Technology-Led approaches, while firms with established relationships with audit clients and ESG expertise secure better outcomes through Knowledge-Led pathways. Firms with limited resources benefit most from Balanced approaches that diffuse investment risk across multiple dimensions of capabilities.

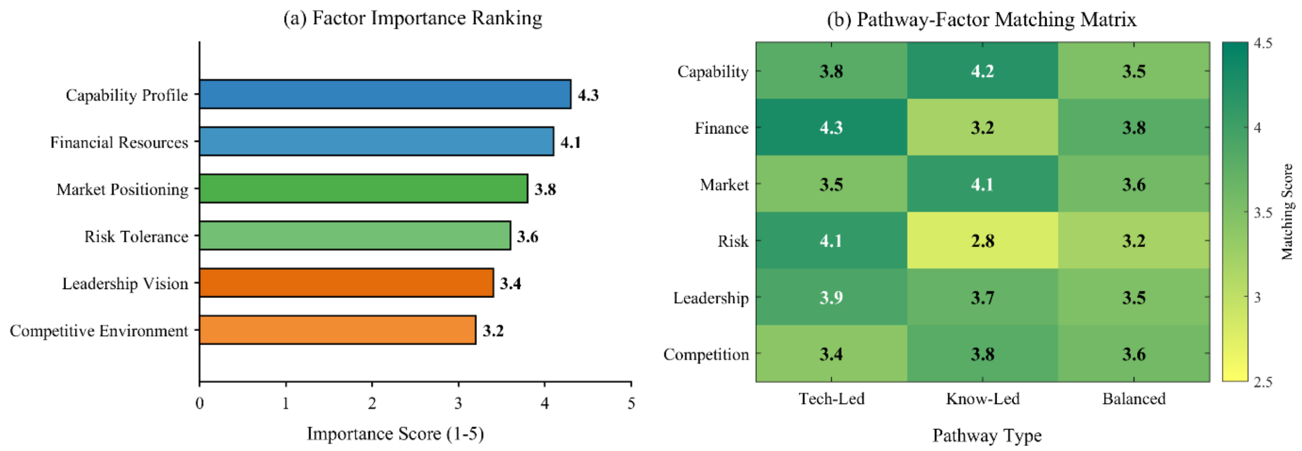

Figure 7. Influencing factors and matching conditions for pathway selection

5. Discussion

5.1 Theoretical implications

Implications of the results have been discussed in relation to the theory of dynamic capabilities, and they help explain how small audit firms recreate and augment their ESG capabilities through AI. The earlier model in the theory of dynamic capabilities comprises the aspects of sensing, transforming, and seizing. However, the original Teece framework exhibits several limitations when applied to resource-constrained professional service contexts. First, the sensing-seizing-transforming trichotomy emphasizes opportunity identification and resource reconfiguration but offers limited guidance on the sequential development of capabilities for firms lacking foundational competencies. Second, the original model implicitly assumes existing organizational capabilities as a starting point, without adequately addressing situations where firms must simultaneously develop dual capabilities in both technology adoption and domain expertise. Third, the framework offers insufficient specification of temporal dynamics and stage-specific resource requirements for transformation processes. The present study addresses these limitations by proposing a four-stage model—foundation, development, integration, and optimization—that delineates concrete activities, resource thresholds, and milestone indicators for each phase, thereby extending dynamic capabilities theory to AI-enabled professional service transformation in resource-constrained settings.

These findings are consistent with emerging knowledge on digital transformation in SMEs. The critical role of dynamic capabilities in the development of digital leadership and digital culture in SMEs, focusing on both technology and organization, has been established by Held et al. [25]. The present work builds on their insights by demonstrating that the development of AI-ESG capability-building entails concept integration, in which technology and subject-area knowledge align. The evidence supporting this observation comes from the strong positive relationship reported in the present work between the AI Intensity Index and the Capability Maturity Index, with a correlation coefficient of $r = 0.68$. The three types of transformative paths provide theoretical insights into the strategic choice process in capability development.

Although there have been studies on corporate entrepreneurship and digital transformations within the dynamic capabilities framework, including Chen et al. [26], most are conceptual and address broader settings. The present work reveals that small audit firms exhibit different pathway choices, determined by capability profiles, resource access, and risk propensity. The evidence that Knowledge-Led has a higher success ratio (72.3%) than Technology-Led (67.5%), given the assumed need for prior technology investment in the process, raises questions about absorptive capacity requirements for domain knowledge in relation to technology adoption. Theoretical underpinnings frame the role of AI technology in the industry as a capability multiplier, enabling smaller, resource-scarce firms to achieve service sophistication that had hitherto been available only through larger competitors.

5.2 Practical implications

The results of the research provided useful insights and directions for various stakeholders involved in the process of change in small audit firms. The four-stage model of change can serve as an instrument for industry leaders to evaluate their positions and make appropriate resource allocations. The recognition of the three pathway types now enables strategies to be aligned with in-house competencies: Technology-Led types are most appropriate for companies with extensive experience in technology, whereas Knowledge-Led strategies build on existing experience with clients. The measured efficiencies, averaging 46.2%, provide a strong rationale for investment in AI. The most significant returns could be achieved in report writing and data gathering.

These results should be informative for technology suppliers seeking to develop AI-supported ESG solutions for auditing. As Sewpersadh asserts, technologies change the basic process architecture in auditing; consequently, strategies for technology application and development require corresponding adjustments [27]. Evidence that companies with matching scores over 3.5 have much higher success ratios in the technology and capability matching testifies that suppliers should offer solutions that align with different capacities and development phases, rather than developing technology platforms with uniform capabilities and advancements. Seamless integration capabilities with existing auditing systems are essential. These results could be used by policymakers and professional bodies to design support programs that foster capability development in the industry. Lou and Zhou identify linkages among digital transformation, green innovations, and audit service development, pointing out the regulatory implications of technology-enabled sustainability practices [28]. Training the curriculum in AI skills and ESG knowledge, and in the use of technology platforms that reduce the needs of individual investors, could expedite the process for smaller companies. Certification systems that identify AI-enabled ESG consulting skills send a positive signal that encourages those who invest in capabilities, and they also address service quality. Guidelines on expectations regarding technology governance and data protection would reduce uncertainties that currently hamper investment in the transformation process.

5.3 Limitations and future research

In the present investigation, several limitations should be considered when interpreting the results. Firstly, the subjects in the present investigation are primarily from developed nations in North America, Europe, and the Asia-Pacific region. Therefore, generalizability to emerging markets could be hampered, as institutional settings and technology infrastructure differ substantially. The survey employed in the present investigation reveals associations rather than causation; that is, the 30-36-month timeframe reported in the study may be subject to recall bias. Despite the use of multiple sources, measurement limitations may exist because self-reported measures were used. The purposive sampling limits statistical generalizability, and the predominantly developed-economy sample may not apply to emerging markets with different institutional environments. The cross-sectional design precludes causal inference, and self-reported measures are subject to recall bias. Missing data (n=12 cases) were handled via listwise deletion; sensitivity analyses using multiple imputation produced similar results.

Future studies should address the questions raised in this paper and build on the insights presented here. Longitudinal studies that include the entire process undergone by firms during their transformations would strengthen causal claims. Qiu and Chang provide insight into the role of dynamic capability in digital innovation as a mediator linking digital transformation to innovation performance [29], and highlight the need to examine the process of AI-ESG development. Comparative analyses across different regulatory systems would provide insights into the role of institutional factors in the processes and determinants of success. In this respect, the work of Broadstock et al. outlines an indirect relationship between the implementation process of ESG and the ability to innovate [30]. Here, there appears to be a need for future research on the relationship between companies' ESG consulting capabilities and their sustainable development and innovative performance.

6. Conclusion

This paper examines the process by which small auditing firms undergo the transformation required to offer AI-enabled ESG consulting services. Using dynamic capabilities theory and mixed methods, with both qualitative interviews and survey data, this paper has discovered three types of transformation pathways and a four-stage model over a period of up to 30-36 months. The findings reveal significant heterogeneity in current capability levels: only 12.2% of companies use advanced AI applications, and only 11.5% have achieved established maturity in their ESG services. The strong positive correlation between AI adoption and ESG capability development (r=0.68) indicates a reinforcing relationship between the technology and knowledge dimensions. Theoretical contributions arise from extending dynamic capability theory by developing sequential capability-building process models in resource-scarce professional service settings. The four-phase approach illustrated the effectiveness of intentional movement through foundation, development, integration, and optimization phases, each with its own resource configuration. The Technology-Led, Knowledge-Led, and Balanced approach path types offered richer insights into strategy formulation in capability development, with the Knowledge-Led approach achieving a slightly higher success rate at 72.3% than the Technology-Led approach at 67.5%. The applied contributions guide the following fronts. Small audit firms provide numerous beneficial directions for planning and implementation strategies in auditing, with average efficiency gains of approximately 46.2%. Technology companies guide the development of adaptable solutions, taking into account diverse capacities, while policymakers guide the development of technology platforms. Based on the conclusions derived from the work, AI-enhanced ESG capability development has both a strategic imperative and an attainable goal for smaller audit firms that can commit long-term resources to their strategic transformations. Small audit firms need to conduct practical assessments of their current capabilities, align their transformation strategies, and remain flexible during implementation.

Acknowledgements

The authors would like to thank the practitioners and respondents from small audit firms for their voluntary cooperation and contributions to this research. They would also like to extend their thanks to the expert panel members for their constructive criticism of the analytical framework.

Ethical issue

This study was approved by the Institutional Review Board before carrying out any data collection. Consent was obtained from all participants, and participation was voluntary. Data from the interviews and surveys was anonymized and stored on encrypted servers accessible only to the team. The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, figure manipulation, competing interests, and research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, additional data will be provided by the corresponding author upon reasonable request.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process?. Review of Accounting Studies, 27(3), 938-985. DOI: https://doi.org/10.1007/s11142-022-09697-x

[2] Law, K. K., & Shen, M. (2025). How does artificial intelligence shape audit firms?. Management Science, 71(5), 3641-3666. DOI: https://doi.org/10.1287/mnsc.2022.04040

[3] Kim, J., & Yang, W. (2025). Environmental, Social, and Governance (ESG) Research: A Systematic Review of Recent Trends (2020–2024). Sustainable Development. DOI: https://doi.org/10.1002/sd.70370

[4] Liao, H. T., Pan, C. L., & Zhang, Y. (2023). Collaborating on ESG consulting, reporting, and communicating education: Using partner maps for capability building design. Frontiers in Environmental Science, 11, 1119011. DOI: https://doi.org/10.3389/fenvs.2023.1119011

[5] Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. Journal of business ethics, 209-234. DOI: https://doi.org/10.1007/s10551-019-04407-1

[6] Wassie, F. A., & Lakatos, L. P. (2024). Artificial intelligence and the future of the internal audit function. Humanities and Social Sciences Communications, 11(1), 1-13. DOI: https://doi.org/10.1057/s41599-024-02905-w

[7] Al-Moaid, N. A. A., & Almarhdi, S. G. (2024). Developing dynamic capabilities for successful digital transformation projects: The mediating role of change management. Journal of Innovation and Entrepreneurship, 13(1), 85. DOI: https://doi.org/10.1186/s13731-024-00446-9

[8] Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. Long range planning, 52(3), 326-349. DOI: https://doi.org/10.1016/j.lrp.2018.12.001

[9] Kulichyova, A., Kazantsev, N., White, L., & Islam, N. (2025). Digital transformation in large established organisations: Four restructuring dilemmas based on dynamic capabilities. International Journal of Management Reviews. DOI: https://doi.org/10.1111/ijmr.12395

[10] Rizana, A. F., Wiratmadja, I. I., & Akbar, M. (2025). Exploring Capabilities for Digital Transformation in the Business Context: Insight from a Systematic Literature Review. Sustainability, 17(9), 4222. DOI: https://doi.org/10.3390/su17094222

[11] Helfat, C. E., Kaul, A., Ketchen Jr, D. J., Barney, J. B., Chatain, O., & Singh, H. (2023). Renewing the resource - based view: New contexts, new concepts, and new methods. Strategic Management Journal, 44(6), 1357-1390. DOI: https://doi.org/10.1002/smj.3500

[12] Teece, D. (2020). Hand in glove: Open innovation and the dynamic capabilities framework. Available at SSRN 5399445. DOI: http://dx.doi.org/10.2139/ssrn.5399445

[13] Khamisu, M. S., & Paluri, R. A. (2024). Emerging trends of environmental social and governance (ESG) disclosure research. Cleaner Production Letters, 7, 100079. DOI: https://doi.org/10.1016/j.clpl.2024.100079

[14] Goerzen, A., Van Assche, A., Zhan, J. X., & Zhang, L. (2025). From the editors: Global sustainability reporting standards and the future of international business. Journal of International Business Policy, 1-12. DOI: https://doi.org/10.1057/s42214-025-00213-x

[15] Dekeyser, S., Gaeremynck, A., & Willekens, M. (2024). Competitive strategies for small audit firms. The International Journal of Accounting, 59(2), Article 2450012. DOI: https://doi.org/10.1142/S1094406024500124

[16] Raihan, M., & Kurniawati, H. (2025). Transformation of external auditors in audit practices through the use of cloud technology. International Journal of Cloud Applications and Computing (IJCAC), 15(1), 1-30. DOI: 10.4018/IJCAC.381895

[17] Goud, N. N. Corporate Sustainability Performance vis-à-vis ESG Disclosure and R&D: Does It Matter to Influence Corporate Performance—Evidence from India. Indian Journal of Corporate Governance, 09746862251384720. DOI: https://doi.org/10.1177/09746862251384720

[18] Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). The digital transformation of external audit and its impact on corporate governance. Technological Forecasting and Social Change, 150, 119751. DOI: https://doi.org/10.1016/j.techfore.2019.119751

[19] Bani, P., Siregar, N., Subiyanto, B., & Awaludin, D. T. (2025). Digital Transformation in the Audit Process: A Systematic Review of Innovation, Challenges, and its Impact on Audit Quality. Journal Research of Social Science, Economics & Management, 5(3). DOI: https://doi.org/10.59141/jrssem.v5i3.1109

[20] Vitali, S., & Giuliani, M. (2024). Emerging digital technologies and auditing firms: Opportunities and challenges. International Journal of Accounting Information Systems, 53, 100676. DOI: https://doi.org/10.1016/j.accinf.2024.100676

[21] Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. Academy of management journal, 50(1), 25-32. DOI: https://doi.org/10.5465/amj.2007.24160888

[22] Gyamerah, S., Afshari, L., & Asante, D. (2025). Digital transformation in the SME context: The nexus between leadership, digital capabilities and digital strategy. International Small Business Journal, 43(3), 303-328. DOI: https://doi.org/10.1177/02662426251314108

[23] Adardour, Z., Ed-Dafali, S., Mohiuddin, M., El Mortagi, O., Sbai, H., & Bouzahir, B. (2025). Exploring the drivers of environmental, social, and governance (ESG) disclosure in an emerging market context using a mixed methods approach. Future Business Journal, 11(1), 107. DOI: https://doi.org/10.1186/s43093-025-00530-w

[24] Alrub, Y. A., & Sánchez-Cañizares, S. M. (2025). Dynamic capabilities and digital transformation: Toward strategic planning in the digital age—Evidence from palestine. Administrative Sciences, 15(1), 21. DOI: https://doi.org/10.3390/admsci15010021

[25] Held, P., Heubeck, T., & Meckl, R. (2025). Boosting SMEs' digital transformation: the role of dynamic capabilities in cultivating digital leadership and digital culture. Review of Managerial Science, 1-29. DOI: https://doi.org/10.1007/s11846-025-00919-5

[26] Chen, H., Popaitoon, S., & Mumi, A. (2025). Investigating corporate entrepreneurship strategy through digital transformation: a dynamic capabilities perspective. Journal of Innovation and Entrepreneurship, 14(1), 95. DOI: https://doi.org/10.1186/s13731-025-00570-0

[27] Sewpersadh, N. S. (2025). Adaptive structural audit processes as shaped by emerging technologies. International Journal of Accounting Information Systems, 56, 100735. DOI: https://doi.org/10.1016/j.accinf.2025.100735

[28] Lou, P., & Zhou, X. (2024). Digital transformation, green innovation, and audit fees. Frontiers in Environmental Science, 12, 1323282. DOI: https://doi.org/10.3389/fenvs.2024.1323282

[29] Qiu, P., & Chang, B. (2025). The impact of digital transformation on open innovation performance: The intermediary role of digital innovation dynamic capability. PloS one, 20(3), e0317785. DOI: https://doi.org/10.1371/journal.pone.0317785

[30] Broadstock, D. C., Matousek, R., Meyer, M., & Tzeremes, N. G. (2020). Does corporate social responsibility impact firms' innovation capacity? The indirect link between environmental & social governance implementation and innovation performance. Journal of Business Research, 119, 99-110. DOI: https://doi.org/10.1016/j.jbusres.2019.07.014