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Exploring AI Application in ESG Assurance: Insights from UTAUT and Perceived Risk Theory

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ABSTRACT. The burgeoning field of Environmental, Social, and Governance (ESG) reporting, coupled with the transformative potential of Artificial Intelligence (AI), presents a paradigm shift for assurance services in Vietnam. This article explores the multifaceted factors influencing the adoption of AI in ESG assurance within the Vietnamese context, employing a dual theoretical framework of the Unified Theory of Acceptance and Use of Technology (UTAUT) and Perceived Risk Theory (PRT). By synthesizing existing literature, this paper identifies key determinants, from performance and effort expectancies to the pivotal role of perceived risks, that are likely to shape the trajectory of AI integration in this critical domain. The analysis provides valuable insights for assurance providers, regulators, and companies navigating the complexities of technological adoption in an emerging economy.

1. INTRODUCTION

The global shift toward sustainable business practices has elevated ESG considerations to a central position in corporate reporting. Over the past decade, four principal drivers of ESG adoption have been identified [1]. First, empirical evidence indicates a positive association between ESG engagement and financial performance, with firms demonstrating higher ESG ratings consistently achieving superior financial returns compared to those with weaker ESG performance [2]. Second, evolving societal expectations - shaped by climate change, responsible business conduct, and workplace diversity - are increasingly influencing both consumer preferences and corporate performance [1]. Third, firms and financial institutions are progressively adopting a long-term perspective in assessing risk and return, aligning their strategies with the pursuit of sustainable financial outcomes [2]. Finally, ESG has evolved from a

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voluntary aspect of corporate social responsibility into a legally mandated framework, particularly within the European Union [1]. In the context of Vietnam - characterized by rapid economic expansion and deepening integration into global markets - the demand for transparent and reliable ESG disclosure is intensifying. Key stakeholders, including investors, regulators, and consumers, increasingly reject self-reported information and emphasize the need for independent assurance mechanisms to reduce the risk of greenwashing and to enhance the credibility of ESG reporting.

Concurrently, the advent of the Fourth Industrial Revolution, characterized by the proliferation of AI, has introduced transformative opportunities for enhancing the efficiency, effectiveness, and scope of assurance services. AI-enabled technologies are capable of processing extensive datasets, detecting anomalies, and generating advanced insights into corporate ESG performance and associated risks, thereby surpassing the analytical capacity of conventional audit and assurance methodologies. Nevertheless, the integration of AI into ESG - related processes also introduces new layers of complexity [3]. AI has emerged as a critical driver of digital transformation, influencing firms' growth trajectories, innovation potential, and value creation capacity [4]. Given that ESG and sustainability reporting depend fundamentally on accurate, comprehensive, and timely data, AI technologies - particularly machine learning and natural language processing - offer the capacity to process diverse forms of information, ranging from emission disclosures to employee records, thereby identifying patterns, risks, and opportunities that might remain undetected by human analysts.

Despite these benefits, the application of AI in ESG reporting and assurance raises significant concerns that may offset its advantages. While AI contributes to data collection, ESG rating development, accounting, financial reporting, and risk management, it simultaneously introduces challenges related to data privacy, algorithmic bias, and transparency [3]. Communicating such technology-related intangible assets to investors and stakeholders is essential to enable accurate market valuation and to foster sound governance practices [4]. However, the opacity of AI's decision-making mechanisms continues to raise pressing questions regarding transparency, accountability, and compliance. These concerns hold particular relevance in the context of the Corporate Sustainability Reporting Directive, which mandates comprehensive and verifiable ESG disclosures. Furthermore, the reliance of AI systems on vast volumes of data generates additional ESG implications, including biased algorithmic outcomes and the environmental costs of carbon-intensive training processes. Consequently, internal decision-makers, financial markets, and broader stakeholder groups must critically assess both the risks and impacts of AI in relation to ESG performance. The adoption of such transformative technologies, however, presents unique challenges within emerging economies such as Vietnam, where regulatory frameworks, institutional capacity, and technological infrastructure remain in the process of development.

This article aims to provide a comprehensive analysis of the factors affecting the application of AI in ESG assurance in Vietnam. To achieve this, we employ a robust theoretical lens combining the UTAUT and PRT. UTAUT offers a framework for understanding the key drivers of technology acceptance, while PRT provides a crucial perspective on the potential barriers and uncertainties that may hinder adoption. By integrating these two theories, we can develop a more nuanced understanding of the complex interplay of forces shaping the future of ESG assurance in Vietnam.

2. LITERATURE REVIEW

2.1. The Rise of ESG and the Need for Assurance

The global shift from voluntary to mandatory ESG reporting has exposed a critical "assurance gap," where the verification of ESG data significantly lags behind the rigor of traditional financial audits [5]. This gap is particularly pronounced as stakeholders, including investors and regulators, increasingly demand transparent and reliable non-financial disclosures to assess risks related to climate change and corporate sustainability [5, 6]. In emerging markets like Vietnam, this demand is escalating in alignment with international standards, yet traditional sample-based assurance methods are ill-equipped for the volume and complexity of ESG data [7]. A primary challenge undermining the credibility of ESG initiatives is the prevalence of greenwashing, where organizations make exaggerated or misleading claims about their sustainability efforts [8]. This issue is exacerbated by a lack of standardized reporting frameworks, leading to inconsistent and incomparable data that erodes investor trust and accountability [9, 10]. The problem is further compounded within corporate governance structures, as audit and risk committees often lack the specialized technical expertise to effectively oversee ESG-related operational risks, focusing instead on familiar financial and legal domains [5]. Consequently, without robust, independent assurance, the integrity of ESG disclosures remains compromised [11].

In response, regulatory bodies worldwide are introducing stringent mandates, such as the European Union's Corporate Sustainability Reporting Directive, to enforce standardized and assured ESG reporting [12, 13]. This regulatory push underscores that high-quality, independent assurance is no longer optional but essential for enhancing corporate transparency, building stakeholder confidence, and ensuring the integrity of market information [14, 15]. The transition toward reasonable assurance demands more robust data governance and analytical capabilities, highlighting a significant data literacy gap within many organizations and reinforcing the urgent need for innovative, technology-driven assurance methodologies to validate the credibility of corporate ESG performance [16].

2.2. Artificial Intelligence in Assurance

Recent scholarship has increasingly emphasized the potential of AI to transform ESG reporting and assurance by addressing persistent challenges related to authenticity, credibility, and standardization. Traditional third-party verification processes are often constrained by conflicts of interest, inconsistent evaluation methodologies, and a lack of trust in reported information - failures that have been underscored by high-profile scandals such as Volkswagen's "Dieselgate" [17]. To address these shortcomings, Liu et al. [17] propose Veri-Green, a blockchain-based framework that integrates AI-driven verifier selection and incentive mechanisms. By employing advanced machine learning algorithms to match firms with appropriate verifiers and using a Vickrey-Clarke-Groves auction system to encourage accurate assessments, this approach aims to enhance transparency, impartiality, and efficiency in ESG assurance.

Building on this, Adam et al. [5] argue that AI holds the potential to revolutionize audit assurance more broadly, particularly by improving the speed and accuracy of data analysis. AI systems can monitor greenhouse gas emissions, detect discrepancies in environmental reporting, and support compliance with regulatory standards. These capabilities enhance the precision and timeliness of ESG disclosures, thereby improving audit quality. However, risks remain: over-reliance on AI, inadequate governance, and limited expertise in understanding industry-specific risks highlight the need for careful oversight.

Other studies highlight the application of AI in combating greenwashing, a practice that undermines stakeholder trust. Chiou and Hsieh [8] suggest that AI-powered tools such as text mining and machine learning can systematically detect misleading sustainability claims, thereby strengthening the reliability of ESG assurance. Similarly, Ilori et al. [18] propose an AI-powered auditing framework that enhances data verification and corporate governance through real-time analytics. While these technologies improve accuracy, they also face barriers to adoption, particularly among small and medium-sized enterprises that often lack the financial resources, digital infrastructure, and technical expertise required for implementation.

AI applications are also increasingly being explored in supply chains and unstructured data environments. Komronbek [7] identifies natural language processing and computer vision as particularly promising for extracting ESG metrics from sources such as corporate disclosures, regulatory filings, satellite images, and drone data. These methods facilitate independent verification of environmental impacts, such as deforestation or pollution. Yet, limitations remain concerning algorithmic bias, misinterpretation of context, and the opacity of AI decision-making, necessitating hybrid "AI-human" assurance models to maintain compliance with emerging standards such as ISSA 5000.

The potential of AI to improve efficiency and credibility in sustainability reporting is further reinforced by Vaio et al. [6], who highlight applications in real-time accounting, continuous auditing, and automated attestation. Natural language processing and machine learning can support compliance monitoring, content analysis, and readability assessments of sustainability disclosures, while techniques such as Latent Dirichlet Allocation help summarize reports and identify thematic trends. These innovations not only streamline the assurance process but also mitigate the risks of selective disclosure and misrepresentation. Complementing this perspective, Budhathoki et al. [19] note the emerging role of generative AI, such as ChatGPT, in processing large datasets for assurance purposes. Although such tools can enhance efficiency, concerns persist regarding accuracy, misinformation, and bias, underscoring the necessity of human verification.

Several contributions also emphasize AI's role in standardization and real-time monitoring. Majekodunmi [10] demonstrates that AI can harmonize ESG data by mapping diverse inputs to common frameworks (e.g., GRI, SASB), enabling greater consistency and comparability. Automated assurance engines further allow continuous monitoring of ESG performance indicators, thereby improving the rigor of reporting practices. Similarly, Halim et al. [11] introduce the concept of Audit 4.0, which integrates AI, big data analytics, and the Internet of Things to provide real-time, evidence-based assurance. These developments enhance the ability of auditors to detect anomalies, validate disclosures, and mitigate greenwashing, while also supporting firms in achieving sustainability targets such as net-zero emissions.

Nevertheless, scholars also highlight critical limitations of AI adoption in assurance. Nene [14] cautions that while AI tools can analyze entire datasets and generate predictive insights, they cannot substitute human judgment in areas such as ethical decision-making, corporate governance, and regulatory negotiations. This reinforces the need for "hybrid intelligence," where AI augments, but does not replace, professional expertise. Senturk [15] similarly argues that AI-driven auditing offers significant efficiency gains and enables continuous auditing, yet unresolved challenges - such as cybersecurity risks, algorithmic opacity, and ethical accountability - remain barriers to full adoption.

Taken together, these studies demonstrate both the promise and the complexity of integrating AI into ESG assurance. On the one hand, AI can enhance efficiency, standardization, transparency, and the detection of misconduct such as greenwashing. On the other, concerns regarding bias, interpretability, governance, and infrastructural readiness persist, particularly in emerging markets such as Vietnam, where institutional and technological capacities are still developing.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT, developed by Venkatesh et al. [20], synthesizes prior models of technology acceptance into a comprehensive framework that explains user adoption behavior. The model posits that four core constructs - performance expectancy, effort expectancy, social influence, and facilitating conditions - directly shape behavioral intention and subsequent technology use. These constructs provide a valuable lens through which to examine the adoption of AI technologies in ESG assurance.

Performance Expectancy (PE) refers to the extent to which individuals believe that using a technology will enhance their performance [20]. Within the ESG assurance context, this construct captures the belief that AI tools can improve accuracy, efficiency, and the depth of the assurance process. For instance, Liu et al. [17] demonstrate how the AI-enabled Veri-Green system enhances PE by automating verifier selection and increasing the reliability of ESG verification. Similarly, Adam et al. [5] highlight that auditors perceive AI as a means to improve both the quality and efficiency of ESG-related audits, particularly in areas such as emissions monitoring and anomaly detection. Accordingly, the first hypothesis is as follow:

H1: Performance Expectancy positively influences the intention to apply AI in ESG Assurance.

Effort Expectancy (EE) denotes the perceived ease of using a technology [20]. In ESG assurance, this relates to whether auditors consider AI - powered tools user -friendly and intuitive. Liu et al. [17] suggest that AI can reduce complexity by streamlining verifier selection, while Adam et al. [5] emphasize the importance of ongoing training to ensure auditors can effectively engage with new tools. Dasinapa and Ermawati [9] further note that resistance to change and shortages of technical talent can diminish effort expectancy, slowing the pace of adoption. In this study, EE represents the belief that AI tools are straightforward and require minimal effort to operate. Thus, I hypothesize:

H2: Effort Expectancy positively influences the intention to apply AI in ESG Assurance.

Social Influence (SI) refers to the degree to which individuals perceive that significant others - such as colleagues, regulators, or professional bodies - expect them to use a particular technology. Regulatory momentum has been identified as a key driver of adoption: Adam et al. [5] point to the influence of regulators such as the U.S. Securities and Exchange Commission, whose calls for enhanced climate disclosures create external pressure for the use of AI in assurance. In the Vietnamese context, the positions of professional associations and leading audit firms are likely to be decisive in shaping adoption patterns. Therefore, I hypothesize:

H3: Social Influence positively influences the intention to apply AI in ESG Assurance.

Finally, facilitating conditions encompass the perception that organizational and technical infrastructures exist to support technology use. According to Venkatesh's UTAUT model (2003), favorable conditions do not affect the intention to use technology but directly affect the user's technology usage behavior. Meanwhile, this study only focuses on factors affecting the intention to use, so this factor is not included in the research model.

Collectively, these findings underscore UTAUT's explanatory power for analyzing the adoption of AI in ESG assurance. Performance expectancy and effort expectancy capture perceptions of AI's utility and usability, while social influence reflects the institutional enablers that determine adoption. Prior studies affirm UTAUT's predictive strength compared to other frameworks such as the Technology Acceptance Model, making it a robust theoretical foundation for understanding AI adoption in the assurance of ESG reporting [19].

2.4. Perceived Risk Theory (PRT)

PRT, first articulated by [21], posits that individual behavior is shaped not only by expected benefits but also by the risks associated with a given action. In technology adoption research, the framework has been applied to explain uncertainties that discourage users from embracing innovation. In the context of AI adoption for ESG assurance, perceived risk encompasses several dimensions, including performance, financial, security, ethical, and regulatory risks, all of which influence stakeholder trust and adoption decisions.

Performance risk refers to the possibility that AI technologies may not perform as intended, thereby compromising assurance quality and exposing organizations to reputational harm. This risk is amplified by the "black box" nature of many AI algorithms, which undermines interpretability and accountability [5]. Liu et al. [17] similarly identify concerns about data authenticity and credibility in traditional verification systems, arguing that their proposed Veri-Green framework reduces perceived performance risks through transparent and impartial AI-driven processes. Data accuracy and availability, as highlighted by Chiou and Hsieh [8], further reflect this dimension, as inconsistencies in ESG reporting create uncertainty regarding the reliability of assurance outcomes. Therefore, the related hypothesis is as follow:

H4: Performance Risk negatively influences the Intention to use AI in ESG Assurance.

Ethical and algorithmic bias risks also represent a critical dimension. Since AI algorithms are shaped by the quality and representativeness of their training data, biased datasets may yield discriminatory or unfair assurance outcomes [9]. These risks contribute to broader concerns about accountability, given that AI systems cannot be held responsible for their decisions [14]. Relatedly, Budhathoki et al. [19] highlight "anxiety" as a manifestation of perceived risk, noting that negative emotions such as stress and apprehension significantly inhibit technology adoption, even when performance benefits are acknowledged. Data security and privacy risks are especially salient in ESG assurance, where sensitive corporate information is routinely processed. The integration of AI heightens exposure to cyberattacks and unauthorized data access, thereby eroding confidence in assurance processes [9, 14]. These concerns extend to broader cybersecurity vulnerabilities linked to centralizing sensitive data within AI systems, a point underscored by

Nene [14], who warns of the hazards posed by poorly designed or maliciously exploited AI models. Their findings also suggest cultural and contextual differences in how perceived risks are experienced, reinforcing the relevance of examining AI adoption in specific contexts such as Vietnam. Consequently, I hypothesize:

H5: Ethical Risk negatively influences Intention to use AI in ESG Assurance.

Taken together, these insights illustrate how PRT provides a robust framework for understanding barriers to AI adoption in ESG assurance. The multifaceted risks spanning performance and ethical domains create significant uncertainty for organizations, auditors, and stakeholders. Addressing these risks through transparency, robust governance, and regulatory clarity will be essential to realizing the potential benefits of AI in emerging markets such as Vietnam.

3. METHODOLOGY

3.1. Research Paradigm and Approach

This study employs a quantitative, cross-sectional survey design to examine the factors influencing the application of AI in ESG assurance within the Vietnamese context. A deductive approach was adopted, with hypotheses derived from the established theoretical foundations of the UTAUT and PRT. Philosophically, the research is situated within a post-positivist paradigm, which acknowledges that social phenomena can be systematically investigated through empirical testing, while recognizing that findings are probabilistic and context-dependent [22]. This paradigm is consistent with the study's aim of testing a theoretical model using quantitative data, while also accounting for the contextual specificities of AI adoption in Vietnam's assurance sector.

While UTAUT provides a robust framework for explaining the utilitarian drivers of technology adoption, it offers limited insight into the barriers that inhibit user acceptance - barriers that are particularly relevant in the case of disruptive technologies such as AI. To address this limitation, the study integrates PRT. Within the assurance context, perceived risks - such as performance failures, data security vulnerabilities, regulatory uncertainty, and threats to professional credibility - represent critical factors that shape adoption decisions. By combining UTAUT and PRT, this study develops a more comprehensive model that captures both the motivations driving the application of AI in ESG assurance and the deterrents that may hinder its uptake in emerging markets such as Vietnam.

3.2. Population and Sampling Procedure

The target population for this study consisted of professionals engaged in ESG assurance activities in Vietnam, including auditors, consultants, and corporate sustainability officers. As no comprehensive sampling frame was available, a non-probability sampling strategy was employed, combining convenience and snowball techniques. Initial survey invitations were distributed through professional networks, industry associations, and corporate contacts in key economic centers such as Hanoi, Ho Chi Minh City. Respondents were subsequently encouraged to share the survey with colleagues working in related assurance and sustainability functions, thereby extending the reach of the sample. This approach enabled the study to capture a broad and diverse pool of perspectives from practitioners directly involved in ESG assurance.

3.3. Data Collection and Instrument

Data were collected through an online questionnaire administered via Google Forms. To ensure both conceptual clarity and linguistic accuracy, the instrument underwent a two-step translation process: it was initially translated from English into Vietnamese by a bilingual academic, and then back-translated into English by an independent expert to verify equivalence.

The final questionnaire was divided into two sections. The first section captured demographic and professional information, including gender, age, educational background, job position, years of work experience, and prior exposure to AI applications in assurance or sustainability reporting. The second section contained the measurement items for the eight latent constructs of the research model. These constructs – PE, EE, SI, PR, ER BI - were operationalized using multi-item scales adapted from previously validated studies to ensure content validity. Table 1 presents the measurement items for each construct alongside their original sources. All items were contextualized to the application of AI in ESG assurance and measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Prior to full-scale distribution, a pilot test was conducted with 20 auditors. Feedback from this phase was used to refine the wording of several items to enhance clarity and relevance, thereby ensuring the final instrument's content validity.

Table 1. Construct Measurement Items and Sources

Factors	Items	Item detail	Source
Performance Expectancy (PE)	PE1	I think using AI tools is useful for ESG assurance	[20]; [17]; [5]; [19]
	PE2	I think AI tools can make ESG assurance tasks easier to complete	
	PE3	I think Using AI tools can improve my productivity in conducting ESG assurance	
Effort Expectancy (EE)	EE1	I think my interaction with AI tools for ESG assurance is clear and understandable	[20]; [17]; [9]; [19]
	EE2	I think learning how to operate AI tools for ESG assurance is easy for me	
	EE3	I think AI tools for ESG assurance are easy to use	
	EE4	I think it is easy for me to become skillful at using AI tools for ESG assurance	

Social Influence (SI)	SI1	People who influence my professional decisions think that I should use AI tools for ESG assurance	[20]; [5]; [19]
	SI2	Senior management and colleagues whose opinions I value support the use of AI tools in ESG assurance	
	SI3	Professional accounting bodies and regulators encourage the adoption of AI in ESG assurance	
Performance Risk (PR)	PR1	I am concerned that using AI tools for ESG assurance may generate inaccurate or unreliable results	[5]; [17]; [8]
	PR2	I am concerned that AI tools for ESG assurance could produce misleading or deceptive information	
	PR3	I am concerned that AI tools for ESG assurance might reinforce biases in ESG data analysis.	
Ethical Risk (ER)	ER1	I am concerned that using AI tools for ESG assurance could lead to ethical or legal violations	[9]; [14]; [19]
	ER2	I find it difficult to determine whether outputs generated by AI tools in ESG assurance are fully compliant with professional standards	
	ER3	I am concerned about the privacy and confidentiality of sensitive ESG data when using AI tools	
Behavioral Intention (BI)	BI1	I intend to use AI tools for ESG assurance tasks in the near future	[20]; [19]
	BI2	I predict that I will use AI tools regularly for ESG assurance over the next few months	
	BI3	plan to integrate AI tools into my regular ESG assurance activities	

3.4. Data Analysis

The collected data were analyzed using a two-stage process with IBM SPSS Statistics 26 and AMOS 24.

Preliminary Analysis: The dataset was first screened for missing values, outliers, and normality. Descriptive statistics were generated in SPSS to summarize the demographic and professional characteristics of the respondents. The internal consistency and reliability of each construct were assessed using Cronbach's Alpha to ensure scale reliability.

Structural Equation Modeling (SEM): SEM served as the primary analytical technique to evaluate the hypothesized research model. The analysis proceeded in two sequential stages. First, a Confirmatory Factor Analysis (CFA) was conducted to assess the psychometric properties of the measurement model. Convergent validity was established by examining the Average Variance Extracted (AVE), while discriminant validity was assessed using the Fornell-Larcker criterion. Composite Reliability (CR) was also calculated to confirm construct reliability. Second, the structural model was tested to examine the hypothesized relationships among the latent constructs. Model fit was evaluated using multiple goodness-of-fit indices, including the Chi-square/degrees of freedom ratio, Comparative Fit Index, Tucker-Lewis Index, and Root Mean Square Error of Approximation.

4. RESULTS

4.1. Respondent Demographics

A total of 222 valid responses were collected for the study. As shown in Table 2, the sample comprised 124 males (55.86%) and 98 females (44.14%). The majority of respondents were between 25 and 34 years old (56.75%), followed by those aged 35–44 years (35.14%). Only a small proportion were under 25 years (5.41%) or between 45 and 54 years (2.70%), while none were aged 55 and above.

In terms of educational background, most respondents held a Bachelor's degree (68.92%), while 27.93% had a Master's degree and 3.15% a Doctorate. Regarding professional experience, 37.84% reported between 6 and 10 years of work experience, 27.93% between 3 and 5 years, 21.17% more than 10 years, and 13.06% less than 3 years.

Overall, the demographic profile indicates that the sample primarily consisted of relatively young professionals with substantial academic qualifications and moderate to extensive professional experience, making them suitable respondents for examining factors influencing the adoption of AI in ESG assurance.

Table 2. Demographic Profile of Respondents (N=222)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	124	55.86
	Female	98	44.14
Age Group	Under 25 years	12	5.41
	25-34 years	126	56.75
	35-44 years	78	35.14
	45-54 years	6	2.70
	55 years and above	0	0
Educational Qualification	Bachelor	153	68.92
	Master	62	27.93
	Doctorate	7	3.15
Years of Professional Experience	< 3 years	29	13.06
	3-5 years	62	27.93
	6-10 years	84	37.84
	> 10 years	47	21.17

4.2. Measurement Model Assessment

Internal consistency was evaluated using Cronbach's Alpha and Composite Reliability (CR). As shown in the table, the Cronbach's Alpha values for all constructs ranged from 0.825 to 0.965. All values are well above the commonly accepted threshold of 0.70, indicating strong internal consistency [23]. Furthermore, the Composite Reliability (CR) values, which ranged from 0.831 to 0.970, also surpassed the 0.70 benchmark, reinforcing the high reliability of the measurement scales.

Convergent validity, the extent to which items of a specific construct converge or share a high proportion of variance, was assessed using two criteria: factor loadings and the Average Variance Extracted (AVE).

Factor Loadings: All individual item factor loadings were significant and ranged from 0.769 to 0.979, exceeding the recommended minimum value of 0.70.

Average Variance Extracted (AVE): The AVE for each construct was calculated, with values ranging from 0.553 to 0.916. All AVE values are above the suggested threshold of 0.50, which signifies that each construct explains more than half of the variance of its corresponding indicators.

Table 3. Factors loading, Cronbach's Alpha, Reliability and Convergent Validity

Factors	Items	Cronbach's Alpha	Factor loadings	KMO	Composite reliability	Average variance extracted
Performance Expectancy (PE)	PE1	0.929	0.951	0.751	0.930	0.815
	PE2		0.940			
	PE3		0.916			
Effort Expectancy (EE)	EE1	0.827	0.806	0.766	0.831	0.553
	EE2		0.801			
	EE3		0.870			
	EE4		0.769			
Social Influence (SI)	SI1	0.870	0.890	0.741	0.870	0.690
	SI2		0.890			
	SI3		0.892			
Performance Risk (PR)	PR2	0.901	0.909	0.753	0.902	0.754
	PR3		0.921			
	PR4		0.913			
Ethical Risk (ER)	ER1	0.825	0.876	0.665	0.838	0.639
	ER2		0.792			
	ER3		0.915			
Behavioral Intention (BI)	BI1	0.965	0.979	0.770	0.970	0.916
	BI2		0.961			
	BI3		0.975			

Additionally, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for all factors was above 0.60, confirming that the data was appropriate for factor analysis. In conclusion, the results provide robust evidence for the reliability and convergent validity of the measurement model, establishing a strong foundation for the subsequent structural model analysis.

4.3. Correlation and Discriminant Validity Analysis

The correlation matrix in Table 4 indicates the strength and direction of the relationships between the study's core variables: SI, PR, EE, PE, ER, and BI.

The results show that BI has a significant, strong, and positive correlation with SI ($r=0.674$, $p<0.001$), PE ($r=0.667$, $p<0.001$), EE ($r=0.521$, $p<0.001$), and PR ($r=0.475$, $p<0.001$). These findings suggest that as perceptions of social pressure, expected performance, ease of use, and risk management increase, so does the intention to engage in the behavior. Conversely, ER exhibits a significant but weak negative correlation with BI ($r=-0.222$, $p<0.01$).

Discriminant validity was assessed to ensure that each construct is distinct and measures a unique concept. The Fornell-Larcker criterion was used for this purpose. This criterion states that a construct has adequate discriminant validity if the square root of its Average Variance Extracted (AVE) is greater than its correlation coefficients with all other constructs. A review of the entire table confirms that every diagonal value is higher than all the off-diagonal values in its corresponding row and column. Therefore, the Fornell-Larcker criterion is met for all constructs, establishing strong discriminant validity for the measurement model.

Table 4. Correlation coefficient among core variables

	SI	**PR**	**EE**	**PE**	**ER**	**BI**
SI	**0.831**					
PR	0.476***	**0.868**				
EE	0.294***	0.524***	**0.744**			
PE	0.424***	0.653***	0.292***	**0.903**		
ER	-0.083	-0.033	0.045	0.007	**0.800**	
BI	0.674***	0.475***	0.521***	0.667***	-0.222**	**0.957**

*Note: In the table, *** denotes a significance level of p<0.001, and ** denotes p<0.01.*

4.4. Structural Model and Hypothesis Testing

Assessment of Structural Model Fit

As presented in Table 5, the results indicate an excellent fit between the model and the empirical data. The chi-square to degrees of freedom ratio (CMIN/DF) was 1.480, which is well below the recommended threshold of <3. Other fit indices also met or exceeded the established criteria: the Goodness-of-Fit Index (GFI) was 0.915 (>0.8), the Comparative Fit Index (CFI) was 0.980 (>0.9), and the Tucker-Lewis Index (TLI) was 0.975 (>0.9). Finally, the Root Mean Square Error of Approximation (RMSEA) was 0.047, comfortably below the <0.08 threshold. Collectively, these indices confirm that the structural model is robust and provides a strong basis for testing the proposed hypotheses.

Table 5. Model fitting results

Fit index	Recommended Threshold	Observed Value	Evaluation Result
CMIN/DF	<3	1.480	Exellent
GFI	>0.8	0.915	Exellent
CFI	>0.9	0.980	Exellent
TLI	>0.9	0.975	Exellent
RMSEA	<0.08	0.047	Exellent

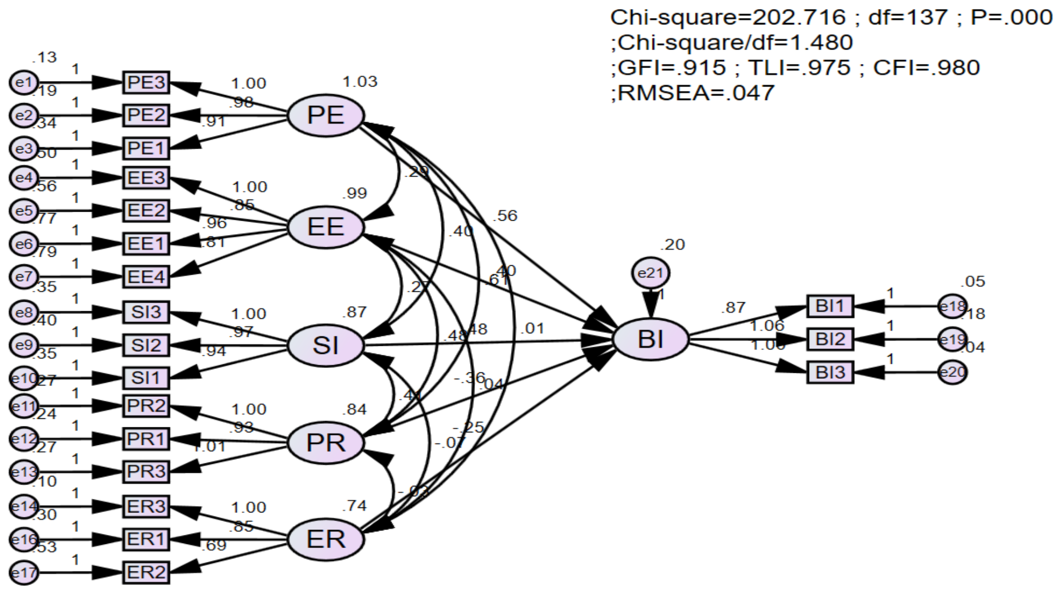

Figure 1. Research model values (the author's own work)

Hypothesis Testing Results

The hypothesized relationships in the research model were tested using data from the 404 valid responses. The standardized path coefficients (β), critical ratios, and p-values were analyzed to determine whether the hypotheses were supported. The results, as detailed in Table 6, show that all seven proposed hypotheses were statistically significant and supported.

Table 6. Results of Hypothesis Testing

Hypothesis	Path	Std. Beta (β)	Critical Ratio	p-value	Result
H1	PE -> BI	0.579	9.704	0.000	Supported
H2	EE -> BI	0.406	7.060	0.000	Supported
H3	SI -> BI	0.452	8.389	0.000	Supported
H4	PR -> BI	-0.338	-4.687	0.000	Supported
H5	ER-> BI	-0.219	-5.101	0.000	Supported

The model first examined the factors predicting academics' intention to use AI writing tools. Collectively, the predictors explained a substantial 79.0% of the variance in BI ($R^2 = 0.790$). All five related hypotheses were supported:

PE was the most powerful predictor, with a very strong positive influence on BI ($\beta = 0.579$, $p < 0.001$), supporting H1.

EE ($\beta = 0.406$, $p < 0.001$) and SI ($\beta = 0.452$, $p < 0.001$) also had strong positive effects, supporting H2 and H3.

Conversely, PR ($\beta = -0.338$, $p < 0.001$) and ER ($\beta = -0.219$, $p < 0.001$) both had significant negative impacts on BI, supporting H4 and H5.

5. Discussion

This study investigated the factors influencing the intention of Vietnamese professionals to apply AI in ESG assurance. By integrating UTAUT and PRT, the research provides a comprehensive model that explains 79.0% of the variance in behavioral intention. The findings confirm that PE, EE, and SI are significant positive drivers, while PR and ER act as critical deterrents.

5.1. Key Drivers of AI Adoption in ESG Assurance

The results underscore that PE is the most influential factor shaping the intention to use AI in ESG assurance (β=0.579). This finding aligns with a substantial body of literature asserting that the perceived utility of a technology is paramount to its adoption [20]. In the context of ESG assurance, professionals in Vietnam clearly recognize AI's potential to enhance their work's effectiveness and efficiency. This resonates with studies by Adam et al. [5] and Vaio et al. [6], which highlight AI's capacity to process vast datasets, improve the accuracy of emissions monitoring, and detect anomalies in sustainability reports. The strong influence of PE suggests that practitioners are motivated by the prospect of AI tools delivering tangible benefits, such as mitigating greenwashing [8] and enabling continuous, real-time assurance [11].

SI also emerged as a powerful positive predictor (β=0.452). This indicates that the expectations of significant stakeholders - including senior management, professional accounting bodies, and regulators - are crucial in shaping individual adoption intentions. This is particularly relevant in Vietnam's professional landscape, where hierarchical structures and collective norms often guide decision-making. The finding supports the argument that regulatory pressure, such as the global momentum created by directives like the CSRD, creates a cascading effect, encouraging firms and assurance providers to embrace innovative technologies to meet new compliance demands [5, 12].

Similarly, EE was found to be a significant determinant (β=0.406). This confirms that the perceived ease of use of AI systems is a key consideration for assurance professionals. While AI technologies are often complex, their successful integration depends on user-friendly interfaces and the availability of adequate training and support. This result echoes concerns raised by Dasinapa and Ermawati [9] and Ilori et al. [18] regarding the technical skills gap, which can act as a barrier to adoption, particularly for professionals who may not have a background in data science or information systems.

5.2. Significant Barriers to AI Adoption

The study also validated the critical role of perceived risks as inhibitors of technology adoption. PR was a significant negative predictor ($\beta=-0.338$), reflecting professionals' concerns about the reliability and accuracy of AI-generated outputs. This apprehension is rooted in the "black box" nature of some AI algorithms, which can make it difficult to verify their conclusions and maintain professional accountability [5, 14]. The potential for AI to produce misleading information or reinforce existing biases in ESG data is a tangible concern that can erode trust and expose assurance providers to reputational damage.

Furthermore, ER also negatively influenced behavioral intention ($\beta=-0.219$). This finding highlights the salience of concerns surrounding data privacy, confidentiality, and compliance with professional standards [9]. In the ESG domain, where sensitive non-financial data is paramount, the risk of data breaches or the misuse of information is a significant deterrent. This aligns with scholarship that calls for robust governance frameworks to manage the ethical implications of AI, from algorithmic bias to cybersecurity vulnerabilities [14, 15].

6. Conclusion

6.1. Summary of Findings

This research successfully developed and tested an integrated model to explain the factors affecting the adoption of AI in ESG assurance in Vietnam. The study confirms that the decision to use AI is a calculated one, balancing expected gains in performance and efficiency against significant perceived risks. The findings demonstrate that while Vietnamese assurance professionals are optimistic about the benefits of AI, their enthusiasm is tempered by valid concerns regarding its performance reliability and ethical implications.

6.2. Theoretical Contributions

This study makes several contributions to the literature. First, it extends the UTAUT model by integrating PRT, providing a more nuanced and balanced framework for understanding technology adoption in a high-stakes professional context. While UTAUT effectively captures the utilitarian drivers of adoption, the inclusion of PRT addresses the critical role of risk perceptions as barriers, which is essential for disruptive technologies like AI.

Second, this research is one of the first to apply this integrated model to the nascent and critical field of AI in ESG assurance, offering a pioneering empirical investigation in this domain.

Finally, by situating the study in Vietnam, it provides valuable insights into technology adoption dynamics within an emerging market, contributing a non-Western perspective to a field largely dominated by research from developed economies.

6.3. Practical Implications

The findings offer several actionable implications for stakeholders in Vietnam:

For Assurance Providers and Audit Firms: To foster AI adoption, firms should focus on demonstrating its value proposition (PE). This can be achieved through pilot projects, case studies, and internal showcases. Simultaneously, they must invest heavily in training and development programs to enhance employees' skills and confidence in using AI tools, thereby improving EE.

For Technology Developers: AI software developers should prioritize creating user-friendly, transparent, and interpretable systems. "Explainable AI" features that allow users to understand the rationale behind algorithmic outputs can directly address PR and ER.

For Regulators and Professional Bodies: These institutions have a vital role in creating a supportive ecosystem (SI). They should develop clear guidelines and professional standards for the use of AI in assurance, addressing ethical considerations, data governance, and accountability. This will help standardize practice and reduce the uncertainty that fuels perceived risks.

For Companies: As clients of assurance services, Vietnamese companies should begin investing in their data infrastructure to ensure the availability of high-quality, machine-readable ESG data. This will not only facilitate AI-driven assurance but also improve their own internal sustainability management.

6.4. Limitations and Future Research

This study has several limitations that open avenues for future research. First, the use of a non-probability sampling method may limit the generalizability of the findings. Future studies could employ random sampling techniques to achieve a more representative sample of the assurance community in Vietnam. Second, the cross-sectional design captures intentions at a single point in time. A longitudinal study would be valuable to track how perceptions and adoption behaviors evolve as AI technology matures and becomes more integrated into professional practice. Finally, this study focused on intention to use; future research should investigate the factors that influence the *actual use* and the post-adoption impact of AI on the quality and effectiveness of ESG assurance. Further qualitative studies could also provide deeper insights into the lived experiences and specific challenges faced by professionals when implementing AI in their daily work.

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