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Factors Influencing Intelligent Auditing and Audit Efficiency Among Accounting Auditors in China

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Abstract

Big data and intelligent audit were new products in the Internet era in recent years. Audit information system based on high-speed data processing emerged, and this was intelligent audit. Big data has been applied to all aspects of life, and intelligent audit based on big data has also developed rapidly in the audit industry. The objectives of this study were to find out the proper index which related to the intelligent audit, to verify the role of mediator and moderator variables between intelligent audit and audit efficiency, to put forward effective recommendations for improving audit efficiency with intelligent audit. Based on a thorough review of the literature, the paper identified two primary variables: intelligent audit and audit efficiency. Through qualitative analysis of depth interview and quantitative analysis of questionnaire survey. The influencing factors of intelligent audit on audit efficiency were divided into audit evidence, data storage, data analysis, system maintenance, enterprise management level and auditor's competence. The results showed that data storage in the intelligent audit had a significant negative impact and data analysis had a significant positive impact on audit efficiency; audit evidence in the intelligent audit had not a significant impact and system maintenance had not a significant impact on audit efficiency, however, enterprise management level played a significant moderating role between system maintenance and audit efficiency, auditor's competence played a moderating role between audit evidence and audit efficiency, thus, the audit efficiency was improved to some extent. The suggestion were improving the quality of auditors, strengthening the organization of audit work and coordinating well with the audited unit.

Key Words: Intelligent audit, Audit efficiency, Big data

Introduction

For more than a century, companies have attempted to increase operating efficiencies and boost income through work automation. More automation and computerization in the manufacturing process have improved worker safety and

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produced better economic outcomes, including faster production, fewer manufacturing failures, and reduced production costs (James R. Bright, 1958). With the improvement of the informatization of human society, the Internet, Internet of Things, intelligent terminals and social networks have become a normal part of social and economic life. In this environment, data is generated anytime and anywhere, and data is growing exponentially. Human society has entered the era of Big Data. Zheng Shiqiao (2021) noted that audit was a kind of governance mechanism created by human beings. It obtains audit evidence from the audit carrier through systematic methods, and forms conclusions on whether a particular event deviates from the established standards. Its core technology is also a kind of information data collection and information data utilization. On the other hand, since internal audit was first created to ensure that the financial statements "present fairly...the financial position of the company" (AICPA, 2014), owners have been shielded from the financial misdeeds of agent managers. However, internal audit has evolved into a broad control function that enacts "stewardship" by supervising processes that establish management actions as prudent, sober, and responsible rather than reckless and dangerous. With big data, audit risk management is more convenient and efficient (Laurel, 2016).

Intelligent audit is an advanced stage of traditional audit and data-based audit. Audit efficiency can be reflected from many aspects of audit business, such as the accuracy of audit results, the rapidity of audit business, the convenience of obtaining audit evidence, and so on. In the context of big data and artificial intelligence, intelligent audit was more and more frequently applied to audit practices in all kinds of companies. However, compared with traditional audit, whether it can better improve audit efficiency and whether there are drawbacks needs further research.
Accord with the requirement of the research, the theory basis of the topic chose risk-oriented audit theory, synergistic effect theory, business process reengineering theory and principal-agent theory. In addition, the paper was completed through experts interview, the design of Likert scale and questionnaire survey data collection, and then through the results of variable measurement, regression analysis of the relationship with SEM among variables, testing relationship between them, and finally verifying the hypothesis.

Research Objectives

The object of study was intelligent audit applied in Chinese enterprises. Research question about the item was that relationship between intelligent audit and audit efficiency was not clear. The study aimed to investigate the various variables and their relationships that contributed to or hindered the efficiency of intelligent auditing practices in China. By examining and understanding these influencing factors, the study aimed to provide insights and recommendations for improving the efficiency of intelligent auditing processes in China. The findings were expected to contribute to the development of more effective strategies and practices in the field of intelligent auditing, ultimately enhancing the overall audit quality and effectiveness.

1. To find out influencing factors of intelligent audit which affect audit efficiency, and verify the role of these factors of intelligent audit to audit efficiency.

2. To put forward effective recommendations to improve audit efficiency with intelligent audit.

Conceptual Framework and Hypotheses

According to the literature, the influence factors of intelligent audit on audit efficiency were divided into audit evidence, data storage, data analysis, system maintenance, enterprise management level and auditor's competence, and the scale was designed for measurement and analysis.

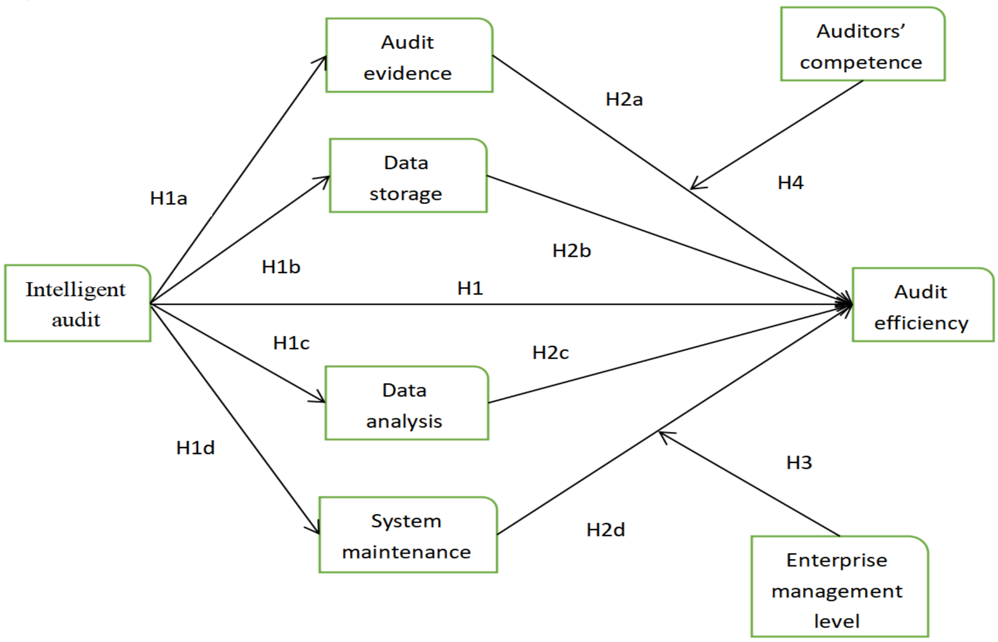

Figure 1: Conceptual framework

Source: Modify from original of research

Eleven hypotheses regarding the relationships between intelligent audit and audit efficiency are as follows:

H1: Intelligent audit has a significant positive impact on the audit efficiency in Chinese enterprises;

H1a: Intelligent audit has a significant positive impact on the audit evidence in

Chinese enterprises;

H1b: Intelligent audit has a significant positive impact on the data storage in Chinese enterprises;

H1c: Intelligent audit has a significant positive impact on the data analysis in Chinese enterprises;

H1d: Intelligent audit has a significant positive impact on the system maintenance in Chinese enterprises;

H2a: Audit evidence in the intelligent audit has a significant positive impact on audit efficiency in Chinese enterprises;

H2b: Data storage in the intelligent audit has a significant negative impact on audit efficiency in Chinese enterprises;

H2c: Data analysis in the intelligent audit has a significant positive impact on audit efficiency in Chinese enterprises;

H2d: System maintenance in the intelligent audit has a significant negative impact on audit efficiency in Chinese enterprises;

H3: Enterprise management level plays a moderating role between system maintenance and audit efficiency in Chinese enterprises;

H4: Auditor's competence plays a moderating role between audit evidence and audit efficiency in Chinese enterprise.

Research Methodology

This paper studied the relationship between intelligent audit and audit efficiency in Chinese companies. This research was designed as mixed method with qualitative and quantitative.

In qualitative research, combined with relevant literature, the interview process to some audit experts was used to enhance the reliability of research, so as to determine appropriate variables. During the depth interview, there was about 30 minutes' one-to-one conversation between researchers and respondents around the topic. The conversation materials were transformed into Word documents, which were subsequently imported into Nvivo software for further analysis. In the analysis process, concept extraction and node creation were performed to identify and categorize the main ideas and concepts present in the documents. Through careful examination and analysis of the documents, key ideas and concepts were identified and marked as free nodes. This categorization allowed for a systematic organization and representation of the data, enabling a deeper understanding of the underlying themes and patterns within the research material (Bazeley, 2019). With the help of interview survey, we explored more influencing factors that affected intelligent audit efficiency, and sorted out the potential relationship between different variables.

In quantitative research, the paper was completed through the design of Likert scale and questionnaire survey data collection. First of all, the questionnaire was designed according to conceptual model referred to relevant literature. Before the formation of the large questionnaire, five auditing experts or scholars were invited to conduct IOC tests is 0.89, and then conducted a small-scale pilot test to provide a reliable basis for the formal questionnaire. At last, the questionnaire was utilized to collect data from auditors and managers in China, who had relevant knowledge on auditing. SEM was mainly used for confirmatory factor analysis, testing the path relationship between variables represented by theoretical assumptions, mediating effects analysis and moderating effects analysis were made by software SPSS and AMOS. Finally, research hypothesis was tested.

Population and Sample size

Population. The target population in this study were accounting auditors who were familiar with audit work in China. According to data released by Chinese National Bureau of Statistics, there were 482,000 people employed in auditing in China by the end of 2022.

Sample. In the research with mixed method, there were two types of samples. First, the interviewee sample was designed in depth interview, the interviewees are 17 experienced auditors who had been working in Chinese listed enterprises for more than ten years. Second, questionnaire sample was designed in quantitative research. The sample size of this study was calculated by Yamane formula with the confidence 95%, and the sample size was more than 400 auditors who were familiar with audit work in China.

Research Results

Qualitative Analysis Results

In this paper, the interview contents were recorded and subsequently transcribed into word documents. These documents were then imported into Nvivo software for analysis. The analysis process followed the principles of Grounded Theory, utilizing Nvivo software to code and analyze the materials, comparing similarities and differences between cases and synthesizing the analysis results.

Table 1: Interview Classification and Coding

First-Level Node	Second-Level Node	Free Node	Reference Number
Intelligent Audit	Audit Evidence	speed of obtaining	14
		comprehensiveness	20
		accuracy	11
		difficulty	8
		reliability	9
	Data Storage	security	19
		cost	6
		convenience	8
	Data Analysis	speed	10
		automation degree	17
		accuracy	7
	System Maintenance	cost	11
		difficulty	8
		time-consuming	5
Audit Efficiency		comprehensive	20
		accuracy	18
		reliability	9
		speedability	24
		security	19
Enterprise Competence	Enterprise Management Level	performance evaluation	6
		governance system	9
		organizational culture	7
	Auditors' Competence	professional knowledge	15
		audit experience	14
		technical level	21

Source: Adapted from Nvivo Software Result according to the author's survey

Table 1 shows that in the process of core coding, after further textual exploration and selective coding, intelligent audit is coded as the first-level, its four secondary nodes are named as audit evidence, data storage, data analysis and system maintenance (code reference point 153). Audit efficiency is divided to free nods directly (code reference point 90). The other two secondary nodes obtained in the previous step, namely enterprise management level and auditors' competence constitute the first-level node of enterprise competence (code reference point 72).

Quantitative Analysis Results

Data from the first part of questionnaire about respondents' demographic profile were analyzed by frequency and percentages through software SPSS, which including gender, age, occupation, and education. The statistical results are shown in Table 2.

Table 2: Descriptive Statistics of Respondents' Demographic Profile

Profile	Category	N	%
Gender	Male	197	47.13
	Female	221	52.87
Age	22~29	160	38.28
	30~49	150	35.89
	50~59	82	19.62
	60 up	26	6.22
Occupation	Auditors or related personnel of listed enterprises	100	23.92
	Auditors or related personnel of small, medium and micro enterprises	84	20.10
	Auditors or related personnel in government or public institutions	56	13.40
	Auditors or related personnel in accounting firms	91	21.77
	Others	87	20.81
Education	Bachelor	224	53.59
	Master or above	110	26.32
	Others	84	20.10

Source: Adapted from SPSS Software Result according to the author's survey

There were 197 males (47.13%) and 221 females (52.87%) in the collected sample. The age of the respondents was mainly between 22~49, which is the main group in the audit job. Respondents' occupation was distributed as follows: 100 auditors or related personnel of listed enterprises (23.92%), 84 auditors or related personnel of small, medium and micro enterprises (20.10%), 56 auditors or related personnel in government or public institutions (13.40%), 91 auditors or related personnel in accounting firms (21.77%) and others (20.81%) which include students who are familiar with audit practice or people who study audit theory.There were 224 respondents with bachelor’s degree (53.59%) and 110 respondents with master’s degree or above (26.32%). Generally speaking, the distribution of the demographic profile of the respondents is diversified strong representativeness.

Confirmatory Factor Analysis

In this paper, structural equation modeling (SEM) and model fitting were performed using AMOS software. Based on SEM, before constructing structural model, 8 measurement models in conceptual framework should be confirmed at first. The author divided them into 2 categories to carry on confirmatory factor analysis (CFA).
Four independent variable (intelligent audit) and mediator variables (audit evidence, data storage, data analysis, system maintenance) were analyzed as one category. Moderator variables (enterprise management level and auditors’ competence) and dependent variable (audit efficiency) were analyzed as the other category.

Table 3: Confirmatory Factor Analysis (CFA) of Independent and Mediator Variables

Variables	Items	Significance Estimation of Parameter				
		Un-std.	S.E.	t-value	P	Std.
Intelligent Audit	IA1	0.87	0.08	10.75	***	0.55
	IA2	1.03	0.08	12.95	***	0.67
	IA3	1.04	0.08	12.61	***	0.68
	IA4	0.96	0.08	12.47	***	0.68
	IA5	1				0.71
Audit Evidence	AE1	0.98	0.08	12.43	***	0.75
	AE2	0.98	0.08	12.42	***	0.77
	AE3	0.88	0.07	11.96	***	0.76
	AE4	0.98	0.08	12.02	***	0.79
	AE5	1				0.82
Data Storage	DS1	1.21	0.09	12.69	***	0.83
	DS2	1.05	0.09	11.84	***	0.75
	DS3	1				0.83

Table 3: Cons.

Variables	Items	Significance Estimation of Parameter				
		Un-std.	S.E.	t-value	P	Std.
Data Analysis	DA1	1.03	0.08	13.51	***	0.76
	DA2	1.03	0.08	13.53	***	0.83
	DA3	1				0.80
System Maintenance	SM1	1.02	.07	14.14	***	0.81
	SM2	1.08	.07	14.68	***	0.93
	SM3	1				0.80

Source: Adapted from Amos Software according to the author's survey. *p<0.1, **p<0.05, ***p<0.01

We can infer the following conclusions from the given data based on the CFA results in Table 3: Intelligent Audit variables: parameters for comprehensiveness of audit process (IA1), accuracy of audit process (IA2), reliability of audit process (IA3), and speedability of audit process (IA4) are estimated at 0.87, 1.03, 1.04, and 0.96, respectively, with highly significant t-values (10.75, 12.95, 12.61, and 12.47, respectively), indicating a significant positive relationship with the Intelligent Audit variable ($p < 0.001$).

Audit Evidence variables: parameters for speedability of obtaining audit evidence (AE1), comprehensiveness of audit evidence (AE2), accuracy of audit evidence (AE3), and convenience of obtaining audit evidence (AE4) are estimated at 0.98, 0.98, 0.88, and 0.98, respectively, with highly significant t-values (12.43, 12.42, 11.96, and 12.02, respectively), indicating a significant positive relationship with the Audit Evidence variable ($p < 0.001$).

Data Storage variables: parameters for security of data storage (DS1) and cost of data storage (DS2) are estimated at 1.21 and 1.05, respectively, with highly significant t-values (12.69 and 11.84, respectively), indicating a significant positive relationship with the Data Storage variable ($p < 0.001$).

Data Analysis variables: parameters for speedability of data analysis (DA1) and automation degree of data analysis (DA2) are estimated at 1.03 and 1.031, respectively, with highly significant t-values (13.51 and 13.53, respectively), indicating a significant positive relationship with the Data Analysis variable ($p < 0.001$).

System Maintenance variables: parameters for cost of system maintenance (SM1) and difficulty of system maintenance (SM2) are estimated at 1.02 and 1.08, respectively, with highly significant t-values (14.14 and 14.68, respectively), indicating a significant positive relationship with the System Maintenance variable ($p < 0.001$).

Table ผิดพลาด! ไม่มีข้อความของสไตล์ที่ระบุในเอกสาร: Confirmatory Factor Analysis (CFA) of Moderator and Dependent Variables

Variables	Items	Significance Estimation of Parameter				
		Un-std.	S.E.	t-value	P	Std.
Enterprise Management Level	EM1	0.93	0.06	16.92	***	0.76
	EM2	0.66	0.05	12.37	***	0.59
	EM3	1				0.84
Auditors' Competence	AC1	0.89	0.06	15.27	***	0.74
	AC2	0.91	0.06	15.05	***	0.73
	AC3	1				0.78
Audit Efficiency	AF1	0.89	0.08	10.78	***	0.62
	AF2	1.03	0.09	11.49	***	0.67
	AF3	1.11	0.09	11.57	***	0.68
	AF4	1.13	0.09	11.26	***	0.66
	AF5	1				0.67

Source: Adapted from Amos Software according to the author's survey. *p<0.1, **p<0.05, ***p<0.01

Based on the provided data, the results of the Confirmatory Factor Analysis (CFA) for the moderator and dependent variables in Table 4 are as follows:

Enterprise Management Level: the parameter estimate of enterprise performance evaluation system (EM1) is 0.93 with a highly significant t-value of 16.92 ($p < 0.001$). The parameter estimate of enterprise organizational culture (EM2) is 0.66 with a highly significant t-value of 12.37 ($p < 0.001$).

Auditors' Competence: the parameter estimate of professional knowledge level (AC1) is 0.89 with a highly significant t-value of 15.27 ($p < 0.001$). The parameter estimate of auditors' competence is audit experience (AC2) is 0.91 with a highly significant t-value of 15.05 ($p < 0.001$).

Audit Efficiency: the parameter estimate of auditing comprehensiveness (AF1) is 0.89 with a highly significant t-value of 10.78 ($p < 0.001$). The parameter estimate of auditing accuracy (AF2) is 1.03 with a highly significant t-value of 11.49 ($p < 0.001$). The parameter estimate of auditing reliability (AF3) is 1.11 with a highly significant t-value of 11.57 ($p < 0.001$). The parameter estimate of auditing speedability (AF4) is 1.13 with a highly significant t-value of 11.26 ($p < 0.001$).

Hypotheses Test

For examining the indirect effects of independent variables on the dependent variable through the mediator variables in the structural model, the researcher employed percentile and bias-corrected bootstrapping with 5,000 bootstrap samples at a 95% confidence interval. Following the guidelines provided by Hayes (2013), the author calculated the lower and upper bounds of the confidence interval to determine the significance of the indirect effects.

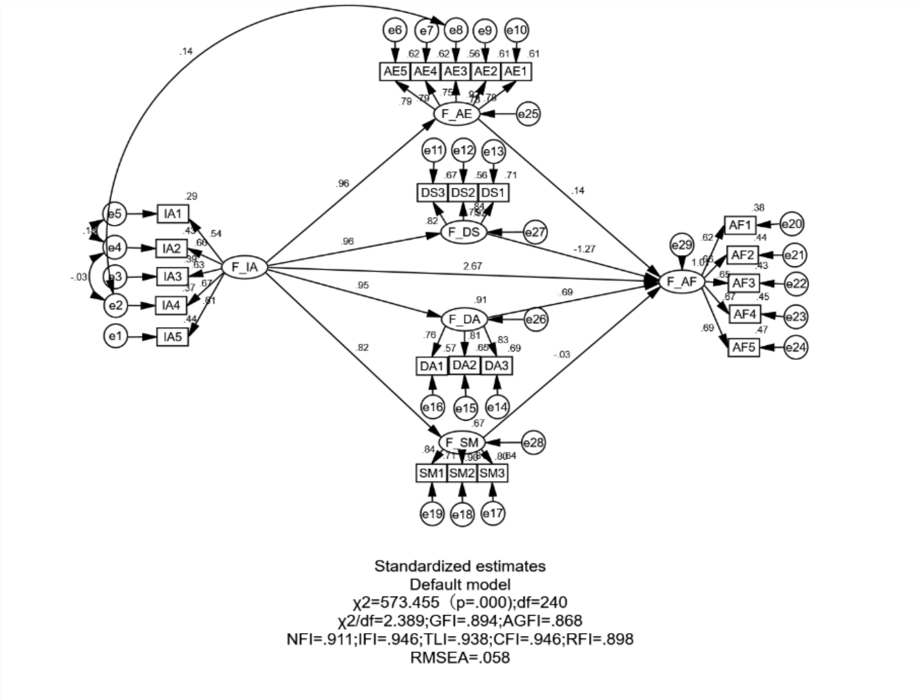

Figure 2 shows the standardized loadings of the measured items for each latent variable and the path coefficient between the latent variables.

Table 5: Results of SEM Regression

			Estimate	S.E.	C.R.	P	Label	Std.Estimate
F_AF	<---	F_IA	2.19	.77	2.87	.004	H1	2.67
F_AE	<---	F_IA	1.01	.07	14.04	***	H1a	.96
F_DS	<---	F_IA	1.04	.07	14.38	***	H1b	.96
F_DA	<---	F_IA	1.05	.07	14.55	***	H1c	.95
F_SM	<---	F_IA	1.03	0.08	12.74	***	H1d	0.82
F_AF	<---	F_AE	0.14	0.27	0.53	0.595	H2a	0.14

Table 5: Cons.

			Estimate	S.E.	C.R.	P	Label	Std.Estimate
F_AF	<---	F_DS	-0.95	0.36	-2.65	0.008	H2b	-1.27
F_AF	<---	F_DA	0.51	0.28	1.84	0.036	H2c	0.69
F_AF	<---	F_SM	-0.02	0.06	-0.31	0.755	H2d	-0.03

Source: Adapted from Amos Software according to the author's survey. *P<0.05, **P<0.01, ***P<0.001

Intelligent audit has significant positive effects on audit evidence, data storage, data analysis and system maintenance, which can be showed by H1a, H1b, H1c and H1d (***) in Table 5. Besides, intelligent audit has significant positive effect on audit efficiency directly (H1: P<0.01). Data storage and data analysis have significant negative effects on audit efficiency, which can be showed by H2b and H2c. However, audit evidence and system maintenance have no significant effects on audit efficiency (H2a and H2d: p>0.05).

Table 6: Bootstrapping Estimation Results

Parameter	Estimate	SE-Bias	Lower	Upper	P
Standardized direct effect	2.51	0.03	0.02	6.74	0.048
(std) F_IA⟶F_AE⟶F_AF	0.17	0.01	-1.64	1.06	0.833
(std) F_IA⟶F_DS⟶F_AF	-1.13	0.01	-4.22	-0.45	0.001
(std) F_IA⟶F_DA⟶F_AF	0.61	0.01	0.10	3.34	0.001
(std) F_IA⟶F_SM⟶F_AF	-0.02	0.00	-0.30	0.19	0.809
Standardized total effect	0.91	0.00	0.83	0.98	0.000

Source: Adapted from Amos Software. 5000 bootstrap samples; *P<0.05*, **P<0.01, ***P<0.001

Bootstrapping estimation results are presented in Table 6. Standardized direct effect is significant at the 0.048 level, Standardized total effect is significant at the 0.000

level. In the indirect effect, data storage (DS) and data ananlysis (DA) have significant impacts on audit efficiency (AF) (both P=0.001), while the effects of audit evidence (AE) and system maintenance (SM) on AF are not significant (P>0.05).

Hayes' (2018) model 16 and the PROCESS Procedure for SPSS Version 3.5 were specifically used in this study, with X as audit efficiency (AE), Y as intelligent audit (IA), M1 as audit evidence (AE), M2 as data storage (DS), M3 as data analysis (DA), M4 as system management (SM), W as enterprise management level (EM) and Z as auditors' competence (AC). In Table 7, for the moderating effects, Int_1 as AE*EM, Int_2 as DS*EM, Int_3 as DA*EM, Int_4 as SM*EM, Int_5 as AE*AC, Int_6 as DS*AC, Int_7 as DA*AC, Int_8 as SM*AC.

Table 7: Moderating effect test Results

	coeff	se	t	p	LLCI	ULCI
constant	1.02	0.11	9.21	0.000	0.81	1.24
Int_1	0.13	0.10	1.29	0.198	-0.07	0.33
Int_2	0.02	0.10	0.20	0.838	-0.18	0.21
Int_3	-0.01	0.08	-0.10	0.921	-0.16	0.14
Int_4	-0.22	0.08	-2.74	0.006	-0.39	-0.06
Int_5	0.19	0.09	2.18	0.030	0.02	0.36
Int_6	0.07	0.10	0.72	0.472	-0.12	0.27
Int_7	0.08	0.08	1.10	0.271	-0.07	0.23
Int_8	0.13	0.07	1.73	0.084	-0.02	0.27

Source: Adapted from PROCESS Procedure for SPSS Version 3.5 (Hayes, 2018) according to the author's survey. *P<0.05*, **P<0.01, ***P<0.001

Result Discussion

The testing results of the research hypotheses were analyzed using bootstrapping estimation and were presented in Table 8. This table provides a summary of the findings related to the hypotheses tested in the study.

Table 8: Results of Hypothesis Test

Hypotheses	Results
H1: Intelligent audit has a significant positive impact on the audit efficiency in Chinese enterprises;	Support
H1a: Intelligent audit has a significant positive impact on the audit evidence in Chinese enterprises;	Support

Table 8: Cons.

Hypotheses	Results
H1b: Intelligent audit has a significant positive impact on the data storage in Chinese enterprises;	Support
H1c: Intelligent audit has a significant positive impact on the data analysis in Chinese enterprises;	Support
H1d: Intelligent audit has a significant positive impact on the system maintenance in Chinese enterprises;	Support
H2a: Audit evidence in the intelligent audit has a significant positive impact on audit efficiency in Chinese enterprises;	Reject
H2b: Data storage in the intelligent audit has a significant negative impact on audit efficiency in Chinese enterprises;	Support
H2c: Data analysis in the intelligent audit has a significant positive impact on audit efficiency in Chinese enterprises;	Support
H2d: System maintenance in the intelligent audit has a significant negative impact on audit efficiency in Chinese enterprises;	Reject
H3: Enterprise management level plays a moderating role between system maintenance and audit efficiency in Chinese enterprises;	Support
H4: Auditor's competence plays a moderating role between audit evidence and audit efficiency in Chinese enterprises.	Support

Source: According to the author's survey

Table 8 showed that among the 11 research hypotheses, all were supported except H2a and H2d.

Conclusion

Summary of depth interview in qualitative method

Q1: How do you think intelligent audit affects the efficiency of auditing compared with traditional audit?

Through data analysis and mining, intelligent auditing can more accurately identify potential risks and issues, enhancing the comprehensiveness and accuracy of audits, further improving auditing efficiency.

Q2: What aspects does intelligent audit improve audit efficiency?

Intelligent audit enhances the audit process through automated data processing, improves risk management, expands the audit scope, and optimizes the use of audit resources. It also promotes the development and application of continuous audit mode, facilitates efficient data audit, and strengthens the credibility of audit opinions. (Yang, 2022)

Q3: What are the obstacles to the development of intelligent audit? (Xu, 2022)

The obstacles to the development of intelligent auditing mainly include: limitations in technological conditions, data security issues and auditors' capabilities and willingness.

Q4: What can be done to reduce the obstacles of the development of intelligent audit? (Xu, 2020)

Improve mechanisms for linking information across departments and industries; Enhance training and education for auditors; Strengthen enterprise management capabilities; Improve technical infrastructure and data security measures.

Q5: What indicators do you think are appropriate to study the relationship between intelligent audit and audit efficiency?

The acquisition of audit evidence; The situation of data storage and system maintenance; The data analysis in the intelligent audit; The capabilities of auditors and the management level of enterprises.

Summary of confirmatory factor analysis

In Table 3 and 4, The observed variables all have high significance in the model, indicating their important impact on explaining their corresponding potential variables. The standard deviation of a statistic's sampling distribution is represented by the standard error (SE) in statistics. SE is less than 0.1, indicating that the error in this model is small. All items for each variable have significant t-values (indicated by "***"), suggesting that they make a meaningful contribution to their respective latent variable.

Overall, the results of the CFA indicated that the items for each variable had significant relationships with their respective latent variable. The standardized parameter coefficients provided insights into the strength of the relationships. These observed variables can effectively reflect their corresponding potential variables.

Summary of hypotheses test

Table 5 showed that intelligent audit had significant positive effects on audit evidence, data storage, data analysis and system maintenance, which can be proved by H1a, H1b, H1c and H1d (***) in the hypothesis of the study. Besides, intelligent audit had significant positive effect on audit efficiency directly ($P<0.01$).

In Table 5, data storage and data analysis had significant negative effects on audit efficiency, which can be proved by H2b and H2c in the hypothesis of the study. However, audit evidence and system maintenance had no significant effects on audit efficiency ($p>0.05$), the hypothesis H2a and H2d were rejected.

According to bootstrapping estimation in Table 6, standardized direct effect was significant at the 0.048 level, Standardized total effect was significant at the 0.000 level. In the indirect effect, data storage (DS) and data ananlysis (DA) had significant impacts on audit efficiency (AF) (both P=0.001), while the effects of audit evidence (AE) and system maintenance (SM) on AF were not significant (P>0.05).

Table 7 showed that enterprise management level played a significant moderating role between system maintenance and audit efficiency in Chinese enterprises (p<0.01). Auditors’ competence played a significant moderating role between audit evidence and audit efficiency in Chinese enterprises (p<0.05). The hypothesis H3 and H4 were supported. According to the research results, although the changes of audit evidence acquisition ability and system maintenance cost under intelligent audit had no significant impact on audit efficiency, high enterprise management level will reduce the cost of system maintenance and thus improve audit efficiency, the stronger the auditors' ability to obtain audit, the higher the audit efficiency.

New knowledge

This research provided new knowledge about intelligent audit and audit efficiency, including blockchain technology and government policy, which are mainly shown in the following figure.

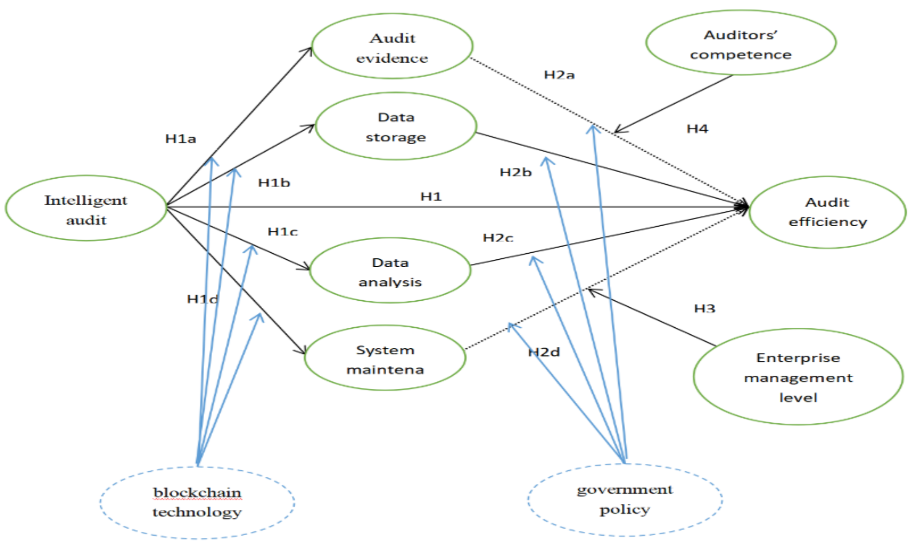

Figure 3: New Knowledge Theoretical Model

Note: Dashed circle indicates the new affecting factors found from research

Showed from the research, blockchain technology plays a significant role in intelligent audit processes. It offers several benefits that enhance the efficiency. Government policy plays a crucial role in enhancing the efficiency of intelligent audit processes. The efficiency of auditing can be improved through the application of blockchain technology and the adjustment of government policies, of course, this also needs further research.

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