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Auditors' Intentions to Use Blockchain Technology: Do Trust in Technology, UTAUT Factors, and Age Matter?

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Abstract

This study examines the effect of trust in technology and the Unified Theory of Acceptance and Use of Technology (UTAUT) on auditors' intention to use Blockchain technology (BT). This study also aims to explore how age moderates the relationship between trust in technology, the UTAUT, and auditors' intention to adopt BT (AIABT). Data from 332 Lebanese auditors were analyzed using partial least squares structural equation modeling (PLS3-SEM), and findings show that trust in technology and UTAUT factors significantly impact AIABT. Besides, results show that age doesn't moderate the role between trust in technology, UTAUT factors, and AIABT. According to researchers' this study is among the first to investigate the variables affecting AIABT in Lebanon. This study highlights the practical implications of BT adoption in auditing in Lebanon by pointing out the need for case studies, workshops, educational programs, investing in IT systems, and developing regulatory frameworks to build trust and boost credibility in BT adoption.

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1. Introduction

Introduced in 2008, Blockchain technology (BT) is a decentralized database that acts as a distributed digital ledger where transactions are recorded linearly on blocks in a chain that provides security and transparency (Chou et al., 2021). Transactions are recorded across multiple computers called nodes, and once entered, they can never be erased or manipulated. In addition, BT has a record of every single transaction ever made (Salem, 2019). BT characteristics include decentralization, immutability, and accountability (Rozario & Thomas, 2019). In addition, BT ensures no delay between the occurrence of a transaction and the time being recorded in the accounting system (Sinha, 2020). Adopting BT in accounting ensures that accounting transactions are correctly recorded and approved based on pre-defined conditions, mitigating fraud risk (Yu, Lin, & Tang, 2018). Besides, information between participants cannot be modified or destroyed, leading to safer data. In addition to safer and more reliable information, introducing an accounting system based on BT helps reduce costs (Church, Smith, & Kinory, 2021).

BT fundamentally changes the auditing process where auditors have complete access to all executed transactions. Unlike traditional auditing, auditors using BT can audit any transaction in any period, allowing continuous audits (Liu, Liu-Lastres, Wang, & Fu, 2019). In addition, by using BT, repetitive tasks are reduced, reconciliation is not needed anymore, manual mistakes and energy consumption are reduced, scalability is achieved, and the ability to test an overall database, not just a sample one (Bellucci, Cesa Bianchi, & Manetti, 2022). One critical benefit of BT is using a smart contract, a computer-based code stored on BT that performs transactions if pre-determined conditions are met. It is a new technology with plenty of advantages compared to traditional contracts. Those advantages are summarized as cost reduction, including services and administration costs, enhancing the efficiency of the business process, creating trust between participants, and reshaping the whole business process (Xu, Chong, & Chi, 2021).

Although a range of studies discuss the benefits of BT in various industries, the intention to adopt it in the auditing context is still unexplored (Ferri, Spanò, Ginesti, & Theodosopoulos, 2021). Furthermore, limited research focuses on the factors that impact AIABT (Salem, 2019). Derived from the challenges of BT, the researchers use trust in technology and UTAUT to investigate AIABT. Even though some Mediterranean countries like Turkey, Greece, Malta, Saudi Arabia, UAE, Qatar, Kuwait, and Bahrain adopted BT (Alomari & Fetais, 2023; Papadaki & Karamitsos, 2021) Lebanon has not yet adopted BT. This study addresses the gap in the existing literature by investigating the factors that impact AIABT in Lebanon, utilizing the concepts of trust in technology and the UTAUT. While BT adoption can reshape the auditing sector, Lebanese auditors face significant challenges in implementing BT effectively, including a lack of academic courses in universities, absence of clear guidelines, inadequate technological infrastructure, and a dearth of practical studies and research. Therefore, this study applies trust in technology and the UTAUT to explore these challenges and examine AIABT in Lebanon. Additionally, this research is the first that examines the AIABT using trust in technology and UTAUT and the first to explore age's moderating role in their relationship.

Researchers suggest that trust in technology and UTAUT factors, including facilitating conditions (FC), effort expectancy (EE), performance expectancy (PE), and social influence (SI), significantly impact the AIABT. This study aims to fill the literature gap by examining the impact of trust in technology and UTAUT on Lebanese AIABT and testing the age's moderating role. The sample of 332 Lebanese auditors provided data through emailed questionnaires, and findings reveal that trust in technology and UTAUT factors significantly affect AIABT. In addition, results show that age plays no moderating role among trust in technology, UTAUT factors, and AIABT.

This study contributes to BT in auditing literature by identifying key factors influencing AIABT. By examining the factors and the challenges to adopt BT, this study presents critical insights for audit firms to assess the current state of integrating BT with the existing systems. The results offer valuable guidance for audit firms assessing BT usage and adoption barriers. After identifying the causal factors that impact auditors to adopt BT, the findings are valuable to help implement BT effectively. Furthermore, the practical implications of the following study present a practical approach to adopt BT in the Lebanese auditing context by highlighting the need for awareness and educational campaigns, collaboration with other departments, developing regulatory framework, investments in infrastructure, and IT systems, and organizing workshops to better prepare users to use and adopt BT efficiently and effectively. In the coming sections, the literature review and hypothesis development are displayed, research design and data are presented, results and discussion are discussed, and lastly, the conclusion is displayed.

2. Literature Review and Hypothesis Development

2.1. Trust in Technology

Trust has been an interesting research topic for a long time and has received prominent attention from researchers. It has been studied in different sectors, including banking information systems (Reid & Levy, 2008) e-government (Carter & Bélanger, 2005) and Blockchain for supply chain (Francisco & Swanson, 2018). Trust in this study refers to trust in technology, which is the perception of how reliable and trustworthy a system is. It is a major variable in predicting individuals' behavioral intention to adopt information systems (IS) and information technology (IT) (Chao, 2019). Trust is expressed through functionality, reliability, and helpfulness beliefs that are critical in technology acceptance (Salem, 2019). It is considered a crucial factor that influences the behavior of users with a high level of uncertainty (Jevsikova, Stupurienė, Stumbrienė, Juškevičienė, & Dagienė, 2021). Trust is a strong variable that impacts BT adoption (Raut, Priyadarshinee, & Jha, 2017) and technology is only adopted when trust exists (Wong, Tan, Lee, Ooi, & Sohal, 2020). Although Wong et al. (2020) reveal that trust does not impact the behavioral intention to adopt technology, most of the studies found that trust affects adopting technology positively (Chao, 2019; Kim, Kim, & Shin, 2009; Queiroz, Fosso Wamba, De Bourmont, & Telles, 2021; Salem, 2019; Sim, Loh, Wong, & Choong, 2021). According to the majority of the literature displayed, the researchers propose that:

H_1: Trust in technology positively impacts AIABT.

2.2. Unified Theory of Acceptance and Use of Technology

Drawn by Venkatesh, Morris, Davis, and Davis (2003) UTAUT is an information system theory and among the most employed models interpreting the acceptance of new technology (Park, 2020). It is the level of accepting IT and IS (Ferri et al., 2021). The literature documented some core variables in the UTAUT model, such as facilitating conditions (FC), effort expectancy (EE), performance expectancy (PE), and social influence (SI) (Venkatesh et al., 2003).

2.2.1. Facilitating Conditions

FC is an employee's belief that the infrastructure of their organization is available to support system use and that technical resources are available to facilitate using new technology (Arias-Oliva, Pelegrín-Borondo, & Matías-Clavero, 2019; Bierstaker, Janvrin, & Lowe, 2014; Venkatesh et al., 2003). Although some studies Lee and Kim (2022) and Maswadi, Ghani, and Hamid (2022) found that FC affects technology use negatively, most studies found a positive impact between users' intentions and technology adoption (Baki & Amoozegar, 2021; Bierstaker et al., 2014; Park, 2020; Sim et al., 2021; Teng, Cai, Gao, Zhang, & Li, 2022). According to the majority of the studies presented, the researchers propose that:

H_2: Facilitating conditions positively affect AIABT.

2.2.2. Effort Expectancy

EE is the level of simplicity involved in using a tool, specific technology, and IS (Arias-Oliva et al., 2019; Bierstaker et al., 2014). It is a major predictor of accepting technology (Chao, 2019). Some studies showed that EE negatively affects technology adoption (Ferri et al., 2021; Sim et al., 2021) while others showed no relationship between EE and technology adoption (Robles-Gómez, Tobarra, Pastor-Vargas, Hernández, & Haut, 2021; Slade, Dwivedi, Piercy, & Williams, 2015). Nevertheless, studies that found a positive effect between EE and technology adoption are studies of Arias-Oliva et al. (2019); Wamba and Queiroz (2019); Park (2020); Almarzouqi, Aburayya, and Salloum (2022); Maswadi et al. (2022); Lee and Kim (2022) and Teng et al. (2022). According to the majority of results of literature displayed, the researchers formulate that:

H_3: Effort expectancy positively affects AIABT.

2.2.3. Performance Expectancy

PE is a powerful predictor of adopting technology (Venkatesh et al., 2003) that affects the behavior of users dealing with AI (Venkatesh, 2022). Some studies Wamba and Queiroz (2019); Ferri et al. (2021) and Queiroz et al. (2021) found that PE affects technology adoption negatively. Other studies reveal a positive association between PE and technology adoption (Arias-Oliva et al., 2019; Bierstaker et al., 2014; Buabeng-Andoh & Baah, 2020; Chao, 2019; Jevsikova et al., 2021; Park, 2020; Sim et al., 2021; Slade et al., 2015). Based on the majority of the literature displayed, the researchers formulate that:

H_4: Performance expectancy positively influences AIABT.

2.2.4. Social Influence

SI is the degree to which the belief of an individual changes according to the opinion of others (Arias-Oliva et al., 2019; Bierstaker et al., 2014). The opinion of the social circle affects individuals' decisions (Ferri et al., 2021). SI can be exerted by friends, family, and peers (Wamba & Queiroz, 2019). The impact of SI on technology adoption has been investigated by literature, and some studies reveal no relationship between the two factors (Arias-Oliva et al., 2019; Bierstaker et al., 2014; Buabeng-Andoh & Baah, 2020; Jevsikova et al., 2021; Park, 2020). Others Ferri et al. (2021); Queiroz et al. (2021); Sim et al. (2021); Lee and Kim (2022) and Teng et al. (2022) found a positive relationship between SI and technology adoption. Based on the majority of presented studies, the researchers propose that:

H_5: Social influence positively affects AIABT.

2.3. Moderating Role of Age in the Relationship between Trust in Technology, UTAUT, and AIABT

Age influences technology acceptance and user behavior (Al Mamun et al., 2023; Cheng, Chao, & Chen, 2019). Some studies found a negative relationship between age and technology adoption (Ferri et al., 2021; Meyer, 2011) while Alexandrakis, Chorianopoulos, and Tselios (2020) found none. Furthermore, studies by Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva (2014); Chawla and Joshi (2018) and Merhi, Hone, Tarhini, and Ameen (2021) found that age plays a moderating role between trust and technology adoption. Other studies found no moderating role between age and UTAUT constructs (Abegao Neto & Figueiredo, 2023; Khechine, Lakhal, Pascot, & Bytha, 2014; Pinto, Abreu, Costa, & Paiva, 2022; Tsourela & Roumeliotis, 2015). Some studies Ghalandari (2012); Magsamen-Conrad, Upadhyaya, Joa, and Dowd (2015) and Puspitasari, Firdaus, Haris, and Setyadi (2019) found that age positively moderates technology adoption. Based on the literature on age's direct and moderating effects, the researchers propose:

H_6: Age negatively impacts AIABT.

H_7: Age moderating role in the relationship between trust in technology and AIABT.

H_8; Age moderating role in the relationship between facilitating conditions and AIABT.

H_9: Age moderating role in the relationship between effort expectancy and AIABT.

H_{10}: Age moderating role in the relationship between performance expectancy and AIABT.

H_{11}: Age moderating role in the relationship between social influence and AIABT.

Based on the hypotheses, the researchers present the research model in Figure 1.

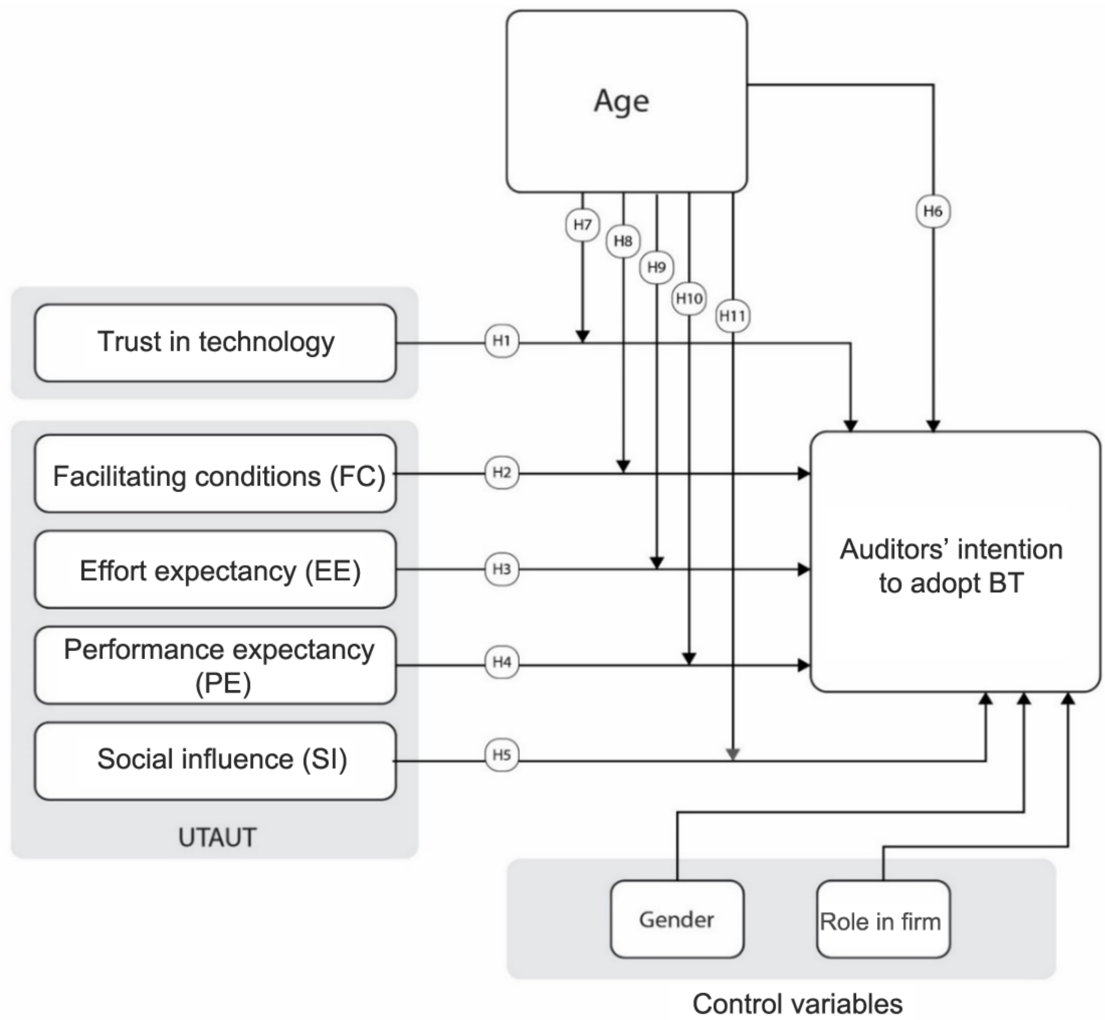

Figure 1. Research model developed by the researchers.

3. Research Design and Data

3.1. Sample Selection and Data Sources

The Appendix 1 shows the socio-demographic characteristics of participants, including auditors' gender, age, highest academic degree, audit firm location, professional certificates auditors hold, years of experience, level of IT expertise, and the position each auditor holds in the audit firm. The researchers collected data from external Lebanese auditors. There are 1,468 certified auditors in Lebanon registered with the Lebanese Association of Certified Public Accountants (LACPA) (Abrach & Feghali, 2023). The researchers carried out pilot testing before distributing the questionnaire to assess its content validity. Three academics and three practitioners in the auditing sector checked the questionnaires' validity, some adjustments were recommended, and the researchers implemented the changes. Furthermore, the researchers employed a convenient sampling technique, which involves selecting members who are readily available, willing to participate, and easily accessible from the target population (Etikan, Musa, & Alkassim, 2016; Golzar, Noor, & Tajik, 2022). Besides, the researchers using the convenience sampling technique do not require specific training to gather data. The researchers collected data using two stages. The first stage is sending the questionnaire online via email, while the second stage is visiting Lebanese audit firms and requesting to fill out the questionnaire. This process was completed within 3 months between October and December 2023. Among the 364 participants, 9 were classified as duplicates, and 23 had a straight-line pattern, reducing the sample size to 332 auditors, which is large enough to run the PLS3 technique (Chin, 1998; Gefen, Straub, & Boudreau, 2000).

3.2. Measuring the Constructs

This study employs PLS3-SEM to check if the latent variable is reflective or formative. In the reflective variable, if any indicator is removed, the relation of other indicators will not change. While in the formative variable, if one observed measure is removed, the whole variable changes (Wilcox, Howell, & Breivik, 2008). In the formative variable, there is no strong correlation among indicators, but a high correlation exists in the reflective variable (Bollen & Lennox, 1991; Jarvis, MacKenzie, & Podsakoff, 2003). Hence, all variables in this study are reflective and strongly correlated, and causality flows from variables to indicators. Four indicators measure each variable. Trust in technology is measured using four indicators adopted from Slade et al. (2015); Chao (2019) and Wong et al. (2020) with one example being, "I trust BT to be reliable." FC is measured using four indicators adopted from Venkatesh et al. (2003); Bierstaker et al. (2014) and Wong et al. (2020) such as, "My audit firm has the right resources for BT." EE is assessed using four indicators adopted from Venkatesh et al. (2003); Slade et al. (2015); Chao (2019) and Wong et al. (2020) with one example being, "I trust BT to be reliable." FC is measured using four indicators, Wong et al. (2020) and Ferri et al. (2021) with one indicator being, "I (would find/find) it simple to use BT for auditing activities."

Furthermore, PE is measured using four indicators adopted from Venkatesh et al. (2003); Slade et al. (2015); Chao (2019); Wong et al. (2020) and Ferri et al. (2021) with one example being, "Using BT (would enable/enables) me to enhance auditing activities." SI is assessed with four indicators adopted from Venkatesh et al. (2003) and Ferri et al. (2021) with an example being, "People who influence my behavior (would think/think) I should use BT." Finally, AIABT is evaluated using two indicators adopted from Ferri et al. (2021) one of which is, "I plan to implement BT in my auditing activities". Furthermore, a 5-point Likert scale (1=strongly disagree, 5=strongly agree) measures auditor agreement. Age, gender, and role were assessed with one question each.

4. Results and Discussion

4.1. Descriptive Statistics

The mean and standard deviation (SD) reflect respondents' views on each questionnaire item. As shown in Table 1, PE has the highest mean (2.744) and SD (1.32), indicating that most auditors agree on it. FC has the lowest mean (1.4789) and SD (0.79), suggesting most auditors lack FC in their workplace to use BT effectively.

Table 1. Descriptive statistics.

Variable	Minimum	Maximum	Mean	Standard deviation	N
Trust in technology	1	5	2.3223	1.26	332
FC	1	5	1.4789	0.79	332
EE	1	5	2.0700	1.09	332
PE	1	5	2.7440	1.32	332
SI	1	5	1.8471	1.18	332
AIABT	1	5	2.1717	1.20	332

Source: PLS3-SEM.

4.2. Research Partial Least Square Structural Model

To analyze data and test the hypotheses, PLS3-SEM is being used. It analyzes intricate models with real-world data and is effective for multiple variables and indicators (Sarstedt, Ringle, Smith, Reams, & Hair Jr, 2014). Besides, PLS3-SEM is preferable to examine theories in their initial stages (Fornell & Bookstein, 1982; Gefen et al., 2000). Regarding this study, PLS3-SEM is used to investigate AIABT and to test the mediating role of age in the relationship between trust, UTAUT, and AIABT in Lebanon. Figure 2 represents the research model developed after eliminating the indicators that affect the reliability and validity of the variables.

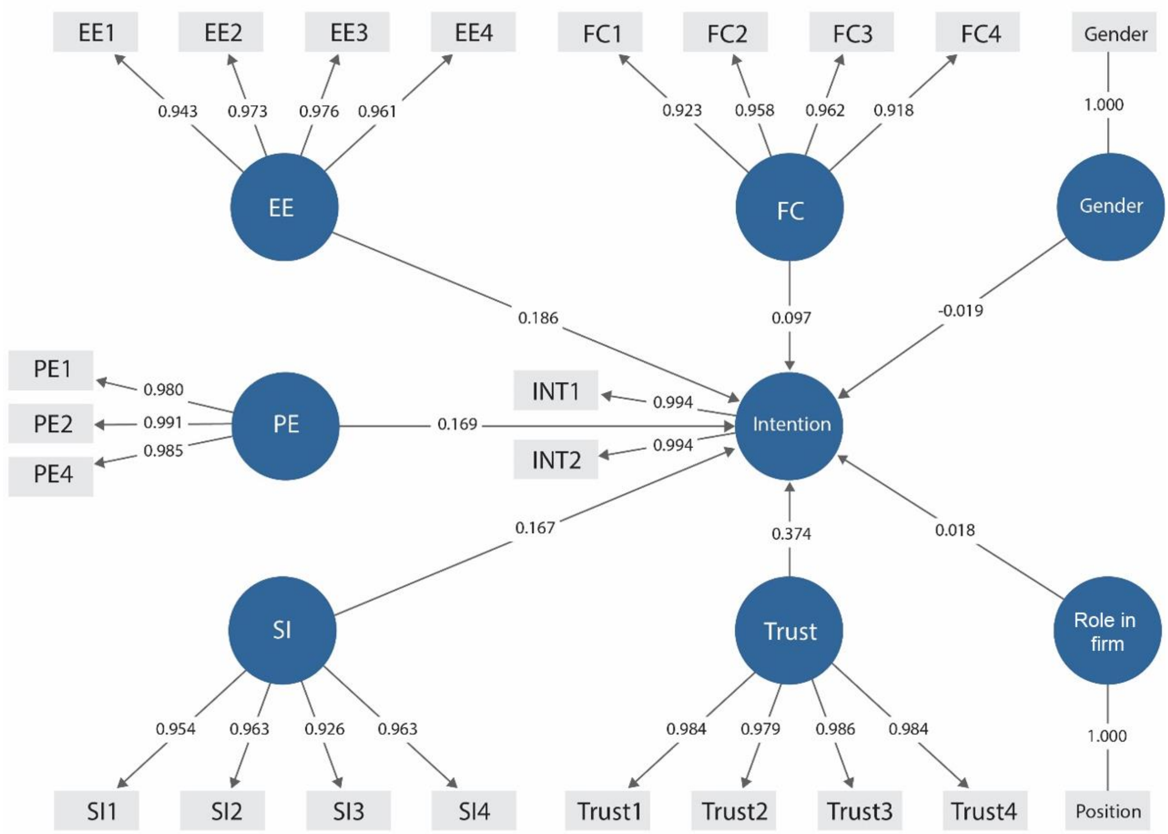

Figure 2. Research model.

Source: PLS3-SEM.

4.3. Reliability and Validity

The researchers executed the permutation test and excluded PE3 indicator in the performance expectancy variable since PE3 has high multi-collinearity among other indicators. This indicator shows a high variance inflation factor (VIF) value (80.230); a VIF < 3.3 indicates no issue in multi-collinearity (Sarstedt et al., 2022). The researchers assess indicator reliability (≥0.708), internal consistency (Cronbach's alpha 0.70-0.95) (Hair Jr, Howard, & Nitzl, 2020) and composite reliability using (Jöreskog, 1971). Convergent validity is assessed through the use of average variance extracted (AVE ≥0.5) (Hair, Risher, Sarstedt, & Ringle, 2019). Table 2 provides an acceptable reliability showing that all indicators of the variables have values more than 0.708. Besides, CA and CR values > 0.7, and AVE values > 0.5. Thus, convergent validity and internal consistency are achieved.

Table 2. Measuring model reliability.

Variable	Item	Loadings	CA	CR	AVE
AIABT	INT1	0.994	0.988	0.994	0.988
	INT2	0.994			
Trust in technology	Trust1	0.984	0.989	0.992	0.967
	Trust2	0.979			
	Trust3	0.986			
	Trust4	0.984			
EE	EE1	0.943	0.974	0.981	0.928
	EE2	0.973			
	EE3	0.976			
	EE4	0.961			
FC	FC1	0.923	0.956	0.968	0.885
	FC2	0.958			
	FC3	0.962			
	FC4	0.918			
PE	PE1	0.980	0.985	0.990	0.971
	PE2	0.991			
	PE4	0.985			
SI	SI1	0.954	0.965	0.975	0.906
	SI2	0.963			
	SI3	0.926			
	SI4	0.963			

Source: PLS3-SEM.

The third step in measurement model analysis is discriminant validity, which ensures each variable differs from others (Hair et al., 2021). Fornell and Larcker (1981) recommended comparing variables' AVE to squared inter-variable correlations, ensuring that shared variance doesn't exceed AVEs. Table 3 exhibits discriminant validity verification.

Table 3. Fornell-Larcker criterion.

Variable	Intention	EE	FC	PE	SI	Trust
Intention	0.994					
EE	0.646	0.963				
FC	0.438	0.485	0.941			
PE	0.611	0.639	0.253	0.986		
SI	0.545	0.617	0.411	0.42	0.952	
Trust in technology	0.68	0.536	0.369	0.604	0.402	0.984

Source: PLS3-SEM.

4.4. Evaluating Structural Models

Before evaluating structural models, the researchers assess collinearity using variance inflation factors (VIFs) for all the constructs (Hair et al., 2021). As exhibited in Table 4, VIF values < 3.3 indicate no issue in multi-collinearity (Sarstedt et al., 2022). Furthermore, the path coefficient and coefficient of determination (R^2) show the causal relation between the variables, and an R^2 of 0.25 shows a weak relationship, 0.5 a moderate one, and 0.75 a strong one (Hair, Sarstedt, Ringle, & Mena, 2012; Henseler, Ringle, & Sinkovics, 2009). Furthermore, Table 4 exhibits that AIABT explains 59.6% of variance, with strong predictive relevance (Q^2_predict = 0.588), indicating strong predictive significance (Q^2_predict > 0.35) (Hair et al., 2021).

4.5. Hypotheses Testing

4.5.1. H1-H5

Table 4 exhibits the findings of the tested hypotheses. Consistent with previous literature (Chao, 2019; Liébana-Cabanillas, Molinillo, & Japutra, 2021; Queiroz et al., 2021; Salem, 2019; Sim et al., 2021; Slade et al., 2015) results show a positive effect between trust in technology and AIABT with a medium effect size (f^2=0.165), thus supporting H1. This shows that most of the respondents trust BT. The f^2 value > 0.02, >0.15, and > 0.35 represent small, medium, and large effect sizes, respectively (Cohen, 1988). Consistent with studies of Bierstaker et al. (2014); Park (2020); Baki and Amoozegar (2021); Queiroz et al. (2021); Sim et al. (2021) and Teng et al. (2022) results reveal that FC has a positive impact on AIABT, and that the technical expertise and resources have a direct effect on AIABT; hence, supporting H2. Besides, results reveal that EE affects AIABT with a small effect size (f^2=0.047), thus supporting H3. This shows that not all respondents find it easy to learn and become skillful in using BT. This is consistent with prior studies (Arias-Oliva et al., 2019; Lee & Kim, 2022; Maswadi et al., 2022; Park, 2020; Queiroz et al., 2021; Teng et al., 2022; Wamba & Queiroz, 2019).

Moreover, consistent with prior studies Bierstaker et al. (2014); Slade et al. (2015); Chao (2019); Arias-Oliva et al. (2019); Buabeng-Andoh and Baah (2020); Park (2020); Jevsikova et al. (2021); Sim et al. (2021); Almarzouqi et al. (2022); Lee and Kim (2022) and Maswadi et al. (2022) results reveal that PE positively affects AIABT with a small effect size (f^2=0.028), hence supporting H4. The following result shows that auditors believe using BT improves auditing activities and enhances effectiveness. In addition, results show that SI significantly affects AIABT with a small effect size (f^2=0.076), supporting H5. This shows that not all of the social circle of auditors think they should use BT. This is consistent with prior studies (Ferri et al., 2021; Lee & Kim, 2022; Maswadi et al., 2022; Queiroz et al., 2021; Sim et al., 2021; Slade et al., 2015; Teng et al., 2022).

Table 4. Assessment of structural model.

Endogenous variable	Exogenous variables	Path coefficient	p-value	VIF	f^2	R^2	Q^2_ predict	Hypotheses	Hypotheses (Decision)
AIABT	EE	0.186	0.013	2.730	0.047	0.596	0.588	H3	Accepted
	FC	0.097	0.029	1.532	0.008			H2	Accepted
	Gender	-0.019	0.58	1.142	0.005				
	PE	0.169	0.001	1.962	0.028			H4	Accepted
	Role in firm	0.018	0.627	1.167	0.001				
	SI	0.167	0.003	1.472	0.076			H5	Accepted
	Trust in technology	0.374	0.000	1.595	0.165			H1	Accepted

Source: Developed by the researchers using PLS3-SEM.

Table 5. Compositional invariance and equality of composites.

Construct	Configural invariance	Compositional invariance			Partial Measurement invariance established	Equal mean value		Equal variances		Full measurement invariance established
		correlation c	Quantile 5%	p-value		Difference	C.I.	Difference	C.I.	
AIABT	Yes	1	1	0.575	Yes	-0.259	[-0.217; 0.208]	-0.144	[-0.271; 0.299]	No
EE	Yes	1	1	0.714	Yes	-0.431	[-0.226; 0.219]	-0.363	[-0.287; 0.296]	No
FC	Yes	1	0.999	0.906	Yes	-0.044	[-0.223; 0.221]	-0.139	[-0.508; 0.573]	Yes
Gender	Yes	1	1	0.053	Yes	0.095	[-0.21; 0.222]	0.02	[-0.031; 0.055]	Yes
PE	Yes	1	1	0.132	Yes	-0.303	[-0.23; 0.223]	0.007	[-0.167; 0.178]	No
Role in firm	Yes	1	1	0.211	Yes	-1.399	[-0.225; 0.219]	-0.376	[-0.208; 0.224]	No
SI	Yes	1	0.999	0.806	Yes	-0.336	[-0.21; 0.226]	-0.518	[-0.303; 0.389]	No
Trust in technology	Yes	1	1	0.424	Yes	-0.21	[-0.22; 0.192]	-0.049	[-0.226; 0.235]	Yes

Source: PLS3-SEM.

4.5.2. H6-H11

Before conducting a multi-group analysis (MGA) for age (moderator), measurement invariance of composite models (MICOM) must be verified to ensure both age groups (G1 < 35, G2 ≥ 35) understand the constructs similarly. MICOM involves three steps: configural invariance, compositional invariance, and equality of composite means and variances (Henseler, Ringle, & Sarstedt, 2016). Configural invariance was achieved, and compositional invariance was confirmed with p-values > 0.05 (Table 5). To check full invariance, researchers compare composite mean and variance differences across groups, ensuring the mean difference is within the 95% confidence range (Henseler et al., 2016). Since these values are unequal, partial measurement invariance is achieved.

After establishing partial measurement invariance, MGA testing begins. The permutation test checks path coefficient equality between G1 and G2. Table 6's first two columns show path coefficients and differences, with results indicating no significant difference (p > 0.05). Further MGA analysis with SmartPLS reveals G1 > G2 (Table 6), but the Welch-Satterthwaite test shows no notable differences, showing that age doesn't affect AIABT, thus, H6 is not supported. This is consistent with Alexandrakis et al. (2020) Additionally, the researchers employ the Independent Samples T-test to examine if age moderates the role between trust in technology, UTAUT factors, and AIABT. The T-test's null hypothesis (p > 0.05) shows no average score differences between G1 and G2 (Ross & Willson, 2017). Levene's Test confirms variance homogeneity (p = 0.097), and Cohen's d supports the T-test with d = 0.2 (small effect) (Cohen, 1988) Since variances are equal, H7-H11 are unsupported, revealing that age does not moderate AIABT. This is consistent with previous literature (Abegao Neto & Figueiredo, 2023; Khechine et al., 2014; Merhi et al., 2021; Pinto et al., 2022; Tsourela & Roumeliotis, 2015).

Table 6. MGA tests path coefficients for age groups.

Association	G1	G2	Path difference	2.50%	97.50%	Permutation p-values	Welch-Satterthwaite test
EE → AIABT	0.162	0.227	-0.065	-0.316	0.321	0.682	0.669
FC → AIABT	0.112	0.072	0.04	-0.182	0.178	0.681	0.664
Gender → AIABT	-0.01	-0.047	0.036	-0.143	0.143	0.595	0.627
PE → AIABT	0.173	0.148	0.025	-0.203	0.221	0.808	0.808
Role in firm → AIABT	0.066	-0.022	0.088	-0.143	0.153	0.25	0.256
SI → AIABT	0.127	0.212	-0.085	-0.226	0.233	0.473	0.447
Trust in technology → AIABT	0.411	0.326	0.086	-0.22	0.218	0.426	0.427

Source: PLS3-SEM.

5. Conclusions

The current study examines AIABT in Lebanon. BT is a decentralized database containing blocks that create a chain-like form and act as a digital ledger where transactions are recorded linearly on blocks in a chain providing security and transparency (Chou et al., 2021). BT characteristics include decentralization, immutability, and accountability (Rozario & Thomas, 2019). BT fundamentally changes the auditing process, and auditors using BT have complete access to all transactions executed, thus saving time to be provided by requested documents. Unlike the traditional auditing process, auditors using BT can audit any transaction in any period, allowing continuous audits (Liu et al., 2019). This study investigate the impact of trust in technology and UTAUT factors on AIABT. The final sample consists of 332 Lebanese external, and PLS3-SEM is used to test the hypotheses. Consistent with previous literature, results show a significant positive relationship between trust in technology, FC, EE, PE, SI, and AIABT. Additionally, results reveal that age has no significant effect on AIABT, nor a moderating role between trust in technology, FC, EE, PE, SI, and AIABT.

5.1. Contributions

The following study is based on the concept that BT can change accounting and auditing practices and has been intended to shed light on BT in auditing in Lebanon, a developing country in the Middle East. In this regard, this study examines the variables that impact AIABT. The analysis allows researchers to reveal practical insights that enable them to contribute to theory, practice, and suggestions for future research.

5.1.1. Theoretical Contributions

Regarding the theoretical contributions, the following study is the first to examine the variables that affect AIABT in Lebanon, along with the moderating role of age in the relationships between trust in technology, UTAUT, and AIABT. Moreover, this study addresses researchers' calls to investigate the variables influencing AIABT across settings and regions (Ferri et al., 2021). In addition, this study enhances BT literature since it's a powerful new method transforming auditors' work, revealing significant positive relationships among trust in technology, UTAUT variables, and AIABT.

5.1.2. Practical Contributions

Concerning practical contributions, this study offers insight into Lebanese AIABT. Furthermore, this study contributes to operational processes and practices to start implementing BT and to prepare training strategies among audit firms to better accept this new technology in Lebanon and other developing countries. Furthermore, after identifying trust in technology, FC, EE, PE, and SI as reliable predictors of Lebanese AIABT, professionals can now develop training programs to accept this new technology better and to identify the obstacles that may be faced.

5.2. Limitations and Future Research

Study limitations are the foundation for future research exploring Lebanese AIABT before its introduction, with further longitudinal studies needed to measure pre- and post-adoption attitudes and intentions. Besides, the study sample is restricted to Lebanese auditors; hence, other Lebanese industries may show different user intentions to adopt BT. Thus, future research can investigate the factors that affect adopting BT in various sectors. Moreover, this study is limited to using trust in technology and the UTAUT model in investigating AIABT; therefore, future research could incorporate additional models to enhance BT adoption. This study is limited to Lebanese auditors, thus; future research can expand to other regions.

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Appendix 1. Socio-demographic characteristics.

Characteristics	**n**	**%**
Gender		
Female	150	45.2
Male	182	54.8
Age		
Less than 35 years old	202	60.8
35 years 'old and above	130	39.2
Area of audit firm		
Greater Beirut	151	45.5
Bekaa & Baalbeck	2	0.6
Mount Lebanon	111	33.4
North Lebanon & Akkar	33	9.9
South Lebanon & Nabatieh	32	9.6
I would rather not specify	3	0.9
Highest academic degree		
Bachelor degree	169	50.9
Master's degree/ MBA degree	153	46.1
PhD/DBA degree	5	1.5
Others	5	1.5
Professional certificates		
Do not hold a professional accounting certificate	130	39.2
CPA	20	6
LACPA	118	35.5
CMA	7	2.1
CIA	36	10.8
Others	21	6.3
Experience in accounting and auditing profession		
1-5 years	109	32.8
6-9 years	67	20.2
10-15 years	80	24.1
More than 15 years	76	22.9
Rating IT expertise		
Novice	94	28.3
Intermediate	200	60.2
Expert	38	11.4
Current job position within the audit firm		
Junior auditor	113	34
Senior auditor	68	20.5
Supervisor &/Or Assistant manager	73	22
Manager &/Or Senior manager	39	11.7
Director &/Or partner	39	11.7

Source: PLS3-SEM Software.