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Factors of Auditor's Readiness in Using Big Data Analytics Empirical Study in Indonesia

Havens Rafael[1], Heromedus Abednego[1], Kevin Deniswara[1]*

Abstract

Modern audit engagement frequently includes reviewing clients' use of Big Data platforms to ensure that they remain competitive and have access to important data. The client's system is based on external data sources obtained using big data application software. This integration is being carried out because clients are now adopting the most advanced and complicated business analytical approaches to help them make decisions. As new technologies disrupt firms, external auditors must integrate tools like Big Data Analytics (BDA) to enhance operations. As a result, this scenario gives an excellent chance for auditors to apply big data technologies to advanced analysis. The research is motivated by observational data that shows auditors' readiness to use technology is still in the planning stage. To address this, researchers distributed questionnaires to auditors in Indonesia with the goal of increasing an auditor's readiness to use TRAM. This research will achieve the following goals: (1) Knowing the understanding of an auditor in using Big Data Analytics in audit procedures, (2) Understanding the relationship between the use of technology and data processing. (3) The problem is that there are still many auditors who are not ready to use big data systems to manage financial data in the entire TRAM-based audit process using quantitative methods based on questionnaire results assisted by the SmartPls application in performing data management. This research contributes through the development of TRAM and Big Data Analytics models for the audit process in public accounting firms based on applicable audit standards.

Keywords: *TRAM, Big Data Analytics, Auditor, Public Accounting Firm*

1. Introduction

The increasingly rapid technological developments in the industrial revolution 4.0 era have transformed all business operations to become fast and integrated through the presence of IoTs, Big Data, Cloud and Blockchain. (Dalenogare et al., 2018; Haseeb et al., 2019). This integrated change is motivated by a variety of factors, including the company's needs in business processes, prompting company leaders to invest in the company by purchasing technology that can help the company's performance become more organized and effective. The company's impact on its sustainability is significant. Access to technology that organizes and speeds up work can benefit both company leaders and employees. In this way, the Company can contribute to global competition. Micro, Small, and Medium Enterprises (MSMEs) in Indonesia in 2019 have contributed 60.34% of gross domestic product over the last five years (Ministry of Industry, 2019).

Big Data is one technology that plays an important role in company sustainability. The

[1] Accounting Department, School of Accounting, Accounting Program, Bina Nusantara University, Jakarta, Indonesia. 11480
***Corresponding Autor:** kevindeniswaraignatius@binus.ac.id

advantage of using Big data that it has better advantages to implement new technologies due to its positive effect on IT implementation that promotes better ways to store data efficiently (Gu et al. 2014; Lynch 2008; Dhar and Mazumdar 2014; Raguseo 2018). It affects the financial industry in Indonesia totally. Companies' performance is defined as their ability to meet their goals and meet the expectations of their stakeholders while also surviving in the market (Griffin JM, Ji X, & Martin JS, 2003; Richard PJ, et al., 2009). The Company's Performance compares the organization's actual productivity or outcomes to the desired outcome or objectives. Big data analytics (BDA) is an amalgamation of a large volume of data gathered from various sources that allows a business to gain a competitive advantage through improved business performance (Kude T, Hoehle H, & Sykes TA, 2017). define BDA as a technique for determining and executing significant measures from big data to support decision making (Cao M, Chychyla R, & Stewart T, 2015). As a result, the use of Big Data Analytics extends beyond IT departments and into various divisions/sections within an organization. Accountants and auditors who deal with finance, for example, require a Big Data Analytics system to collect financial archives and other company financial data such as assets and liabilities centrally in a system, raising the question of whether big data analytics can be a solution to the efficiency of time used by auditors in producing audit reports.

The result could be seen on the data provided by Kominfo showing that the financial industry increases 22% up to 25% for the period of 2022-2025 (Kominfo, 2022). Furthermore, Indonesia experienced 4.94% economic growth from 2022 to 2023 (Bank Indonesia, 2023). Of course, this increase in economic growth is influenced by various types of financial data generated by investment, both public and private, which means that the amount of accelerated data growth is also increasing. The auditors still rely on the sampling method to provide reasonable assurance of the corporate financial statements materially and in accordance with the applicable financial accounting standards so that with the presence of big data technology the risks arising from the sample-taking method can be minimized and help auditors avoid the occurrence of audit delays that greatly affect the market reaction. (Suyanto, 2018; Yoon et al., 2015). In terms of presenting corporate financial statements using big data is to increase the value of a company that can be considered by investors, creditors, and the public in terms of putting confidence in the growth of the company. (Binus Accounting, 2019). The process that companies go through in the age of disruption determines the strategies that the company will employ now and in the future. As a result, company management requires Big Data as knowledge management to increase competitive advantage (Santoro et al., 2017). Capability in management is a complete and inseparable foundation, so it is critical in its application to all company activities, such as coordination, investment, and control over the control and management of information technology resources, whether they are used in accordance with the needs and priority scale of the company (Kim et al. 2012).

Companies also compete by investing in technology that will increasingly add value to the company. As a result, 69% of business leaders believe that using information technology can help them achieve their goals faster (Canaday, 2018) . Since information technology plays such an important role in management, it has an impact on the operational activities of companies undergoing technological transformation. As a result, the company's profit margin has increased due to reduced human resource expenses, and the sales process has been integrated with the system via e-commerce. Profits generated will also be very easy to read and record by the system, as the process of creating the company's financial reports will be automatically integrated through the company's internal system. All archives, history, and details of production and sales will be immediately recorded in one Big Data system, making it easier for company auditors to present operational and financial details when presenting company reports later. As a result, the purpose of using big data has a significant positive impact on financial data processing and business decision making. Therefore, companies will benefit greatly from investing in this field of technology.

In order to carry out their duties, auditors must be technologically savvy where many information systems have evolved significantly to aid the audit process until the auditor completes the reporting process with as much as 82% of effectiveness (Sangkala et al., 2021). These changes began with manual processes for obtaining, analyzing, and presenting report results, and have progressed to automatic integration for obtaining real-time information (Friday & Japhet, 2020). It also poses challenges and threats to the auditor and gives direct impact to their performance. However, the threat can be mitigated with sufficient experience and knowledge (Krahel & Titera, 2015).

As a result, the auditor must accept the development and use of technology within the scope of the audit. This readiness is discussed using the Technology Readiness Acceptance Model framework which proved by previous research that it has effects between technology readiness and consumer's intention to use technology (Lin et al., 2005).The scope of the external audit varies greatly depending on the country's external audit regulations, but in general, the scope of the external audit includes (NewVantage Partners, 2016) Compliance Audit, Financial Audit and Performance Auditing. Almost all industrial sectors have used technological advances to aid in production, distribution, data processing, marketing, and other activities. As we know audit data contains various types of information ranging from transactions, industrial sectors, subsidiaries, and charts of accounts owned by clients over a long period of time, auditors manage this data with the help of Big Data technology in order to be more effective in carrying out the audit process. Technological advancements have had a positive impact on the job of an auditor. The result is that the time required for audit sampling becomes more efficient, and the data collected is much more comprehensive in terms of time range and categories. With the transition, it is clear that the growth and development of Big Data has been rapid, and it is now being used by various professions such as auditors.

Big Data is one of the technologies that an auditor can use to carry out his duties present day. The risks that various parties face are increasing in tandem with the rapid development of technology. Of course, there will always be risks, such as fraud or deception. Fraud can occur not only in financial transactions, but also in corporate governance. The audit program can use Big data technology to make it easier for auditors to collect the necessary data. Furthermore, auditors can use big data analytics to detect fraud and make decisions. Accounts that are overstated or understated are examples of fraudulent actions that can occur in this case. Of course, this is done so that if an act of fraud occurs in the company, the auditor can quickly identify it and investigate the causes and origins of the company's fraud so that corrective and preventive actions can be taken.

According to PwC (2016) stated that PwC itself had transformed their internal audit through data analytics, data driven audit will be more challenging to other organizations which may lack in the specialized resources and capabilities which are necessary to transform the mindset and processes. Besides that PwC respondents are CAEs and other internal auditor professionals which indicates that the usage of Big Data Analytics (BDA) should be the top focus for internal audit in the next 12 months.

Besides that, EY (2015) said that Big data is the term used to describe this massive portofolio of Data that is growing significantly. Audit firms must continue their robust audits to serve the public. The profession has long recognized the impact of Big Data Analytics (BDA) on enhancing the quality of the audit due to lack of efficient technology solutions. This is providing an opportunity to rethink the way of audit procedure to make significant progress and to see the benefits of Big Data analytics on audit scope. The Value of Integrating Big Data Analytics is not only realized when used by an auditor but to develop new skills on using the analytics program to produce the audit process evidence and the audit conclusions. Knowing the preparedness of an auditor or auditor profession in the readiness to operate the use of big data analytics in conducting audit cycles/processes up to the decision-making of highly confidential financial reports of the company. The problems faced by the auditor in using the Big Data Analytics (BDA) are the privacy and confidentiality of data, the completeness and integrity of the extracted client data may not be guaranteed, problems of compatibility with the client system, gaps in expectations among stakeholders, and issues of management practices arising related to the storage and accessibility of data during the retention period required for audit evidence (Acca Global, 2023).Based on the Technology Readiness Acceptance Model (TRAM) obtained in real time using the questionnaire, this study was conducted to determine the relationship between the problem of BDA use and the profession of auditor in Indonesia.

2. Literature Review

The requirement to collect various types of data connected to financial client reports utilizing technologies that evolved in the twenty-first century influenced the development of the auditor profession. Of course, this will substantially improve an auditor's capacity to locate and accommodate vast amounts of data. Of course, there are some procedures that need the auditor to continue using manual tools. As a result, an auditor must still be prepared to use technology in his audit work.

2.1. Technology Readiness Level in Auditing

Technology Readiness Level (TRL) is a tool for system engineering that was developed to carry out technology maturity assessments (Sauser et al. 2008 & 2010). Regardless of the user's technical expertise, recognizing a technology's technical maturity during its acquisition phase gives people a constant frame of reference for comprehending technological evolution. A parameter that shows how much the technology is ready to be applied globally and used by users. (Olechowski, Eppinger, and Joglekar, 2015).

This is based on the Theory of Reasoned Action (TRA) as a link between the use of technology in the real world and the ease of use of technology by users so that they can easily determine the user's attitude towards using technology in their work. (Venkatesh et al., 2000). User intentions in using technology are also influenced by user beliefs about the ease and results of using technology in daily work. Both of these factors are influenced by several external variables, namely the Process of social influence and Cognitive instrumentation (Venkatesh & Davis, 2000), as well as the support, training, and accessibility felt by users. (Karahanna & Straub, 1999).

The Technology Acceptance Model is also applied as a prediction of new technologies. Users will be more free to choose several alternative paths in applied technology (Lin, Shih, & Sher, 2007). Fred Davis introduced the Technology Acceptance Model (TAM) in 1986 for his doctoral proposal, as shown in Figure 5. TAM, an adaptation of Theory of Reasonable Action, is designed specifically for modeling users' acceptance of information systems or technologies.Fred Davis introduced the Technology Acceptance Model (TAM) in 1986 for his doctoral proposal. TAM, an adaptation of Theory of Reasonable Action, is designed specifically for modeling users' acceptance of information systems or technologies.

Auditing at the state level is both a humdrum set of techniques seeking to tabulate, numerate, and comprehend numerous functions and operations at a finer level, and a basic foundation upon which both liberal and neoliberal regimes are created. The liberal State, which represents a belief in more evaluative forms of governance (Ferlie, Musselin, and Andresani 2008) and is emblematic of curiously self-limiting modes of intervention (McKinlay, Carter, and Pezet 2012), is critical in propagating self-discipline as a widespread means of instituting social order. As a result, government auditing has far-reaching consequences and stakes.

When auditors are believed to have performed insufficiently, there are often critiques and reactions from authorities, who subsequently move to rigorously regulate auditing. Since the early twentieth century, this has been a recurrent cycle, and any deregulation has been extremely rare. Several rounds of such problems and reactions have recently occurred in many parts of the world. Auditing is unusually complex due to a number of factors, and it is likely that some issues will arise that will never be resolved. The complexities of auditing include the challenges of organizing highly skilled professionals to take on a position of great responsibility such as developing new techniques to meet changing business needs, and meeting the needs of stakeholders.

2.2. Big Data and Analytics in Auditing

Accounting and auditing professions became more digital as time passed (Kurniawan & Mulyawan, 2023). A collection of data in large volumes and various forms of data with the aim of performing data processing and analyzing on a system with a low probability of failure. The research process using large-scale data to find hidden patterns and secret correlations is called the big data analytics method (SAGIROGLU, 2013). Saving costs and time are also supporting factors that companies must be interested in using Big Data in their operational systems. Previous research indicates that there are main characteristics of big data, which IDC (2013) identifies as the data itself, the analytics of the data, and the presentation of the results of the analytics, and another research stated that big data involves technology, analysis, social, technical, and legal (Fosso Wamba et al., 2015; Boyd & Crawford, 2012; IDC, 2013). Other than from that, previous research has attempted to quantify the level of reliance on supply data. Salonee Patel & Manan Shah, 2022).

The characteristics of various Big Data models are divided into 4 parts which are called "The Five V of Big Data" containing Volume, Velocity, Variety, Veracity, and Value. (CGMA 2013; Chen et al. 2012; Davenport 2014; McAfee & Brynjolfsson 2012; Rahayu et al., 2017). The five V form was not employed in prior study because it was still in the four V form, but it is still essential because it is used to identify chances for financial fraud modeling, as well as trends for stock market prediction and quantitative modeling.(Tom Smith, Adrian Gep, Martina K, & Terrence J, 2018)

Big Data Analytics or BDA is defined as the process of discovering and managing useful information, patterns, or conclusions from Big Data in order to support managerial decisions (Cao et al. 2015). Big Data truly assists businesses—even auditors—in making judgments. This is because the more high-quality data saved, the more information available for decision-making, which has a direct and favorable impact on the auditor profession's performance. (Wieder & Ossimitz, 2015). Big Data Analytics (BDA) has several integration methods, as shown in Figure 2.

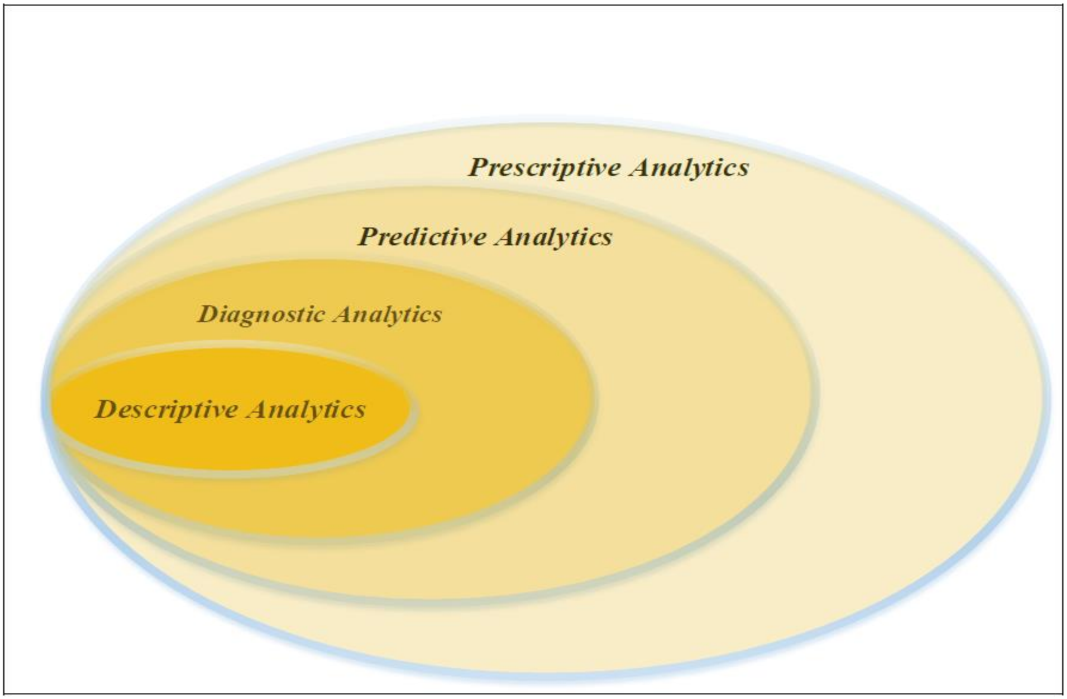

Figure 1: Big Data Analytics Method Integrations.

As shown in Figure 1 (Husamaldin & Saeed, 2020), Big Data Analytics Method Integrations are divided into four stages, with descriptive analytics being the easiest and prescriptive analytics being the most difficult. In the descriptive analytics stage, the data is categorized, and the diagnostic analysis stage comprises data collection, reporting, digging, and grouping the data into subcategories. Predictive analytics is a crucial stage since it designs future outcomes using statistical and machine-learning technologies. Furthermore, the gathered data will be evaluated, simulated, and summarized at this step to provide predictions that provide a good knowledge of what can happen. The Prescriptive analytics method then improves the data from the previous three ways to generate a good framework and incorporate decision making based on deeper learning techniques. Table 1 shows the big data analytics techniques that can be used to perform these methods (Husamaldin & Saeed, 2020).

Table 1: Big Data Analytics Techniques.

BDA Method	BDA Techniques
Descriptive and Exploratory Method	Mathematical Calculation Visualization
Predictive	Machine Learning Linear and Non-Linear Regression Classification Data Mining Text Analytics Bayesian Methods Simulation
Prescriptive	Stochastic Models of Uncertainty Mathematical Optimization Under Uncertainty Optimal Solutions

2.3. Technology Readiness Acceptance Model (TRAM)

The Technology Readiness Acceptance Model (TRAM) is a technology adoption that aims to determine a person's readiness, intention and desire to use technology by exploring the latest technological developments. In addition, the Technology Readiness Acceptance Model can assist users in controlling work and improving performance. TRAM (Technology Readiness and Acceptance Model) is the most recent contribution, combining the common personality dimension of TRI with the specific dimension system of TAM.

In a study of Vietnamese companies, perceived utility (PU) and perceived ease of use (PEOU) criteria were used on the Technology Readiness Acceptance Model (TRAM) to explore the impact of auditors' acceptance of artificial intelligence (AI). The findings indicate that perceived usefulness (PU) and perceived ease of use (PEOU) have a beneficial impact on the use of artificial intelligence (AI) in Vietnam's accounting and auditing industries. As a result, implementing appropriate procedures and training for auditors is critical for the company's industry in the long run. (Nguyen Thi Mai Anh, Le Thi Khanh Hoa, Lai Phuong Thao, Duong Anh Nhi, Nguyen Thanh Long, Nguyen Thanh Truc, and Vu Ngoc Xuan, 2024)

This explains how personality dimensions can influence a person's experience and how he uses new technology. More knowledge reflects more extensive, complex, experienced, expert, and familiar knowledge, and thus high-knowledge consumers may process issue-related information and make evaluative inferences about product features with greater effort.

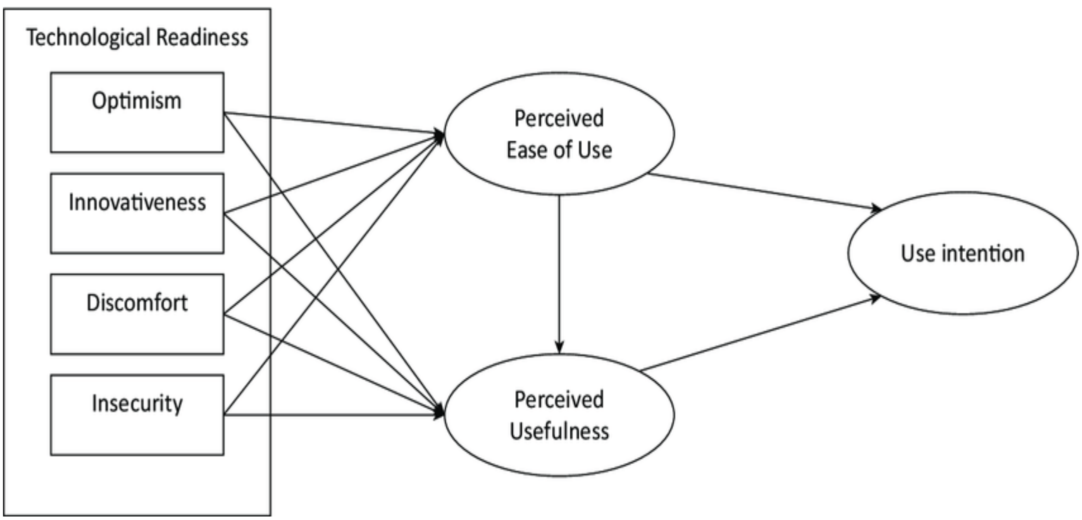

Figure 2: TRAM Conceptual Framework.

Technology Readiness includes four connected dimensions which are Optimism, Innovativeness, Discomfort, and Insecurity.

2.4. Hypothesis Development

2.4.1 Relationship between Optimism (OP) and Perceived Ease of Use (PEU) and Perceived Usefulness (PU) of Big Data Analytic

H1 : *Optimism (OP) has a positive impact on Perceived Ease of Use (PEU) of Big Data Analytic*
H2 : *Optimism (OP) has a positive impact on Perceived Usefulness (PU) of Big Data Analytic*

Optimism will affect one's perception of the ease of use of readiness technology, which will make users free from any effort. In addition, optimism in the use of technology will increase efficient control of the role and use of technology (Hallikainen and Laukkanen, 2016). Users also believe that an optimistic attitude towards the use of technology will greatly affect the performance of the performance carried out, such as in the use of Big Data analytics, which will be easier to master by users (Buyle et al., 2018).

2.4.2 Relationship between Innovativeness (IN) and Perceived Ease of Use (PEU) and Perceived Usefulness (PU) of Big Data Analytic

H3 : *Innovativeness (IN) has a positive impact of Perceived Ease of Use (PEU) of Big Data Analytic*
H4 : *Innovativeness (IN) has a positive impact of Perceived Usefulness (PU) of Big Data Analytics*

Technological progress will continue indefinitely. Technology will continue to grow, making it easier and more straightforward for people to master it at work and in everyday life. Of course, this will have an impact on Big Data Analytics, which will become more prevalent in audit work contexts. Fresh objects symbolize innovation, and they also bring fresh ideas on how to use and generate more diverse data from Big Data Analytics. As a result, auditors are increasingly interested in adopting Big Data Analytics and processing data from sources other than standard data gathering technologies to increase work performance (Buyle et al., 2018).

2.4.3 Relationship between Discomfort (DC) and Perceived Ease of Use (PEU) and Perceived Usefulness (PU) of Big Data Analytic

H5 : *Discomfort (DC) has a negative impact on perceived ease of use (PEU) of Big Data Analytics*
H6 : *Discomfort has a negative impact on perceived usefulness (PU) of Big Data Analytics*

One of the factors that discourage auditors from using big data analytics is discomfort, which can manifest as overly sophisticated technological features that require an auditor to incur a relatively high learning cost, resulting in a poor product evaluation and making users overwhelmed in learning existing features. The difficulty of researching these characteristics affects an auditor's performance (Buyle et al., 2018).

2.4.4 Relationship between Insecurity (INS) and Perceived Ease of Use (PEU) and Perceived Usefulness (PU) of Big Data Analytic

H7 : *Insecurity (INS) has a negative impact on perceived ease of use (PEU) of Big Data Analytics*
H8 : *Insecurity (INS) has a negative impact on perceived usefulness (PU) of Big Data Analytics*

Someone's insecurity about the role of technology readiness creates a negative perception that technology will become a problem in everyday life because it cannot work properly (Godoe & Johansen, 2012). This distrust will have implications for users and other people who will use technology such as Big Data Analytics in the world of auditing work (Buyle et al., 2018).

2.4.5 Relationship between Perceived Ease of Use (PEU) towards Use Intention (UI) of Big Data Analytic

H9 : *Perceived Ease of Use (PEU) has a positive impact on Use Intention (UI) of Big Data Analytics*

Big Data Analytics features make it easier for auditors to collect and analyze massive amounts of data in a timely and effective manner. As a result, the time necessary for an auditor to accurately prepare a client audit report and produce good performance is lowered (Buyle et al., 2018).

2.4.6 Relationship between Perceived Usefulness (PU) towards Use Intention (UI) of Big Data Analytic

H10 : *Perceived Usefulness (PU) has a positive impact on Use Intention (UI) of Big Data Analytics*

Increasing performance that is positively matched with the usage of technology will make one's work performance much easier, such as data processing and application. For example, the goal of employing Big Data Analytics is to make it easier for someone to handle massive amounts of data quickly and easily. This aim is essential for someone to use technology as a valuable tool in their daily lives and at work (Buyle et al., 2018).

2.4.7 Relationship between Perceived Ease of Use (PEU) towards Perceived Usefulness (PU) of Big Data Analytic

H11 : *Perceived Usefulness (PU) has a positive impact on Perceived Ease of Use (PEU) of Big Data Analytics*

With Big Data Analytics features that do not require a lot of effort, an auditor can produce good audit results and performance without spending a lot of time and effort collecting and processing large-scale data at the same time (Buyle et al., 2018).

3. Research Methodology

The target of our research is the scope of auditors in the company by using quantitative research methods, namely obtaining quantitative data using questionnaires as a method of survey. The survey was conducted by utilizing Google Forms as the medium. The questionnaires were adapted from Buyle et al., 2018; Al-Duwaila & AL-Mutairi, 2017; Moradi & Nia, 2020; Andayani & Ono, 2022; FAJRI, 2016; Arlin et al., 2015 for Technology Readiness Acceptance Model variables. Our questionnaires are divided into 3 categories: (1) respondent data such as name, age, domicile, job position, work experience (i.e. respondents are auditors who has been working for 2-5 years) ; (2) respondent's knowledge about Technology Readiness Acceptance Model (TRAM); (3) Items that indicate each variable on a four-point likert scale (one to four points representing strongly disagree to strongly agree) to evaluate the most appropriate answers to the questions supplied (Beglar & Nemoto, 2014). Based on the auditor's experience conducting field work audits with Big Data Analytics (BDA), the qualitative method aids in the accurate collection of data from the field in real time. This is due to the fact that each public accounting firm's systems and problems are diverse. The survey was conducted in two stages. First, the questionnaire was pretested on 50 people for two weeks to determine the validity and reliability of the questions. We tried to get more responses after the results were shown to be invalid, therefore the questionnaire was distributed again for two weeks, and we got 107 in total who are external auditors who work at Public Accounting Firm in DKI Jakarta. The questionnaire approach has time limits in terms of finding the number of respondents and low levels of confidence because the samples taken do not represent the existing population, thus the research must continue. We utilize the Hair et al equation to get the minimum sample number, which according to Hair et al is at least five to ten times bigger than the number of indicators, therefore the ratio is 10:1. There are seven indicators in our study. The equation is as follows:

Equation:

$S = Sample$
$I = Indicators$
$S = i \times 10$
$S = 7 \times 10$
$S = 70$

According to the Hair et al equation, our minimal sample size would be 70 samples drawn from 227 Public Accounting Firms in DKI Jakarta that work as External Auditors. The following are the characteristics of our sample selection:

Table 1: Characteristic of Respondents.

No	Criteria:	Respondents
1	Respondents who filled the questionnaire	107
2	Respondents who is a Junior Auditor	40
3	Respondents who is an Associate	36
4	Respondents who is a Senior Associate	25
5	Respondents who is a Partner	2
6	Respondents who is a Manager	2
7	Respondents who is an Intern	2
	Final Respondents as the sample	107

We utilized SmartPls version 4 as a research data processing application.

Equation

$$UI = \alpha + \beta OP + \beta IN + \beta DIS + \beta INS + \beta PEU + \beta PU + \varepsilon$$

UI is use intention, OP refers to optimism, IN represents innovativeness, DIS indicates discomfort, INS stands for insecurity, PEU represents perceived ease of use, PU refers to perceived usefulness, and ε implies error. Alpha α is constant β to represent the independent variable's respective coefficient that explains the correlation towards the dependent variable.

4. Data Analysis and Results

4.1 Descriptive Statistics

In all, 107 respondents had completed the questionnaire which consisted of 45.4% female and 54.6% male where 75% most of them are at the age between 20-25, 23.1% at the age of 26-30, 0.9% between 36-40, and 0.9% over 50 years old. Regarding the respondents work positions, 37% are junior auditors, 34.3% are associates, 23.1% are senior auditors, 1.9% are partners, 1.9% are managers, 1.9% are audit interns. Where 79.7% of the respondents live in DKI Jakarta, the other 15.7%, 0.9%, and 3.7% live in Tangerang, Bogor, and Bekasi. Their auditing work experience likewise ranges from one year to fifteen years. The results demonstrate that the majority of respondents (44.4%) are aware of the Technology Readiness Acceptance Model (TRAM) and have previously employed Big Data Analytics (BDA) in their auditing processes. Articles on the internet, with the highest percentage of 38.9%, play an essential role in developing information about TRAM and BDA, which makes auditing easier, followed by work experiences, friends, and social media with 35.2%, 26.9%, and 15.7%, respectively.

4.2 Validity and Reliability

According on the information gathered from our questionnaires, we have 107 respondents. We also processed our data with SmartPls Version 4, which revealed that our data is valid and dependable. Where the dependability is 0.918 for Discomfort, 0.812 for Innovativeness, 0.904 for Insecurity, 0.833 for Intention to Use, 0.851 for Optimism (OP), 0.849 for Perceived Ease of Use (PEU), and finally 0.900 for Perceived Used.

4.3 Result

The bootstrapping approach is used to calculate the R-squared value and to determine the required T-values and P-values with minimum T-values and P-values of 0.05 (Ghozali, 2016). When the T-statistics data approach produces acceptable results, the offered hypothesis may be considered acceptable.

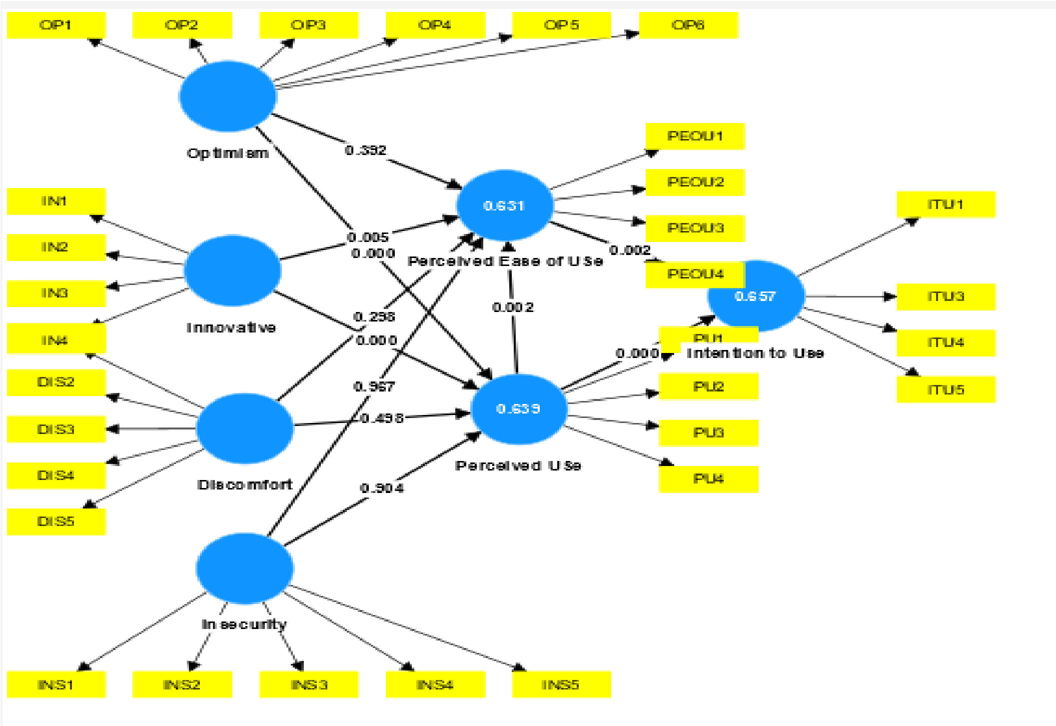

Figure 3: T-Test Result.

Based on the hypothesis test using the bootstrapping method which conducts a T-test where for the hypothesis to be accepted the value of its T-Value has to be below 0.05. As a result, some hypotheses are accepted, which are H2, H3, H4, H9, H10, H11. Where the t-values are in the range of 0.00 up to 0.05. The optimistic attitude toward the use of Big Data Analytics influences an auditor's Perceived Usefulness (PU) in employing big data analytics to complete auditing tasks because of the benefits it provides, such as auditing tasks taking less time and being easier to complete, which also relates to auditor's work stress. Besides that auditor's innovative approach toward the usage of Big Data Analytics influences his or her perceived ease of use (PEU) in bringing the convenience and ease of an auditor's endeavor to carry out the audit process where the innovative approach can be seen by learning each features of big data analytics enthusiastically and use it comfortably where using big data analytics helps conducting auditing processes, improve performance, and minimize work difficulties and to produce competent audit results. With the compact features offered by big data analytics, it brings convenience to its users which encourages its users to prefer using Big Data Analytics (BDA) in their auditing activities, which also reduces the workload and stress experienced by an auditor, which is caused by the large number of clients that must be handled in a limited amount of time, so audit technology that can collect and process audit data on a large scale and quickly is required. Thus, with user confidence in the facility provided by the Big Data Analytics (BDA) to improve performance that affects the effectiveness and productivity of the auditing process, the Perceived Usefulness (PU) variable has a positive influence on the perceived ease of use (PEU) of a Big Data Analytics (BDA) for auditing (Razinskas & Hoegl, 2020; Trihutama, 2020; Laora et al., 2021).

According to the computations, certain dimensions do not affect other variables. Discomfort (DC), the data from the T-Value calculation in Figure 3 is 0.238, indicating that an auditor's

Discomfort (DC) attitude toward using Big Data Analytics (BDA) does not influence the Perceived Ease of Use (PEU) moderator. This is because it does not meet the T-value requirements, which call for a maximum value of 0.005. Meanwhile, the P-value is 0.167, indicating that the proposed hypothesis is unrelated to the research. Also, the Discomfort (DC) Given that the T-Value calculation data is 0.498, the results indicate that an auditor's uneasiness with Big Data Analytics (BDA) does not affect the Perceived Usefulness (PU) moderator. The P-value of 0.498, on the other hand, that means is irrelevant to the investigation. As a result, the Discomfort (DC) dimension in this study was rejected as unqualified since it does not significantly alter the variable moderator and dependent. As a result, data analysis reveals that a person's discomfort level when using Big Data Analytics (BDA) does not affect the perceived ease of use (PEU) and Perceived Usefulness (PU) of Big Data analytics in boosting an auditor's performance due to its convenience to use and ease of use in audit process besides that Big Data Analytics (BDA) one of the audit technology that auditors used the most (Rahayu et al., 2017).

Besides that, Insecurity (INS) also has no effect on the perceived ease of use the T-value calculation data is 0.967, and the results demonstrate that an auditor's fear of employing Big Data Analytics (BDA) does not affect the Perceived Ease of Use (PEU) moderator. Aside from that, the findings of calculating the degrees of insecurity (INS) relating to Perceived Usefulness (PU) The T-Value calculation data is 0.904, the results suggest that an auditor's fear of employing Big Data Analytics (BDA) does not affect the Perceived Usefulness (PU) moderator. However, the P-value of 0.904. According to the data analysis results, misunderstandings about the use of Big Data Analytics (BDA) do not cause an auditor to give up, even if there are difficulties that interfere with the auditor's comfort in using Big Data Analytics (BDA), because Big Data Analytics (BDA) is very compact and every feature is simple to learn (Rahayu et al., 2017).

4.4 Theoretical and Managerial Impact

4.4.1 Theoretical Impact

The Technology Readiness Acceptance Model (TRAM) is a combination of common personality dimensions of TRI that serve as a link between the use of technology in the real world and the ease of use of technologies by users, allowing them to easily determine the user's attitude toward using technology in their work. The specific dimension system of TAM, it assists users in controlling work and improving performance. Big Data Analytics is the process of identifying and managing meaningful information, patterns, or conclusions from Big Data. It is separated into four stages, with descriptive analysis being the simplest and prescriptive analytics being the most difficult. Combining TRAM and Big Data in this study reveals the correlation between workloads, time efficiency, and ease in collecting data and completing auditing processes with the level of confidence and innovation of auditors in using big data analytics is very influential in the use of big data analysis to ease the work of the auditor and speed up an auditor to gather. Furthermore, many studies indicate workload and work stress drive auditors to require data processing programs that are simple, efficient, fast, easy, and may improve auditing outcomes because the data collected is very large and handling many clients in a short time requires auditors to work quickly and accurately (Razinskas & Hoegl, 2020; Rahayu et al., 2017). Insecurity and discomfort do not affect the intention to use big data analytics to perform audit procedures and data processing on a large scale by discovering and managing useful information, patterns, or conclusions from Big Data to support managerial decisions (Cao et al., 2015). Thus, Big data analytics can be easily learned by anyone, so ignorance or lack of understanding in using big data analysis is not an obstacle to an auditor, such as relatively high learning costs that result in a poor product evaluation and overwhelm users in learning existing features (Hallikainen and Laukkanen, 2016).

4.4.2 Managerial Impact

The Managerial impact of the research calculation results shows that enhancing an auditor's readiness to use Big Data Analytics (BDA) requires an auditor's optimistic and innovative mindset. An optimistic attitude can help an auditor's competency in using Big Data Analytics (BDA) because optimism (OP) boosts the auditor's self-confidence and encourages them to implement knowledge-tracking behavior, which can be very useful in process audits. So there is a need to learn more about the usage of Big Data Analytics because it greatly benefits the audit process. Besides that, the findings of this study demonstrate that Big Data Analytics (BDA) is well-developed in the auditing field and is critical for improving auditor performance. As a result, the Innovativeness (IN) dimension will keep auditors informed and prepared when studying the Big Data Analytics (BDA) system, which will become increasingly innovative because of its ease of use, which auditors can master with thorough preparation and is very useful in carrying out management from various types of audit data. The auditor's performance proficiency in managing various sorts of data and sizes will boost the Use of Intention (UI) data analytics (BDA), making data processing simpler and more efficient. The other impact dalam proses

As a result, the Discomfort (DC) and Insecurity (INS) dimensions have no impact on an auditor's comprehension of Big Data Analytics (BDA) or willingness to use the Big Data system in processing financial data throughout the audit process. It is because auditing work is done in groups so that they can help each other to continue to be able to use Big Data Analytics (BDA) in the audit process with a positive impact resulting in efficiency and high productivity thus big data analytics plays an important role in collecting audit data on a large scale to ease the auditing process (Razinskas & Hoegl, 2020). Therefore, the Discomfort (DC) and Insecurity (INS) dimensions will not prevent auditors from employing Big Data Analytics (BDA) in their audit job. Another benefit is that Big Data Analytics (BDA) will not be a problem during the audit process, even if it cannot be used or is not working effectively. This is because, in the workplace, auditors must maintain an aware attitude toward all technological advances and innovations, such as Big Data Analytics (BDA), by always being open to new knowledge by learning theoretically and practically, aided by data problems and data types that will become increasingly diverse in the future.

Therefore, Big Data Analytics (BDA) can help auditors make choices. This is due to the Big Data Analytics (BDA) system's ability to examine and find patterns and trends in a variety of variations that conventional data analysis may miss. As a result, by making audit judgments based on Big Data Analytics (BDA), the Audit Director and other Public Accounting firm authorities can establish policies for the future audit process, including techniques, computations, and audit investigations. This is because the Big Data Analytics (BDA) information system is built on data mining, which makes it easier to examine the previous year's audit process. Aside from that, there is another managerial benefit: the audit process will be considerably more cost-effective because the Big Data Analytics (BDA) storage system keeps it in the cloud. As a result, auditors can communicate all audit data immediately without the need for IT infrastructure. In that manner, the audit process will be more efficient in terms of time, and the auditor's performance will be much better suited to carrying out each audit method.

5. Conclusion

Adopting emerging technology is imperative for auditors to enhance quality, efficiency, and insight. This study makes a valuable contribution in assessing Indonesian auditors' readiness to integrate Big Data Analytics (BDA) into assurance processes using a robust technology acceptance model. The results confirm optimistic (OP) and innovative (IN) orientation among auditors towards BDA, while perceived discomfort (DC) is still an obstacle. Additionally, perceived usefulness (PU) was most integral for driving usage intentions. These findings can guide regulators and firm management in improving training, infrastructure, and policy to support Big Data Analytics (BDA) integration. However, the novice prototype system built has limited practical application from a functionality standpoint. Further research should focus on developing more scalable Big Data Analytics (BDA)solutions tailored to audit workflows and stakeholder needs while expanding the assessment to wider industry populations.

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