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Reciprocal Use of Artificial Intelligence in Audit Assignments

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Abstract

The purpose of this study is to examine the use of artificial intelligence to improve audit quality, combined with the competence and skepticism of auditors on client satisfaction. The unit of analysis in this study was selected as a sample based on the purposive sampling method which was chosen deliberately with certain criteria that have been determined by the researcher. The main source of data used in this study comes from primary data, namely questionnaires distributed directly via email to each respondent. Respondents in this study were middle level management, who were directly related to auditors at the time of the audit of companies listed on the Jakarta Stock Exchange. The sample in this study numbered 229 respondents who were processed and analyzed using SEM PLS. This research is based on the Society 5.0 era where data connects and moves everything; a system that connects the virtual world and the real world. The era of the fourth industrial revolution, where the discovery of the internet of things allows the interconnection between machines, big data, acquisition, machine learning, smart factories and others, and financial reports to be made using a computerized system. The global Covid-19 pandemic has had an impact on almost all sectors and restrictions on activities. As a result of the corona virus, most activities or work are carried out from home. The results of this study prove that the effect of the application of artificial intelligence combined with auditor competence and auditor professional skepticism creates client satisfaction.

Keywords:
Artificial intelligence
Auditor competence
Auditor's professional skepticism
Client satisfaction.

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1. Introduction

This research discusses the use of artificial intelligence (AI) in the audit field. The research is vital because the audit process will be AI-based in the future (The Institute of Internal Auditors, 2017). The era of the fourth industrial revolution brought the discovery of the internet of things (IoT) which allows the interconnection between machines, big data, acquisition, machine learning, smart factories, and others, and financial reports are also created using a computerized system. When conducting an audit, auditors will experience obstacles and difficulties in obtaining an objective assessment if the audit is carried out in a conventional or traditional manner. Since being announced by WHO in early March 2020, the global Covid-

19 pandemic has impacted almost all sectors and brought about the enactment of activity restriction rules and regulations to prevent the transmission of the Covid-19 virus. As a result of the corona virus, most activities or work are carried out from home, (WFH). (This is the society 5.0 era, where data connects and moves everything using a system that connects the virtual real worlds. Auditor reports contain opinions and can create client satisfaction or dissatisfaction. Satisfaction is a feeling of achievement and pleasure because expectations and reality have been fulfilled. Satisfaction can be found by comparing the perception of "the service received with the service actually expected." Client satisfaction is a reflection of a good image or reputation that is received and felt, if what is received by the client is in accordance with, or exceeds, their expectations. In this case, the client will be satisfied. Client satisfaction is an important thing to understand concerning the quality of services provided by an auditor to survive and thrive in the face of competition. According to Caruana (2002), client satisfaction includes three main constructs, namely expectation, performance, and disconfirmation.

The dynamic, changing world is moving towards the application of digitalization technology today, creating innovations that are proven to be very strong, intelligent, scalable, and integrated so as to create the perfect collaboration between innovation, cognitive intelligence, and AI (Davenport, 2018). "The big four public accounting firms have invested heavily in technological innovation. KPMG and IBM Watson have partnered to develop a tool called the artificial intelligence audit (Carlos, 2016)." KPMG sees innovation in the world of auditing as not only a substitute procedure, but also a series of continuous innovations, thus creating an evolutionary audit called KPMG Clara. KPMG Clara is an innovation in audit services created by KPMG. KPMG Clara can develop from time to time and has the ability to take advantage of new technology which results in an increase in the level of insight and behavior of KPMG auditors. The increased ability of auditors can be in the form of analytical skills as well as predictive abilities that enable auditors to take information from various sources and apply it to prospects and risks in assessing client business. One technological approach in the audit sector in recent years is audit cognitive technology. This cognitive technology is a type of AI which can read through large amounts of data and perform digital analysis of the available data in a way that is impossible with the current team of auditors. One form of cognitive technology is the graphics processing unit (GPU), which is very helpful with auditors' problems and provides additional resources in unlimited data processing (Davenport, 2018). KPMG has made a major investment in developing its audit capabilities in the last few years with its Dynamic Audit. The Dynamic Audit refers to electronic-based audits, increased data usage capabilities, data automation procedures, and data visualization. The Dynamic Audit is an integral part of all members and auditors to obtain audit evidence and define how auditors interact with clients in today's digital era. PricewaterhouseCoopers (PwC) have developed the innovative "HALO," an analysis platform that serves as a medium for the creation of an efficient and quality audit process (Presswire, 2016). Deloitte has developed "Argus" to improve the capabilities of its auditors in analyzing available data. Ernst & Young (EY) uses new technology to increase the meaning of AI to reduce the number of employees each year due to auditors who usually perform traditional data processing (Harriet, 2016).

Along with the development of information communication and technology, other methods have been proposed, including computer assisted auditing techniques. Therefore, increasing market pressure and competition has encouraged audit companies to provide benefits in terms of increasing competitiveness (Affes, 2016). The introduction of computerized systems in companies, growing competition, and the drive for gradually increasing competitiveness has led audit firms to adopt new approaches and more efficient procedures. Auditors can use AI to design audit work so that auditors can perform structured and unstructured data analysis and use advanced analysis to draw a clearer view of possible risk and projected assets. "Artificial intelligence is a cognitive technology involving algorithms that allow software to absorb information, reason, and think in a similar way to humans." Cognitive technology enables auditors to analyze structured and unstructured data and can also improve the auditor's ability to obtain evidence and insights that enable them to make accurate decisions and conclusions. Analytical and predictive capabilities using cognitive technology (AI and machine learning) allow auditors to visualize the impact of various audit scenarios on asset projections (Kokina & Davenport, 2017). Cognitive technology enables auditors to obtain and analyze information that does not only come from clients, but also from other sources outside the client, be it print, digital, or social media to get a solid understanding of the client's potential business risks (Davenport, 2018). Cognitive technology also includes a process known as machine learning, wherein computers can correct and try new strategies when auditors encounter obstacles in their audit work (Kokina & Davenport, 2017). Analytical and predictive capabilities using cognitive technology (artificial intelligence and machine learning) enable auditors to visualize the impact of various audit scenarios on asset projections (Kokina & Davenport, 2017) with the following stages: 1. Simplify and standardize data. Cognitive technology enables auditors to analyze unstructured data, and it can also improve the auditor's ability to obtain evidence and insights that enable auditors to make correct decisions and conclusions. Cognitive technology allows auditors to obtain and analyze information that comes not only from clients but can also digest data from other sources outside the client, from print, digital, and social media sources, to get a clear understanding of the client's potential business risks. 2. Digitizing and structuring data. Data acquisition is the essence of auditing. Auditors need to obtain raw business data before they can audit it, which means checking the accuracy and alignment of subsequent datasets. Auditors regularly examine external data sources to understand risks, audit plans, and confirm company statements. To incorporate artificial intelligence into an audit methodology, auditors need to systematically understand how data sets are structured; in other words, how a structured data set differs from a single industry, client, or source system and how it reliably converts the data for use. Almost all business records today are stored in one electronic data format or another. Some data are easier to digest by software programs than others (text data-based document files, pdf format files and others). Before the data set can be reconciled there needs to be an interface to interpret and align the relevant data points across the shared file formats and, before today, the interfaces were both human and manual. 3. Automation technology. Compared with humans, machines excel at performing repetitive, time-consuming tasks such as data acquisition. Machines and technology that support AI will streamline the data acquisition challenges faced by auditors. AI will minimize the workload and take a short time to find relevant information, pull it from documents, and convert it into a usable format. AI systems can help auditors obtain and process data generated by business financial reporting systems. AI can more quickly and completely identify patterns and anomalies in large data sets, and more value comes from investigating and inferring the reasons behind patterns or anomalies. AI will do what an auditor tells it to do; nothing more, nothing less. 4. Data analysis and analysis. AI in auditing makes it possible to move towards auditing 100% of data. Auditors will be empowered to study the entire business efficiently. AI can help auditors move from traditional audit sampling frameworks to full-picture visualization and evaluation. AI can help in most of the cases where intensive activities are carried out manually and it represents a significant transformation in traditional auditing, namely data extraction, data comparison, and data validation. AI can significantly speed up the digitization of data entry and extraction activities performed manually, reducing the time spent on audit data preparation. This delivers process efficiency, whereby clients devote less time and fewer resources to responding to inquiries and documentation requests, and auditors have more time for risk analysis (Brennan, Baccala, & Flynn, 2017). 5. Cognitive Transformation Process. AI technology, also called cognitive technology, can extend the power of information technology to tasks traditionally performed by humans, enabling users of cognitive technology to solve the trade-offs between speed, cost, and quality (Raphael, 2015). AI is a tool that can solve the problem of auditor limitations and can improve audit quality.

The sophistication of AI or cognitive technology will be meaningless if it is not balanced with competence. Competence is an ability or skill possessed by a person in carrying out a job or task in a certain field, according to the position they hold. Competence is the skill, knowledge, basic attitude, and values contained in a person which is reflected in the ability to think and act consistently. Competence is not only about a person's knowledge or abilities, but also the willingness to do what is known to produce benefits. Auditor competence is the qualification needed by an auditor to carry out an audit properly to improve audit quality.

In summarizing audit engagements, the auditor's report must make a statement of opinion on the financial statements as a whole, or deliver an assertion. If an overall opinion cannot be given, then the reasons must be put forward. If the name of the auditor is associated with the financial statements, the auditor's report must contain clear instructions regarding the nature of the audit work carried out, if any, and the level of responsibility assumed by the auditor. This scenario carries risks and requires the auditor's professional skepticism. Skepticism is a notion of always viewing something as uncertain; disbelief or doubt about something that is not necessarily true. Skepticism is a doubtful attitude towards statements that are not sufficiently strong in evidence. Professional skepticism is the tendency to disagree with management assertions without corroborating evidence, or the tendency to ask management to provide facts on the assertions that are accompanied by evidence. Professional skepticism is an attitude that always questions and evaluates audit evidence critically. Auditor professional skepticism is the attitude of auditors who doubt and question everything, critically assess audit evidence, and make audit decisions based on their audit expertise. An auditor's professional skepticism is crucial in improving audit quality.

Auditor reports contain opinions and can create client satisfaction or dissatisfaction. Satisfaction is a feeling of pleasure because expectations and reality have been fulfilled. Satisfaction can be achieved by comparing the perception of the service actually received with the service expected. Client satisfaction is a reflection of a good image or reputation that is received and felt; if what is received by the client is in accordance with expectations or exceeds expectations, the client will be satisfied. Client satisfaction is an important element of understanding the quality of services provided by an auditor to survive and thrive in the face of competition.

The purpose of this study is to test the application of AI to improve audit quality, combined with the professionalism of auditors' skepticism of client satisfaction.

2. Literature Review

2.1. Theoretical Framework

The theory of perception is used in this research, where satisfaction is the feeling of being satisfied and happy because expectations and reality have been fulfilled. Satisfaction can be measured by comparing the perception of the actual service received with the service expected. According to Langton Robbins (2006), "perception is a process used by individuals to manage and interpret their sense impressions in order to give meaning to their environment." Atkinson, Atkinson, and Hilgard (2000) argued that perception is the process by which humans interpret and organize stimulus patterns in the environment. Gibson, Ivancevich, James, and Donnelly (1994) explained that perception is the process of giving meaning to the environment by individuals. Langton Robbins (2006) argued implicitly that a person's perception of an object is very likely to have differences with other people's perceptions of the same object. This phenomenon is due to several factors, namely perception and situation factors. Perception factors are influenced by attitudes, motives, interests, experiences, and expectations, while situation factors are influenced by time, circumstances, location, and social conditions. Krech, Crutchfield, and Livson (1974) stated that perception is influenced by personal and structural factors, in addition to being heavily influenced by attention. Personal factors come from needs, past experiences, and other things that determine perception; not the type or form of stimuli, but the characteristics of the person who responds to the stimuli. Structural factors are derived solely from the nature of the stimuli and the effects of the nerves on the individual nervous system. Furthermore, attention is a mental process when a stimuli or series of stimuli become prominent in consciousness when other stimuli give in.

Client satisfaction is a reflection of a good image or reputation that is received and felt, if what is received by the client is in accordance with expectations or exceeds expectations, then the client will be satisfied. Client satisfaction is an important thing to understand the quality of services provided by auditors in order to survive and develop in the face of competition. Lovelock and Patterson (2015) defines satisfaction as follows: "Satisfaction is a consumer's post-purchase evaluation of the overall service experience (process and outcome), specifically an affective state or a feeling reaction where the needs, wants, and expectations of consumers during the service experience have exceeded expectations". Iddrisu, Nooni, Fiankoc, and Mensah (2015) "customer satisfaction refers to the extent to which customers are satisfied with the products and services provided by a business entity". Burton, Sheather, and Roberts (2003) "described customer satisfaction and dissatisfaction as customer responses to perceived discrepancies between previous expectations or other performance norms and the actual performance of the product / service perceived after its use". According to Caruana (2002), client satisfaction includes three main constructs, namely expectations, performance, and disconfirmation. Expectations are expectations that consumers have in buying a product or service. Performance is the ability of a product or service to meet consumer needs and wants. Disconfirmation is a situation where expectations are higher than performance, while satisfaction is a condition where customer expectations can be met from the performance of products and services.

2.2. Hypothesis Development

2.2.1. Effect of AI on Client Satisfaction

The more complex data storage capabilities and the limited capabilities of auditors require the development of application systems to overcome these limitations. A tool to solve the problem of the limitations of accountants concerning technological advances is the presence of cognitive technology. One form of cognitive technology is the graphics processing unit (GPU), which is very helpful for auditor problems and provides additional resources in unlimited data processing (Davenport, 2018). The big four public accounting firms have invested heavily in technological innovation. KPMG has partnered with IBM Watson to develop a device called Audit Artificial Intelligence (Kokina & Davenport, 2017). PricewaterhouseCoopers (PwC) have developed the innovation of Halo, an analysis platform that serves as a medium for the creation of an efficient and quality audit process (Presswire, 2016). Deloitte has developed Argus to improve the capabilities of its auditors in analyzing available data. Ernst and Young (EY) uses new technology to increase the meaning of financial intelligence to reduce the number of employees each year, due to the fact that auditors usually examine traditional data processing Harriet (2016). KPMG has invested heavily in developing audit capabilities in recent years, namely Dynamic Audit, electronic-based audits, increased data usage capabilities, data automation procedures, and data visualization. These changes are due to the changing world which is very dynamic and moving towards the application of the technology and digitalization era. Dynamic Audit is an integral part of all members and auditors to obtain audit evidence and how auditors interact with clients in this digital era. These changes create innovations that are proven to be very strong and smart, scalable, and capable of being integrated, thus creating the perfect collaboration between innovation, cognitive intelligence, and AI (Kokina & Davenport, 2017). KPMG sees innovation in the world of auditing as not only a substitute procedure part, but also a series of innovations that have a sustainability that creates the evolution of the audit KPMG Clara. KPMG Clara is an innovation created by KPMG in audit services. KPMG Clara can develop from time to time as well as adopt abilities that can take advantage of a new technology that results in an growth in the level of insight and behavior of KPMG auditors. Increasing the ability of the auditor can be in the form of analytical skills as well as predictive abilities that allow the auditor to retrieve information from various sources and apply it to prospects and risks in assessing client's business.

Analytical and predictive capabilities using cognitive technology (AI and machine learning) enable auditors to visualize the impact of various audit scenarios on asset projections (Kokina & Davenport, 2017) with the following stages: 1. Simplifying and standardizing data, 2 Digitizing and structuring data, 3. Automating technology, 4. Data analysis and analysis, 5. Cognitive transformation processes. The researcher proxies these into 5 (five) main tasks of AI to improve audit quality, namely: 1. Checking transaction evidence and data using samples up to 100%; 2. Checking stock of name using cognitive technology, such as the use of cameras powered by drones and other technologies; 3. Performing and processing confirmation automation and analyzing the confirmation results; 4. Performing an analysis of projected assets and risks, where the conclusions are drawn by the auditor; 5. Transforming data and information sourced from clients and outside clients, both structured and unstructured.

AI creates an efficient and inexpensive work atmosphere that causes the quality of the auditor's work to be higher. The quality of service can provide value for a company if done well. An AI auditor will: 1. Increase the relevance of the audit, 2. Enable audit firms to expand service offerings by proposing new services, 3. Improve audit quality, especially by analyzing all client data, 4. With digitization, a new auditor profile has emerged, 5. Enable a culture of innovation in auditing firms, thereby improving corporate governance (Rodgers, Mubako, & Hall, 2017). AI is a tool that can improve the quality of audit services. Parasuraman, Zeithaml, and Berry (1994) explained that technology and equipment are tangible so that AI is a component that shapes the quality of audit services. A higher level of service quality results in a better level of client satisfaction Ohman, Häckner, and Sörbom (2012), and client satisfaction is the center of organizational success (Minton, 2015), so the following hypothesis can be formulated:

H_{01}: An auditor's AI has a positive effect on client satisfaction

2.2.2. Effect of Auditor Competence on Client Satisfaction

Competence is a person's personal attribute that allows for superior performance. Auditor competence is the qualification needed by the auditor to carry out the audit properly. Halim, Sutrisno, and Achsin (2014) "revealed that auditor competence can be measured by four formative indicators, namely planning, knowledge, experience, and supervision." Planning is an essential, vital aspect of an audit. An auditor's competence is determined by the auditor's planning ability. Good audit planning makes the auditor potentially have the competence to find material misstatements. In addition, the audit plan must consider the systems of internal control, audit risk, and substantive test procedures. Knowledge is one of the determinants of technical competence and is very useful in structured auditor duties. In addition, the auditor's knowledge of accounting and audit procedures is critical in determining audit quality (Halim, 2014). One of the key indicators of auditor competence is experience and supervision. Experienced auditors will make judgments with a lower error rate than inexperienced auditors, thus affecting competence. Strong oversight will prevent the possibility of auditors from acting in ways that reduce audit quality, and process-supervised audits are likely to result in correct disclosure and higher audit quality.

In this study, the focus is directed on the competence of auditors who have been appointed by a public accounting firm to conduct audits on clients (signing auditor competence). This is because their competence is crucial in determining the level of client satisfaction with the audit services performed. Not all auditors who offer their services to clients have sufficient knowledge of accounting and auditing rules and standards, so they can have an impact on the performance and satisfaction of their clients (Ohman et al., 2012). The level of client satisfaction is influenced by both internal and external factors. Internal factors are the client's feelings for the services provided and the confidence provided by the auditor based on the auditor's competence. "Meanwhile, external factors come from the reputation of the auditors and the public accounting firm where the auditors work. So that these two factors play a role in determining client satisfaction. The greater these factors, the higher client satisfaction will be achieved (Ohman et al., 2012)." Several previous studies have explained a positive relationship between auditor competence and client satisfaction. It has been reported that the ability of auditors to understand clients 'business conditions and the industrial sector significantly affects clients' perceptions of audits conducted by Carcello, Hermanson, and McGrath (1992); Humphrey and Ashforth (1994); Warming-Rasmussen and Jensen (1998); Pandit (1999). It has also been reported that the content and thoroughness of the audit procedure (Windsor & Ashkanasy, 1995); Jenkins and Lowe (2011), together with the auditor's problem-solving ability, affect how the client perceives the work of the auditor (Behn, Carcello, Hermanson, & Hermanson, 1997; Libby & Tan, 1994). On the other hand, Ohman et al. (2012) found that signing auditor competence affects client satisfaction. According to DeAngelo (1981), competence is proxied in three aspects, namely knowledge, experience, and education. According to Armstrong and Baron (1998), competence is what people bring to a job in the form of different types and levels of behavior and competence is proxied in 4 (four) main components, namely 1. Knowledge, 2. Experience, 3. Education, and 4. Behavior. Based on this explanation, the following hypothesis can be formulated:

H_{02}: Auditor competence has a positive effect on client satisfaction

2.2.3. Effect of an Auditor's Professional Skepticism on Client Satisfaction

Auditors need to have professional skepticism, especially when obtaining and evaluating audit evidence. Professional skepticism is the basis for achieving a high-quality audit performance. The auditor's professional skepticism, or the auditor's doubts about client statements and information, both orally and in writing, is part of the audit process. An auditor's skepticism is very decisive in the audit work. Ruiz, Gomez-Aguilar, De Fuentes-Barbera, and Garcia-Benau (2004) claim that the auditor's decision-making regarding the company's survival consists of two stages. The first stage identifies the issues at stake related to the competence of auditors. The second stage, deciding what to do, is related to professional skepticism. This can occur because of the auditor's hesitation, which must ensure the maintenance of their skepticism and satisfaction of their clients. Auditor skepticism is a negatively related determinant to client satisfaction. Based on a qualitative approach, the audit client can perceive the auditor's skepticism as negative. In addition, research conducted by Ohman et al. (2012)) found that audit skepticism has a negative effect on client satisfaction. It can be understood that the higher the auditor's skepticism level, the more the client's discomfort, which will decrease client satisfaction.

It is stated (Hurrt, Brown, Early, & Krishnamoorthy, 2013) that professional skepticism is the basis for achieving a high-quality audit performance. The auditor's professional skepticism or the auditor's doubts about the client's statements and information, both orally and in writing, is part of the audit process. (Hurrt et al., 2013) "developed 6 (six) characteristics of professional skepticism, the 1st (first) consisting of 3 (three) characteristics related to examination and testing of evidence, 4 (four) characteristics related to the consideration of human aspects and understanding of information providers when evaluating audit evidence, and the last 2 (two) characteristics relating to professional courage auditors". In brief, 6 (six) characteristics of professional skepticism are described as follows, 1. Critical thinking. The first characteristic of professional skepticism is that the skeptic's mind will question the reasons, adjustments, and evidence of something he has faced or obtained. 2. Suspension of judgment. The second characteristic of professional skepticism leads to behavior that delays drawing audit conclusions until sufficient evidence is gathered. This characteristic is formed from several indicators, such as requiring more information, requiring time to make decisions, and not making decisions if all information has not been properly confirmed. 3. Search for knowledge. The third characteristic of professional skepticism is based on high curiosity. This curiosity is intended to increase knowledge that can be used in conducting audits. This characteristic is formed from several indicators, such as more searching and trying to find current and fun information when looking for new things and will not conclude or make a decision if not all information has been revealed. 4. Interpersonal understanding. The fourth professional skepticism characteristic can be conceived as the efforts of a skeptical person to understand the purpose, motivation, and integrity of the information provider. This needs to be done to find out whether the information provided is valid or not. This character is formed from several indicators, namely trying to understand the behavior of others and the reasons why someone behaves as they do. 5. Self-confidence. The fifth characteristic of professional skepticism is the professional skepticism that involves self-confidence (in the form of self-direction and moral independence). A skeptical auditor believes in their professional ability to respond to and process all evidence that has been obtained. They prefer to find information by themselves and do not depend on the statements and information obtained. This characteristic is formed from several indicators, such as confidence in their own capacities and capabilities. 6. Self-determination. The sixth characteristic of professional skepticism is the auditor's skepticism in concluding objectively the evidence that has been gathered. They decide for themself which evidence is needed to accept a particular hypothesis. This characteristic is formed from several indicators such as indirectly accepting or justifying other people's statements, paying attention to other people's explanations and responses, emphasizing something inconsistent, and not being easily swayed by others about something. Based on this explanation, the following hypothesis can be formulated:

H_{05}: An auditor's professional skepticism has a negative effect on client satisfaction.

3. Research Methods

This research uses the causal hypothesis testing type, which tests the cause and effect between the dependent and independent variables (Sekaran & Bougie, 2016). This research method aims to provide a description to produce a construct of a phenomenon based on the relationship model derived from the theoretical model. The approach used in this research is quantitative. This approach relies on numbers in the form of scores as the basic framework for analysis. The score is obtained by the survey method. Kerlinger and Lee (2000) argued that this method is generally used in large and small populations, but the data studied is from samples taken from that population. Thus, the relative distribution and relationship between variables are found.

3.1. Measurement of Study Variables

The instrument used in this study was arranged in the form of a questionnaire. The questionnaire to collect data on exogenous and endogenous variables was closed, and contained statements or questions that were submitted directly to the respondent or via e-mail, and respondents were only given the opportunity to answer according to the answer choices contained in the questionnaire. The answer choices in the questionnaire were in the form of an ordinal numeric scale. A numerical ordinal scale is used to measure the attitudes, opinions, and perceptions of a person or group about social phenomena. With a numeric ordinal scale, the variables to be measured are translated into variable indicators. Furthermore, these indicators are used as items for arranging instrument items in the form of questions or statements. The measurement of each variable is shown in Table 1.

Tabel-1. Summery measurement of study variables.

Variables	Operational indicators	Measure	Questionnaire item	Supporting literature
AI	Five tasks of the AI	7-point ordinal numerical scale type questions	5	Kokina and Davenport (2017)
Auditor competence	Four proxies form the main auditor competency	7-point ordinal numerical scale type questions	4	DeAngelo (1981); Armstrong and Baron (1998)
Auditor professional skepticism	Six characteristics of skeptical professionals	7-point ordinal numerical scale type questions	6	Hurrt et al. (2013)
Client satisfaction	Three main constructs of client satisfaction	7-point ordinal numerical scale type questions	3	Caruana (2002)

3.2. Outlier Test

Ferguson (1961) defined outliers as data that deviates from other data sets. Freeman, Barnett, and Lewis (1995) "outliers are observations that do not follow most patterns and are located far from the data center." Sembiring (1995) outliers are observations far from the data center that may have a major effect on the regression coefficient. Before the respondents' data was processed, the researcher screened the data to determine whether there was outlier data that could affect the research results. One method to determine outliers is the boxplot method, namely the method using the quartile value. The quartile value is determined to be Quartil1, Quartil2, and Quartil3 to divide a data sequence into 4 (four) parts. The range (Interq quartile / IQR) is defined as the difference between Quartile3 and Quartile1 or IQR = Q3 – Q1. Outlier data can be determined, namely a value that is "less than," 1.5 (IQR) against Quartile1 (lower limit) or Q1–1.5 (IQR) and a value that is "more than," 1.5 (IQR) against Quartile3 (upper limit) or Q3 + 1.5 (IQR). There were 265 respondents canvassed in this study, and there were 36 outliers, so the processed data were 229 respondents.

3.3. Model Specification

The regression equation model for this research is:

$CS = \alpha + \beta_1 AI + \beta_2 AC + \beta_3 APS + \mathcal{E}$

or

$client\_satisfaction = \alpha + \beta_1 Artificial\_Intelligence + \beta_2 Auditor\_Competency + \beta_3 Auditor\_Professional\_Skepticism + \varepsilon_u$

4. Results and Discussion

4.1. Sample Characteristics

The population of this study was middle and upper level management who are directly related to auditors in companies listed on the Indonesia Stock Exchange (IDX) that have published, audited financial reports for the 2019 period by the big 4 public accounting firms or public accountants of foreign-affiliated companies. Samples were selected using a purposive sampling method with certain criteria. The criteria determined by the researchers included middle and upper level respondents consisting of supervisors, managers, and senior accounting staff having at least three years' experience in the position, having experience in audits by the big 4 public accounting firms or foreign-affiliated public accounting firms, and having experience in auditing with AI, cognitive technology assistance, or audit software.

4.2. Analysis and Results (Outer Model and Inner Model)

4.2.1. Inferential Analysis

Inferential analysis is a series of methods used to process data and test research hypotheses. In this study, the inferential analysis used parametric inferential statistical techniques assisted by using analytical tools in accordance with the research model, namely path analysis, with the help of the "Structural Equation Modeling" program – "Partial Least Square" (SEM-PLS) SmartPLS Version 3". The inferential analysis in this study was carried out in two stages. The first stage was evaluating the measurement model or outer model, and the second stage was evaluating the structural model or inner model. The types of evaluation in the two stages that will be discussed are for research models that use reflective indicators only, not formative indicators or a mixture of formative and reflective. The measurement model uses a latent construct with reflective indicators, so the validity and reliability of these indicators need to be tested. This study used five latent constructs and 18 indicators. The following four evaluations of measurement models or external models were obtained using the PLS Algorithm in SmartPLS Version 3. This procedure will collectively generate the VIF, R-Square, f-Square, and path coefficient values used in the inner model evaluation.

4.2.2. Outer Model Evaluation

4.2.2.1. Reliability of Model Indicators

An indicator is declared to meet the indicator reliability requirements if it has a loading value > 0.7, this also shows that the construct can explain more than 50% of the variance of the indicator Hair, Sarstedt, Hopkins, and Kuppelwieser (2014). Of the 18 indicators in the logarithmic coefficient path in this study, there were two indicators in the latent variable of professional auditor skepticism which were unreliable and cut-off is carried out, so that the reliable indicator of each latent variable is > 0.7 as follows: latent variable AI AI1; (0.769), A2 (0,747), A3 (0.838), A4 (0.831), A5 (0.866), Auditor Competence; AC1 (0.784), AC2 (0.798), AC3 (0.791), AC4 (0.745), Auditor Professional Skepticism, APS3 (0.812), APS4 (0.810), APS5 (0.731), APS6 (0.833) dan Client Satisfaction, CS1 (0.716), CS2 (0.754), CS3 (0.776).

4.2.2.2. Internal Consistency Reliability Model

A composite reliability value of > 0.7 is considered to have good reliability (Sarstedt el al., 2017). Composite Reliability Value of Latent Variable Artificial Intelligence (0.905); Auditor Competence (0.861); Auditor Professional Skepticism (0.791) and Client Satisfaction (0.882); > 0.7.

4.2.2.3. Validitas Konvergen Model

An Average Variance Extracted (AVE) value is > 0.5 or more means that the construct can explain 50% or more of its item variance (Hair et al., 2014). AVE value of Latent Variable (0.657); AC (0.608); APS ((0.636) dan CS (0.561); > 0.5.

4.2.2.4. Discriminant Validity

The discriminant validity test in this study was carried out using the Fornell-Larcker Criterion value. The Fornell-Larcker Criterion is obtained by comparing the square root value of the Average Variance Extracted (AVE) for each construct with the correlation between the other constructs in the model. A model with a good discriminant validity value can be concluded if the AVE square root of each construct is greater than the correlation value between the construct and the other constructs in the model.

Tabel-2. Discriminant Value Model.

Variable	AI	AC	APS	CS
Artificial intelligence (AI)	0.810			
Auditor Competence (AC)	0.353	0.780		
Auditor Professional Skepticism (APS)	0.602	0.584	0.798	
Client Satisfaction (CS)	0.537	0.487	0.602	0.749

The data in Table 2 shows that the AI latent variable has an AVE square root value of 0.810 and this value is greater than the correlation value of the AI latent variable against other latent variables. The same is the case with the latent variable AC of 0.780; ASP of 0.798; CS of 0.749 also have a square root value of AVE that is greater than the correlation value with other latent variables. Because each latent variable used in the study has a square root value of AVE that is greater than the correlation value with other latent variables, all latent variables in this study are declared to meet the discriminant validity requirements.

4.2.3. Structural Model Evaluation (Inner Model)

The initial stage of evaluating the structural model is to check the collinearity between the construct and the predictive ability of the model (Hair et al., 2014) followed by measuring the predictive ability of the model using four criteria such as the coefficient of determination (R^2) and effect size (f^2). and path coefficients.

4.2.3.1. Variance Inflation Factor (VIF)

Evaluation of the Variance Inflation Factor (VIF) aims to determine whether there is a collinearity relationship between variables or constructs. The VIF value must be less than five. If it is more than five it indicates collinearity between constructs. If the overall value of the indicators in each latent variable is less than five, then the research model can be declared free from multicollinearity, so that the data can be used for further research. Hair et al. (2014). VIF value of latent variable Artificial intelligence: AI1 (1,760); AI2 (1.705); AI3 (2.100); AI4 ((2.182); AI5 (2.407); Auditor Competence: AC1 (1.541); AC2 (1.672); AC3 (1.512); AC4 (1.539); Auditor Professional Skepticism; APS3 (1.669); APS 4 (1.816); APS5 (1.449); APS6 (1.866); Client Satisfaction; CS1 (1.201); CS2 (1.222); CS3; (1.215); is less than 5, so the data can be used for further research.

4.2.3.2. Coefficient of Determination (R Square)

The coefficient of determination (R^2) is a way to estimate how much an endogenous construct can be explained by an exogenous construct. The expected coefficient of determination is between 0 and 1. The R^2 value is 0.75; 0.50 and 0.25 means that the model is strong; moderate and weak (Hair et al., 2014). R^2 of client satisfaction is 0.471 or the client satisfaction construct can be explained (Artificial Intelligence, Auditor Competence and Auditor Professional Skepticism is 47.1%, so it is stated that the research model is moderate).

4.2.3.3. Effect Size (f^2)

The effect size in this study is used to assess the magnitude of the influence between variables. The f-square value is 0.02 as small, 0.15 as moderate, and a value of 0.35 as large. Values less than 0.02 are either negligible or have no effect. The f^2 effect of client satisfaction from the exogenous AI variable on client satisfaction is 0.061 which means moderate, auditor competence on client satisfaction is 0.034, which means moderate, auditor professional skepticism on client satisfaction is 0.153 which means large.

4.2.3.4. Path Coefficients

Measurement of the path coefficient between constructs is used to determine the significance and strength of the relationship between variables and to test the research hypothesis. The path coefficient ranges from -1 to +1. The relation between the two constructs is considered positive if the path coefficient is getting closer to the +1 value. The relation that is getting closer to the value of -1 indicates that the relationship between the two constructs is negative Hair et al. (2014). *Path coefficients* from *AI* to client satisfaction is *0.231, which means positive*, from competence auditor to client satisfaction is *0.166 which means positive, from* auditor professional skepticism to client Satisfaction is *0.411 which means positive.*

4.3. Discussion

This analysis produces a t-statistic value for each relationship path used to test the hypothesis. The t-statistic value will be compared with the t-table value. This study uses a 95% confidence level, therefore the level of accuracy or the limit of inaccuracy (α) = 0.05 (5%), the value of the t table is 1.96. If the t-statistic value is less than the t-table value (t-statistic < 1.96) then Ho is accepted, and Ha is rejected. Meanwhile, Ho is rejected, and Ha is accepted if the t-statistic value is greater than or equal to the t-table (t-statistic > 1.96). The results of the calculation of hypothesis testing can be seen in Table 3.

Table-3. Hypotesis structure model test.

Description	Original Sample (O)	Mean Sample (M)	Standard Deviation (STDEV)	t statistics (O/STDEV)	P Value
AI → CS	0.231	0.241	0.067	3.429	0.000
AC → CS	0.227	0.228	0.062	3.637	0.000
APS → CS	0.166	0.167	0.070	2.379	0.009

Based on the path coefficient analysis with the SmartPLS Version 3 bootstrapping procedure in Table-3 data, namely the Structural Model Hypothesis Test, can be explained as follows:

The influence testing of AI on client satisfaction, obtained a statistical t value of 3.429 > 1.96 (t table value), p value 0.000 < 0.05 (α) and the original sample / mean sample value is positive, so it can be stated that the AI auditor has a positive and significant effect towards client satisfaction. The results of this study are in line with the findings of Ismail, Haron, Ibrahim, and Isa (2006) which state that the satisfaction of audit clients listed on the Malaysia Stock Exchange is influenced by tangibles. Mohanty, Seth, and Mukadam (2007) stated that AI creates an efficient and inexpensive work atmosphere and can lead to better audit quality. Audit quality can provide value to a company if it is done well. A higher level of audit quality results in a level of client satisfaction (Ohman et al., 2012) and client satisfaction is central to organizational success (Minton, 2015). AI Auditor is AI used by auditors in performing auditing duties. The definition of known AI was first proposed by McCarthy, Minsky, Rochester, and Shannon (1955) as follows: The goal of AI is to develop machines that behave as if they are intelligent. It is the science and engineering of intelligent machinery, especially intelligent computer programs. Nilsson (2009) defines it thus: AI is an activity aimed at making intelligent machines and intelligence is a quality that enables entities to function appropriately and with foresight in their environment. There are two main research streams related to advances in AI. The services and technology literature tend to focus more on the positive side of using AI technology, whereas the economic literature tends to focus on the effects of AI on jobs. The service literature tends to focus on smart technology applications (Colby, Mithas, & Parasuraman, 2016; Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017). AI offers a way to bridge the gap between data science and execution by filtering and analyzing enormous, corrupted data that was once an insurmountable process. The use of AI in the field of auditing enables the auditor to visualize the impact of various audit scenarios on asset projections. AI offers a way to fill the gap between data science and execution by filtering and analyzing corrupted big data that was once an insurmountable process. In addition, AI also allows auditors to obtain and analyze information that comes not only from clients, but can also digest data from other sources outside the client, from print, digital, and social media sources, to get a solid understanding of the client's potential business risks (Davenport, 2018). Along with the rapid development of technology, namely the era of digitalization and big data, financial reports cannot be audited as traditional or conventional anymore, so auditors must change their attitude of making choices, namely conducting audit assignments using AI to improve audit quality which ultimately creates client satisfaction.

Testing of the effect of auditor competence on client satisfaction obtained a t-statistical value of 3.637 > 1.96 (t table), P value 0.000 < 0.05 (α) and the original sample / mean sample value, it can be stated that the auditor's competence has a positive and significant effect on client satisfaction. This research is in line with the research of (Ohman et al., 2012) which found that signing auditor competence has an effect on client satisfaction. Ali, Mail, and Amirul (2019) stated that auditor competence has a significant effect on client satisfaction. The level of client satisfaction is influenced by the client's internal factors, namely the client's feelings for the services provided and the confidence provided by the auditor based on the competence of the auditor, while external factors come from the reputation of the auditor and the public accounting firm where the auditor works (Ohman et al., 2012). The findings of Al Sawalqa (2014) also show the same thing, that audit quality does not only depend on written rules and procedures, but also on technical capabilities and individual characteristics that form important factors for improving audit quality. Competence is needed to demonstrate the ability of an auditor to provide a good level of performance. Experienced auditors will make judgments with a lower error rate which will affect their audit results. In addition, strong oversight will prevent the possibility of auditors from acting which reduces audit quality and closely monitored audits are likely to result in correct disclosure and higher audit quality. This is in line with the opinion of Chadegani (2013) which states that the characteristics of individual auditors are the most important factors affecting audit quality. Thus, the competence of an auditor will determine the level of client satisfaction. Ismail et al. (2006) stated that respondents were satisfied with the quality of audit services from the tangible dimension., Furiady and Kurnia (2015) stated that auditor competence has a significant effect on audit quality, Handayani and Merkusiwati (2015) stated that auditor competence has a positive effect on audit quality. Therefore, auditors must improve their competence to improve audit quality which in turn can create client satisfaction.

Testing of the influence of the auditor professional skepticism variable on client satisfaction provided a statistical t value of 2.379 > 1.96 (t table value), P value 0.009 < 0.05 (α) and the original sample / mean sample value was positive, so it can be stated that auditor professional skepticism has a positive and significant effect on client satisfaction. Auditor professional skepticism is a determinant that is negatively related to client satisfaction. However, research conducted by Aschauer, Fink, Moro, Van Bakel-Auer, and Warming-Rasmussen (2017) found that identification by auditors has a positive effect on client perceptions and on auditor skepticism; in the end it can create client satisfaction. Ruiz et al. (2004) claims that the auditor's decision-making regarding the company's survival consists of two stages, namely the first stage, identifying the issues at stake, related to the auditor's competence, and the second stage, deciding what to do, related to professional skepticism attitudes. These can occur because of the auditor's hesitation which must maintain skepticism and satisfy the client. The study's findings are not consistent with the findings of Ohman et al. (2012) who found that audit skepticism negatively affected the satisfaction of the client, it can be understood that the higher the level of skepticism auditors will cause inconveniences clients that impact on the satisfaction of the client and the findings are in line with opinion of Hurrt et al. (2013) which states that professional skepticism is the basis for achieving high-quality audit performance. The auditor's professional skepticism or the auditor's doubts about the client's statements and information, both orally and in writing, is part of the audit process. Kusumawati and Syamsuddin (2018) state that professional skepticism has a significant direct effect on audit quality. Brown-Liburd, Cohen, and Trompeter (2013) argues, when auditors show high professional skepticism, auditors are more conservative and stand firmer than when auditors do not show high professional skepticism. Ciołek (2017) professional skepticism is considered fundamental to a high-quality audit performance. Therefore, auditors must increase professional skepticism to improve audit quality which in turn creates client satisfaction.

5. Conclusion and Recommendation

5.1. Conclusion

This study shows the use of AI, combined with the competence and professional skepticism of auditors, has a positive and significant effect on client satisfaction for clients of the big 4 public accounting firms and foreign-affiliated public accounting firms on the Indonesia Stock Exchange. According to the research results, the following conclusions can be drawn: 1. The use of AI has a positive and significant effect on client satisfaction. This has implications for improving audit quality, 2. Auditor competence has a positive effect on client satisfaction. This implies the importance of auditors to continuously maintain and improve their competence, 3. Auditor professional skepticism has a positive and significant effect on client satisfaction. This implies the importance of auditors in preparing audit programs with a standardized critical assessment of the validity or validity of audit evidence. Audit programs with work procedures and critical assessment standards in proving audit evidence will have an impact on the credibility of the audit results. The credibility of financial statements that are audited with high skepticism will increase the trust of clients and other stakeholders. The client will be satisfied with the credibility of the audited financial statements, if this principle of skepticism is applied to every audit program carried out by auditors that ultimately creates client satisfaction.

5.2. Recommendation

The implementation still has several limitations in the research process carried out during the Covid-19 pandemic when the government-imposed work from home (WFH) rules, so it was difficult to get large numbers of respondents. With this research limitation in mind, it is necessary to carry out further research in terms of AI tasks or the use of AI to improve audit quality with a larger amount of data under normal conditions and / or on a regional scale in ASEAN or Asia.

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