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Perception of digital transformation effect on audit quality: the case of Vietnam

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Abstract

Digital transformation has been progressively attracting attention with its important influence on accounting and auditing in recent decades. This study aims at understanding the perception of digital transformation effect on audit quality to find out the digital challenges in auditing works at all stages. This study explores the perception of the effect of digital transformation on audit quality on four aspects, which are audit users' perception, regulations related to audit, auditors' work, and auditors' professional profile. A quantitative method is applied with data collected from a survey with 136 specialists in auditing. The results show a positive relationship between perception of digital transformation and audit quality. Recommendations from the findings are proposed for auditors, audit firms, and policymakers to adapt with the evolution of technology.

Keywords: Digital Transformation, Audit quality, Big data, AI, Blockchain

1. Introduction

Recent theoretical and empirical studies have shown that many factors significantly influence audit and change the nature of accounting and auditing. Digital transformation is considered one of the most powerful factors. Digital transformation is also the current trend of transformation in business. Digital transformation affects all aspects of the business, from high to low positions, from inside to outside businesses, and from production to sales and after-sales (Boillet, 2018).

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As the expansion of digital transformation becomes faster in business activities, it is a challenge for business model and employment knowledge development. Auditors and their work are potentially impacted by the further development of digital transformation (Elliott, 2002). These advances in information technology involve the potential automation of cognitive tasks. In other words, machines would replace physical labor during the growth of the industrial revolution (Brynjolfsson and McAfee, 2014). The development of digital transformation would challenge the entire auditing industry, including audit works of all stages.

This study explores the effects of perception of digital transformation on audit quality using a sample of data collected from participants who are currently working in the audit field. Their answers are related to the questions about changes in audit quality that can be influenced by digital transformation and other modern technology. The study analyzes the trend in changing audit users' perception, auditors' work, auditors' professional profile, and other related regulations due to digital transformation.

The remainder of the paper is structured as follows: Section 1 introduces the topic; Section 2 reviews the related literature; Section 3 describes the research methodology, data collection method, and research model; Section 4 provides regression model results; Section 5 presents findings and discussions; Section 6 is for the conclusion and recommendations.

2. Theoretical framework and literature review

2.1 Theoretical framework for effects of digital transformation on audit

Digital transformation is a disruptive evolution into an entirely new way of thinking and working (More, 2005). Digital transformation in businesses is the step of changing from a traditional enterprise to a digital one. It takes place by attaching new digital transformation measures such as big data, Internet of things, cloud computing, or artificial intelligent to all aspects of an organization including leadership, working process, culture and environment (Siebel, 2019).

Auditing is a governance mechanism that plays an important role in ensuring the reliability and relevance of financial reports. With digital transformation, auditing is in a new era of evolution. Digital transformation vitalizes the development of auditing. Nonetheless, it is a challenge to audit quality. An audit is of good quality when it is achieved in an environment with suport and appropriate interactions among relevant stakeholders in the financial reporting supply chain (International Auditing and Assurance Standards Board, 2014). The framework for audit quality of International Auditing and Assurance Standards Board (2014) emphasized the importance of information systems and technology platforms applied in the audit. Audit software is able to assits auditors with conducting audit reports which results in in efficiencies and improved quality control processes. However, digital software also leads to risk in audit quality. Therefore, the effects of perception of digital transformation on audit quality could be positive or negative. In the following sections, we review the main concepts of digital transformation related to audit, which are big data, artificial intelligence, and blockchain.

Big data and its effect on audit quality

Big data are described by the five V paradigm. This paradigm includes volume, velocity, variety, veracity, and value. The main characteristic that makes data big is the first V, which is the volume. The total amount of information is growing exponentially every year. The second V, which is velocity, is of no less importance. The speed of data transferring has been promptly increasing. The speed of sending a mobile message, Facebook status updates and comments, or credit card swipe on telecom carrier are examples of data transferring velocity. In addition, data are generated from diverse sources with various forms. They include videos, audio, symbol, text, numbers, pictures, and other forms. In other words, data are presented in disorganized forms, representing the third V, which is variety. The fourth V, which is veracity refers to the quality and accuracy of information. Because data are collected from multiple sources, they needs to be checked for quality and accuracy before using. Finally, the last V, which is value, underlines that big data could have great imaginable value, especially when figuring out customer demands and improving products and services (Chen *et al.*, 2014; Shaqiri, 2017). Therefore, big data represent an advanced transforming model to create a large volume of data with high speed, various types, and high quality, and turning them into valuable knowledge (Constantiou and Kallinikos, 2015).

For auditing functions, the need of big data is not indeed necessary because trillions of accounting transactions are relatively poor in the space of big data. Nonetheless, even though accounting transaction data are not recognized to be big, the manner of big data analytics can be implemented to minor volumes of transactions to audit using full dataset rather than audit using only random samples (Yoon *et al.*, 2015). Furthermore, accounting data are usually in a structured form, which includes debit and credit accounts. It seems to not apply the characteristic of variety of big data to accounting data. However, it is not true. In addition to structured accounting data, related data such as other business transaction information could affect auditing decisions. Examples of business transaction information can be asset valuation, bad debt allowance, warranty expense estimation. Big data could solve the problem of unstructured non-accounting data to assist auditors to estimate their appropriateness, reliability, and relevance (Appelbaum *et al.*, 2017). Finally, big data would add value to audit work. They enable auditors to enhance risk judgments and the quality of assessments by finding all the aberrancies and by recommending solutions. They could significantly diminish the managers' contriving behaviors and therefore, improve the audit relevance and reinforce the corporate governance (Manita *et al.*, 2020).

Artificial Intelligence (AI) and its effect on audit quality

In the early 1970s, the term Artificial Intelligence (AI) became notable among scientists. A huge amount of works related to AI and robotics has been conducted. AI refers to machine intelligence which is the simulation of human intelligence (Nilsson, 1980). AI is supposedly designed to think and act like humans. AI is designed to employ the activities that are based on human data (Minsky, 1961). AI answers three significant questions. First, it is all about what knowledge is needed in thinking. Second, how that knowledge is performed. Third, how that knowledge is applied (Brady, 1985). AI covers several technologies including image and speech recognition, data mining, machine learning, emotion and sentiment analysis (Boillet, 2018).

For auditing perspective, AI can identify any outliers or exceptions in accounting data. Currently, machine learning is being employed by the Big4 auditing companies for collecting and validating data. Ernst & Young has used machine learning to enter accounting entries automatically. By developing complicated machine learning models, auditors can enhance fraud detection. Moreover, machine learning tools can analyze a larger amount of unstructured data in a relatively shorter time than doing it traditionally. AI would assist auditors to save their time and enable them to use their judgment to analyze a larger and profound set of accounting and auditing data. AI makes it possible for auditors to work smarter, faster, and better (Boillet, 2018).

However, on the negative side, the development of AI can threaten the role of humans in the audit. AI could even replace human auditors (Kokina and Davenport, 2017). The World Economic Forum survey in 2015 reports that 75% of 800 executives believe that 30% of every organization audit will be completed by AI in 2025 (Tiberius and Hirth, 2019).

Blockchain and its effect on audit quality

A blockchain is a type of database that stores information electronically and chronologically (Christidis and Devetsikiotis, 2016). The words "block" and "chain" in this context are the block stored in a public database, which is the chain. Blocks are made up of digital pieces of information including transactions information such as the time, monetary unit, value, participants and information that differentiates them from other blocks (Reiff, 2020).

When the blockchain has a new block, it is available for anyone to see. In addition to viewing the contents of the blockchain, network users can connect to the blockchain network as a node (Reiff, 2020). Because everybody can view the database, blockchain is transparent.

For auditing purposes, the potential advantages and disadvantages of blockchain have yet been researched (Dai and Vasarhelyi, 2017). With the main function of certifying the fairness of financial statements, auditors could be diminished by the system of blockchain. When a corporate does all its accounting transactions through a public blockchain, it is trusted by those who accept blockchain technology. In contrast, if a company takes all of its transactions via a private blockchain system, the role of traditional auditors is still maintained (Tiberius and Hirth, 2019).

2.2 Literature review

The perception of digital transformation effect on audit quality is a state-of-the-art topic. However, the number of articles in this topic are limited. A few pieces of research about the similar topic that can be mentioned. Littley (2012) states that Big Data would lead to better estimates, forecasts, relevance, frauds, and other concerns of concern internal and external auditors. Auditors firm may see Big Data as an option to reduce the costs of audits and increase profit. In the same line, Zhang *et al.* (2015) conduct research about big data in auditing and conclude that big data analytics will allow auditors to handle data gaps such as data structure identification, consistency of format and synchronization, incomplete or data modification, and aggregation and confidentiality. Furthermore, using cognitive technologies as a part of digital transformation would enhanced data analysis quality and provide a more accurate prediction of potential risks (Cao *et al.*, 2015) such as bankruptcy (Pendharkar, 2005) and financial frauds (Sajady *et al.*, 2008).

Brown-Liburd *et al.* (2015) suggest that big data analytics affect the auditors' behaviors regarding their evaluation and decision. The implications that big data has on audit judgment are by identifying the information overload, information relevance, sampling recognition, and uncertainty. Furthermore, the most important goals of applying digital transformation is to detect frauds in financial reports. Richins *et al.* (2017) recommend using both manual fraud-detection combined with automatic fraud-detection to detect frauds and errors. However, more data might not actually equal more effective information. The more complexity of client transactions and data resources would lead to the increase of audit risk to the auditor team if analytical procedures are manual and simple. According to Fukukawa *et al.* (2014), the volume and complexity of the data might deter the finding of audit evidence for detecting frauds.

Krahel and Titera (2015) indicate that auditors can have more time to spend on the audit analysis rather than on data collection managed by the technology platforms used by audit firm. Technology will add relevance and value to the auditing profession and ultimately enhance the performance of the capital markets. With the similar opinion, Lombardi *et al.* (2015) conclude that digital transformation is shifting manual audit to automated audit and will revolutionize the way of performing audit. Moreover, Alles *et al.* (2002) state that continuous auditing has been progressively adopted largely due to the need for enhancing internal controls over the financial reports. Automated auditing procedures will allow continuous audit to replace periodic audit (Frey and Osborne, 2017).

Even though the digital transformation in audit is trending, however, the main reasons for applying digital transformation in audit firms is unclear. The question is that whether the audit profession would consider digital transformation as an opportunity to reduce the costs of audits and increase profit (Littley, 2012) or only adopt it as a defensive reaction to market pressure from their clients (Alles, 2015).

Empirical studies about this topic are mentioned as Tiberius and Hirth (2019) and Manita *et al.* (2020). Tiberius and Hirth (2019) study the impact of digitalization on auditing in the case of Germany by using the Delphi study. The results show that no significant changes are expected within the next five to ten years. The annual audit will transform toward continuous audit. They believe that digitalization will not take over the auditors but it will provide them with great assistance. The audit job's requirements will be tighter and higher. However, its troublesome effects are not expected in short-term.

Manita *et al.* (2020) study the digitalization of external audits and their impact on corporate governance in France. With the interview from auditors in Big4 audit firms, data analysis results reveal that digitalization enhances the audit quality essentially by analyzing all data's customers. Along with the digital transformation, a new auditor profile will stimulate the innovation of audit firms and allow audit firms to providing new services.

From the above literature, it can be seen that empirical studies about this topic are rare. The topic of this study is considered to be exceptional and meaningful among current research topics on auditing. In Vietnam, there are some studies which have reviewed the importance and trend of applying digital transformation in audit such as Tran (2019) and Nguyen (2020). However, no empirical research about this topic has been taken in the case of Vietnam.

3. Research methodology

3.1 Research method

After reviewing both theoretical and empirical studies, a quantitative method was employed to find out the perception of the effects of digital transformation on audit quality. The adoption of the quantitative method compliments Tiberius and Hirth (2019) and Manita *et al.* (2020). The quantitative method is used to examine the numeric data to confirm or reject the hypothesis. The quantitative research method would lead to more accurate and clear statistical results.

Data were collected from surveys sent to auditors to find out the perception of the effects of digital transformation on audit quality. The study analyzes and processes the survey data by using the SPSS software to conduct the regression and provide the results. Regression results allow authors to decide whether to accept or reject the hypothesis. Based on these findings, discussions and recommendations are provided.

3.2 Data collection

The primary data for the study have been collected by sending survey questionnaires to the participants who are currently working in the audit field. The survey has been conducted from August 2020 to December 2020. The analysis of this study is based on data compiled from 136 responses from the survey.

The survey questionnaire was divided into two main sections. The first section solicits information on audit quality in the digital era. The second section addresses the respective objectives that would affect audit quality. The questionnaire items relating to the study objectives are structured using a 4-point Likert scale format. When an even numbered Likert scale is employed, the tendency toward the middle could be avoided. The survey scale is 1 for disagree; 2 for somewhat disagree; 3 for somewhat agree; 4 for completely agree.

There are 18 questions which are divided into five parts. The information is described in Table 1.

Table 1. Content of the survey

Part	Question	Content	Measurement
1	1 to 5	Audit quality in digital era	Elimination of audit risks, full audit, audit pricing, and replacement of obsolete audit regulation.
2	6 to 9	Changes in audit users' perception due to digital transformation	Value of audit report, reliability of automated audit, obsolete auditors' judgment, and tense relationship between auditor and audit users.
3	10 to 12	Changes in regulation due to digital transformation	Audit standards established and chosen to apply by AI would lead to a gap in regulation.
4	13 to 15	Changes in auditors' work due to digital transformation	More complex tasks, continuous audit, shift from traditional audit to consulting.
5	16 to 18	Changes in auditors' professional profile due to digital transformation	Higher requirements make audit become a less attractive job and massive auditing job losses will occur.

Source: The authors' collection

Measuring audit quality in digital era

According to the literature, audit quality is expected to be enhanced in the digital era. Inherited from Zhang *et al.* (2015), audit quality in the digital era is highlighted with the elimination of audit risk, availability of full audit, reduction of audit pricing, and replacement of obsolete audit regulation. These expectations of higher audit quality are sensitive to digital transformation.

Measuring changes in audit users' perception

The results of digital transformation in audit and audit users' perception will be changed. These predictable changes are the perception of audit report value, reliability of automated audit, obsolete auditors' judgment (Brown-Liburd *et al.*, 2015), and tense relationship between auditors and audit users (Tiberius and Hirth, 2019).

Measuring changes in regulation

With the domination of new technology, audit standards can be established and chosen to apply by AI (Kokina and Davenport, 2017). It would lead to a regulatory gap between auditing standards and the new digital business reality. In many cases, technological progress is faster than legislation and regulation. Because technological movements potentially affect nearly all aspects of auditing, current regulatory and auditing standards may need extensive adjustments (Appelbaum *et al.*, 2017).

Measuring changes in auditors' work

Changes in auditors' work stem from automated audit procedures. Automated auditing procedures can save time for auditors by doing simple tasks. The work of auditors will consist of new and more complex tasks such as consulting (Frey and Osborne, 2017). Furthermore, business new information comes up every day so that stakeholders will be probably interested in more up-to-date, more frequent, or even continuous audits (Elliott, 2002).

Measuring changes in auditors' professional profile

Changes in auditors' professional profiles are necessary for the digital era. High information technology and data analysis skills will be required for auditors (Appelbaum *et al.*, 2017). Because of the higher requirements of auditors' professional profile, the audit would become less attractive jobs (Tiberius and Hirth, 2019). Moreover, massive auditing job losses will occur due to automated auditing procedures (Frey and Osborne, 2017).

3.3 Hypotheses

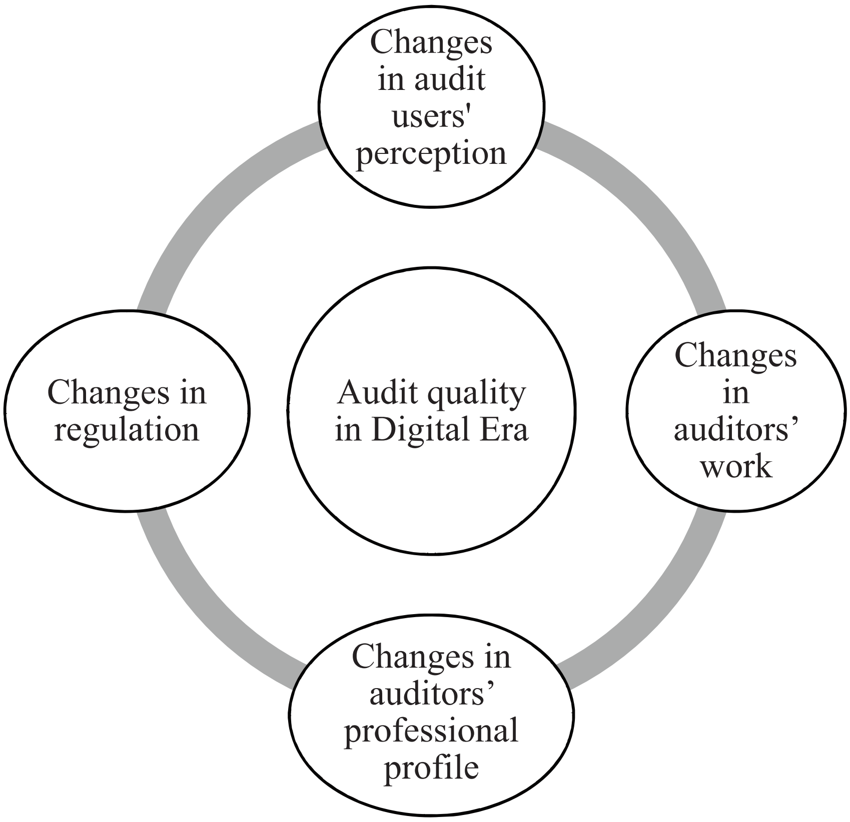

Figure 1. Hypothesis design

Source: The authors' compilation

According to the above literature, there are four hypotheses proposed in this study.

H1: Digital transformation creates changes in audit users' perception that would have a positive relationship with audit quality.

Increasing the use of software in auditing would support automate auditing procedures (Lombardi *et al.*, 2015). Automated auditing procedures are believed to encourage higher audit quality. Even though human auditors still control the process and make decisions, the domination of automated auditing would decrease human mistakes. In the future, more automated auditing procedures will be used than manual ones (Tiberius and Hirth, 2019).

H2: Digital transformation creates changes in regulation that would have a positive relationship with audit quality.

Technological progress is faster than regulation in many cases. If the regulation difference could be defined today, disrupters might find a way to avoid it. A propsed solution is that auditing standards could be established by AI (Tiberius and Hirth, 2019). AI would also identify the proper standards and apply it to the accounting and auditing issues accurately, which would stimulate higher audit quality (Kokina and Davenport, 2017).

H3: Digital transformation creates changes in auditors' work that would have a positive relationship with audit quality.

Automated auditing procedures would save time for auditors. Frey and Osborne (2017) indicate that about 94% of accountants' and auditors' tasks could be automated in the coming time. Therefore, auditors' free time will be used for more sophisticated tasks that are unable to be automated such as making decision or consulting. In addition, with the support of big data, automated auditing procedures could change audit standards by transforming annual audits to continuous audits. The continuous audit is expected to generate more accurate and timely audit reports (Zhang *et al*., 2015).

H4: Digital transformation creates changes in auditors' professional profiles that would have a positive relationship with audit quality.

To catch up with the progress of digital transformation, high IT and data expertise might be required to be qualified as an auditor. Auditors' professional profiles will be fulfilled with higher qualities, especially with technology skills and knowledge. Higher quality auditors are expected to produce higher audit reports. However, with an increasing number of requirements, the audit profession could be less interesting and lead to a decrease in number of potential auditors in the near future (Frey and Osborne, 2017; Appelbaum *et al*., 2017).

4. Results and discussion

There were valid 136 responses from the survey. SPSS software version 20.0 is employed to analyze the data. Data were analyzed with the following steps: description, Cronbach's Alpha, Exploratory Factor Analysis, Pearson correlation analysis, and regression analysis.

4.1 Results

Description

The description of personal information of the respondents is presented in Table 2.

In our sample, 39% of the respondents are male and 61% of them are female. Most of them are below 40 years old and have access to new technology. They are also open to new technology. Most of them are working in the audit field. 44% of the respondents are Big4 auditors. The rest of them are non-Big4 auditors, lecturers, and employees in the other accounting and auditing organizations.

Table 2. Description of personal information

Criteria	Detail	n	%
Gender	Male	53	39
	Female	83	61
Age	Below 30 years old	88	65
	From 31 to 40 years old	29	21
	From 41 to 50 years old	18	13
	From 51 to 60 years old	0	0
	More than 60 years old	1	1
Position	Big4 auditor	60	44
	Non-Big4 auditor	25	18
	Lecturer in accounting and auditing	20	15
	Accounting and auditing association	7	5
	Department of accounting and auditing regulations	2	1
	Others	22	16

Source: The authors' calculation

Cronbach's Alpha

Cronbach's Alpha is developed by Cronbach in 1951, which is used to measure reliability or internal consistency of variables. Theoretically, Cronbach's Alpha results should range from 0 to 1. The general rule of thumb is that a Cronbach's Alpha of 0.6 is acceptable; the value of 0.7 and above is good; the value of 0.8 and above is very good; and the value of 0.9 and above is the best (Taber, 2017). Furthermore, Corrected item - Total correlation should be at least 0.3. In addition, Cronbach's Alpha if item deleted is not higher than Cronbach's Alpha (Nunnally and Bernstein, 1954).

The results show that Cronbach's Alpha of both dependent and independent variables of this study meets the requirements. These results are presented in Table 3.

Table 3. Cronbach's Alpha result

Variables	Cronbach's Alpha	Observed variables	Corrected item - Total correlation	Cronbach's Alpha if item deleted
Audit quality	0.640	AQ1	0.393	0.587
		AQ2	0.449	0.559
		AQ3	0.302	0.627
		AQ4	0.331	0.616
		AQ5	0.494	0.532

Table 3. Cronbach's Alpha result *(continued)*

Variables	Cronbach's Alpha	Observed variables	Corrected item - Total correlation	Cronbach's Alpha if item deleted
Changes in audit user perception	0.646	CU1	0.384	0.612
		CU2	0.473	0.546
		CU3	0.443	0.566
		CU4	0.412	0.588
Changes in regulation	0.664	CR1	0.515	0.536
		CR2	0.519	0.508
		CR3	0.417	0.649
Changes in auditors' work	0.611	CW1	0.368	0.581
		CW2	0.495	0.396
		CW3	0.401	0.540
Changes in auditors' professional profile	0.670	CP1	0.491	0.562
		CP2	0.530	0.512
		CP3	0.427	0.647

Source: The authors' calculation

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis is a classical formal measurement analysis. The appropriateness of data for EFA was measured through KMO (Kaiser, 1974) and Bartlett's Test of Sphericity (Bartlett, 1954). The sampling is sufficient if the KMO value is more than 0.5 (Kaiser, 1974). Meanwhile, Bartlett's Test of Sphericity value at 5% significant level indicates that these data would not lead to an identity matrix. Thus, it is approximately multivariate normal and fair for other analysis (Field, 2000).

Table 4. KMO and Bartlett's test of Sphericity result

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.770
Barlett's Test of Sphericity	Approx. Chi-Square	389.151
	Df	78
	Sig.	0.000

Source: The authors' calculation

According to the results in Table 4, KMO is 0.770, which is greater than 0.5. Bartlett's Test of Sphericity has a value of 0.000, which is less than 5% significant level. Thus, factor analysis is appropriate and the variables are correlated as a whole.

In EFA, the combination between observed variables and latent are known as factor loadings. It is standardized regression weights (Kempf-Leonard, 2005). In theory, there are many thresholds of factor loadings. According to Hair *et al.* (1998), if the factor loading is greater 0.3, the sample size should be at least 350. If the sample size is about 100, it should be selected with the factor loading higher than 0.5. If the sample size is about 50, the factor loading should be greater than 0.75. This study contains 136 observations. As a result, the factor loading should be more than 0.5. The factor loading results are presented in Table 5.

Table 5. Factor loadings result

	Components			
	1	**2**	**3**	**4**
CU1	0.739			
CU2	0.712			
CU3	0.614			
CU4	0.594			
CR1		0.875		
CR2		0.749		
CR3		0.532		
CW1			0.760	
CW2			0.709	
CW3			0.678	
CP1				0.817
CP2				0.749
CP3				0.645

Source: The authors' calculation

Based on the factor loadings results in Table 5, all factor loadings in this study have met the requirements. The regression model includes four independent variables, which are changes in audit user perception (CU), changes in regulation (CR), changes in auditors' work (CW), and changes in auditors' professional profile (CP). The regression model is formed as follows:

$$AQ = \beta_0 + \beta_1 \text{ x } CU + \beta_2 \text{ x } CR + \beta_3 \text{ x } CW + \beta_4 \text{ x } CP + \varepsilon_{it}$$

where AQ represents the dependent variable; CU, CR, CW, CP are independent variables; β_0 is the constant term; $\beta_{1,}$ $\beta_{2,}$ $\beta_{3,}$ β_4 are coefficients; ε_{it} is the error term.

Regression results

Table 6. Model summary

Model	**R**	**R^2**	**Adjusted R^2**	**Std. Error of the estimate**	**Durbin-Watson**
1	0.699[a]	0.489	0.474	0.401	1.830

a. Predictors: (Constant), CP, CW, CU, CR
b. Dependent Variable: AQ

Source: The authors' calculation

In Table 6, R^2 is 0.489. It means that independent variables CP, CW, CU, and CR explain 48.9% of the variance in the dependent variable AQ.

The Durbin-Watson statistic is a test for autocorrelation in regression analysis. The Durbin-Watson statistic always fall between 0 and 4. A value approximate to 2 indicates no autocorrelation. A value toward 0 and 4 indicates positive and negative autocorrelation, respectively. This sample has a Durbin-Watson score of 1.830, which indicates that there is no autocorrelation detected in the sample.

Table 7. ANOVA result

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	20.158	4	5.040	31.375	0.000[b]
	Residual	21.041	131	0.161		
	Total	41.200	135			

a. Dependent Variable: AQ
b. Predictors: (Constant), CP, CW, CU, CR

Source: The authors' calculation

The F-test in ANOVA in Table 7 indicates the appropriateness of the regression model. The significant value of the regression model is 0.000, which is lower than 0.5% significant level. It indicates that the null hypothesis "There is no significant relationship between dependent and independent variables" is rejected. Therefore, a significant relationship between dependent and independent variables would exist so that our model is appropriate, and the result is reliable.

Table 8. Regression result

Model		Unstandardized coefficients		Standardized coefficients	T	Sig.	Collinearity statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.603	0.184		3.270	0.001		
	CU	0.259	0.062	0.301	4.161	0.000	0.743	1.346
	CR	0.210	0.063	0.248	3.318	0.001	0.697	1.436
	CW	0.120	0.059	0.136	2.023	0.045	0.860	1.162
	CP	0.207	0.053	0.273	3.897	0.000	0.792	1.263

a. Dependent Variable: AQ

Source: The authors' calculation

The multi-collinearity test is to determine whether one predictor variable can be predicted based on the others. The multi-collinearity problem is quantified by the Variance Inflation Factor (VIF) in an ordinary least squares regression analysis. If VIF is more than 10, the multi-collinearity is problematic. As the results in Table 8, VIF for all variables included in the models is close to 1, which indicates that there is no multi-collinearity problem in the sample dataset.

The results of regression in Table 8 show that the Sig. t-test of the independent variables CU, CR, CW, CP is less than 5% significant level, which means that all of these independent variables are statistically significant. The regression model turned into:

$$AQ = 0.603 + 0.259 \times CU + 0.210 \times CR + 0.120 \times CW + 0.207 \times CP$$

4.2 Discussion

Firstly, the independent variables have explained 48.9% of the variance in the dependent variable. It means that audit quality is highly affected by changes in audit users' perception, regulation, auditors' work, and auditors' professional profile as the result of digital transformation.

Secondly, all of the independent variables have shown a positive impact on the dependent variables. It indicates that the perception of changes in audit quality due to digital transformation is recognized and people believe that digital transformation changes would affect audit quality positively. The result is similar to the findings of Tiberius and Hirth (2019) and Kokina and Davenport (2017) about changes in audit users' perception and changes in regulation. The results are also similar to Manita *et al.* (2020) about changes in auditors' work and changes in auditors' professional profiles.

Thirdly, the coefficients of these independent variables to the dependent variable is quite similar, which is around 20% except for the variable "changes in auditors' work" with only 12%. It reflects the greater importance of audit users' perception, regulation, and auditors' professional profile, which contribute to higher audit quality. This result stems from the fact that respondents of this study's survey are not only current auditors but also other audit-related people who are not performing auditor's work. Therefore, their answers for "changes in auditors' work" become less significant.

Based on the above findings, some discussions are given. Changes in audit users' perception due to digital transformation would affect audit quality expectation because audit users rely on automated audits and information transparency will influence the auditor's behavior concerning their judgments and decisions. It contributes to the paper of Brown-Liburd *et al.* (2015). Regulation changes will happen in the near future because the audit standards that will be established and chosen to apply by AI would lead to a gap in regulation. The finding is in addition to Tiberius and Hirth (2019), which fail to conclude about the gap in regulation. Changes in auditors' work will occur because the job requires more complex tasks, continuous audits instead of annual audits, and auditors will shift from traditional audit to consulting. It is similar to the conclusions of Zhang *et al.* (2015), and Tiberius and Hirth (2019). Finally, auditors' professional profiles will contain higher requirements, especially technology skills as the result of digital transformation on audit. It complements the study of Manita *et al.* (2020).

5. Conclusion and recommendations

5.1 Conclusion

In conclusion, the study contributes to the literature on the effects of perception of digital transformation on audit quality by analyzing data collected in Vietnam. It demonstrates that changes in audit users' perception, changes in regulation, changes in auditors' work, and changes in auditors' professional profile have a significantly positive relationship with audit quality in the digital era. The results contribute to enrich the literature on audit quality and enhance the required change in an audit by integrating new technology. Recommendations are, thus, highlighted for auditors and audit firms with the issue of digital transformation. The implications on audit practice and the expectation of audit users are also presented.

5.2. Recommendations

Recommendations for auditors

Our research findings reveal that auditing is still considered an attractive job in the future as AI cannot completely replace traditional auditors. However, to maintain the significant role of traditional auditors, auditors are required to improve their knowledge of information technology and data analysis to maintain their positions. Perception of audit users about a digital audit is widespread. However, the role of traditional auditors maintains important. Repetitive audit tasks can be done by AI. Meanwhile, the work of auditors will shift from classic auditing to consulting.

AI and Blockchain will certainly play an increasingly important role in the audit industry by helping auditors to audit all data and provide more accurate audit work. However, the audit uncertainty will not be eliminated. AI and blockchain cannot replace humans because it is a product of human intelligence. Qualified auditors still play an important role in consulting customers in the digital transformation process.

Recommendation for audit firms

Higher technology development has directly affected accounting and auditing. To solve the problems of technology absorption and spillover in the accounting and auditing field, small and medium-sized auditing companies need to speedily research and apply digital transformation to survive in the competition. Audit firms need to develop internally to not be left behind in the 4.0 Industrial Revolution.

Recommendations for policymakers

The study suggests that the government, the Ministry of Finance, the Department of Accounting and Auditing Regulations should develop and issue a framework on accounting and auditing to significantly narrow the gap between accounting - audit standards and actual auditing business practices, which are transformed by digital technology dramatically.

Recommendations for future studies

Future studies are recommended to examine more complex research models using a larger sample size to offer reliable research results on the perception of digital transformation effect on audit quality in Vietnam. Future studies should also considering the different aspects of audit that can be affected by digital transformation.

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