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Man & Machine: Artificial Intelligence's Role in Shaping Auditor's Professional Scepticism

Ilyass Chaker
Department of Accounting – Auditing – Control and Finance, IAE Tours Loire Valley – VALLOREM (VAL de LOire REcherche en Management), University of Tours, Tours, France

This study aims to investigate how auditors' reliance on artificial intelligence (AI) impacts their professional scepticism in the French auditing profession. While artificial intelligence offers benefits, like improved audit efficiency, concerns arise regarding its potential to reduce scepticism. Using a multiple regression approach with maximum likelihood estimation, we analyzed 107 responses from external auditors. The findings reveal a significant positive association between AI reliance and professional scepticism, moderated by trait scepticism. The study contributes to the existing literature by shedding light on the complex interplay between technological adoption and individual judgment in auditing. It offers insights into the French context and emphasizes the importance of understanding how AI affects professional scepticism among auditors. Additionally, the findings underscore the crucial role of individual auditor traits, such as scepticism levels, in shaping their responses to technological advancements in auditing practices.

Keywords: artificial intelligence, automated tools, scepticism, due professional care

Introduction

Artificial intelligence (AI) is a field within computer science and engineering which focuses on creating intelligent machines capable of autonomous reasoning, learning, and action. Artificial intelligence is a mechanized simulation system designed to collect and process knowledge and information, while also harnessing the intelligence present in the universe (Grewal, 2014). This entails gathering, analysing, and distributing knowledge, information, and intelligence in a way that enables actionable insights for relevant parties. This refers to the capacity of a system to precisely comprehend massive data, assimilate knowledge from it, and then utilize that knowledge to achieve predetermined objectives and tasks, including forecasting the future and performing duties akin to those undertaken by humans.

There is a noticeable surge in using AI in auditing, primarily driven by the automation of tasks traditionally performed by humans, such as data entry and analysis (Meuldijk, 2017; Raphael, 2017). This automation enhances audit efficiency, reduces costs, and gives audit teams deeper insights into the businesses they examine (Hasan, 2021). Another advantage of adopting AI in auditing lies in its potential to mitigate the risk of human error. Through the automation of specific tasks, not only can audit teams promptly identify any irregularities (Omoteso, 2012) but can also predict them through intelligent audits (Moffitt, Rozario, & Vasarhelyi, 2018). The

Ilyass Chaker, Ph.D. Student, Temporary Teaching and Research Assistant, University of Tours, Tours, France.

applications of AI in auditing encompass data analysis, document review, decision-making support, and the generation of customized reports tailored to an organization's specific needs (Chowdhury, 2021). Sun (2019) suggested a paradigm that envisions the incorporation of AI throughout all phases of auditing from planning to reporting. This framework outlines how the specialized capabilities of AI in structured data interact within the context of auditing. AI has the potential to automate diverse audit procedures, including substantive testing and internal control tests (Cho, Vasarhelyi, Sun, & Zhang, 2020). Implementing machine learning could impact audit procedures across all stages, starting from data preparation and extending through the decision-making process.

Many studies in auditing highlight auditors' tendencies to potentially underutilise automation, indicating a reluctance to embrace artificial intelligence (Christ, Emett, Summers, & Wood, 2021; Cao, Duh, Tan, & Xu, 2022; Commerford, Dennis, Joe, & Ulla, 2022). However, both scholars and policymakers express concerns regarding the inverse situation of excessive dependence on automation (Harris, 2017; IAASB, 2021; PCAOB, 2022). They advocate that excessive dependence on automation may lead to a decline in professional scepticism. Despite this, there remains a dearth of understanding regarding the potential ramifications of auditors' over-reliance on automation, particularly concerning professional scepticism.

The objective of this study is to address this gap by investigating the impact of auditors' use of AI on their professional scepticism. Professional scepticism is a fundamental concept in auditing, characterized by a mindset of inquiry and critical evaluation of audit evidence. It entails auditors applying their expertise (knowledge, skills, and abilities required by the profession) to diligently gather, in good faith and with integrity, besides impartially assessing evidence (IIA, 2024; PCAOB, 2024). Scepticism involves consistently questioning or doubting the accuracy and reliability of assertions, statements, and data, and actively seeking evidence to substantiate claims made by management, rather than unquestioningly accepting information at face value.

Professional scepticism can be comprehended as the auditor's capacity to apply professional judgment, which is intrinsically linked to the concept of audit quality (Hurtt, Brown-Liburd, Earley, & Krishnamoorthy, 2013). We hypothesize that auditors exhibit reduced levels of professional scepticism when relying on work performed by artificial intelligence. To investigate this, we analyze a sample of 107 responses from external auditors to evaluate the impact of reliance on artificial intelligence on their professional scepticism.

Our findings offer nuanced insights into the relationship between auditor's reliance on artificial intelligence and their professional scepticism. A significant and positive association is found between reliance on artificial intelligence and professional scepticism, indicating that as auditors increasingly depend on these tools, their scepticism in the audit process also grows. However, trait scepticism acts as a significant moderator. Auditors with higher levels of inherent scepticism exhibit a stronger relationship between reliance on artificial intelligence and professional scepticism, emphasizing the role of individual traits in shaping auditors' responses to technology in auditing practices.

This study sheds new light on the complex relationship between structure and individual judgment in auditing. By exploring the link between artificial intelligence and professional scepticism, we contribute to existing literature by offering fresh insights previously unexplored in the French context. Moreover, our findings provide valuable insights for auditors to gain a deeper understanding of how artificial intelligence affects professional scepticism, highlighting the importance of individual auditor traits in shaping scepticism levels.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature and develops our hypothesis. Section 3 outlines our research design. Section 4 reports descriptive statistics, correlations, and the main results of our multivariate analysis. The final section concludes this study by summarizing findings, discussing the implications of our results, identifying limitations, and making suggestions for future research.

Background Literature and Hypothesis Development

Audit firms increasingly exploit artificial intelligence and techniques to enhance both the effectiveness and efficiency of audits (Cooper, Holderness Jr, Sorensen, & Wood, 2019; Huang & Vasarhelyi, 2019; Vitali & Giuliani, 2024). Automation in auditing offers several advantages, including the ability to analyse the entire transaction population rather than samples (Huang, No, Vasarhelyi, & Yan, 2022), extract insights from a large amount of structured and unstructured data (Brown-Liburd, Issa, & Lombardi, 2015), and share valuable insights with clients (Austin, Carpenter, Christ, & Nielson, 2021; Vitali & Giuliani, 2024). Research indicates that automation improves performance in specific audit areas (e.g. Krieger, Drews, & Velte, 2021). For example, Christ et al. (2021) demonstrate that drones and automated counting software enhance efficiency, effectiveness, and documentation quality in inventory counts.

Automating tasks enables, using AI, auditors to dedicate additional resources to judgment-driven activities and irregularities detection, thus bolstering the quality of audits (Moffitt et al., 2018) by means on focusing on crucial and intricate tasks (Zemánková, 2019; Kend & Nguyen, 2020; Manita, Elommal, Baudier, & Hikkerova, 2020; A. Fedyk, Hodson, Khimich, & T. Fedyk, 2022).

Adopting artificial intelligence and robotics in auditing can access unbiased and more accurate information. Furthermore, machine learning machine learning facilitates the interpretation of visual and natural language data, amalgamating insights from diverse Big Data repositories (Dong & Rekatsinas, 2018). Alongside comparing actual data with predictive data outputs, auditors can harness machine learning-derived pattern recognition to detect outliers and abnormalities. Artificial intelligence, through the analysis of auditing methodologies, can enrich audit capabilities and overall quality (Boillet, 2018) by employing practical, efficient, accurate, and comprehensive methods to furnish reliable audit evidence and support the decision-making process.

Artificial intelligence and robotics reduce manual workload, allowing auditors to spend more time on tasks requiring critical thinking and evaluation. Consequently, these technologies enable auditors to engage in judgment-based activities swiftly, adding greater value to the audit process.

Despite the automation of tasks, auditors’ judgment remains indispensable (Tiberius & Hirth, 2019; Zhang, Thomas, & Vasarhelyi, 2022). Automation does not seek to replace auditors but aims to augment their efficiency and effectiveness. Ultimately, auditors retain responsibility for critical decisions and provide essential analysis and insights.

With the integration of automation, auditors are increasingly tasked with applying professional scepticism to information generated by automated systems (Appelbaum, Kogan, & Vasarhelyi, 2017). Policymakers, researchers, and audit standards underline the crucial role of maintaining an adequate level of professional scepticism (e.g. Abernathy, Barnes, & Stefaniak, 2013; Rainsbury, 2019; Aksoy & Bicer, 2021). Regulators identify a deficiency in professional scepticism as a fundamental cause of audit failures (e.g. PCAOB, 2010; IFIAR, 2018). Professional scepticism is a requirement of due professional care, necessitating auditors to maintain an inquisitive mindset and critically evaluate audit evidence throughout the audit process (IIA, 2024; PCAOB, 2024).

The appropriate exercise of professional scepticism is important for detecting and addressing indications of material misstatements, thereby reducing the risks of overlooking unusual circumstances, drawing overgeneralized conclusions from audit findings, and employing incorrect assumptions in audit procedures and result evaluation (IAASB, 2021).

Following Nolder and Kadous (2018), professional scepticism encompasses both a sceptical attitude, typically regarded as an inherent individual trait (Cohen, Dalton, & Harp, 2017), and a sceptical mindset, which can be influenced by situational factors (Hurtt et al., 2013; Robinson, Curtis, & Robertson, 2018). One significant situational factor is whether the task is performed by humans or automated systems (Olsen & Gold, 2018).

Following the tenets of automation bias and behavioural mindset theory, over-reliance on imperfect automated tools and techniques can lead auditors to prematurely commit to cognitive decisions, resulting in a bias towards reduced cognitive processing. Cognitive processing plays a crucial role in an auditor's ability to exercise appropriate sceptical judgment, especially in tasks requiring deeper analysis (Nolder & Kadous, 2018).

Scepticism involves conscious and effortful processing (Grenier, 2017). Given that manual processes are more deliberate, conscious, and effort-intensive compared to automatic processes, auditors have a deeper self-awareness when engaging in manual processing (Peytcheva, 2013). If an auditor's sceptical judgment is hindered by automation usage, it is likely to lead to a decline in their intentions and actions aligned with scepticism (Nelson, 2009). These observations lead to the following hypothesis:

Hypothesis: Auditors demonstrate less professional scepticism when they depend on work performed by artificial intelligence

Research Methodology Empirical Findings

Methodology

This paper explores whether auditors' professional scepticism is influenced by their dependence on artificial intelligence. We rely on data collected through an electronic survey distributed to 633 external auditors, resulting in 107 responses (see Appendix B).

The Cronbach's alpha, which measures the internal consistency of the measurement scale, is highly satisfactory. Furthermore, the KMO and the significance of the Bartlett tests indicate that the data are factorizable. The commonalities are all greater than 0.5, demonstrating a strong correlation between the items with the factors (see Appendix A). Thus, we can conclude that our measurement scales are reliable and valid.

Results

Descriptive statistics. Appendix C presents the characteristics of our sample. 45% of the respondents were female, with an average age of 34 years. In our sample, auditors' average reliance on artificial intelligence stands at 5.47 on a 10-point Likert scale, indicating that respondents generally fall midway between completely disagreeing and completely agreeing to rely on artificial intelligence for tasks. The standard deviation is significant, indicating considerable variation in the extent to which French auditors depend on artificial intelligence.

Regarding scepticism, our respondents displayed relatively high levels of both trait scepticism (mean = 8.61) and professional scepticism (mean = 8.59).

Correlation matrix. Appendix D reveals several pairwise correlations. Women perceive themselves as having a higher level of professional scepticism. Additionally, age shows a positive and significant correlation with both their trait (r = 0.122*) and professional (r = 0.134*) scepticism. Moreover, holding a partner position is also positively and significantly correlated with professional scepticism (r = 0.087*), indicating that partners perceive themselves as exercising more professional scepticism. Reliance on artificial intelligence is negatively correlated with affiliation with a Big 4 firm ($r = -0.345^{**}$) and positively associated with trait scepticism ($r = 0.188^{**}$).

Moreover, none of the correlations exceeds the critical threshold of 0.70 which would raise multi-collinearity concerns.

Regression analysis. Appendix E presents the results of the maximum likelihood estimation regression analysis for the Models (1) and (2). In Model (1), we examine the impact of reliance on artificial intelligence on professional scepticism, while in Model (2), we investigate whether the relationship between reliance on artificial intelligence and professional scepticism is moderated by auditor’s trait scepticism (Reliance on artificial intelligence × Trait scepticism):

The results from the Model (1) indicate a significant and positive association between reliance on artificial intelligence and professional scepticism. These findings suggest that as auditors increasingly depend on artificial intelligence, their exercise of professional scepticism also increases. Model (1) further suggests that gender has a positive and significant influence on professional scepticism, indicating that female auditors tend to demonstrate higher levels of professional scepticism.

In contrast, the results from the Model (2) reveal some variations. While the overall effect of reliance on artificial intelligence on professional scepticism diminishes, trait scepticism demonstrates a positive moderating effect on this relationship. Specifically, the impact of reliance on artificial intelligence and professional scepticism is more pronounced for auditors with high trait scepticism but less pronounced for those with low trait scepticism. This suggests that artificial intelligence can positively and significantly influence professional scepticism, but only when the auditor’s inherent scepticism is high. If the auditor possesses lower levels of scepticism, reliance on AI will have minimal effect on professional scepticism. Consequently, our hypothesis is not supported.

Model (2) also reveals that trait scepticism positively influences professional scepticism. Auditors who possess a higher innate level of scepticism tend to conduct audits characterized by greater professional scepticism.

Conclusion

Professional scepticism refers to the auditor’s ability to exercise professional judgment, a fundamental aspect closely tied to the concept of audit quality (Hurtt et al., 2013). In this study, we propose that auditors demonstrate diminished levels of professional scepticism when they depend on work executed by automated tools, such as Artificial Intelligence. To test this hypothesis, we examine a dataset comprising 107 responses from external auditors, aiming to assess how reliance on artificial intelligence influences their professional scepticism.

Our findings highlight a positive effect of artificial intelligence on professional scepticism, with this effect being moderated by the auditor’s level of trait scepticism. These results contribute to ongoing discussions about the impact of digitalization on auditing and align with previous studies by Al-Hiyari, Al Said, and Hattab (2019) and Pedrosa, Costa, and Aparicio (2020), indicating that artificial intelligence enhances audit efficiency and allows auditors to allocate more time to non-routine and advanced tasks requiring professional scepticism. We observe that the positive effect of artificial intelligence on professional scepticism is particularly evident among auditors with high trait scepticism, suggesting that individual differences in auditor personality play a crucial role in shaping the relationship between reliance on artificial intelligence and professional scepticism. Artificial intelligence can catalyse enhanced professional scepticism among auditors. Thus, we conclude that the impact of artificial intelligence on professional scepticism hinges on the auditor's inherent level of scepticism.

This study significantly contributes to the literature by shedding light on the intricate interplay between structure and individual judgment. By investigating the relationship between the use of artificial intelligence and professional scepticism, we offer valuable insights that have not previously been explored in the French context. Furthermore, our findings provide evidence of a positive and significant relationship between artificial intelligence and professional judgment within the audit profession in France. We also uncover evidence that trait scepticism acts as a moderator, strengthening the relationship between artificial intelligence and professional scepticism. To our knowledge, this investigation represents an original perspective on this relationship. While previous studies (e.g. Robinson et al. (2018)) have examined trait scepticism to measure professional scepticism and explain individual behaviour, our study employs it as a moderating variable affecting professional scepticism. Additionally, we find that higher levels of trait scepticism amplify the positive relationship between reliance on artificial intelligence and professional scepticism, highlighting the pivotal role of individual characteristics in shaping auditors' responses to technological advancements.

Audit standards mandate auditors to exercise professional scepticism throughout the audit process. This underscores the importance of understanding and applying professional scepticism in auditing, particularly in detecting material misstatements in financial statements (IAASB, 2021). The findings of this study provide valuable insights into how auditors' professional scepticism is influenced by the use of artificial intelligence, thereby aiding them in better comprehending this relationship. Moreover, our results highlight the significant moderating effect of trait scepticism on the association between artificial intelligence and professional scepticism, emphasizing the role of individual auditor characteristics in shaping their scepticism levels.

However, it's important to acknowledge two key limitations in our study. Firstly, we examine professional scepticism as an outcome of reliance on artificial intelligence, rather than examining the factors that enhance it. Secondly, we rely on self-reported perceptions of professional and trait scepticism, which may introduce biases such as prestige bias or limited self-awareness among respondents. Future research could explore alternative measures to capture the degree of scepticism and address these limitations.

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Appendix A: Measures Adapted From Robinson et al. (2018)

Dependent variable						
Professional scepticism	Questioning mind (QM)	QM1	While auditing, I tend to question the statements that I receive from the company.	Scale: 1 = Strongly disagree 10 = Strongly agree	KMO = 0.912 Cronbach's Alpha = 0.906 Barlett = 310.456 Ddl = 66 p = 0.000	KMO = 0.905 Cronbach's Alpha = 0.903 Bartlett = 300.123 Ddl = 66 p = 0.000
		QM2	While auditing, I frequently question the things that I see or read.			
		QM3	While auditing, I tend to reject statements unless I have proof that they are true.			
	Suspension of judgment (SJ)	SJ1	While auditing, I do not like to make decisions until I have a chance to look at all the available information.		KMO = 0.869 Cronbach's Alpha = 0.852 Barlett = 410.235 Ddl = 28 p = 0.000	
		SJ2	While auditing, I wouldn't say I like having to make decisions quickly.			
		SJ3	While auditing, I like to ensure that I consider the most available information.			
		SJ4	While auditing, I do not form an opinion until I get more information.			
	Search for knowledge (SK)	SK1	While auditing, I actively seek out all the information that I can gather.		KMO = 0.961 Cronbach's Alpha = 0.879 Barlett = 1,850.123 Ddl = 10 p < 0.001	
		SK2	While auditing, I search for more evidence to improve my chances of getting the correct answers for key audit matters.			
		SK3	While auditing, I use all resources available to get all the information that I can.			
Independent variable						
Reliance on artificial intelligence (RAI)		RAI1	While auditing, how much did you rely on artificial intelligence when testing samples?	Scale: 1 = Not at all 10 = Very much	KMO = 0.853 Cronbach's Alpha = 0.848 Bartlett = 400.568 Ddl = 28 p = 0.000	KMO = 0.853 Cronbach's Alpha = 0.848 Bartlett = 400.568 Ddl = 28 p = 0.000
		RAI2	While auditing, how much did you rely on artificial intelligence in the evaluation of inventory existence and completeness?			
		RAI3	While auditing, how much did you rely on artificial intelligence when identifying journal entries and other adjustments to be tested?			
		RAI4	While auditing, how much did you rely on artificial intelligence in the aspect of internal controls?			
		RAI5	While auditing, how much did you rely on artificial intelligence when evaluating fraud risk?			

Moderating variable						
Trait scepticism	Interpersonal understand (IU)	IU1	I like to understand the reason for the auditee's behaviour.	Scale: 1 = Strongly disagree 10 = Strongly agree	KMO = 0.861 Cronbach's Alpha = 0.913 Barlett = 420,678 Ddl = 28 p = 0.000	KMO = 0.928 Cronbach's Alpha = 0.872 Bartlett = 18,000.457 Ddl = 10 p < 0.001
		IU2	The actions people take and the reasons for those actions are fascinating.			
		IU3	I seldom consider why people behave in a certain way.			
	Self-determining (SD)	SD1	I usually question things I see, read or hear at face value.		KMO = 0.958 Cronbach's Alpha = 0.874 Barlett = 1,900.567 Ddl = 10 p < 0.001	
		SD2	It is not easy for other people to convince me.			
		SD3	I usually notice inconsistencies in explanations.			
	Self-confidence (SC)	SC1	I have confidence in myself.		KMO = 0.963 Cronbach's Alpha = 0.851 Barlett = 1,820.456 Ddl = 10 p < 0.001	
		SC2	I am self-assured.			
		SC3	I am confident in my abilities.			

Appendix B: Respondents' Response Rate

Number of electronic surveys distributed	633
Number of completed questionnaires	107
Response rate	16.90%

Appendix C: Descriptive Statistics

	Variables	N	Min	Max	Mean	SD
1	Gender	107	0	1	0.45	0.59
2	Age	107	23	64	34.56	11.76
3	Partner	107	0	1	0.39	0.29
4	Big 4	107	0	1	0.58	0.37
5	Reliance on artificial intelligence	107	1	10	5.47	3.32
6	Trait scepticism	107	5.43	10	8.61	1.23
7	Professional scepticism	107	5.21	10	8.59	1.45

Appendix D: Correlation Matrix

	Variables	1	2	3	4	5	6	7
1	Gender							
2	Age	-0.337**						
3	Partner	-0.271**	0.473**					
4	Big 4	-0.090	0.249**	0.481**				
5	Reliance on artificial intelligence	0.030	-0.023	-0.193**	-0.345**			
6	Trait scepticism	0.014	0.122*	0.076	-0.026	0.188**		
7	Professional scepticism	0.123**	0.134*	0.087*	0.090	0.086	0.486**	

Notes. * $p < 0.05$, ** $p < 0.01$.

Appendix E: Regression Results

Variables	Model (1)	Model (2)
(Intercept)	0.00018** (8.693)	0.00014** (4.734)
Gender	0.00002** (0.290)	0.6016 (0.122)
Age	0.32352 (0.087)	0.72227 (0.075)
Partner	0.79592 (0.089)	0.4506 (0.067)
Big 4	0.38189 (0.056)	0.8952 (0.034)
Reliance on artificial intelligence	0.0357* (0.189)	0.765 (0.054)
Trait scepticism		0.0029** (0.694)
Reliance on artificial intelligence × Trait scepticism		0.043* (0.94)
N	107	107
F-statistics	5.849	13.223
Adj. R squared	.056	0.237
VIF	1.864	1.873

Notes. ** Significance at the 1% level (two-tailed t-tests), * Significance at the 5% level (two-tailed t-tests).