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The Extended Unified Theory of Adoption and Use of Generative Artificial Intelligence in Accounting Profession: Evidence from Emerging Economy

Shahima Jabin*

Abstract: *The research aims to determine the impact of the implementation of generative artificial intelligence (AI) on the accounting profession in Bangladesh by using the extended Unified Theory of Adoption and Use of Technology (UTAUT) model. Another purpose is to show the mediating effect of perceived risk and the moderating effect of experience and job type on the UTAUT model. Data are collected from 215 accountants using a structured questionnaire. The hypotheses of the specified structural equation model are tested statistically using AMOS 24 and SPSS 23. The research found that traditional variables of the UTAUT model which are performance expectancy, effort expectancy, social influence, and newly introduced variables reliability perception positively affect the intention to use generative AI in the accounting profession. Facilitating condition positively affects generative AI usage, privacy and security concern negatively impacts the intention to use generative AI, and training & development positively affects effort expectancy. All the mediation and moderation analyses are statistically significant. Therefore, chartered accountancy firms should prioritize taking training initiatives, resolving privacy and security issues, and creating a positive work atmosphere. The study offers unique empirical insights about generative AI preparedness, obstacles, and opportunities by focusing on a variety of roles within the profession.*

Keywords: *Generative AI, Accounting, technology, emerging economy.*

1. Introduction

The accounting industry has experienced a significant transformation due to the fast progress of technology in recent times. The burgeoning field of generative artificial intelligence (AI) presents opportunities for financial data analysis, work automation, and improved decision-making in the accounting industry (Alves & Kochetkov, 2021) by generating reports, analyzing data trends, and performing repetitive tasks (Bender & Augustin, 2020).

Nevertheless, the uptake of these technologies varies and is contingent upon several circumstances. A strong framework for evaluating technology adoption is offered by the Unified Theory of adoption and Use of Technology (UTAUT), which looks at important variables including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)

* Lecturer (Accounting), School of Business, Bangladesh Open University, Gazipur-1705. E-mail: shahimajabin@bou.ac.bd

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(Ashrafi et al., 2014). In this study, the author adds factors to the UTAUT model that are especially pertinent to the adoption of generative AI in Bangladesh's accounting industry.

Other factors include reliability perception (Basoglu and Hess, 2014), privacy and security concerns (Moran, 2019), and training and development (Rech, 2022) are critical to the adoption of generative AI in accounting since people's confidence in the accuracy of AI and protection of their data impacts their willingness or desire to adopt generative AI (Pramanik et al., 2017). Furthermore, this study acknowledges that experience (Wessels & Steenkamp, 2021) and Job Type (Rech, 2022) have moderating effects on the adoption of generative AI.

By determining the elements influencing the widespread adoption of generative AI within the framework of Bangladesh's accounting industry, this study attempts to address this research gap. In this study, extending the existing UTAUT model, the mediating role of perceived risk and moderating roles of experience and job type, and how they contribute to generative AI adoption in the accounting industry, are explored. Due to the fast-growing economy, increasing foreign investment, and a relatively young and changing regulatory framework along with some constraints like lack of technical professionals, outdated structures, and technophobia, Chartered accountancy firms in Bangladesh are a perfect case for analysing the implementation of technologies like generative AI in accounting. This paper examines the factors that led to the adoption of AI in Bangladesh's accounting industry, thereby addressing an important deficit in the literature, thus offering useful recommendations for enhancing technological competencies and professional career development in developing nations.

The following are this study's main goals:

- To assess the major factors that may hinder or promote the application of generative artificial intelligence technology in Bangladesh's accounting industry, a developing nation.
- To serve relevant recommendations on how to enhance the technological literacy of accounting professionals to utilize generative AI.
- To provide empirical evidence for the significance and generalizability of the developed extended UTAUT model for generative AI adoption in the accounting profession within the framework of the emerging nation.

This study enriches the current research in accounting by establishing the relationships between performance expectancy, social influence, perceived risk, and job type on the use of generative AI by applying the extended UTAUT model. By including reliability perception, privacy, and security concerns it expands the construct of risk perception and behavioral resistance toward emerging technologies more specifically in the context of an emerging economy like Bangladesh. The research offers practical recommendations for the change of behavior regarding training, risks, and supportive policies in organizations; At the identical time, it contributes to the body of experimental data and conceptual comprehension of technology adoption.

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2. Context of the Accounting Profession in Bangladesh

In Bangladesh, the Institute of Chartered Accountants of Bangladesh (ICAB) oversees accounting practices, issues license and sets professionals' ethical standards. Among the professions are public practice accountants and support staff such as controllers, management accountants, tax consultants and auditors (Ahmed et al., 2020). The majority of accounting work these days relies on manual handling or simple applications such as spreadsheets or out of date ERP systems (Ashrafi et al., 2014). In the past few years, the government and the private sector have both contributed to a major digital transformation in Bangladesh. The fast increase in fintech, mobile banking and digital services means that accountants need to modernize (Ahmed et al., 2020). In this period, observing how accounting professionals view and use generative AI contributes important information about the connection among technology, professional expertise and the economy in a developing country.

3. Literature Review

3.1. The Role of Generative AI in the accounting profession

Generative AI refers to computer systems that can produce text, code and images by analyzing data they have been taught with. Many repetitive tasks in accounting, like preparing financial statements, making tax reports, reconciling accounts and previewing what will be audited, can now be handled by generative AI. This technology makes it possible for accountants to handle fewer rote data work and take on more analytical and planning positions (Pramanik et al., 2017).

Numerous ways to do accounting work benefit greatly from the use of generative AI. With generative AI support, Tax Accountants can quickly and automatically file taxes, find potential problems with compliance and keep up to date on any changes in tax laws (Alves & Kochetkov, 2021), Management Accountants can analyze data easily, see financial trends ahead and test how certain actions might influence their plans, Auditors and Financial reporting professionals can assess risks, identify suspicious patterns, prepare reports and make sure large volumes of data are reported exactly as they ought to be.

Traditional AI research in accounting often looks at broader advances or mixes AI with RPA, skipping over the special qualities and dangers of generative AI, including hallucinations, lack of transparency and possible ethical problems when handling sensitive financial information. This research identifies where generative AI matters and investigates its meaning and value in the major functions of accounting in Bangladesh (Islam & Azad, 2021).

3.2. Traditional variables of the UTAUT model and adoption of generative AI in the accounting profession

3.2.1. Performance Expectancy

Performance expectancy refers to the belief that technology will enhance job performance. Studies show that workers are more willing to adopt new technologies when they believe they will improve their performance (Rana et al.,

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2015). Generative AI can automate tasks like data input, invoice processing, and audits, reducing manual errors and increasing financial reporting accuracy (Bender & Augustin, 2020). Accountants have greater performance expectancy when they believe AI models provide quicker, more informed insights based on data, enhancing their decision-making abilities (Mansouri & Pisaruk, 2022).

H1: Performance Expectancy positively affects the intention to use generative AI in the accounting profession.

3.2.2. Effort Expectancy

Effort expectancy (EE) is the level of convenience that comes with utilizing a specific technology (Dwivedi et al., 2019). Research indicates that the intention to employ AI in accounting is influenced by effort expectancy (Mansouri & Pisaruk, 2022). Generative AI may automate repetitive procedures, and save accountants' time and effort. This fits with the high expectancy for effort, as it reduces the cognitive load for accountants (Meng et al., 2019).

H2: Effort Expectancy positively affects the intention to use generative AI in the accounting profession.

3.2.3. Social influence

The accounting industry's adoption of generative AI is greatly influenced by social influence. Conventional procedures like compliance checks, reporting, and audits can be revolutionized by these technologies (Dong & Xu, 2021). Nonetheless, the social contexts in which these instruments are used have a significant impact on their acceptance. Since leaders serve as role models and urge subordinates to embrace generative AI, leadership and management advocacy can hasten the adoption of generative AI (Hosseini et al., 2019). The adoption of technology in accounting teams is also significantly influenced by peer networks and teamwork, like preparing financial reports or audits (Chen et al., 2020). Accounting businesses may be forced to embrace these technologies by large customers who demand speedier reports created by generative AI, or by external auditors who apply AI to their audit procedures and put pressure on accounting firms to follow suit (Aggarwal et al., 2021).

H3: Social Influence positively affects the intention to use generative AI in the accounting profession.

3.2.4. Facilitating Condition

The availability of the right technological infrastructure, smooth integration with the current accounting software, sufficient training, and IT and technical support are all necessary for the successful use of generative AI in accounting (Meng et al., 2019). Generative AI integration reduces the apparent learning curve for new systems by integrating with current software, such as ERP or bookkeeping software. The deployment of AI is also greatly facilitated by IT and technical support systems; generative AI is more likely to be effectively implemented by specialized IT departments or AI professionals (Camilleri & Sultana, 2020).

H4: Facilitating Condition positively affects generative AI usage in the accounting profession.

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3.2.5. Intention to use Generative AI and Generative AI usage

Accounting professionals' desire to accept AI technologies for automating tasks like data analysis, report production, and auditing (Hosseini et al., 2019). Using generative AI technology to optimize repetitive tasks, improve decision-making, increase accuracy, and lower operating costs is known as "generative AI usage in accounting." The promise of artificial intelligence (AI) in fields like fraud detection, predictive analytics, and regulatory compliance may revolutionize and improve the effectiveness of conventional accounting procedures. However, both the intention to employ AI and its actual use are influenced by data security, ethical hazards, and the learning curve involved with its adoption (Islam & Azad, 2021).

H5: Intention to use generative AI affects positively on generative AI usage.

3.3. New variables included in the UTAUT Model

3.3.1. Reliability Perception

For accountants to use AI tools, perception of reliability in the accounting field is essential. It alludes to the confidence that accountants have in the precision, consistency, and adherence to legal requirements produced by artificial intelligence systems (Basoglu & Hess, 2014). If accountants believe that generative AI routinely produces reliable results, they will be more inclined to employ the technology and feel more comfortable assigning duties that might otherwise need human supervision (Chen et al., 2020; Hosseini et al., 2019). Therefore, accountants' desire to utilize such tools in their work is increased by the improved perceived dependability of generative AI in producing correct, consistent, and compliant outputs (Moran, 2019).

H6: Reliability perception positively affects the intention to use generative AI in accounting.

3.3.2. Privacy and Security Concerns

Privacy and security considerations have an impact on the accounting profession's application of generative AI technologies. Confidentiality of data is a serious issue as it can result in legal infractions and harm to one's reputation. Because AI systems are susceptible to cyber-attacks, security problems are an additional issue (Chen et al., 2022). It is less probable for accountants to use generative AI technologies if there are weak security safeguards. Thus, resolving these issues with strong privacy rules, data security protocols, and regulatory compliance will enhance confidence and raise the desire to utilize AI technologies in the accounting industry (Moran, 2019).

H7: Privacy and Security Concerns negatively affect the intention to use generative AI in accounting.

3.3.3. Training and Development

Training and development are important factors that influence effort expectancy in the accounting industry. If accountants believe AI is simple to use and doesn't need a lot of work, they are more inclined to use it. Entire training programs and

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continuous development efforts provide accountants with the know-how to handle AI technology, lowering the learning curve and increasing productivity (Aggarwal et al., 2021). As a result, efficient training and development programs have a direct impact on effort expectancy by increasing the usability and accessibility of generative AI products (Chen et al., 2020).

H8: Training and development positively affect effort expectancy.

3.4. Mediating Variables

3.4.1. Perceived Risk

The accounting industry's adoption of generative AI is greatly influenced by perceived risk. It resolves the conflict between the desire to deploy generative AI and concern about data security and privacy (Chen et al., 2022). The adoption of generative AI solutions may be impeded by accountants' concerns about data breaches, illegal access, and regulatory compliance. Reduced perceived risks can promote adoption, whereas increased perceived risk is associated with a decreased desire to utilize generative AI. Improved security procedures or assurances of compliance can aid in reducing perceived risk, and, decreasing perceived risk can increase adoption in the accounting industry (Yan et al., 2019).

H9: Privacy and security concerns positively on perceived risk.

H10: Perceived risk affects negatively on intention to use generative AI.

H11: Perceived risk mediates the relationship between privacy and security concerns and the intention to use generative AI.

3.5. Moderating Variables

3.5.1. Experience

The association between effort expectancy and intention to employ generative AI is moderated by experience. Due to their increased familiarity with technology and expectation of fewer obstacles, accountants with high experience levels exhibit a larger positive correlation between effort expectancy and intention to adopt generative AI (Rech, 2022). On the other hand, inexperienced users may still find it difficult to adjust to the new system, thus even if they may believe generative AI would be simple to use, their intention to embrace it may be lower. Ultimately, experienced users are better able to translate high-effort anticipation into real adoption (Wessels & Steenkamp, 2021).

H12: Experience moderates the relationship between effort expectancy and intention to use generative AI in accounting.

3.5.2. Job Type

The many functions and responsibilities of accounting jobs, including auditors, tax accountants, financial analysts, and management accountants, may influence their inclination to employ generative artificial intelligence (Wessels & Steenkamp, 2021). Generative AI is valued by auditors for its ability to automate audit trails and enhance fraud detection, while tax accountants gain from generative AI technologies for tax computation and filing. The association between performance expectation and intention to employ generative AI is moderated by the type of job type (Ali et al, 2021). The inclination to employ generative AI is more positively impacted by performance expectations in positions where generative AI significantly improves performance, though it does not immediately or significantly benefit from them (Moren, 2019).

H13: Job type moderates the relationship between performance expectancy and intention to use generative AI.

4. Methodology

4.1. Research Design and Approach

This research thereby utilizes a quantitative approach to ascertain the elements influencing the adoption of generative AI in Bangladesh's accounting industry. Based on an extended UTAUT model, the authors analyze several factors that could influence generative AI adoption: performance expectancy, effort expectancy, social influence, facilitating conditions, reliability perception, privacy and security concerns, training and development, perceived risk, experience, and job type. The research approach is survey-based, data has been collected from the accountants of chartered accountancy firms in Bangladesh by using structured questionnaires.

4.2. Operational Definition of Variables

Performance Expectancy (PE): The level of perceived usefulness that the accountants have regarding the application of generative AI, in improving job performance, productivity, and analytical skills (Venkatesh et al., 2003).

Effort Expectancy (EE): The comprehensibility of implementing generative AI into the day-to-day workflow of accounting (Dwivedi et al., 2019; Venkatesh et al., 2003).

Social Influence (SI): The degree to which accountants feel that co-workers, managers, or external professional support plays a significant role in the decision to adopt AI (Dwivedi et al., 2019; Venkatesh et al., 2003).

Facilitating Conditions (FC): The perceived instruments of resources, structures, and support that facilitate the use of generative AI (Dwivedi et al., 2019; Venkatesh et al., 2003).

Reliability Perception: The idea that generative AI is reliable and produces values that are correct and precise at creating solutions, especially in dealing with financial data (Basoglu & Hess, 2014).

Privacy and Security Concerns: The level of concern that accountants have over the security of such information disclosure to the outside world with the relativity of generative AI tools (Moran, 2019). This involves aspects concerning unauthorized access control or breaches of personal and financial information.

Training and Development: The extent to which accountants have access to training and development opportunities that improve their ability to utilize generative AI applications (Rech, 2022).

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Perceived Risk: The actual perceived risk by the accountants on the potential losses or negative impacts, or even the level of uncertainty about using generative AI in the accounting practices (Yaseen et al., 2016).

Experience: The manner and extent to which participants are familiar with generative AI technologies, especially in their careers, which may determine the extent of accountant adoption of generative AI (Rech, 2022).

Job Type: The discretional characteristics of an accountant may affect how relevant and useful they think is generative AI in their profession (Ali et al, 2021).

4.3. Respondents

The study had stringent criteria for participant selection; the participants must be willing to answer questions exclusively for academic purposes, know about generative AI, and its uses in accounting, and answer the questionnaire coherently. Of the 260 questionnaires sent out, 82.7 percent came back in complete order (215 valid responses). A brief summary of the respondents' demographic details, including gender, age, qualification, job type, and experience is given in Table 1.

4.4. Sampling Technique and sample size

This research has used the stratified random sampling method to increase the possibility of selecting different strata of the accounting profession in Bangladesh. Based on these premises, the strata are defined in regards to experience, job description, and organizational status, (junior and senior accountants and managers) (Zikmund, 2003). It provides the necessary population heterogeneity that maximizes the range of variation in beliefs in the relative application of generative AI over the accounting universe's subpopulations. The sample size is 260.

Table 1: Demographic Profile

Demography	Category	Frequency (n=215)	Total
Age	25-30	32	215
	31-35	118	
	36-40	45	
	41-45	15	
	46 over	5	
Gender	Male	180	215
	Female	35	
Qualification	Graduation	190	215
	Masters	25	
Job Type	Tax Accountant	50	215
	Management Accountant	120	

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Demography	Category	Frequency (n=215)	Total
	Auditor	40	
Experience	0-1	20	215
	1-5	32	
	5-10	105	
	10-20	30	
	20 over	23	

4.5. Questionnaire survey

To investigate the generative AI adoption in accounting, the researcher constructed a 44-item questionnaire from the literature and obtained participants' consent, anonymity, and cultural sensitivity. Items' specifics are provided in Appendix 1. It was on a 5-point Likert scale. Then all participants provided signed informed consent confirming their willingness to participate in the study. After excluding unqualified responses from 260 responses through SPSS 23.0, 215 valid responses were examined through Amos 24.0 and SPSS, while conducting validity and reliability tests.

4.6. Data Analysis

The extended UTAUT model for generative AI adoption in accounting was evaluated in this study using SEM with AMOS 24.0.

SEM is appropriate for inspecting how latent constructs relate and in checking the validity of a model in vast samples (Ringle et al., 2012). The steps involved first checking measurement quality with CFA and Cronbach's Alpha, Composite Reliability and Average Variance Extracted and second, analyzing the structural model using path analysis and R^2 values for each hypothesis. Multi-group analysis was used to test mediating and moderating effects using popular SEM procedures (Hu & Bentler, 1999).

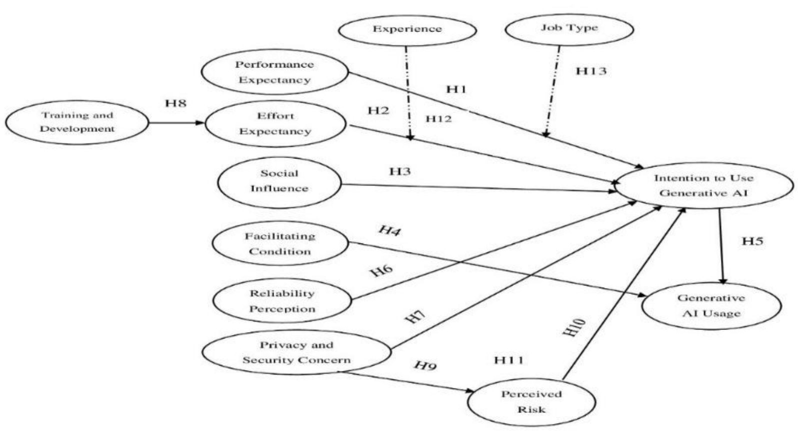

Figure 1: Developed Model

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5. Results

5.1. Assessment of Measurement Model:

Using AMOS 24.0 and CFA, the reliability and validity of each construct were tested by measuring the model. All computations—Standardized Factor Loadings, Composite Reliability (CR), Average Variance Extracted (AVE) and Cronbach's Alpha—were made using the guidance from Hair et al. (2017). Most items showed factor loadings greater than 0.70. Although the loadings for these items (SI1 and SI2) were just below the standard, they were kept since peer and managerial factors are prominent in shaping Bangladeshi technology adoption (Dwivedi et al., 2019). All constructs had acceptable results because of good reliability and showing convergent validity.

Using the Fornell–Larcker criterion (Fornell & Larcker, 1981), it was confirmed that discriminant validity exists. While the AVE of SI was just below the correlation it had with related constructs, SI and those related constructs had almost no overlap. Because SI passed both the metrics and satisfies the theory, it was retained in the analysis. The discussion of these decisions continues in the limitations section.

The fit of the model was measured with various indices: Chi-square/df (CMIN/DF) was 1.49, Comparative Fit Index was 0.93, Tucker–Lewis Index was 0.95, Root Mean Square Error of Approximation was 0.051 and Standardized Root Mean Square Residual was 0.044. Each index was either at or above usual thresholds, meaning that the proposed model fit the data acceptably (Hu & Bentler, 1999).

Table 2: Measurement of Reflective Construct

Construct	Label	Factor Loading >0.50	Cronbach's Alpha >0.70	CR >0.70	AVE >0.50
Performance Expectancy (PE)	PE1	0.784	0.768	0.827	0.5452
	PE2	0.743			
	PE3	0.701			
	PE4	0.723			
Effort Expectancy (EE)	EE1	0.789	0.751	0.824	0.540
	EE2	0.732			
	EE3	0.711			
	EE4	0.706			
Social Influence (SI)	SI1	0.753	0.749	0.807	0.512
	SI2	0.675			
	SI3	0.699			
	SI4	0.734			

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Construct	Label	Factor Loading >0.50	Cronbach's Alpha >0.70	CR >0.70	AVE >0.50
Facilitating Conditions (FC)	FC1	0.745	0.736	0.840	0.568
	FC2	0.763			
	FC3	0.723			
	FC4	0.783			
Reliability Perception (RP)	RP1	0.722	0.729	0.809	0.515
	RP2	0.694			
	RP3	0.718			
	RP4	0.736			
Privacy and security concern (PSC)	PSC1	0.723	0.758	0.829	0.548
	PSC2	0.735			
	PSC3	0.762			
	PSC4	0.741			
Training and Development (TD)	TD1	0.698	0.736	0.801	0.502
	TD2	0.683			
	TD3	0.711			
	TD4	0.742			
Perceived Risk (PR)	PR1	0.726	0.715	0.769	0.526
	PR2	0.719			
	PR3	0.732			
Intention to Use Generative AI (IUGA)	IUGA1	0.772	0.762	0.810	0.587
	IUGA2	0.768			
	IUGA3	0.759			
Generative AI usage (GAU)	GAU1	0.732	0.717	0.765	0.520
	GAU2	0.709			
	GAU3	0.724			

Table 3: Discriminant validity (Fornell–Larcker Criterion)

	PE	EE	SI	FC	RP	PSC	TD	PR	IUGA	GAU
PE	0.7383									
EE	0.363	0.7352								
SI	0.599	0.396	0.7158							
FC	0.467	0.524	0.585	0.7538						
RP	0.493	0.467	0.395	0.534	0.7176					
PSC	-0.422	-0.472	-0.496	-0.504	-0.597	-0.740				
TD	0.396	0.496	0.322	0.411	0.398	-0.354	0.7088			
PR	-0.345	-0.326	-0.331	-0.302	-0.347	0.299	-0.318	-0.7256		
IUGA	0.652	0.687	0.629	0.634	0.699	-0.587	0.693	-0.623	0.766353	
GAU	0.623	0.639	0.593	0.685	0.694	-0.556	0.663	-0.621	0.623	0.72173

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Table 4: Model Fit Indices

Model Fit	Cut-off Criteria	Model statistics
GFI	≥.8	0.85
PGFI:	≥.5	0.77
CMIN		1798.92
DF		1206.54
CMIN/Df	≤3	1.490
CFI	≥.9	0.93
TLI	≥ 0.90	0.95
SRMR	<0.08	0.044
RMSEA	<0.06	0.051

5.2. Assessment of Structural Model

Using path analysis, meditating analysis, moderating analysis, and coefficients of determination, the researchers assessed the structural model. According to findings, the structural model equation can explain 65.9.0% of the variance in Accountants' generative AI usage, 73.4% of the variance in accountants' intention to use generative AI and 62.7% of the variance in accountants' perceived risk. These values have a strong or moderate explanatory power.

Amos 24.0 conducted path analysis, verifying earlier notions and evaluating the relationships between the twelve constructs. The enlarged UTAUT model was shown in Fig. 2 by the author, and the standardized estimates were published in Table 5. All 14 of the hypotheses were accepted. H1 (β=0.84, p<0.001), H2 (β=0.51, p<0.003), H3 (β=0.71, p<0.001), H4 (β=0.90, p<0.001), H5 (β=0.69, p<0.001), H6 (β= 0.51, p<0.001), H7 (β= -0.73, p<0.001), H8 (β=0.66, p<0.001), H9 (β=0.65, p<0.001), and H10 (β= -0.35, p<0.001).

Table 5: Path Analysis

	Unstandardized Regression Weight (B)	Standardized Regression Weight (β)	Standard Error (SE)	Critical Ratio (CR)	P-Value	Results
H1: Performance Expectancy → Intention to Use Generative AI	0.74	0.84	0.13	5.69	0.00	Accepted
H2: Effort Expectancy → Intention to Use Generative AI	0.41	0.51	0.11	3.73	0.002	Accepted
H3: Social Influence → Intention to Use Generative AI	0.61	0.71	0.13	4.69	0.00	Accepted
H4: Facilitating Conditions → Generative AI Usage	0.91	0.90	0.14	6.5	0.00	Accepted
H5: Intention to Use Generative AI → Generative AI Usage	0.66	0.69	0.12	5.5	0.00	Accepted

	Unstandardized Regression Weight (B)	Standardized Regression Weight (β)	Standard Error (SE)	Critical Ratio (CR)	P-Value	Results
H6: Reliability perception → Intention to Use Generative AI	0.46	0.51	0.11	4.18	0.00	Accepted
H7: Privacy and Security Concerns → Intention to Use Generative AI	-0.66	-0.73	0.13	5.08	0.00	Accepted
H8: Training & Development → Effort Expectancy	0.61	0.66	0.12	5.08	0.00	Accepted
H9: Privacy and Security concern→ Perceived Risk	0.63	0..65	0.15	4.87	0.00	Accepted
H10: Perceived Risk→ Intention to Use Generative AI	-0.33	-0.35	0.16	4.75	0.00	Accepted

5.3. Mediating Analysis

Mediating factors have the potential to bolster the study model's hypotheses. To administer a mediation analysis with 5,000 bootstrap samples and a 95% confidence interval, the researchers used Amos 24.0. The bias-corrected percentile approach was used for the 95% confidence interval. Mediation analysis is shown in table 6. The research found that with an indirect impact of -0.23, perceived risk (PR) acts as a negative mediating factor between privacy and security concerns (PSC) and Intention to use generative AI (IUGA). This suggests that as privacy concerns rise, so does perceived risk, which in turn lowers the Intention to use generative AI.

5.4. Moderating analysis

In this research experience and job type were taken as moderating variables which is represented in Table 7. The study found that the substantial interaction effect (B = -0.31) demonstrates that as experience levels rise, the impact of effort expectancy on intention to use generative AI decreases. Effort Expectancy has less of an impact on the intention to use generative AI for experienced users. The substantial interaction term (B = 0.36) suggests that people in high-tech employment have a higher influence of Performance Expectancy on intention to use g**en**erative AI than those in low-tech ones.

Table 6: Mediating Analysis

Mediator Path	Indirect Effect	Product of coefficients		P-Value	Bootstrap 5000 times 95%CI	
		SE	Z		Lower	Upper
H11: PSC->PR-> IUGA	-0.23	0.011	-2.21	0.001	-0.42	-0.051

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Table 7: Moderating Effect

H	Relationship	Moderator	Estimate	P- Value	t-value	Result
H12	EE-> IUGA	Experience	-0.31	0.004	2.81	Accepted
H13	PE-> IUGA	Job Type	0.36	0.004	2.76	Accepted

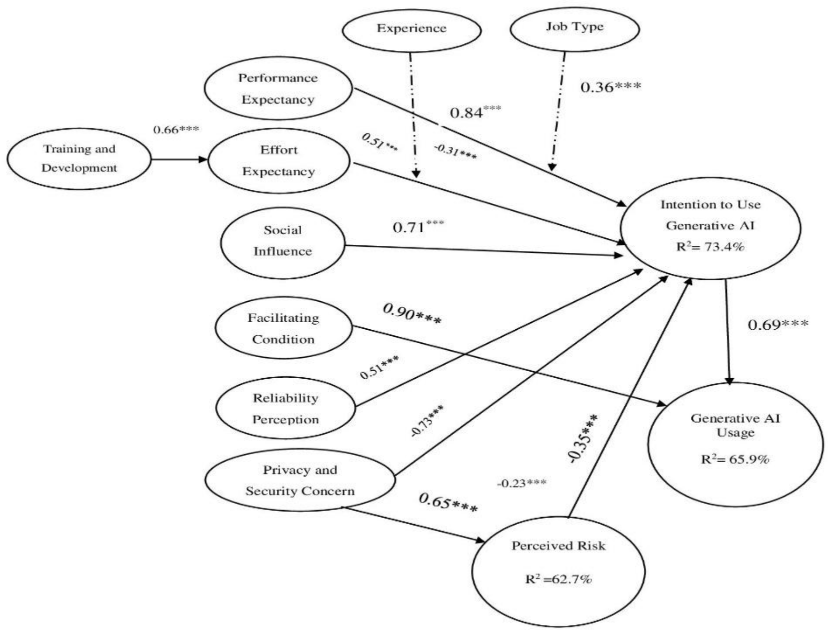

Figure 2: Path Analysis (The line represents paths in the model. R^2 of the dependent variables are included. ***P< 0.001)

6. Discussion and Conclusion

6.1. Major Findings

The results confirmed the core variables of the UTAUT model as indicating Performance Expectancy (PE), Effort Expectancy (EE) Social Influence (SI), and Facilitating Conditions (FC), continue to exert a strong influence over user acceptance and use intention for generative AI in accounting profession in Bangladesh. The application of PE made a great impact. It significantly increased the Intention to use, suggesting that adoption by accounting professionals will be greater where generative AI is perceived as having positive effects on performance. Effort expectancy meant that Users are more likely to adopt generative AI technology if it is simple for them to understand and utilize. According to social influence factors, the targeted audience of professionals tended to have had a wider role model set that influenced their attitudes towards technology, gravitating towards industry norms and following what others used.

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The study discovered that accounting professionals' intentions to employ generative AI were significantly affected by data privacy and security concerns. Adoption declined as a result of concerns about data leaks and abuse. Adoption intentions, however, were positively impacted by reliability perception, suggesting that adoption intentions increase when generative AI is viewed as reliable. This adds to the corpus of work that emphasizes how important trust and dependability are in generative AI.

Moreover, Perceived risk mediates the relationship between data privacy and security concerns and the intention to use generative AI.

Experience moderates the relationship between Effort Expectancy (EE) and Intention to Use Generative AI. Experienced accounting professionals have lower EE and stronger generative AI intention, suggesting a lower perceived learning curve. However, job type significantly moderates EE and intention to use generative AI. Specialized professionals, like auditing, financial analysis, and forensic accounting, show stronger associations between PE and intention to use, suggesting different roles perceive generative AI's usefulness differently and require tailored generative AI solutions.

The expanded UTAUT model found in this study explains 73.4% of why people intend to use generative AI and 65.9% of its actual use. The fact that these theories can explain so well proves that the model is robust. Adding perceived risk, previous experience and type of work improves the model’s accuracy and gives it more relevance. Since their goals are different, tax accountants using AI for compliance and auditors opting for accuracy and automation, there should be special frameworks for each type of job. As a result, this model can be applied in other developing countries and continues to shape vital research in the accounting industry.

6.2. Theoretical Implication

This research contributes significantly to theory by adding to the UTAUT model in light of using generative AI in accounting. While the early UTAUT framework has four basic aspects called Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions, this work adds the context-related factors Reliability Perception, Privacy and Security Concerns and Training and Development. Considering trust, risks with data and workers’ skills shows how major some fields such as accountancy, have become in using generative AI applications.

In addition, this research adds Perceived Risk as a mediator to better understand the connection between trust concerns and how likely a person is to act in a given way. Job Type and Experience are included as moderators, recognizing the diversity in positions and technology within accounting. With these improvements, the UTAUT model addresses matters related to professional hierarchy and field significance that are largely ignored in standard research on technology adoption.

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Above all, the study places the model within Bangladesh, a developing nation and uses data from a country where digital development is in progress though held back by structural, governmental and learning limitations. As a result, the study adds information on using AI technologies in any low-resource environment and strengthens the universality of UTAUT.

6.3. Practical Implication

Accounting practitioners in emerging countries, firm managers, educators and policymakers will directly gain from this study. By noticing which factors stop or promote AI adoption among tax accountants, management accountants and auditors/reporting staff, this research guides how to incorporate AI in various accounting functions. The data demonstrate that accounting firms should incorporate training focused on roles that help employees overcome psychological blocks related to risk management. Since reliability and privacy/security impact people's intention to use AI, companies should design tools that are clear, open and secure to ensure users are confident in them.

The results suggest to ICAB and similar organizations that creating guidelines for ethical AI practices, data management and certification processes for AI in accounting is needed. AI literacy modules should be part of the curriculum in both educational and CPD settings to train future accountants for a digital industry.

Many emerging technologies cannot be successfully used in accounting in the Global South without aligning AI with how useful users find them, how relevant to their job they are and how well the infrastructure can support them.

6.4. Limitation

Although the study's modified UTAUT model took into account several significant characteristics, there are still more variables that might affect how generative AI is accepted and applied. Personality qualities, company culture, and cognitive aspects like perceived satisfaction are a few examples of potential influences. Prospective studies should consider these elements in order to have a more thorough understanding of AI adoption. Discriminant validity for Social Influence was found to be just slightly high. It would be useful for future research to improve SI items for use in similar cases.

6.5. Future Research

Further research ought to examine the effects associated with management techniques, corporate culture, and leadership on the adoption of generative artificial intelligence (AI). It matters to examine how an organization's focus on digital transformation, leadership philosophies, and openness to innovation affect AI adoption. Additionally, future studies should examine how AI technologies affect employment roles and skill needs, particularly in the accounting industry.

The study offers fresh insights into accounting professionals' understanding and use of generative AI which is only just being introduced in Bangladesh. Whereas past research examines the role of AI in every business area, the study

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specifically focuses on each function in audit, tax and management accounting, offering a new and applicable point of view for these professions.

Reference

Aggarwal, R., Gugnani, R., & Goel, U. (2021). AI in accounting: A bibliometric analysis and future research directions. *Journal of Accounting Literature, 45*, 21–36.

Ahmed, S., Kabir, R., & Rahman, T. (2020). The adoption of AI in the accounting profession: Insights from Bangladesh. *Asian Journal of Accounting Research, 5*(2), 138–152.

Ali, M., Farooq, W., & Abbas, G. (2021). Artificial intelligence and its role in enhancing accounting professionals' productivity. *Journal of Accounting and Finance in Emerging Economies, 7*(1), 145–156.

Alves, A., & Kochetkov, I. (2021). Generative AI and its application in accounting: A roadmap for research. *Journal of Accounting and Technology, 11*(2), 123–136.

Ashrafi, A., Sharma, S. K., Al-Badi, A., & Al-Murtthi, W. (2014). Use of the UTAUT model to assess the factors affecting the adoption of cloud computing in Oman. *International Journal of Management and Humanities, 20*(2), 12–22.

Basoglu, N., & Hess, T. (2014). Exploring the moderation effect of trust in UTAUT: The case of e-voting adoption in Turkey. *Journal of Information Technology Research, 7*(2), 18–33.

Bender, D., & Augustin, S. (2020). Generative AI in financial auditing: A case study. *Journal of Emerging Technologies in Accounting, 17*(1), 1–19.

Camilleri, M. A., & Sultana, R. G. (2020). Artificial intelligence and the future of work in accounting. *Journal of Business Research, 120*, 141–151.

Chen, Y., Kannan, K. N., & Padmanabhan, B. (2020). AI and the future of accounting: A data-driven approach. *Journal of Accounting Information Systems, 34*(3), 150–163.

Chen, Y., Peng, Y., & Qin, C. (2022). Exploring the mediating role of perceived risk in AI adoption. *Journal of Business & Industrial Marketing, 37*(4), 503–512.

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management.* https://doi.org/10.1007/s10490-023-09871-y

DeSanctis, G., & Poole, M. S. (2007). Transitions in UTAUT: A comparison of social cognitive and technology acceptance models. *Information Technology & People, 20*(1), 45–66.

Dong, L., & Xu, J. (2021). AI applications in accounting: A synthesis and a research agenda. *Journal of Accounting and Public Policy, 40*(3), 128–145.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719–734.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18,* 39–50. https://doi.org/10.2307/3151312

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*, 107–120. https://doi.org/10.1504/ ijmda.2017. 087624

Hosseini, M., Butcher, K., & Veidt, M. (2019). Exploring generative AI's potential in corporate reporting. *Journal of Corporate Finance, 60*(5), 1007–1034.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1–55.

Islam, A. Y. M. A., & Azad, M. A. K. (2021). The impact of artificial intelligence on accounting systems: Evidence from Bangladesh. *Journal of Business and Management, 23*(1), 102–115.

Lankton, N. K., & Wilson, E. V. (2007). Modeling IT acceptance through TAM and UTAUT: A comparison of past work. *Information & Management*, *44*(1), 362–372.

Mansouri, M., & Pisaruk, S. (2022). Adoption of AI in the auditing profession: Evidence from the UTAUT model. *International Journal of Accounting Information Systems, 39*, 120–137.

Meng, X., Culibrk, D., & Shao, L. (2019). AI and accounting practices: An empirical investigation. *Expert Systems with Applications*, *123*, 1–16.

Moran, J. (2019). Artificial intelligence and accounting in the 21st century: Threat or opportunity? *Journal of Accounting & Finance, 19*(1), 102–118.

Pramanik, A., Acharjya, D. P., & Mitra, P. (2017). A hybrid approach using AI in financial accounting: The case of Bangladesh. *Journal of Financial Management, 12*(2), 81–93.

Rana, N. P., Dwivedi, Y. K., & Williams, M. D. (2015). A meta-analysis of the unified theory of acceptance and use of technology (UTAUT). *International Journal of Indian Culture and Business Management, 11*(2), 191–222.

Rech, J. (2022). Generative AI in audit procedures: The moderating effects of experience and job type. *Journal of Accounting and Technology, 16*(4), 188–204.

Ringle, C. M., Sarstedt, M., & Straub, D. (2012). A critical look at the use of PLS-SEM in MIS quarterly. *MIS Quarterly, 36*, iii–xiv.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. *Advances in International Marketing*, *22*, 195–218.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Wessels, L., & Steenkamp, L. P. (2021). AI applications in auditing: Moderating effects of experience and expertise. *Journal of Emerging Technologies in Accounting, 17*(1), 50–72.

Yan, X., Hu, L., & Shen, J. (2019). The impact of perceived risk on intention to use AI-driven accounting systems. *Journal of Information Technology, 34*(3), 234–252.

Yaseen, H., Dingley, K., & Adams, C. (2016). The role of risk perception in AI adoption in accounting: A Bangladesh perspective. *International Journal of Business Innovation Research, 10*, 521–539.

Zikmund, W. G. (2003). *Business research methods.* Dryden Press.

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Appendix

Variables	Items	Description
Performance Expectancy (PE)	PE1	My ability to do accounting tasks will be improved with the use of generative AI.
	PE2	Generative AI will make my accounting work move more efficiently.
	PE3	Generative AI will help me produce better financial reports.
	PE4	Generative AI will speed up the completion of various tasks.
Effort Expectancy (EE)	EE1	I would find it easy to use generative AI in my education.
	EE2	I would find it easy to use generative AI in my education.
	EE3	It would not be difficult for me to get skilled in using generative AI for what I do.
	EE4	I think it's easy to use and understand the tools that generate artificial intelligence.
Social Influence (SI)	SI1	My colleagues feel it would be beneficial to leverage generative AI in accounting.
	SI2	I am supporting the use of generative AI by staff at work.
	SI3	Many people in my circles support learning how to use generative AI.
	SI4	Generative AI is now being applied in accounting commonly within our company.
Facilitating Condition (FC)	FC1	I can make use of generative AI because I have the proper resources.
	FC2	I get the help and advice I need to work with generative AI.
	FC3	We have adequate lessons at work to learn how to use AI tools.
	FC4	When I face issues with generative AI tools, I can contact a specific person or unit within the company for help.
Reliability Perception (RP)	RP1	Generative AI offers accounting with continual and dependable work results.
	RP2	I am sure that the financial data produced by generative AI is accurate.
	RP3	Generative AI follows the rules set by professional accounting organizations.
	RP4	It is possible to review and examine the output from generative AI systems.
Privacy and Security Concern (PSC)	PSC1	I worry that generative AI systems might expose financial data that people want to keep safe.
	PSC2	Concern about unwanted access to my data is another worry when I use generative AI.
	PSC3	Generative AI systems may be exposed to attacks by cyber criminals.
	PSC4	Data breaches could become more likely when generative AI is used.
Training and Development (TD)	TD1	Our organization runs sessions on generative AI in accounting.
	TD2	I have already participated in one training session about AI systems.
	TD3	I feel ready to use generative AI at work.

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Variables	Items	Description
	TD4	I have access to ongoing professional growth in AI.
Perceived Risk (PR)	PR1	Generative AI might introduce errors into my work which could harm my employment.
	PR2	There is some uncertainty when it comes to the legal outcomes of using generative AI tools in accounting.
	PR3	I am unsure how trustworthy generative AI is in accounting tasks that require accuracy.
Intention to Use Generative AI (IUGA)	IUGA1	I plan to make use of generative AI instruments as part of my accounting work.
	IUGA2	I will advise my colleagues to make use of generative AI tools.
	IUGA3	I intend to start using more generative AI resources before long.
Generative AI usage	GAU1	I use some generative AI tools for particular accounting duties.
	GAU2	I rely on generative AI daily in what I do for work.
	GAU3	I count on generative AI for from report generation to forecasting.

A1: Items of Variables