Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

Does Big Data Analytics Implementation Have a Mediating Role in The Examination of Public Sector Audit Quality?

Taufik Nasrudin[1], Amrie Firmansyah[2*]
Universitas Trisakti[1)], Universitas Pembangunan Nasional Veteran Jakarta[2)]
taufiknasrudin@gmail.com, amriefirmansyah@upnvj.ac.id

*Corresponding Author
Submitted: May 13, 2024
Accepted: May 27,2024
Published: October 1, 2024

ABSTRACT

This study examines the effect of auditor competence and motivation on audit quality by implementing big data analytics as an intervening variable. The data used in this study comes from a questionnaire survey distributed to respondents during December 2023. The respondents in this study were selected using purposive sampling, with the criteria being auditors at the State Finance Auditorate I BPK. The final sample used in this study was 37 respondents. This study uses the SEM approach with the SmartPLS version 3.0 application to test the data. The findings of this study indicate that competence and motivation have a positive and significant effect on the implementation of big data analytics. In addition, competence has a positive effect on audit quality, but motivation does not affect audit quality. Furthermore, implementing big data analytics does not affect audit quality or mediate the effect of competence and motivation on audit quality. With the results of this study, it is hoped that there will be an increase in training programs, socialization, and the use of big data analytics in audit activities so that it can be useful for improving audit quality.

Keywords: *Audit Quality; Competence; Implementation of Big Data Analytics; Motivation*

INTRODUCTION

According to the law, state finances are all state rights and obligations that can be valued in money, as well as everything in the form of money and in the form of goods that can be used as state property related to implementing these rights and obligations. The development of information technology will require a change in an organization's business processes. The Ministry of Finance utilizes the development of information technology as a government internal control measure in state financial management by creating an integrated application, one of which is the Agency Level Financial Application System (SAKTI). The application is used as a means for agencies to support the implementation of SPAN to carry out financial management, including the stages of planning and budget accountability, which can be accessed online and offline.

The development of information technology also has risks. Recent misuse of state finances has increased the potential for state losses. Among them is the misappropriation of performance allowances for employees of the Ministry of Energy and Mineral Resources (ESDM) with data manipulation and payment of performance allowances that are not under the provisions, resulting in state financial losses. Cases of data manipulation also occurred in the education sector, where cases of misappropriation of BOS funds used the mode of creating fictitious data to obtain larger BOS funds to the detriment of state finances. The data manipulation case can illustrate a gap in the big data used as the basis for calculations in spending state money.

The number of problems in managing state finances requires quality audits to detect misuse of state finances and save them. As the law mandates, the Supreme Audit Agency (BPK) can audit state finances' management and responsibility freely and independently. Audits conducted by BPK include audits of financial statements, performance audits, and audits with specific objectives.

However, the results of the BPK examination may be subject to lawsuits, which can reduce the

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

quality of the audit. Rajagukguk (2022) stated that in the last 14 years (2009-2022), there have been 58 civil lawsuits against BPK, including 26 cases of lawsuits against LHP. It dramatically affects the audit quality of an auditor who carries out state financial audits. BPK auditors must be more qualified to produce quality audit results as a preventive effort in dealing with potential lawsuits to maintain public trust in BPK.

The problem of misuse of state finances by manipulating data and the potential for BPK audit results to be sued also shows that the audit quality is poor because it has not been able to detect the fraud. Poor audit quality can affect public trust in BPK. Sari & Lestari (2018) explain that audit quality in the public sector is the probability that a government auditor can find and report fraud that occurs in an agency or central or local government. The elements needed to produce audit quality include the ability and personal quality of audit partners and staff, an effective audit process, and the reliability and usefulness of the audit report (Gray et al., 2019).

Technological developments also have significant implications for the audit field because they provide convenience regarding automation and control and efficiently improve the decision-making process for audit opinions (Mancini et al., 2015). Tedjasuksmana (2021) reveals that digital data has a risk that data can be engineered or manipulated, so auditors must be aware of the validity of audit evidence. BPK also utilizes the development of information technology in conducting state financial audits to minimize audit risks and improve the quality of its audits by creating big data analytics applications known as BIDICS. Big data analytics explains how entities can obtain, store, share, evaluate, and perform an activity based on information created by electronic devices and humans as users, which will later be distributed through computers and network technology (Tunggal & Elliza, 2021). Therefore, this research must be conducted to determine the factors that affect audit quality and the influence of big data analytics on audit quality directly and mediating independent variables.

Several previous studies have analyzed audit quality and big data analytics in the government sector. Siregar et al. (2022) found that auditor competence positively and significantly affects audit quality. It shows that the higher the auditor's competence, the higher the audit quality. Darmadi & Thaha (2019), in a qualitative descriptive study analyzing the quality of the audit of state financial management by BPK, found that the independence and competence of the auditors strongly influence the quality of the audits. However, Nisfu (2023) found that auditor work experience does not affect audit quality. Furthermore, Darmadi & Thaha (2019) explained that the quality of the implementation of the BPK audit is still very vulnerable to opportunities for fraud. This is indicated by the large number of discussion rooms for entities and examiners; even before the findings are finalized, the examiner will still ask for an explanation from the examined entity.

Putra et al. (2023) revealed that the utilization of big data analytics (independent variable) has a significant effect on audit quality (dependent variable) at BPK. Implementing big data analytics also affects the effectiveness of audits in government agencies, such as the Majalengka Regency Inspectorate (Ahmad & Aliyudin, 2020). Alsahli & Kandeh (2020) also found that big data analytics affects audit quality. Research conducted by Syahputra & Afnan (2020), which examines the influence of big data as an independent variable on fraud detection with forensic audit as an intervening variable, found that big data is also proven to have a positive effect on fraud detection and forensic audit. It shows that big data analytics can also help in fraud detection. In addition, Tunggal & Elliza (2021) found that the higher the implementation of big data analytics, the lower the potential for audit delay for the company. However, Listya et al. (2023) found insufficient evidence that big data analytics affects audit delay and quality.

Furthermore, Al-Ateeq et al. (2022) conducted research using independent variables, namely perceived usefulness and perceived ease of use, moderating variables, namely the use of big data analytics, then the dependent variable is audit quality. The results of his research found that perceived usefulness and ease of use positively affect audit quality. In addition, the results found a moderating effect of using big data analytics on the relationship between perceived usefulness and audit quality. However, the study has no support regarding the moderating effect of using big data analytics on perceived ease of use on audit quality.

On the other hand, data analytics has challenges in its utilization, namely auditor training and expertise, data availability, and expectations of regulators and users of financial statements (Putra et al., 2023). Omitogun & Al-Adeem (2019) revealed that auditors are required, in addition to having the skills needed to collect and evaluate audit evidence objectively and be diligent in

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

carrying out tasks with integrity. Auditors must also have specialized knowledge. Thus, the public will consider auditors trustworthy. Implementing big data analytics in auditing requires auditor competence to use it. Auditors must understand the impact and risks of big data and strive to acquire the necessary professional skills to remain relevant to their society in general and their clients in particular (Omitogun & Al-Adeem, 2019).

IT application control is a great opportunity for auditors to increase their knowledge of the company and reduce the manual substantive testing that auditors must do (Küçükgergerli & Atılgan Sarıdoğan, 2022). The better the skills possessed by the auditor in carrying out his duties, the better the performance that the auditor will show (Pesireron, 2016). Alsughayer (2021) reveals that auditor competence is based on knowledge, continuous improvement, training, the ability to find professional experience certification, as well as education, significantly impacting audit quality. Auditors with adequate skills will carry out their main duties and functions effectively, prepare examination work papers properly, and carry out audit planning and coordination properly, which affects audit quality. This makes the basis for considering this study using the independent variable, namely competence, to analyze the effect of competence on audit quality directly or mediated by the implementation of big data analytics.

Motivation is an impulse that arises in a person consciously or unconsciously to act with a specific purpose. In their research, Sahid et al. (2021) argue that big data analytics is starting to be utilized by Malaysian public agencies and believe it can be successful. The assumption is that the technology will produce feasible results to improve expected performance. Malaysian Public Agencies expect big data to assist in advancing the public's demands for government services. Dagilienė & Klovienė (2019) revealed audit firms' intentions to use big data and big data analytics and to expand their understanding of the use of big data and big data analytics tools in external auditing. The adoption of big data analytics-based audit practices for audit firms as a way to improve audit quality and drive audit efficiency, which can result in competitive audit fees.

The degree of computer technology use by application users can be predicted through their attitudes toward technology, such as the desire to add supporting peripherals, the motivation to keep using, and the desire to motivate other users (Heryanta, 2018). Ferri et al. (2020), in their research measuring auditors' willingness to implement blockchain technology, found that performance expectations, social influence, and auditor effort expectations affect the implementation of blockchain technology. Therefore, the second independent variable in this study is motivation. It tests the auditor's motivation to use existing big data analytics, which can affect audit quality directly or mediated by big data analytics.

The results of previous studies, including those conducted by Putra et al. (2023) and Al-Ateeq et al. (2022), revealed that big data analytics significantly affects audit quality. Auditor competence based on, among others, knowledge, experience, training, understanding of risks, and an auditor's skills significantly impact audit quality (Omitogun & Al-Adeem, 2019; Alsughayer, 2021). In addition to auditor competence needed to improve audit quality, an auditor's motivation to use big data analytics also affects audit quality, as found by Ferri et al. (2020) (Heryanta, 2018). It shows that competence, motivation, and big data analytics are believed to have benefits in improving audit quality. However, research by Nisfu (2023) found that auditor work experience does not affect audit quality. Research conducted by Al-Ateeq et al. (2022) shows that using big data analytics has no moderating effect on perceived convenience on audit quality.

Listya et al. (2023) also found that using big data analytics does not affect audit delay and quality. There are differences in the results of these previous studies and the phenomena that occur behind this study to test the effect of competence and motivation on audit quality with the implementation of big data analytics as an intervening variable. In addition, research using big data analytics as an intervening/mediating variable in testing audit quality has yet to be found. Therefore, another differentiator from previous research is the application of big data analytics as a mediating/intervening variable. In addition, this study uses the independent variable of competence following the research suggestion of Putra et al. (2023) and adds the independent variable of motivation. This research can be a concern for auditors to increase their competence and motivation to use big data analytics to improve audit quality. In addition, this research can also help BPK identify factors that influence the use of big data analytics and audit quality.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

STUDY OF LITERATURE

Attribution Theory

Attribution theory explains how a person determines the causes and motives of a person's behavior (Ferdiansyah, 2016). Internally caused behavior is behavior that is in the personal behavior of an individual himself. Meanwhile, externally caused behavior is behavior considered to be the impact of outsiders, namely individuals, indirectly or because a condition forces such behavior. Attribution theory assumes that humans are rational and driven to identify and understand their environment's causal structure, which characterizes attribution theory (Ferdiansyah, 2016). This theory explains the attitude/behavior of auditors, namely, the competence and motivation of auditors in using big data analytics can affect audit quality.

Hypothesis Development

According to the State Financial Audit Standards (SPKN) in the Statement of Examination Standards 100 General Standards, it is explained that auditor competence is the education, knowledge, experience, and/or expertise that a person has, both about the examination and about certain matters or fields. Meanwhile, competent is capable or capable in the field it controls. Future professional auditors must have competence in three sensitive areas: analytical skills, developing new metrics, and creating a visual language for data (Yeo & Carter, 2017). Yeo & Carter (2017) revealed that the current generation of auditors possess the necessary IT skills (e.g., systems and product applications [SAP] and enterprise resource planning [ERP] as well as big data infrastructure and management skills (e.g., data analysis).

Auditors require further training in data analysis techniques and applications to enhance their investigative capabilities (Yeo & Carter, 2017). Auditors have a high appreciation of accounting-related IT systems (e.g., ERP) and big data and their application to the audit profession (Omitogun & Al-Adeem, 2019). To produce quality audit reports, auditors must have the right knowledge and experience to conduct their audits (Alsughayer, 2021). In addition, the data analytic skills of frontline and back-office employees contribute equally to audit quality (Gao et al., 2020).

Hai et al. (2019) and Sari & Lestari (2018) found that good auditor competence will result in higher audit quality. Auditor skills and competency requirements are increasingly complex and diverse. Auditors need to improve their IT skills and competencies with a primary focus on Excel (Alsahli & Kandeh, 2020). Several previous studies state that auditor competence affects the implementation of big data analytics and is very important in the audit process to improve audit quality, namely Alsughayer (2021), Omitogun & Al-Adeem (2019), Küçükgergerli & Atılgan Sarıdoğan (2022), Alsahli & Kandeh (2020), Siregar et al. (2022), Darmadi & Thaha (2019), Hai et al. (2019), and Gao et al. (2020). Based on this explanation, the hypotheses in this study are:
H1: Auditor competence positively and significantly affects implementing Big Data Analytics.
H2: Auditor competence has a positive and significant effect on audit quality.

Motivation is an impulse that arises in a person consciously or unconsciously to act with a specific purpose. Dagilienė & Klovienė (2019) reveal that, in general, auditors work with structured financial data. However, the volume and complexity of the company's business require faster and more sophisticated information and analysis of unstructured or semi-structured non-financial big data from both internal and external sources. Audit firms and auditors are interested in implementing Big Data-based audit practices and Big Data Analytics to improve audit quality and drive audit efficiency, which can result in competitive audit fees (Dagilienė & Klovienė, 2019).

Sahid et al. (2021) found two main determinants of behavioral intentions to use big data analytics: the assumption that the technology will deliver feasible results that increase performance expectations and system characteristics that match users' specific tasks. Verma & Chaurasia (2019) found that a key factor in the decision to use big data analytics is whether someone feels the need for this technology to overcome a performance gap.

Ferri et al. (2020) used The Unified Theory of Acceptances and Use of Technology (UTAUT) model to measure auditors' desire to implement blockchain technology. UTAUT defines performance expectations as the level of expectation of information system actors concerning improving their working conditions due to implementing certain technologies. Professional auditors' intention and capacity to use ICT with a particular focus on blockchain technology. Performance expectations, social influence, and auditor effort expectations influence the

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

implementation of blockchain technology (Ferri et al., 2020). Hai et al. (2019) found that when auditor motivation is good, it will result in higher audit quality. Several previous studies have stated that auditor motivation has a positive effect on the implementation of big data analytics, namely Dagilienė & Klovienė (2019), Sahid et al. (2021), Verma & Chaurasia (2019), Hai et al. (2019), Sari & Lestari (2018), and Ferri et al. (2020). Based on this explanation, the hypothesis in this study is**:**

H3: Auditor motivation positively and significantly affects implementing Big Data Analytics.
H4: Auditor motivation has a positive and significant effect on audit quality.

Klynveld Peat Marwick Goerdeler (KPMG) (2019) defines audit quality as a result of the audit being carried out consistently, in line with professional standards, in a robust quality control system, and carried out independently. PwC (2019) and Sari & Kurniawati (2021) explain that to achieve a quality audit, a deep and broad understanding of the client's business and environment is required in conducting the audit. Audit quality is a reliable and independent audit opinion and interactive communication as a basis for trust and confidence for stakeholders through consistent processes and innovative technology by people with integrity, objectivity, and professional skepticism (Ernst & Young LLP, 2019 in Sari & Kurniawati, 2021).

Gartner (2016) and Omitogun & Al-Adeem (2019) define big data as high-volume, high-speed, and/or diverse information assets that demand cost-effective and innovative forms of information processing, enabling improved insights, decision-making, and process automation. Al-Ateeq et al. (2022) used the Technology Acceptance Model (TAM) to examine the application of big data analytics to audit quality. TAM uses two dimensions, namely perceived usefulness and perceived ease of use. The research results by Al-Ateeq et al. (2022) concluded that auditors' perceived usefulness and ease of use in applying big data analytics positively affect audit quality.

Several previous studies have stated that the implementation of big data analytics has a positive effect on audit quality, namely Putra et al. (2023), Omitogun & Al-Adeem (2019), Küçükgergerli & Atılgan Sarıdoğan (2022), Alsahli & Kandeh (2020), Gao et al. (2020), Dagilienė & Klovienė (2019), Ferri et al. (2020), Al-ateeq et al. (2022), Ahmad & Aliyudin, (2020), and Syahputra & Afnan (2020). Based on this explanation, the hypotheses in this study are:

H5: the implementation of big data analytics has a positive and significant effect on audit quality
H6: competence positively and significantly affects audit quality by implementing big data analytics as an intervening variable.
H7: motivation has a positive and significant effect on audit quality with the implementation of big data analytics as an intervening variable.

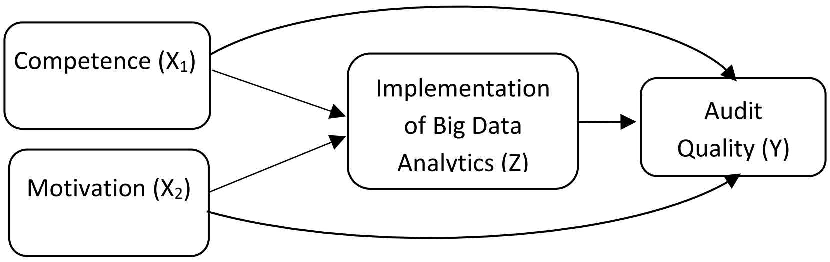

Figure 1 Research Framework
Source: data processed

METHOD

This research uses quantitative methods and primary data. The research data were obtained from a questionnaire survey distributed to respondents during December 2023. The questionnaire was distributed directly to respondents through the WhatsApp group using internet media via Google Forms. The respondents were selected based on purposive sampling, with the criteria being the State Finance Auditorate I examiners.

The data analysis method used in this research is descriptive analysis and hypothesis testing using a structural equation model. This study uses validity and reliability tests. The validity test is used

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

to measure whether a questionnaire is valid, whereas the measurement of indicators in this study uses a Likert scale with values from 1 to 6. The reliability test measures a questionnaire, an indicator of a variable or construct. Structural Equation Modeling (SEM) is a multivariate analysis used to analyze the relationship between variables in a complex manner (Hair et al., 2017).

The dependent variable used in this study is audit quality. The indicators of this variable refer to indicators from research by Al-Ateeq et al. (2022), which include as many as 15 indicators. The indicators of the dependent variable on audit quality are as follows:

KUAL1	Good experience and specialization in various fields are required when performing audit tasks.
KUAL2	To perform audit tasks, it is necessary to understand the auditee's accounting information system.
KUAL3	When conducting an audit, there is no need to know the auditee's environment.
KUAL4	Identify the auditee's critical and sensitive processes when starting the audit task.
KUAL5	auditee's internal reports are reviewed to assess foreseeable risks.
KUAL6	Start the audit task by creating a plan and ensuring it is followed.
KUAL7	Discussed some financial reports with the team leader.
KUAL8	Discussed some financial statements with auditee managers.
KUAL9	Never mind the weaknesses and risks identified in previous years.
KUAL10	The audit programs used are often inappropriate and unrelated to the identified weaknesses.
KUAL11	Provide some non-audit services to auditees.
KUAL12	No need to contact the auditee's internal auditor when conducting an audit.
KUAL13	Consider auditor specialization when distributing tasks between auditors.
KUAL14	Usually, I spend a long time with auditees who have been audited.
KUAL15	Every process in the audit work is reviewed to ensure quality control.

The intervening variable used in this study is the implementation of big data analytics. This variable has two dimensions: Perceived Usefulness with 15 indicators and Perceived Ease of Use with 12 indicators. The dimensions and indicators of this variable refer to the research of Al-Ateeq et al. (2022). The indicators of the audit quality intervening variable are as follows:

IBDA1	Using big data analytics in work will make it possible to complete tasks faster.
IBDA2	The use of big data analytics will improve job performance.
IBDA3	The use of big data analytics in work will increase productivity.
IBDA4	The use of big data analytics increases the effectiveness of work.
IBDA5	The use of big data analytics makes work easier.
IBDA6	Big data analytics is useful in work.
IBDA7	Frequently use big data analytics to deal with auditees.
IBDA8	Often, big data analytics find information about specific issues in the audit process.
IBDA9	Advanced techniques are required to collect, manage, and analyze data.
IBDA10	The use of big data analytics helps in obtaining evidence promptly.
IBDA11	Using big data analytics helps obtain more relevant evidence for the items to be audited.
IBDA12	Using big data analytics increases the ability to prepare evidence with strong arguments.
IBDA13	Using big data analytics can reduce the cost of completing the audit process.
IBDA14	The use of big data analytics helps in better distribution of tasks among team members/audit teams.
IBDA15	Using big data analytics increases the ability to audit the largest amount of data and possibly increase the size of test samples.
IBDA16	Know what the term "Big Data" means.
IBDA17	"Big Data" is collected in the workplace.
IBDA18	Big data analytics is available in the audit program used.
IBDA19	Learning to work with big data analytics will be easy.
IBDA20	Ease of getting big data analytics to do what you want to do.
IBDA21	Big data analytics is flexible to interact with
IBDA22	Expert in using big data analytics.
IBDA23	Big data analytics is easy to use.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

IBDA24 Handle large amounts of variable and complex data.
IBDA25 The increase in transaction volume leads to the possibility of errors in analysis and handling.
IBDA26 An increased volume of information leads to the possibility of errors not being detected.
IBDA27 Data storage creates a big challenge for data analysis.

The independent variables used in this study are competence and motivation. Indicators of competency variables refer to research by Omitogun & Al-Adeem (2019) and Alsughayer (2021). The indicators of the independent variable competence are as follows:

COMP1 Able to research and collect reliable data effectively using Information Technology (IT) resources in a relatively short period
COMP2 Has the ability to discover and detect patterns in large volumes of data.
COMP3 Participated in training on the use of the SAKTI application.
COMP4 Participated in training on the use of SQL applications.
COMP5 Participated in training on the use of the BIDICS application.
COMP6 Understand the use of the SAKTI application.
COMP7 Understand the use of SQL applications and use them frequently during inspection assignments.
COMP8 Understand the use of the BIDICS application and use it frequently during inspection assignments.
COMP9 Effective in communicating the results of data processing.
COMP10 Knowledge of professional auditing standards significantly and positively affects audit quality.
COMP11 Knowledge of regulations has a significant and positive effect on audit quality.
COMP12 Continuous improvement and training programs enhance audit competency and quality.
COMP13 Competence can increase the ability to find material errors in financial statements, thus improving audit quality.
COMP14 Professional experience leads to competence and has a positive effect on audit quality.
COMP15 Professional certification improves audit competence and quality.
COMP16 Educational qualifications have a direct effect on competence and audit quality.

Meanwhile, the independent variable of auditor motivation has three dimensions: Effort Expectancy with three indicators, Performance Expectancy with four indicators, and Social Influence with four indicators. The dimensions and indicators of this variable refer to research by Ferri et al. (2020). The indicators of the independent variable auditor motivation are as follows:

MOTI1 Experience the ease of using big data analytics for audit activities.
MOTI2 Learning to use big data analytics will be easy.
MOTI3 It will be easy to become skilled in using big data analytics.
MOTI4 The desire is to use big data analytics to improve audit performance.
MOTI5 Desire to use big data analytics to simplify audit activities.
MOTI6 Desire to use big data analytics to improve/enhance effectiveness in audit activities.
MOTI7 Desire to use big data analytics to improve/enhance efficiency in audit activities.
MOTI8 The desire to use big data analytics because of the influence of people who influence my behavior.
MOTI9 The desire to use big data analytics in audit activities is due to the influence of people who are important to me.
MOTI10 Desire to use big data analytics because superiors think that they should learn how to use big data analytics for audit activities.
MOTI11 Desire to use big data analytics because the people I work with would argue that I should use big data analytics in audit activities

RESULTS

Table 1 shows that the total respondents were 37 examiners at the Main Auditorate of State Finance I, with 27 male respondents, or 72.97% of the total respondents, and 10 female respondents,

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

or 27.03% of the total respondents.

Table 1. Number of Respondents Based on Gender

Gender	Total	Percentage
Men	27	72,97%
Women	10	27,03%
Total	**37**	**100,00%**

Source: data processed

Based on Table 2, it is known that the majority of respondents' educational backgrounds Account for as many as 22 people or 59.46%, with the highest level of education, namely S1 (Bachelor Degree), as many as 19 people. The second most common are those other than accounting, economics, management, and information technology, with as many as 8 people (21.62%). Economics as many as 4 people or 10.81%. Meanwhile, the educational background in Information Technology is 2 people (5.41%), and Management is 1 person (2.7%) of the total respondents.

Table 2. Number of Respondents by Background and Education Level

Background	Bachelor (S1) / (D4)	Postgraduate (S2)	Total	Percentage
Accounting	19	3	22	59,46%
Economic Science	2	2	4	10,81%
Management	0	1	1	2,70%
Information Technology	1	1	2	5,41%
More	4	4	8	21,62%
Total	**26**	**11**	**37**	**100,00%**

Source: data processed

From these backgrounds and education levels, the respondents' positions consisted of First Expert Examiners, as many as 20 respondents or 54.05%, and Junior Expert Examiners, as many as 17 respondents or 45.95%. Table 3 shows that most respondents have 10-15 years of work experience at BPK, as many as 16 or 43.24% of the total respondents. Respondents with work experience in the 5-10 year range were 12 respondents or 32.43%, then those with more than 15 years of work experience were 6 respondents or 16.22%, and those with less than 5 years were 3 respondents or 8.11%.

Table 3. Respondent's Work Experience

Work Experience	Total	Percentage
< 5 Years	3	8,11%
5 - 10 Years	12	32,43%
10 - 15 Years	16	43,24%
> 15 Years	6	16,22%
Total	**37**	**100,00%**

Source: data processed

The research data obtained through the questionnaire was then processed with the Partial Least Square (PLS) approach using the SmartPLS3.0 application. Indicator validity is measured as a variable effect seen from the outer loading of each variable indicator. An indicator is reliable if the outer loading value is above 0.70 (Ghozali & Latan, 2015). Meanwhile, the outer loading value can still be tolerated up to 0.60, and anything below 0.50 to 0.60 can be excluded from the analysis (Ghozali & Latan, 2015). The results of measuring the validity of indicators can be seen in Table 4. Several indicator items were excluded from the analysis because the value was brought to 0.60.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Table 4. Validity Test Results

	COMP	**MOTI**	**IBDA**	**KUAL**
COMP1	0.754			
COMP2	0.760			
COMP9	0.737			
COMP10	0.784			
COMP11	0.761			
COMP12	0.687			
COMP13	0.760			
COMP14	0.838			
COMP16	0.753			
MOTI1		0.807		
MOTI2		0.854		
MOTI3		0.853		
MOTI4		0.948		
MOTI5		0.954		
MOTI6		0.937		
MOTI7		0.918		
MOTI8		0.670		
MOTI11		0.619		
IBDA1			0.801	
IBDA2			0.776	
IBDA3			0.769	
IBDA4			0.849	
IBDA5			0.781	
IBDA6			0.799	
IBDA7			0.688	
IBDA8			0.735	
IBDA10			0.703	
IBDA11			0.670	
IBDA12			0.754	
IBDA14			0.709	
IBDA15			0.650	
IBDA16			0.726	
IBDA18			0.689	
IBDA19			0.616	
IBDA20			0.823	
IBDA21			0.823	
IBDA22			0.697	
IBDA23			0.755	
IBDA24			0.788	
IBDA25			0.769	
IBDA26			0.682	
IBDA27			0.633	
KUAL1				0.761
KUAL4				0.782
KUAL5				0.836

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

	COMP	MOTI	IBDA	KUAL
KUAL7				0.789

Source: data processed
Description:
COMP: Competence
MOTI: Motivation
IBDA: Implementation of Big Data Analytics
KUAL: Audit Quality

The figure below is a structural model analysis (inner model).

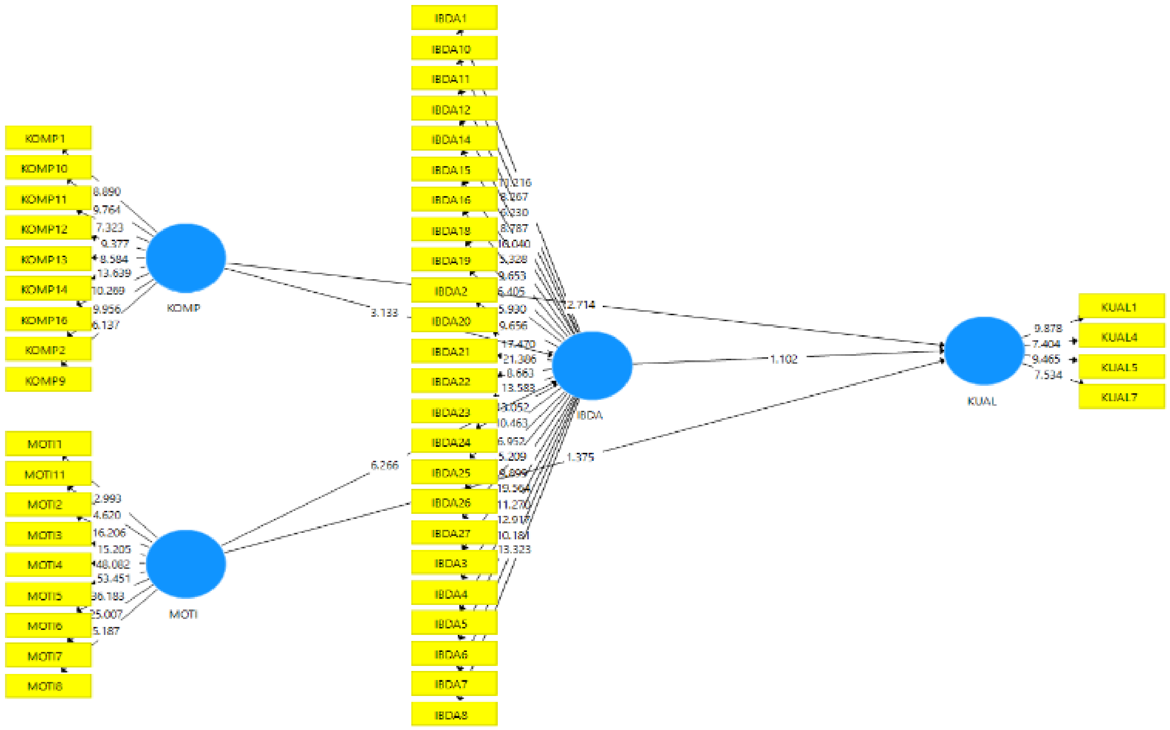

Figure 1. Inner Model
Source: data processed

All latent variables used in this study are reliable because the Cronbach alpha and composite reliability values are above 0.7 or the AVE value is above 0.5 (Hair et al., 2017). A summary of the reliability test can be seen in Table 5.

Table 5. Reliability Test Results

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Competence	0.908	0.910	0.925	0.578
Motivation	0.948	0.957	0.958	0.719
Implementation of Big Data Analytics	0.963	0.966	0.966	0.547
Audit Quality	0.807	0.819	0.871	0.628

Source: data processed

The summary of descriptive statistics for the Competency variable can be seen in Table 6.

Table 6. Descriptive Statistics of Competence

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

	Mean	Median	Min	Max	Standard Deviation	Respondents
COMP1	4.811	5.000	3.000	6.000	0.651	37
COMP2	4.405	4.000	3.000	6.000	0.914	37
COMP9	4.676	5.000	3.000	6.000	0.773	37
COMP10	5.162	5.000	3.000	6.000	0.678	37
COMP11	5.351	5.000	4.000	6.000	0.625	37
COMP12	5.405	5.000	4.000	6.000	0.591	37
COMP13	5.027	5.000	3.000	6.000	0.677	37
COMP14	5.135	5.000	3.000	6.000	0.741	37
COMP16	4.973	5.000	3.000	6.000	0.716	37

Source: data processed

Table 6 shows that the minimum value of the Competency indicator is 3 for questionnaire items 1, 2, 9, 10, 13, 14, and 16. It illustrates that some still consider themselves unable to quickly collect and analyze large data to find material errors and communicate them effectively. Therefore, auditors consider the knowledge of regulations and continuous improvement of training programs important. In addition, the maximum value of all questionnaire items for Competence is 6. Based on the average value of respondents' answers to the Competency variable questionnaire items, it ranges from 4-5, and the standard deviation is below 1. A summary of the descriptive statistics of the Motivation variable can be seen in Table 7.

Table 7. Descriptive Statistics of Motivation

	Mean	Median	Min	Max	Standard Deviation	Respondents
MOTI1	4.622	5.000	2.000	6.000	0.881	37
MOTI2	4.568	5.000	3.000	6.000	0.823	37
MOTI3	4.703	5.000	3.000	6.000	0.834	37
MOTI4	4.919	5.000	3.000	6.000	0.882	37
MOTI5	4.919	5.000	3.000	6.000	0.818	37
MOTI6	4.892	5.000	3.000	6.000	0.863	37
MOTI7	4.865	5.000	3.000	6.000	0.843	37
MOTI8	4.243	4.000	3.000	6.000	0.913	37
MOTI11	4.595	5.000	2.000	6.000	1.052	37

Source: data processed

Table 7 shows that the minimum value of the Motivation indicator is 2 for questionnaire items 1 and 11. It illustrates that there are still respondents who think they are not motivated to use big data analytics because they have not found it easy to use and coworkers who have not required them to use it. However, respondents are still motivated to learn and use big data analytics to facilitate the implementation of audits and improve audit quality, as indicated by the maximum value of all questionnaire items of the Motivation variable, namely 6. Based on the average value of respondents' answers to the motivation variable questionnaire items, it ranges from 4 to a standard deviation below 1. A summary of descriptive statistics for the Big Data Analytics implementation variable can be seen in Table 8.

Table 8. Descriptive Statistics of Big Data Analytics Implementation

	Mean	Median	Min	Max	Standard Deviation	Respondents
IBDA1	4.919	5.000	3.000	6.000	0.632	37
IBDA2	4.946	5.000	3.000	6.000	0.733	37
IBDA3	4.973	5.000	3.000	6.000	0.753	37

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

	Mean	Median	Min	Max	Standard Deviation	Respondents
IBDA4	5.054	5.000	3.000	6.000	0.769	37
IBDA5	4.973	5.000	3.000	6.000	0.716	37
IBDA6	4.946	5.000	3.000	6.000	0.769	37
IBDA7	4.243	5.000	1.000	6.000	1.149	37
IBDA8	4.351	5.000	1.000	6.000	1.120	37
IBDA10	4.649	5.000	3.000	6.000	0.813	37
IBDA11	4.838	5.000	3.000	6.000	0.717	37
IBDA12	4.784	5.000	4.000	6.000	0.576	37
IBDA14	4.595	5.000	3.000	6.000	0.787	37
IBDA15	4.811	5.000	4.000	6.000	0.562	37
IBDA16	4.973	5.000	4.000	6.000	0.545	37
IBDA18	4.324	5.000	1.000	6.000	1.187	37
IBDA19	4.892	5.000	3.000	6.000	0.689	37
IBDA20	4.568	5.000	3.000	6.000	0.917	37
IBDA21	4.595	5.000	3.000	6.000	0.971	37
IBDA22	4.378	5.000	2.000	6.000	0.940	37
IBDA23	4.378	4.000	2.000	6.000	0.968	37
IBDA24	4.459	4.000	3.000	6.000	0.888	37
IBDA25	4.541	5.000	3.000	6.000	0.857	37
IBDA26	4.432	5.000	2.000	6.000	1.079	37
IBDA27	4.865	5.000	3.000	6.000	0.777	37

Source: data processed

Table 8 shows that the minimum value of the Big Data Analytics Implementation indicator is 1 for questionnaire items 7, 8, and 18. It illustrates that some respondents have not used big data analytics to find information on certain issues in the audit process. In addition, the maximum value of all questionnaire items for Big Data Analytics Implementation is 6. It also shows that respondents use big data analytics to make it easier to process big data used as audit evidence so that the evidence can increase stronger audit arguments. Based on the average value of respondents' answers to the Big Data Analytics Implementation variable questionnaire items, which ranged from 4-5 and had a standard deviation below 1, A summary of the descriptive statistics of the Audit Quality variable can be seen in Table 9.

Table 9. Descriptive Statistics of Audit Quality

	Mean	Median	Min	Max	Standard Deviation	Respondents
KUAL1	5.108	5.000	3.000	6.000	0.689	37
KUAL4	5.054	5.000	4.000	6.000	0.517	37
KUAL5	5.054	5.000	4.000	6.000	0.462	37
KUAL7	5.000	5.000	4.000	6.000	0.520	37

Source: data processed

Table 9 shows that the minimum value of the Audit Quality indicator is 3 for questionnaire item 1. It illustrates that some respondents still consider good experience and specialization in various fields necessary for auditing activities. In addition, the maximum value of all questionnaire items for Audit Quality is 6. It also shows that improving audit quality requires identifying all processes and understanding the entity, reviewing the auditee's internal control reports, and active discussions within the team. Based on the average value of respondents' answers to the questionnaire items, the Audit Quality variable is around 45, and the standard deviation is below 1. Furthermore, Table 10 is a summary of the results of hypothesis testing.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

Table 10. Hypothesis Testing Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
COMP -> IBDA	0.338	0.339	0.113	2.977	0.002
COMP -> KUAL	0.615	0.646	0.218	2.824	0.002
MOTI -> IBDA	0.618	0.624	0.105	5.880	0.000
MOTI -> KUAL	-0.340	-0.354	0.241	1.409	0.080
IBDA -> KUAL	0.378	0.372	0.336	1.123	0.131
COMP -> IBDA -> KUAL	0.128	0.131	0.126	1.014	0.156
MOTI -> IBDA -> KUAL	0.233	0.227	0.218	1.071	0.142

Source: data processed
Description:
COMP: Competence
MOTI: Motivation
IBDA: Implementation of Big Data Analytics
KUAL: Audit Quality

Table 10 shows that competence and motivation positively and significantly affect the implementation of big data analytics. In addition, competence has a positive and significant effect on audit quality, while motivation has no negative effect. It proves that auditors' competence and motivation will encourage them to use big analytics and improve their audit quality. However, the big data analytics implementation variable does not affect audit quality or mediate between competence and motivation with audit quality. Auditors have the competence and desire to use big data analytics in their audit activities, but auditors still consider the use of big data analytics to be new and require adaptation in its use so that it cannot directly affect audit quality. The descriptive results of Table 8 show that the lowest value of ease of use of big data analytics is a minimum value of 2.

DISCUSSION

The association between competency and big data analytics implementation

The results of hypothesis testing in Table 10 show that the relationship between competence and big data analytics implementation has a positive coefficient value of 0.338 and a p-value of 0.002 smaller than 0.05. It shows that H_1 is accepted; competence positively and significantly affects implementing big data analytics. The results of this study support the findings which explain that auditor competence has a positive effect on the implementation of big data analytics by Omitogun & Al-Adeem (2019), Yeo & Carter (2017), Küçükgergerli & Atılgan Sarıdoğan (2022), Alsahli & Kandeh (2020), and Gao et al. (2020). Based on SPKN, auditor competence is a person's education, knowledge, experience, and/or expertise in auditing and certain matters or fields. The competencies used in this study include the ability to collect, analyze, and examine large data in a relatively short time and convey the results effectively, the ability to find and detect indications of problems in large volumes of data, education, and training, experience related to the use of big data analytics. This research shows that the competencies that auditors currently have encourage the use of big data analytics in the audit process. Increased analytical skills and knowledge of information technology are the most important things auditors need in incorporating big data analytics in the audit process. In addition, auditor competence is also required to communicate the results of using big data analytics effectively. Therefore, BPK is expected to improve auditor competence to increase the utilization of big data analytics in its audit process. Auditor competence in this study supports attribution theory, where competence comes from within oneself in response to technology development in the audit process.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

The association between competence and audit quality

The results of hypothesis testing in Table 10 show that the relationship between competence and audit quality has a positive coefficient value of 0.615 and a p-value of 0.002 smaller than 0.05. It shows that H_2 is accepted; competence positively and significantly affects audit quality. The results of this study support the findings explained that auditor competence has a positive effect on audit quality by Alsughayer (2021), Alsahli & Kandeh (2020), Gao et al. (2020), Siregar et al. (2022), Darmadi & Thaha (2019), Hai et al. (2019), Sari & Lestari (2018), and Omitogun & Al-Adeem (2019). The competencies used in this study include knowledge, ability to use big data analytics, ability to find and detect indications of problems, education and training, and professional experience of auditors. This study shows that the competence possessed by auditors today influences improving audit quality. BPK auditors are expected to improve their competence to improve audit quality as required by the SPKN. Auditor competencies such as processing large data and then analyzing it communicates that it is needed in risk assessment, control testing, substantive testing, and problem identification to improve audit quality. Therefore, BPK can conduct auditor competency mapping to provide auditors with continuous education and training programs.

The association between motivation and big data analytics implementation

The results of hypothesis testing in Table 10 show that the relationship between motivation and big data analytics implementation has a positive coefficient value of 0.618 and a p-value of 0.000 smaller than 0.05. It shows that H_3 is accepted; motivation positively and significantly affects implementing big data analytics. These findings support the findings that explain that motivation affects the implementation of big data analytics by Dagilienė & Klovienė (2019), Sahid et al. (2021), Verma & Chaurasia (2019), and Ferri et al. (2020). It shows that auditors are motivated to use big data analytics in their audit activities. Auditors are motivated to use big data analytics to increase or improve effectiveness and efficiency in audit activities. In addition, colleagues motivate auditors to use big data analytics. Auditors can create discussion groups to conduct discussions and transfer knowledge to other auditors to motivate them to use big data analytics in their audit activities.

The association between motivation and audit quality

The results of hypothesis testing in Table 10 show that the relationship between motivation and audit quality has a negative coefficient value of 0.340 and a p-value of 0.080 greater than 0.05. It shows that H_4 is rejected; motivation does not affect audit quality. The results of this study contradict those conducted by Dagilienė & Klovienė (2019), Sahid et al. (2021), Hai et al. (2019), and Ferri et al. (2020), where motivation affects audit quality. However, the relationship between auditors' motivation to use big data analytics and audit quality is not bad. It is shown in the negative coefficient value and p-value of more than 0.05. These findings indicate that auditors are motivated to use big data analytics in their activities but not improve audit quality. It is shown in respondents' answers who consider auditors motivated to use big data analytics to improve/enhance effectiveness and efficiency in audit performance/activities. This finding is also corroborated by the research conducted by Alsahli & Kandeh (2020), which found that auditors use big data analytics as part of audit procedures. Organizations and colleagues' role in motivating auditors to use big data analytics is needed to increase the use of big data analytics in the audit process to improve audit quality. This can be done by incorporating big data analytics into audit steps and increasing its ease of use.

The association between big data analytics implementation and audit quality

The hypothesis testing results in Table 10 show that the relationship between big data analytics implementation and audit quality has a positive coefficient value of 0.378 and a p-value of 0.131 greater than 0.05. It shows that H_5 is rejected; implementing big data analytics does not affect audit quality. In addition, the relationship between the implementation of big data analytics as a mediating variable between competence and motivation also does not affect audit quality, so H_6 is rejected; namely, competence has no positive and significant effect on audit quality with the implementation of big data analytics as an intervening variable, and H_7 is rejected; namely, motivation has no positive and significant effect on audit quality with the implementation of big data analytics as an intervening variable. These findings contradict the results of research conducted

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 8 Nomor 4, Oktober 2024
DOI : https://doi.org/10.33395/owner.v8i4.2374

by Putra et al. (2023), Omitogun & Al-Adeem (2019), Küçükgergerli & Atılgan Sarıdoğan (2022), Alsahli & Kandeh (2020), Gao et al. (2020), Dagilienė & Klovienė (2019), Sahid et al. (2021), Verma & Chaurasia (2019), Hai et al. (2019), Ferri et al. (2020), Al-ateeq et al. (2022), Ahmad & Aliyudin, (2020), and Syahputra & Afnan (2020) which explain that big data analytics has a positive effect on audit quality.

The results of this study indicate that the implementation of big data analytics does not affect audit quality. These results support the research findings of Listya et al. (2023), who found insufficient evidence that big data analytics affected audit quality. Auditors are motivated to use big data analytics to improve/refine audit procedures, and auditors consider the use of big data analytics to be relatively new so that it has no direct effect on audit quality. Alsahli & Kandeh (2020) reveal that auditors use big data analytics as a tool that helps auditors perform better audits and understand auditees and their transactions in a better way to get a visualization of the transaction.

Implementing big data analytics in the context of intervening variables is not an absolute thing auditors use to improve audit quality. However, auditors can use big data analytics to increase effectiveness and efficiency in carrying out audit procedures, which can be seen from the effect of competence on the implementation of big data analytics and audit quality, and auditor motivation affects the implementation of big data analytics. Furthermore, based on the BIDICS process scenario, it is explained that the implementation of big data analytics is not problem-based but goal-based. A big data analytics process begins when an interesting question arises, often called research or interesting. Then, the examiner and the data analytics team discuss the needs and availability of data, then the data analytics team conducts an analytical process to answer the question so that the auditor can utilize it. In addition, based on the demographics of the respondents, it is known that the majority of respondents' positions are First Expert Examiners with a majority of 10 to 15 years of work experience, which is quite long and based on the findings of this study that motivation affects the implementation of big data analytics, it shows that auditors with long experience consider big data analytics currently useful in the audit process but not yet to improve audit quality. In the first two years of using big data analytics tools in the audit methodology, adjusting to using them takes much time (Alsahli & Kandeh, 2020).

CONCLUSION

Based on the test results, it can be concluded that competence and motivation positively and significantly affect the implementation of big data analytics. In addition, competence has a positive effect on audit quality, but motivation does not affect audit quality. Furthermore, implementing big data analytics does not affect audit quality or mediate the effect of competence and motivation on audit quality. Auditors consider that implementing big data analytics is useful in improving audit procedures but not yet enhancing audit quality. This study has several limitations, namely the small number of respondents (samples) due to the period of filling out the questionnaire during the assignment season. In addition, the questionnaires were distributed online so that questions that needed to be confirmed could not be confirmed directly. Future research can test big data analytics and audit quality with other variables, such as fraud detection, and expand the test sample. The results of this study provide an understanding to BPK auditors of the importance of competence in big data analytics in their audit assignments to improve audit quality. Increased competence can be obtained from increased training programs. In addition, this research also provides understanding to BPK stakeholders to further improve the socialization and use of big data analytics, as well as improve the features/capabilities of big data analytics applications so that BPK auditors are motivated to use big data analytics so that it can support improved audit quality.

REFERENCE

Ahmad, E. F., & Aliyudin, R. S. (2020). Pengaruh implementasi big data terhadap audit di lembaga pemerintah (studi pada kantor inspektorat kabupaten majalengka). *Jurnal Ekonomi Manajemen, 14*(2), 356-363. https://jurnal.stiecirebon.ac.id/index.php/jem/article/view/62

Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). *Corporate Governance and Organizational Behavior Review, 6*(1), 64–78. https://doi.org/10.22495/cgobrv6i1p5

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Alsahli, M., & Kandeh, H. (2020). *Effect of big data analytics on audit: An exploratory qualitative study of data analytics on auditors' skills and competence, perception of professional judgment, audit efficiency and audit quality* (Master's Thesis). Umeå University. https://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-172302

Alsughayer, S. A. (2021). Impact of auditor competence, integrity, and ethics on audit quality in Saudi Arabia. *Open Journal of Accounting, 10*(04),125–140. https://doi.org/10.4236/ojacct.2021.104011

Dagilienė, L., & Klovienė, L. (2019). Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal, 34*(7), 750–782. https://doi.org/10.1108/maj-01-2018-1773

Darmadi, D., & Thaha, R. (2019). Analisis kualitas pemeriksaan pengelolaan keuangan negara oleh badan pemeriksa keuangan republik indonesia (BPK-RI) perwakilan sulawesi selatan. *Publik (Jurnal Ilmu Administrasi), 8*(1), 75–88. https://doi.org/10.31314/pjia.8.1.75-88.2019

Ferdiansyah, R. (2016). Analisis faktor-faktor yang mempengaruhi kualitas hasil pemeriksaan audit pemerintah (studi empiris pada bpkp perwakilan provinsi dki jakarta). *Jurnal Akuntansi Dan Bisnis, 16*(2), 109–121. https://doi.org/10.20961/jab.v16i2.200

Ferri, L., Spanò, R., Ginesti, G., & Theodosopoulos, G. (2020). Ascertaining auditors' intentions to use blockchain technology: Evidence from the big 4 accountancy firms in Italy. *Meditari Accountancy Research, 29*(5), 1063–1087. https://doi.org/10.1108/medar-03-2020-0829

Gao, R., Huang, S., & Wang, R. (2020). Data analytics and audit quality. *Singapore Management University School of Accountancy Research Paper No. 2022-151*. https://doi.org/10.2139/ssrn.3928355

Ghozali, I., & Latan, H. (2015). *Partial least squares: Concepts, techniques and applications using the smartpls 3.0 program for empirical research*. Semarang: UNDIP Publishing Agency

Gray, I., Crawford, L., & Manson, S. (2019). *The audit process: Principles, practice and cases* (7th ed.). Cengage.

Hai, P. T., Toan, L. D., & Nguyen, L. D. Q. (2019). Effect of audit rotation, audit fee and auditor competence to motivation auditor and audit quality: Empirical evidence in Vietnam. *Academy of Accounting and Financial Studies Journal, 23*(2). https://www.researchgate.net/publication/331829052_Effect_of_Audit_Rotation_Audit_Fee_And_Auditor_Competence_to_Motivation_Auditor_and_Audit_Auality_Empirical_Evidence_in_Vietnam

Hair, J. F., M., H. G. T., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications, Inc.

Heryanta, J. (2018). Pengaruh behavioral intention terhadap actual use pengguna go-jek Indonesia dengan pendekatan technology acceptance model dan innovation diffusion theory. *Jurnal Ilmiah Mahasiswa FEB Universitas Brawijaya, 7*(2). https://jimfeb.ub.ac.id/index.php/jimfeb/article/view/5754

KPMG. (2019, June). *Audit quality and transparency report*. https://home.kpmg/content/dam/kpmg/ca/pdf/2019/02/kpmg-audit-quality-2018.pdf.

Küçükgergerli, N., & Atılgan Sarıdoğan, A. (2022). The impact of application control on the quality of the audit evidence: An application example. *Journal of Accounting Institute, 0*(66), 65–77. https://doi.org/10.26650/med.1020306

Listya, A., Aspahani, A., & Sitepu, C. D. (2023). Implementasi big data analytics dan opini audit terhadap kualitas audit dengan audit delay sebagai variabel mediasi. *Owner: Riset dan Jurnal Akuntansi, 7*(3), 2062–2071. https://doi.org/10.33395/owner.v7i3.1531

Mancini, D., Dameri, R. P., & Bonollo, E. (2015). *Looking for synergies between accounting and information technologies*. Lecture Notes in Information Systems and Organisation, 1–12. https://doi.org/10.1007/978-3-319-26488-2_1

Nisfu, N. (2023). Faktor-faktor yang mempengaruhi kualitas audit badan pengawas keuangan republik indonesia. *MANTAP: Journal of Management Accounting, Tax and Production, 1*(1),26–34. https://doi.org/10.57235/mantap.v1i1.1201

Omitogun, A., & Al-Adeem, K. (2019). Auditors' perceptions of and competencies in big data and data analytics: An empirical investigation. *International Journal of Computer Auditing, 1*(1), 92–113. https://doi.org/10.53106/256299802019120101005

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Pesireron, S. (2016). Pengaruh keterampilan, jobb stress dan disiplin kerja terhadap kinerja auditor inspektorat (study empiris pada inspektorat kabupaten seram bagian timur dan kabupaten maluku tengah). *Jurnal Maneksi*, *5*(1), 26–31. https://ejournal-polnam.ac.id/index.php/JurnalManeksi/article/view/153

Putra, N. S., Ritchi, H., & Alfian, A. (2023). Hubungan big data analytics terhadap kualitas audit: Penerapan pada instansi pemerintah. *Jurnal Riset Akuntansi dan Keuangan, 11* (1), 57-72. https://doi.org/10.17509/jrak.v11i1.55139

Rajagukguk, B. W. (2022). Menghadapi gugatan dengan lhp yang berkualitas. *Warta Pemeriksa*, Edisi 3, Vol V. https://jdih.bpk.go.id/File/Download/f1be9337-869c-4b2f-83d4-dc53555e31d2/menghadapi%20gugatan_Maret%202022.pdf

Sahid, N. Z., Abdullah Sani, M. K., Noordin, S. A., Zaini, M. K., & Baba, J. (2021). Determinants factors of intention to adopt big data analytics in Malaysian public agencies. *Journal of Industrial Engineering and Management*, *14*(2), 269–293. https://doi.org/10.3926/jiem.3334

Sari, E. N., & Lestari, S. (2018). Pengaruh kompetensi dan time budget pressure terhadap kualitas audit pada bpk ri perwakilan provinsi sumatera utara. *Jurnal Riset Akuntansi Dan Keuangan*, *6*(1), 81–92. https://dx.doi.org/10.17509/jrak.v6i1.11280

Sari, Y., & Kurniawati, K. (2021). Apakah skeptisisme profesional, kompleksitas tugas dan teknik audit berbantuan komputer berdampak terhadap kualitas audit?. *Ultima Accounting Jurnal Ilmu Akuntansi*, *13*(2), 238–256. https://doi.org/10.31937/akuntansi.v13i2.2221

Siregar, M. I., Hidayat, M., Saggaf, A., Maryati, S., & Kesuma, N. (2022). Studi empiris kualitas audit pada badan pemeriksa keuangan republik indonesia perwakilan lampung. *Owner: Riset dan Jurnal Akuntansi*, *6*(4), 3445–3453. https://doi.org/10.33395/owner.v6i4.1098

Syahputra, B. E., & Afnan, A. (2020). Pendeteksian fraud: Peran big data dan audit forensik. *Jurnal ASET (Akuntansi Riset)*, *12*(2), 301–316. https://doi.org/10.17509/jaset.v12i2.28939

Tedjasuksmana, B. (2021). Optimalisasi teknologi dimasa pandemi melalui audit jarak jauh dalam profesi audit internal. *Seminar Nasional Akuntansi dan Call for Paper*, *1*(1), 313–322. https://senapan.upnjatim.ac.id/index.php/senapan/article/view/250

Tunggal, N. A., & Elliza, E. (2021). "Pensi bintey": Pengaruh implementasi big data analytics terhadap terjadinya audit delay. *Jurnal Riset Akuntansi dan Keuangan*, *16*(2), 109-120. https://doi.org/10.21460/jrak.2020.162.378

Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. *Information Resources Management Journal*, *32*(3),1–26. https://doi.org/10.4018/irmj.2019070101

Yeo, A. C., & Carter, S. (2017). Segregate the wheat from the chaff enabler: Will big data and data analytics enhance the perceived competencies of accountants/auditors in Malaysia?. *Journal of Self-Governance and Management Economics*, *5*(3),28-51. https://doi.org/10.22381/JSME5320172

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.