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THE INFLUENCE OF PSYCHOLOGY, PROFESSIONAL SCEPTICISM, AND AI ON AUDITOR PERFORMANCE WITH CONTINUOUS LEARNING MODERATION

PENGARUH PSIKOLOGI, SKEPTISISME PROFESIONAL, DAN AI TERHADAP KINERJA AUDITOR DENGAN MODERASI PEMBELAJARAN BERKELANJUTAN

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ABSTRACT
Purpose:This study looks at how different psychological factors, professional scepticism, and the use of artificial intelligence (AI) affect how well auditors perform.It also considers how continuous learning plays a role in influencing these effects. Method:We collected data through a survey from auditors working in Public Accounting Firms (KAP) and the Audit Board of Indonesia (BPK).We used a statistical method called Partial Least Squares–Structural Equation Modeling (PLS-SEM) with the software SmartPLS 4 to analyze the data. Findings:Psychological traits like confidence and emotional stability strongly help improve auditor performance.Professional scepticism also has a positive effect on audit results. However, using AI has a negative impact, which might be because auditors are relying too much on it or not ready for the technology. Continuous learning helps make the positive effects of psychology and scepticism stronger and weakens the negative effect of AI use. Implications: Based on the Theory of Planned Behaviour (TPB), the study suggests that audit organizations should include training on psychological readiness, scepticism, and technology skills in their ongoing learning programs. Novelty: This study brings together human, professional, and technological aspects into one model with continuous learning as a key factor.It offers a more complete view of how auditors perform in an environment that is increasingly using technology.
***Keywords**: Psychology; Professional Scepticism; Artificial Intelligence; Continuous Learning; Auditor Performance*

ABSTRAK
Tujuan: Studi ini meneliti bagaimana berbagai faktor psikologis, skeptisisme profesional, dan penggunaan kecerdasan buatan (AI) memengaruhi kinerja auditor. Studi ini juga mempertimbangkan bagaimana pembelajaran berkelanjutan berperan dalam memengaruhi efek tersebut. Metode: Kami mengumpulkan data melalui survei dari auditor yang bekerja di Kantor Akuntan Publik (KAP) dan Badan Pemeriksa Keuangan Indonesia (BPK). Kami menggunakan metode statistik yang disebut Partial Least Squares–Structural Equation Modeling (PLS-SEM) dengan perangkat lunak SmartPLS 4 untuk menganalisis data. Hasil: Sifat psikologis seperti kepercayaan diri dan stabilitas emosional sangat membantu meningkatkan kinerja auditor. Skeptisisme profesional juga memiliki pengaruh positif terhadap hasil audit. Namun, penggunaan AI memiliki dampak negatif, yang mungkin disebabkan karena auditor terlalu bergantung padanya atau belum siap untuk teknologi tersebut. Pembelajaran berkelanjutan membantu memperkuat efek positif psikologi dan skeptisisme serta melemahkan efek negatif penggunaan AI. Implikasi: Berdasarkan Teori Perilaku Terencana (TPB), studi ini menyarankan agar organisasi audit memasukkan pelatihan tentang kesiapan psikologis, skeptisisme, dan keterampilan teknologi dalam program pembelajaran berkelanjutan mereka. Kebaruan: Studi ini menggabungkan aspek manusia, profesional, dan teknologi ke dalam satu model dengan pembelajaran berkelanjutan sebagai faktor kunci. Studi ini menawarkan pandangan yang lebih lengkap tentang bagaimana auditor berkinerja dalam lingkungan yang semakin banyak menggunakan teknologi.
Kata Kunci: Psikologi; Skeptisisme Profesional; Kecerdasan Buatan; Pembelajaran Berkelanjutan; Kinerja Auditor

INTRODUCTION

Auditing has changed a lot in recent years because of more rules, people paying closer attention, and better technology. These changes have put more pressure on auditors to make good decisions and give accurate results, even when there's a lot going on, things are complicated, and expectations keep changing. In this situation, things like how people feel inside have become very important, but they aren't studied much. Research shows that how people feel, how strong they are emotionally, and how well they think all affect how well they can make decisions and handle tough tasks (Bakker & Demerouti, 2007; Sonnentag, 2003).Even though these feelings are important, things like worry, confidence, and belief in oneself are not studied enough in the field of auditing, especially when looking at how well auditors do their jobs, which depends on being accurate, careful, and able to think critically.

Studies in psychology suggest that people who have more positive emotions and confidence do better when facing work challenges because they are more hopeful, believe in their skills, and don't give up easily under pressure (Anthonius et al., 2025).In auditing, these traits are really important because auditors often deal with unclear information and big decisions. If someone is anxious, doesn't believe in themselves, or is mentally tired, it can make it harder to stay focused, can make them more likely to make mistakes in thinking, and can stop them from finding problems. But there isn't much research that directly links these feelings to how well auditors perform, instead of just looking at how they feel about their job, how stressed they are, or if they're burned out. This gap in knowledge is a big problem because the quality of audit decisions isn't just about skills—it also depends on how people feel. As the profession grows and changes, it's more important than ever to understand how people's mental states affect how they act and what they produce.Along with looking at mental states, the field of auditing has always placed a strong focus on being sceptical.Being sceptical means being ready to question things and carefully check evidence. This is important because it helps keep audits fair and reliable. Studies have shown that auditors who are more sceptical are better at finding errors and fraud and are less likely to give in to pressure from management (Rashid et al., 2020; Sari & Harto, 2020). Although many studies say that being sceptical is important for good audit quality, not many look into how scepticism works with a person's mental state. An auditor's ability to stay sceptical might depend not just on their knowledge and experience, but also on how strong they are mentally, how well they manage their emotions, and how ready they are to think critically. For example, auditors who are stressed or don't believe in themselves much may not check evidence as carefully or may depend too much on quick rules of thumb. This connection between being sceptical and mental factors is another big gap in the research.Another big change in the audit world is using artificial intelligence (AI) in the audit process.

Tools like machine learning, robotic process automation, and natural language processing have made it easier for auditors to look at large amounts of data, spot unusual patterns, and keep a constant watch (Appelbaum et al., 2020; Noordin et al., 2022). These tools offer better efficiency and more reliable information. However, using AI also brings up mental and behavior-related challenges. Auditors who aren't familiar with AI might feel anxious or not want to use it, while others could become too reliant on AI results, which might make them less careful about checking what the AI says (Imane, 2025; Yoon et al., 2021).Even though AI is becoming more common, the research mostly focuses on the technical benefits or why people adopt AI, not the possible negative effects on how auditors work.Also, there's not much research that connects AI use with psychological factors and scepticism in one study.

In the changing work environment, continuous learning plays an important role.Earlier studies say that learning regularly helps auditors get better at their job, makes them more sceptical, and improves their ability to find fraud (Bierstaker et al., 2020). Continuous learning also helps them feel more confident about using new technologies, including AI (Issa & Sun, 2020). However, how learning affects the relationship between mental health, scepticism, AI use, and audit performance hasn't been studied much. Especially, how learning can help reduce mental stress, improve thinking skills, or make AI use better is still not well understood. As auditors deal with environments that need both tech skills and mental strength, understanding the role of continuous learning is more important than ever.Taken together, these areas of research show that there are some important things that are still missing.First, the studies about auditing don’t have a single model that looks at all the factors that affect an auditor’s work.

These include things like how people think, their professional doubt, and their use of AI. Right now, most studies look at each of these separately, but they don’t consider how they all work together in real situations. This makes it hard to understand how all these factors influence an auditor’s decisions in the real world.Second, there is not enough research on how the mental state of an auditor affects their work.Even though there is a lot of evidence from psychology showing that mental states greatly affect the quality of decisions, this area is not well developed in auditing. This means we don’t know much about the basics of how auditors behave, especially when it comes to their thinking processes.Third, even though ongoing learning is seen as important, there hasn’t been enough research on how it affects things in a fast-paced, tech-driven audit setting.We need to understand whether ongoing learning helps or hinders the impact of psychological, professional, and technological factors. This would be a big step forward in theory.This study tries to fix these issues by creating and testing a model that includes psychological factors, professional doubt, and AI use as things that predict how well an auditor performs.It also looks at how ongoing learning might affect these factors. The model is based on the Theory of Planned Behaviour, which helps explain how people make decisions. In this model, psychological factors influence how auditors feel about their job, professional doubt shows up as social pressures, and the use of AI is part of what they believe they can control. Ongoing learning is seen as a tool that helps people adapt to complex situations.

The study makes three important contributions.Theoretically, it adds to the understanding of how psychological factors affect auditing outcomes. It also expands on research about professional doubt by looking at how mental states affect professional judgment. Methodologically, it introduces a model that includes AI, which is an important and growing factor in the field. Practically, the findings can help audit firms and regulators improve audit quality by creating better support systems, training programs, and ways to encourage ongoing learning. As auditing becomes more of a mix of human and AI work, understanding these factors is key to maintaining good audit quality.

LITERATURE REVIEW

The central theory of this research is the Theory of Planned Behaviour (TPB), developed by Icek Ajzen in 1985 as an advancement of the Theory of Reasoned Action (TRA), which he initially created with Martin Fishbein. TPB aims to explain how human behaviour is shaped through rational and planned thought processes. According to this theory, individual behaviour is influenced by the intention to perform an action, which is affected by three primary factors: attitude towards the behaviour, subjective norms, and perceived behavioural control. Attitude towards behaviour reflects an individual's evaluation of an action, whether positive or negative. This evaluation is typically based on an individual's beliefs about the consequences of the action and an assessment of the expected outcomes. Subjective norms refer to an individual's perception of social pressures from their surrounding environment, such as co-workers, superiors, or professional standards, which can influence whether they feel compelled to take action. Perceived behavioural control describes the extent to which individuals feel they can control their actions, considering their abilities, resources, and obstacles. These three factors collectively shape a person's intention to act. The more positive the attitude, the stronger the social pressure, and the higher the perceived control, the more likely a person will have a firm intention to act. A strong intention combined with adequate behavioural control increases the likelihood of the behaviour occurring. The TPB is a highly relevant framework in examining the influence of psychological factors, professional scepticism, and the use of artificial intelligence (AI) on auditor performance, moderated by continuous learning. Psychological factors such as motivation, confidence, and anxiety are closely linked to auditors' attitudes towards their audit tasks. Professional scepticism reflects the norms established within the auditor's work environment and profession, which shape subjective norms. Technologies like AI and participation in continuous learning indicate how equipped auditors feel to effectively carry out their responsibilities, which relates to perceived behavioural control. Thus, the TPB can provide a solid theoretical foundation for understanding the cognitive processes influencing auditors' intentions and behaviours in an increasingly complex and technology-driven professional landscape. Psychological capital (PsyCap) is a multifaceted construct that includes hope, efficacy, optimism, and resilience, and it is gaining increasing attention from academics and practitioners. Despite promising advancements in the PsyCap literature, further investigation into the mechanisms that link PsyCap to organisational outcomes is needed, mainly through longitudinal research designs. Moreover, the reciprocal relationship between PsyCap and positive affect warrants more exploration. PsyCap is recognised as an important personal resource that benefits various work-related outcomes across multiple countries. Meta-analytic studies have demonstrated significant positive relationships between PsyCap and favorable employee attitudes, such as job satisfaction, organisational commitment, and psychological well-being, as well as desirable employee behaviors, like organisational citizenship behavior (OCB), and various performance metrics (self, supervisor, and objective evaluations). Among the outcomes related to PsyCap, affective organisational commitment (AOC) and organisational citizenship behaviour (OCBO) are particularly emphasised as they are critical to an organisation's vitality, effectiveness, and productivity. Auditors with high professional scepticism tend to possess greater confidence (self-efficacy) in detecting fraud (Rashid et al., 2020; Fitriany et al., 2021). Sari and Harto (2020) further confirm that professional scepticism significantly improves auditors' ability to identify financial statement fraud, which in turn impacts audit quality. Therefore, this study hypothesizes that subjective norms influence professional scepticism, which subsequently enhances auditors' self-efficacy, fraud detection capabilities, and overall audit quality. In auditing, this means auditors' confidence in their ability to use Al technologies significantly affects their intention to integrate such tools into their work (Yoon et al., 2021). Studies by Issa and Sun (2020) and Appelbaum et al. (2020) confirm that higher perceived ease and control in using Al lead to greater adoption, which ultimately enhances audit efficiency and quality. Therefore, this study hypothesizes that perceived behavioral control over AI use affects both auditors' intentions and audit quality.Studies by Fitriany et al. (2021) and Hardiningsih et al. (2020) confirm that continuous learning contributes to higher levels of scepticism and ultimately enhances audit quality. Therefore, this study hypothesizes that continuous learning positively impacts auditors' subjective norms and directly increases their professional scepticism.

HYPOTHESIS DEVELOPMENT

Psychological Factors → Auditor Performance Things like confidence, being able to control anxiety, and staying strong when things get tough are really important for how well auditors make decisions.When people have a positive mindset, they’re more likely to do better because they believe in themselves and stay calm under pressure (Anthonius et al., 2025). Also, feeling good mentally helps them think more clearly and make fewer mistakes while doing difficult audit work (Bakker & Demerouti, 2007; Sonnentag, 2003)

H1: Psychological factors positively influence auditor performance

Professional Scepticism → Auditor Performance

Having a sceptical attitude means being always ready to question. Studies show that auditors who think critically are better at finding fraud and mistakes (Rashid et al., 2020; Sari & Harto, 2020). Keeping this mindset also makes them more objective and improves the quality of their audits (Mardijuwono & Subianto, 2018)

H2: Professional scepticism positively influences auditor performance

AI Use → Auditor Performance

AI tools help auditors work more efficiently and understand data better (Appelbaum et al., 2020; Noordin et al., 2022).But if someone isn’t trained enough or isn’t confident using AI, they might depend too much on it or misread what it shows, which could make their judgment worse (Imane, 2025; Yoon et al., 2021) Therefore, AI can help or hurt auditors depending on how ready they are to use it.

H3: AI use influences auditor performance Moderating Effect of Continuous Learning

Keeping up with learning helps auditors control their actions better, think more professionally, and understand new technologies. Training helps them develop scepticism (Bierstaker et al., 2020) and get better at using AI (Issa & Sun, 2020) Moderation of Psychology Learning continuously helps auditors manage their emotions and feel more confident, which makes their good mental traits lead to better performance (Anthonius et al., 2025)

H4: Continuous learning strengthens the positive influence of psychological factors on auditor performance Moderation of Scepticism

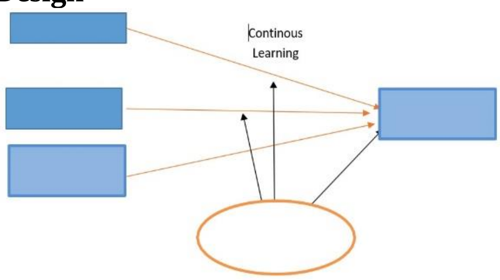
Getting trained and staying updated helps auditors think more critically and better analyze information (Bierstaker et al., 2020)

H5: Continuous learning strengthens the positive influence of professional scepticism on auditor performance Moderation of AI Use

Learning continuously increases auditors' ability and confidence when using AI, which reduces their worry about technology and the risk of relying on it wrongfully (Issa & Sun, 2020; Yoon et al., 2021)

H6: Continuous learning moderates the relationship between AI use and auditor performance.

Design



RESEARCH METHODS

The questionnaire used in this study was created by taking items from already tested tools in psychology, professional scepticism, technology adoption, and auditor performance research. All the questions were changed to better fit the context of auditing. Each question was answered on a five-point scale, from 1 ("strongly disagree") to 5 ("strongly agree").The psychological factors scale was based on tools used in organisational behaviour research to measure psychological capital and well-being (Anthonius et al., 2025).Five questions were included to cover emotional resilience, confidence, how well people manage anxiety, and self-belief (X1.1–X1.5). All of these questions met the standard for validity, as their scores were above 0.70.Professional scepticism was measured using questions from scales used in fraud detection and audit behaviour studies (Rashid et al., 2020; Sari & Harto, 2020).The scale had five questions (X2.1–X2.5) that focused on a questioning mindset, careful thinking, and checking things thoroughly.AI use was measured with questions based on frameworks that look at how familiar people are with AI, how much they rely on it, how easy they find it to use, and how confident they feel as auditors (Issa & Sun, 2020; Yoon et al., 2021).After testing, five questions (X3.1–X3.5) were kept.The continuous learning scale was adapted from research about learning and developing skills in auditing (Bierstaker et al., 2020).Seven questions (Z1–Z7) were used to measure participation in training, readiness to update knowledge, and openness to new audit technologies.Auditor performance was assessed using questions that reflected how well they make decisions, how accurate their work is, how well they follow procedures, and how on time they complete tasks (Y1–Y5).These questions were taken from performance studies in auditing and were checked to make sure they were reliable and valid.A pilot test with 30 auditors was done to check how clear, reliable, and well- structured the items were. All the constructs had Cronbach's alpha scores higher than 0.88, which shows they are very consistent. Based on feedback from the people who took part, some small changes were made to the wording to make it easier to understand and more relevant to the situation.

The full measurement model was tested to check construct validity, and it confirmed convergent validity.All the factors had loadings above 0.70, and the average variance extracted (AVE) values were over 0.50. The reliability was also good, with each construct having Cronbach's alpha and Composite Reliability scores above 0.70, as shown in Tables 1–3 of the results.The population included auditors working at Public Accounting Firms (KAP) and the Audit Board of Indonesia (BPK) in Pekanbaru, Batam, Padang, Medan, and Jakarta.Purposive sampling was used to choose auditors who had at least two years of experience and were familiar with audit technologies.A total of 180 questionnaires were given out, some online and some in person.Out of these, 142 responses were received, and after cleaning the data, 120 responses were kept. Responses that were incomplete or had a patterned answer were excluded.

- Initial distributed: 180
- Returned: 142 • Valid for analysis: 120

This meets the minimum requirement for PLS-SEM, which usually needs 10 times the largest number of paths pointing to a construct. To deal with concerns about not responding or responding late, two methods were used. First, the responses were split into early (first 50%) and late (last 50%) groups. A t-test showed no big differences in key constructs ($p > 0.05$), meaning there was little late response bias. Second, the average scores between early and late groups were compared. All differences were below 0.15 points on the scale, showing that non-response bias was very small.For data analysis, Structural Equation Modeling (SEM) was used with the Partial Least Squares (PLS-SEM) method through SmartPLS 4.

Here's why PLS-SEM was chosen:The model has reflective constructs and complex interactions. PLS-SEM is better at predicting and handling these kinds of relationships.The sample size was small (100–150), which works well with PLS- SEM. Confirmatory Factor Analysis (CB-SEM) usually needs more than 200 cases.PLS-SEM doesn't require data to be normally distributed, which matches the nature of survey data from professionals.Some constructs had formative indicators. PLS-SEM is more flexible in modeling these than CB-SEM.The analysis had two parts: first checking the measurement model (validity, reliability, AVE, Cronbach's alpha, HTMT), and then looking at the structural model (path coefficients, R-square, f-square, effect size, and bootstrapping with 5,000 samples).The R-square for auditor performance was 0.923, showing the model explains most of the variation.

RESULTS 1

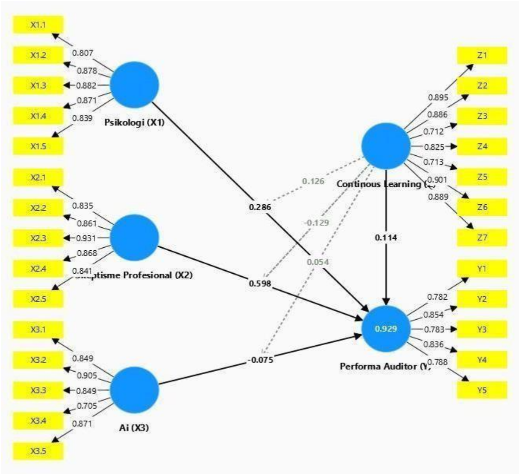


Image 1. Validity Test Results

Table 1. Validity Test Results

	Psikologi (X1)	Skeptisme Profesional (X2)	Ai (X3)	*Continous Learning* (Z)	Performa Auditor (Y)	KET.
X1.1	0.807					VALID
X1.2	0.878					VALID
X1.3	0.882					VALID
X1.4	0.871					VALID
X1.5	0.839					VALID
X2.1		0.835				VALID
X2.2		0.861				VALID
X2.3		0.931				VALID
X2.4		0.868				VALID
X2.5		0.841				VALID
X3.1			0.849			VALID
X3.2			0.905			VALID
X3.3			0.849			VALID
X3.4			0.705			VALID
X3.5			0.871			VALID
Z1				0.895		VALID
Z2				0.886		VALID
Z3				0.712		VALID
Z4				0.825		VALID
Z5				0.713		VALID
Z6				0.901		VALID
Z7				0.889		VALID
Y1					0.782	VALID
Y2					0.854	VALID
Y3					0.783	VALID
Y4					0.836	VALID

Y5	0.788	VALID

It can be seen from the processed data above that the overall loading factor value> 0.70 indicates that the data is said to be valid. Validity testing can also be seen from the Average Variance Extracted (AVE) value, where the data is said to be valid if the AVE value is> 0.50. The following are the test results using the AVE value:

Table 2. Average Variance Extracted (AVE) Test Results

Variabel	Cronbach alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Psikologi (X1)	0.909	0.911	0.932	0.733
Skeptisme Profesional (X2)	0.918	0.919	0.938	0.753
Ai (X3)	0.842	0.866	0.871	0.588
Continous Learning (Z)	0.926	0.929	0.941	0.697
Performa Auditor (Y)	0.868	0.871	0.905	0.655

The processed data indicates that all variables' Average Variance Extracted (AVE) values exceed 0.50. Specifically, the Psychology variable (X1) has an AVE value of 0.733, the Professional Skepticism variable (X2) has an AVE value of 0.753, the Artificial Intelligence variable (X3) has an AVE value of 0.588, the Continuous Learning variable (Z) has an AVE value of 0.697, and the Auditor Performance variable (Y) has an AVE value of 0.655. Therefore, all variables are considered valid.

Reliability Test

Data is considered reliable if the Cronbach's Alpha value is more than 0.70, and the Composite Reliability is more than 0.70. Therefore, the reliability test can be evaluated using these metrics: Cronbach's Alpha and Composite Reliability. Below are the results of the reliability test.

Table 3. Reliability Test Results

Variabel	Cronbach alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Psikologi (X1)	0.909	0.911	0.932	0.733
Skeptisme Profesional (X2)	0.918	0.919	0.938	0.753
Ai (X3)	0.842	0.866	0.871	0.588
Continous Learning (Z)	0.926	0.929	0.941	0.697
Performa Auditor (Y)	0.868	0.871	0.905	0.655

The data indicates that each variable's Cronbach's Alpha value exceeds 0.70, suggesting reliability. Specifically, the Psychology variable (X1) has a value of 0.909, the Professional Scepticism variable (X2) has a value of 0.918, the Al variable (X3) has a value of 0.842, and the Continuous Learning variable (Z) has a value of 0.926. Additionally, the Auditor Performance variable (Y) has a value of 0.868. Since all variables have Cronbach's Alpha values greater than 0.70, they are considered reliable. Furthermore, examining Composite Reliability (rho_a), all variables also have values greater than 0.70, reinforcing their reliability. The Psychology variable (X1) has a Composite Reliability value of 0.911, the Professional Scepticism variable (X2) has a value of 0.919, the AI variable (X3) has a value of 0.866, the Continuous Learning variable (Z) has a value of 0.929, and the Auditor Performance variable (Y) has a value of 0.871. Therefore, all variables are deemed reliable.

Test R-Square

The following are the results of the R-Square value in this study using Smartpls 4:

Table 4. R-Square Test Results

Variabel	R-square	R-square adjusted
Performa Auditor (Y)	0.929	0.923

The table indicates that the adjusted R-squared score is 0.923. This means that the combined ability of variables X1 (Psychology), X2 (Professional Scepticism), X3 (AI), and Z (Continuous Learning) to explain variable Y (Auditor Performance) is 92.3%, which is classified as strong. The analysis of the bootstrapping results is part of the hypothesis testing process. This testing is based on the outcomes of the inner model (structural model) and includes the R-squared output, parameter coefficients, and t-statistics. To determine whether a hypothesis can be accepted or rejected, it is important to consider the significance values between constructs and the t-statistics and p-values derived from the data collected in this study. Hypothesis testing aims to assess the influence of each independent variable on the dependent variable. The following are the criteria for determining influence (Hair et al., 2012): If the P-values <0.05, then the effect is significant, If the P-values> 0.05, then there is no significant effect

The image of the bootstrapping results of this study can be seen in the following figure:

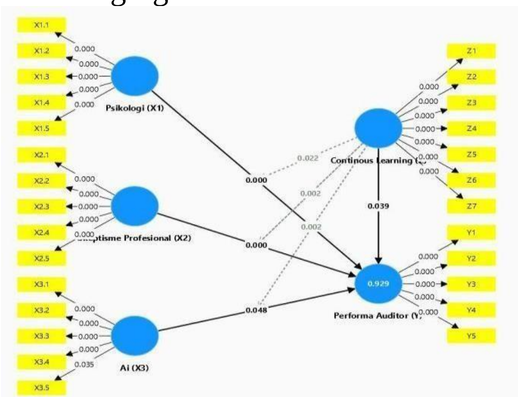


Figure 2. Bootstrapping Results

Table 5. Hypothesis Test Result

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Psikologi (X1) → Performa Auditor (Y)	0.286	0.285	0.056	5.083	0.000
Skeptisme Profesional (X2) → Performa Auditor (Y)	0.598	0.597	0.044	13.536	0.000
Ai (X3) → Performa Auditor (Y)	-0.075	-0.084	0.038	1.978	0.048
Continous Learning (Z) → Performa Auditor (Y)	0.114	0.111	0.055	2.066	0.039
Psikologi (X1) X *Continous Learning* (Z) → Performa Auditor (Y)	0.126	0.131	0.055	2.289	0.022
Skeptisme Profesional (X2) X *Continous Learning* (Z) → Performa Auditor (Y)	-0.129	-0.130	0.042	3.100	0.002
Ai (X3) X *Continous Learning* (Z) → Performa Auditor (Y)	0.054	0.056	0.042	1.267	0.002

The conclusion drawn from testing the effects of Psychology and Professional Scepticism on Auditor Performance is as follows: Psychology: The Psychology variable significantly positively affects Auditor Performance (O = 0.286). The T Statistic value for this relationship is 5.083, greater than 1.98, and the P Value is 0.000, less than 0.05. Therefore, Psychology positively and significantly affects Auditor Performance.Professional

Scepticism: The Professional Scepticism variable also significantly and positively impacts Auditor Performance (O = 0.598). The T Statistic value for this relationship is 13.536, exceeding 1.98, with a P Value of 0.000, less than 0.05. Thus, Professional Scepticism positively and significantly affects Auditor Performance. Artificial Intelligence (AI): The AI variable significantly negatively affects Auditor Performance (O = -0.075). The T Statistic value in this relationship is 1.978, slightly below 1.98, and the P Value is 0.048, less than 0.05. Thus, we conclude that Al negatively and significantly affects Auditor Performance. Continuous Learning: The Continuous Learning variable significantly positively affects Auditor Performance (O = 0.114). The T Statistic value for this relationship is 2.066, greater than 1.98, with a P Value of 0.039, less than 0.05. Therefore, Continuous Learning positively and significantly affects Auditor Performance. Moderating Effects of Continuous Learning: The T Statistic for Continuous Learning moderating the effect of Psychology on Auditor Performance is 2.289, exceeding 1.98, and the P Value is 0.022, less than 0.05. Hence, Continuous Learning can moderate the effect of Psychology on Auditor Performance. - The T Statistic for Continuous Learning moderating the effect of Professional Scepticism on Auditor Performance is 3.100, more significant than 1.98, with a P Value of 0.002, also less than 0.05. Therefore, Continuous Learning can moderate the effect of Professional Scepticism on Auditor Performance Lastly, the T Statistic for Continuous Learning moderating the effect of Al on Auditor Performance is 1.267, less than 1.98, and the P Value is 0.022, below 0.05. This indicates that Continuous Learning can moderate the effect of AI on Auditor Performance.In summary, Psychology and Professional Scepticism positively affect Auditor Performance, while Al has a negative impact. Continuous Learning serves as a valuable moderator in these relationships.

DISCUSSION OF RESEARCH RESULTS

This study examines the impact of psychology, professional scepticism, artificial intelligence (AI), and continuous learning on auditor performance. The analyses lead to key findings that hold significant implications for the audit profession, particularly in enhancing the quality and accuracy of audit work. The Effect of Psychology on Auditor Performance The results indicate that psychology positively and significantly impacts auditor performance. This conclusion is supported by a T-Statistic of 5.083 and a very small P-Value of 0.000, which signifies a highly significant relationship. The psychological factors at play include anxiety, self-confidence, and the stress levels of auditors while performing their audit tasks. Auditors who experience higher levels of anxiety or lack self-confidence are more likely to make suboptimal decisions or overlook critical evidence during the audit process. Conversely, more self-confident auditors tend to evaluate evidence and make informed decisions more efficiently.Supporting literature suggests that psychology influences decision-making across various professional fields, including auditing. (Pierce & Sweeney, 2004) highlight that anxiety and stress can reduce the quality of auditors' decisions, as these factors may distract them from their primary responsibilities. On the other hand, a healthy level of self-confidence can enhance both the speed and accuracy of decision- making. Auditors who manage their stress levels effectively and make confident decisions will likely produce more effective and efficient audits. Additionally, other studies indicate that psychological capital can affect dysfunctional audit behaviour through its impact on auditor performance (Anthonius et al., 2025).

The Effect of Professional Scepticism on Auditor Performance, Professional scepticism has been shown to significantly affect auditor performance, evidenced by a T-statistic value of 13.536 and a P-value of 0.000, indicating a strong and meaningful relationship. Professional scepticism is an essential attitude that auditors adopt when evaluating the evidence presented by the audited party. The results of this study indicate that auditors who exhibit a high level of scepticism tend to be more thorough in verifying evidence, minimising bias, and making more objective decisions. Sceptical auditors do not accept information at face value but engage in in-depth evaluations. This approach is vital for maintaining audit quality and preventing errors or fraud.Previous literature supports these findings, particularly a study by Sweeney and Pierce (2021), highlighting that healthy scepticism upholds audit integrity by compelling auditors to be more discerning when accepting evidence and information. Professional scepticism encourages auditors to question existing assumptions and data and verify the accuracy of the information provided.Effect of AI on Auditor Performance, This study found that AI (X3) had a negative impact on auditor performance, indicated by a T-statistic value of 1.978 and a P-value of 0.048. This suggests that although Al provides numerous benefits in terms of efficiency and accuracy, an over-reliance on this technology may lead to a decline in auditor performance in specific contexts. AI automates various auditing tasks, such as data matching and reviewing extensive transactions. While this reduces the workload for auditors, the adverse effects identified in this study can be attributed to several factors. One key factor is a lack of understanding or skill in using AI. Auditors who lack the necessary skills or knowledge about how Al functions may struggle to use the technology effectively, ultimately compromising the quality of the audit. Additionally, auditors who depend too heavily on the results provided by AI systems may lose their ability to assess these results critically. This reliance can lead them to trust the technology without fully understanding the broader context of the audit. (Imane, 2025) research highlights that Al positively impacts efficiency, value creation, and fraud detection capabilities, which ultimately enhances stakeholder trust in organisations.

The Effect of Continuous Learning on Auditor Performance,The results indicate that Continuous Learning (Z) positively and significantly influences Auditor Performance (Y), with a T-Statistic of

2.066 and a P- Value of 0.039. Continuous learning enables auditors to develop essential skills, stay updated on regulatory changes, and master new technologies, including AI. Auditors participating in continuous learning programs are better equipped to handle professional challenges. They enhance their technical knowledge and cultivate critical and analytical skills crucial in auditing. Auditors engaged in ongoing training adapt more effectively to evolving technological and regulatory landscapes, leading to improved audit performance. Additionally, continuous learning enhances auditors' ability to use Al more judiciously, thereby minimising the risk of errors or excessive reliance on technology. Research findings confirm a positive and significant relationship between the hours spent on continuous learning by audit staff and the overall quality of audits. Moderating Effect of Continuous LearningContinuous learning is crucial in the relationship between psychology, professional scepticism, AI, and auditor performance. For instance, auditors who effectively manage their anxiety and stress through training or relevant courses tend to be more productive and make more accurate audit decisions. Continuous learning enhances professional scepticism by equipping auditors with the skills to question information and verify evidence more effectively. While AI can have adverse effects, such as overreliance, continuous learning can help auditors integrate AI with their critical knowledge and human judgment, thereby mitigating these adverse impacts.It is vital for audit organisations to provide psychological support for auditors, whether through stress management training or techniques to boost self-confidence. A supportive environment for auditors' mental well- being can significantly improve audit quality. Additionally, audit organisations should cultivate a culture of healthy scepticism among their auditors. This can be achieved through training and skill development, ensuring auditors maintain objectivity and do not accept information without proper verification. Moreover, audit organisations must ensure that auditors receive adequate training in using AI, focusing on its role as an assistive tool rather than replacing human analysis and judgment. Integrating technology with ample human engagement will yield the best results for enhancing audit performance.

Finally, audit organisations should provide resources and opportunities for continuous learning. Regular training and access to educational materials can enhance auditors' technical and professional skills, ultimately improving audit quality.

CONCLUSION

This study aimed to comprehensively examine the influence of psychological factors, professional skepticism, and the use of artificial intelligence (AI) on auditor performance, as well as to investigate the moderating role of continuous learning in these relationships. Based on data analysis using Structural Equation Modeling (SEM) through SmartPLS, several key findings emerged that offer valuable insights for the development of the auditing profession. First, psychological factors were found to have a positive and significant impact on auditor performance. Auditors with high self-confidence and effective stress management tend to perform audit tasks more efficiently and accurately.

This finding highlights the importance of mental and emotional well-being as a critical component in supporting audit quality. Second, professional skepticism also demonstrated a positive and significant influence on auditor performance. A critical and objective mindset encourages auditors to thoroughly evaluate and verify evidence rather than accepting information at face value. Thus, professional skepticism serves as a foundation for maintaining the integrity and reliability of audit outcomes. Interestingly, the use of AI was found to have a negative and significant impact on auditor performance. This suggests a potential over-reliance on technology, particularly when not accompanied by sufficient understanding or training. Auditors who depend too heavily on Al-generated results may lose essential analytical and critical thinking abilities required for high- quality audits. In this context, continuous learning emerges as a vital factor. The study revealed that continuous learning not only positively affects auditor performance but also strengthens the positive influence of psychological factors and professional skepticism. Furthermore, it mitigates the negative effects of AI use. Auditors who engage in ongoing professional development are better equipped to adapt to technological changes and maintain high performance standards. Overall, this research emphasizes the importance of a holistic approach in auditor development, which goes beyond technical and technological competencies to include psychological well-being and lifelong learning. Audit organizations are encouraged to foster a work environment that supports auditor mental health, cultivates a culture of healthy skepticism, and offers relevant training in AI use. By integrating human and technological factors effectively, audit quality and accuracy can be significantly enhanced in a sustainable manner.

RESEARCH IMPLICATIONS

This research emphasises the significance of psychological factors, professional scepticism, and the role of artificial intelligence (AI) in influencing auditor performance. Audit organisations should prioritise the mental well-being of their auditors by providing psychological support and stress management training to enhance the quality of audit decisions. Professional scepticism is crucial for maintaining audit objectivity and rigour, so it is essential to cultivate a healthy culture of scepticism through critical training. Although Al can boost efficiency, excessive reliance on this technology can detract from audit quality; therefore, training on the appropriate use of AI should be offered.Continuous learning has strengthened psychological factors and professional scepticism while mitigating the adverse effects of Al use. Organisations should ensure auditors have opportunities for ongoing skill development through relevant training programs. Audit quality can be significantly improved by effectively integrating technology with human factors.

Limitation

Although this study makes a significant contribution to understanding the influence of psychological factors, professional skepticism, and the use of artificial intelligence (AI) on auditor performance with the moderating effect of continuous learning, there are several limitations that should be considered. First, the scope of the sample is limited to auditors working in Public Accounting Firms (KAP) and the Audit Board of Indonesia (BPK) in specific regions, namely Pekanbaru, Batam, Padang, Medan, and Jakarta. This may limit the generalizability of the findings to other regions or countries with different organizational conditions, cultural contexts, or levels of technological adoption. Second, the study employs a quantitative approach using survey methods and structural modeling, which does not delve deeply into the subjective experiences of auditors. A qualitative approach, such as in-depth interviews or case studies, could offer a more comprehensive understanding of how these factors interact in real-world audit practices.

FUTURE RESEARCH

This study highlights several potential research directions that could be further explored. First, future research could investigate how psychological factors and Al technology influence auditors' decisions in diverse contexts, such as audits in complex industry sectors or high-risk environments. Additionally, researchers could examine how AI can be optimised to support audit decisions while maintaining the critical evaluation role of auditors. Future studies might also focus on the impact of continuous learning on cultural change within audit organisations and how this culture affects long-term audit quality. Furthermore, research could analyse the performance differences between auditors who extensively use AI and those who rely more on traditional skills, assessing both the positive and negative impacts of technology in audit practice. Finally, there is an opportunity for further research to understand the long- term psychological effects of continuous learning on auditors and to investigate whether changes in auditors' attitudes and behaviours influence their audit quality over time.

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