Journal of Theoretical and Applied Information Technology
31st July 2023. Vol.101. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NAVIGATING THE TRUST, TECHNOLOGY FIT, AND PERFORMANCE EXPECTATION IN THE ADOPTION OF BIG DATA ANALYTICS IN GOVERNMENT AUDITING

KEVIN RIVALLDO[1] , RINDANG WIDURI[2]

[12] Accounting Department, School of Accounting – Master of Accounting, Bina Nusantara University, Jakarta, 11480 Indonesia

E-mail: [1] kevin.rivalldo@binus.ac.id, [2] rindangw@binus.edu

ABSTRACT

The Audit Board of the Republic of Indonesia (BPK) is a state institution in Indonesia that conducts financial and non-financial audits of other Indonesian state institutions. Big Data Analytics is essential to apply in BPK, where in auditing Indonesian government institutions, BPK has various forms of unstructured, heterogeneous data. Various types of heterogeneous data in BPK are financial and non-financial data that are integrated. Unstructured data can be in the form of text mining (data acquisition through social media). The application of Big Data Analytics in BPK is based on several factors. This study aims to determine the factors influencing BPK in adopting Big Data Analytics using the Initial Trust approach model, Task Technology Fit, and Performance Expectations. Accounting Firms can reference this research in adopting Big Data Analytics during their audit process. This study was conducted by distributing questionnaires, where the study population was 103 people, and the data obtained were 77 respondents. The analysis method in this study uses SEM (Structure Equation Modelling) and PLS (Partial Least Square) approach with Smart PLS software. This study reveals that Personal Propensity to Trust and Structural Assurance positively affect Initial Trust. Initial trust and performance expectations influence Behavioral Intention. Both technological and Task characteristics influence Task Technology Fit. In the meantime, Task Technology Fit has a negative impact on the Behavioral Intention of Big Data Analytics by the Indonesian AuditBoard's auditors. This research contributes to Accounting Firm and BPK in adopting Big Data Analytics through the perspective of the Initial Trust model, Task Technology Fit, and Performance Expectations.

Keywords: *Big Data Analytics, Initial Trust, Task Technology Fit, Performance Expectation, Behavioral Intention*

1. INTRODUCTION

The growth of existing technology connects every individual worldwide very quickly using data collection called Big Data. Big Data is an information technology that allows for managing, storing, and analyzing data in various forms in huge quantities. In the process of Big Data analysis, it can also be referred to as Big Data Analytics. Big Data Analytics is the process of extracting useful information by analyzing various hidden patterns, such as market trends and consumer preferences for decision-king [1].

Applying Big Data Analytics will positively impact every organization that uses it, including government organizations. The availability of large amounts of data should encourage the Indonesian government to implement Big Data Analytics. Using Big Data Analytics in Indonesia can affect the effectiveness of work carried out by government organizations, such as a financial audit. The Majalengka District Inspectorate Office has implemented Big Data Analytics in the audit process, and this makes effectiveness in the audit process can be achieved [2]. One of the financial audit government organizations is the Audit Board (BPK). BPK is a state institution of the Republic of Indonesia tasked with examining the management and responsibility of state finances, as referred to in the 1945 Constitution. BPK conducts inspection, management, and responsibility for state finances by the central government, local governments, and other countries that manage state finances based on the law [3]. In this case, various decision-making processes and data analytics are needed so that all decisions made can be proven based on valid data [4]. According to the results of interviews conducted with BPK, the financial management of the Indonesian state has various forms of unstructured and heterogeneous data. Various unstructured data can be text mining from social media such as Twitter and Instagram. As for heterogeneous data, financial and non-financial data are mutually integrated, such as social assistance recipient data, recipient data pre-employment, and list of civil servants. Conceptually, adopting Big Data Analytics in the external audit process can be considered an effective method because Big Data Analytics can identify anomalous data [5]. In addition, Big Data Analytics can also be used to reduce auditors' dependence on client data. It can provide assessments related to evaluating internal audit evidence from a company [6].

This study has eight variables that want to be tested. According to several previous studies, there is a positive influence between each variable. The variables to be tested are Personal Propensity to Trust, Structural Assurance, Initial Trust, Technological Features, Task Features, Task Technology Fit, Performance Expectation, and Behavioral Intention. Personal Propensity to Trust is derived from an individual's willingness to be trusted by others and trust others [7]. Individual Trust is representative of one's natural inner self in increasing the Initial Trust to adopt Big Data Analytics by BPK auditors. In addition, there is also Structural Assurance, a security system guarantee so that everyone who uses the system can feel safe about the actions taken [8]. Suitable Structural Assurance can make someone believe in the system and can arouse someone's interest in adopting the system. The existence of a Personal Propensity to Trust and Structural Assurance will form an Initial Trust. Initial Trust is a prominent model within the trust theory field. This theoretical framework posits that establishing Trust at the individual level is crucial in enabling individuals to trust others and subsequently engage in cooperative and mutually beneficial relationships [9]. So that way, the Initial Trust factor formed from Personal Propensity to Trust and Structural Assurance can affect the Intention of auditors BPK in adopting Big Data Analytics.

The formation of intentions to adopt Big Data Analytics is influenced by several models, one of which is Initial Trust. Additionally, Task Technology Fit is another model that accounts for the compatibility between technological features and task requirements in shaping the adoption of such analytics. Technological Feature is a variable about using a technology that needs to know specifications that can be tailored to individual needs [10]. In contrast, Task Features use something that can solve various problems from the tasks at hand [11]. There must be an interaction between a technology's features and the tasks to be completed [12]. The interaction created will cause Behavioral Intention from adopting Big Data Analytics by BPK auditors. In addition, performance expectation variables can influence an intention to adopt Big Data Analytics auditors. Performance Expectation is the degree to which individuals and groups believe using a system will help improve individual or group performance of these [11]. This Model describes a benefit of the system for its users that can affect one's work. It can help one determine their attitude to make decisions, including one of the decisions made by BPK in adopting Big Data Analytics.

Based on the description above, this study is expected to determine the factors influencing BPK auditors to adopt Big Data Analytics used in the examination process. The subject significance of this study is the result of research that provides many points of view with different values by comparing several previous studies. However, many studies that have been conducted discuss only one approach model and do not do more collaboration related to various existing approaches, so in this study adopted several research approaches. This study combines three models Initial Trust, Task Technology Fit, and Performance Expectations. The combination of the three models provides several perspectives that can be used as a reference in determining more effective decisions by the Accounting Firm. This research can also provide new insights and considerations for Accounting Firms to apply Big Data Analytics in the audit process. This research is a replication of the research conducted by [13]. The present study is distinct from prior research endeavors in that it focuses specifically on a government auditor employed by BPK. Moreover, an original contribution of this study is the examination of the Trust factor in the context of Big Data Analytics, which represents a unique and previously unexplored variable in the field of research on this topic.

2. LITERATURE REVIEW

2.1 Big Data

Big Data is a system that integrates the real world, humans, and also cyberspace [14]. The real world is related to a social reality reflected in the virtual world through various technologies. The human Task is to produce Big Data, which will then be produced into cyberspace through technology. According to [15], Big Data is characterized by its extensive volume, heterogeneity, autonomous nature, and distributed and decentralized control structure. Given its capacity to facilitate the exploration of complex and constantly evolving relationships, this resource represents a valuable tool in various domains. It is difficult to process using various traditional databases & software techniques when the data is enormous. Big Data has a goal that encourages the use of new technologies to analyze many available data sets to obtain new information on various topics. According to research conducted by [16], there are several characteristics of Big Data, namely:

Table 1. Key Characteristics of Big Data

Characteristic	Explanation
Volume	Amount of data collected
Velocity	The rate at which data arrives is stored, retrieved, and processed
Variety	Diverse data structures and forms
Veracity	Level of confidence in data quality
Value	Altered data can provide a variety of benefits
Variability	The changing nature of data
Viability	The relevance of a data
Visualization	Understanding of data

Source: [16]

The application of Big Data requires support from various dimensions of existing technologies such as Data Mining, Algorithms, Machine Learning, and Artificial Intelligence. In the use of Big Data, there is a data analytics process that refers to collecting, organizing, and analyzing large data sets to find patterns and other important information [17]. Data analytics focuses on a problem-solving process, be it a new problem or an old problem, in a better and more effective way. According to [16], there are several types of analytical processes, namely:

Table 2. Data Analytics

Kind	Question	Understanding
Descriptive Analytics	What happened?	The initial stages of data processing create a unified historical data
Diagnostic Analytics	Why does it happen?	The final stages of the root cause of the problem
Predictive Analytics	What might happen	Past data to forecast the future
Prescriptive Analytics	What to do?	Stages to find the most appropriate action to take

Source: [16]

The study [16] also describes the different benefits of foreign m– each type of analytics. Descriptive Analytics has the benefit of being able to provide possibilities & trends in the future. Furthermore, Diagnostic Analytics can be used to determine why something happened, and this analytics can provide a picture of the cause and effect of an event. Then Predictive Analytics, where this analytics uses various technological assistance such as Data Mining, Artificial Intelligence to analyze data and create scenarios that are likely to occur. Moreover, finally, Prescriptive Analytics uses several parameters to find the best solution for what is likely to happen.

2.2 Implementation of Big Data Analytics in Business & Financial Audit

Big Data Analytics uses a learning technique on large datasets, including data collection, analysis, and prescriptive modeling [18]. Big Data Analytics is a procedure to collect, consolidate, research, and exploit Big Data to find patterns and information otherwise in decision-making [19]. Big Data Analytics is a powerful technique for achieving significant decision-making steps [5]. Big Data Analytics refers to the various volumes of data and technologies used & collected from various sources, allowing to improve the performance of a job [20].

Big Data Analytics can be applied to various types of businesses in various industries to improve performance. Big Data Analytics applied in the business processes of Private Manufacturing Firms explains that the enforcement of Big Data is widely accepted by many enterprise industries leading to growth in Business Process Improvement [21]. That way, Big Data can provide excellent opportunities for a market trying to evaluate better decision-making.

Companies in various sectors have gained important insights into the structured data collected from each company's systems. Companies undergoing the process of reengineering their business operations can enhance their profitability by leveraging the significant impact of Big Data Analytics. By integrating the power of Big Data, firms can effectively optimize their business activities and achieve tremendous success. The influence of Big Data Analytics on infrastructure components allows companies to focus on achieving competitive advantage.

In another aspect, Big Data Analytics is applied in the audit process to identify risks related to the business of the audited client [22]. The application of Big Data Analytics can improve the quality of financial reporting. If a business uses Business Intelligence, it can increase the capacity of auditors to offer quality assessment [23]. Applying Big Data Analytics in an audit methodology significantly impacts the conduct of audits related to engagement activities. Also, it contributes to acquiring more skills & knowledge, especially concerning information technology. Implementing Data Analytics in the advanced stages of auditing can significantly reduce time expenditure. Auditors can leverage such tools to gain deeper insights into client activities and effectively communicate relevant findings and recommendations to clients. In addition, Data Analytics will generate fact-based audit evidence and allow auditors to visualize and analyze audit evidence for materials considerations and basis in making a decision.

Big Data Analytics positively impacts auditing, as it distracts auditors from manual activities and allows them to focus on the Task at hand [24]. More critical such as judgment and decision-making. There are two types of motivation in the audit profession: client-related and audit firm motivation. Later, Big Data Analytics can change audit procedures at all stages to provide more excellent value to the client [25].

2.3 Task Technology Fit Model

Task Technology Fit is a model released by Goodhue & Thompson (1995), where this Model is used to predict behavioral intentions from adopting something [10]. According to the Model, the technology efficacy in supporting task completion is heavily influenced by the interplay between the features of the technology and the inherent task characteristics [12]. Typical dimensions that can be considered when measuring a fit between technology features and task characteristics are data quality, location, access authorization, compatibility, user-friendliness, private manufacturing, system reliability, and information system relationships [10]. The characteristics of a task and the technological features will decide the Task Technology Fit model to contribute to the information system to be used and adapted. The success of an information system implementation correlates between the intended use and use of technology to achieve that goal.

The Task Technology Fit model reflects a positive and significant impact on the intended use of smartphones and the technological features of those smartphones in the digital enterprise environment [26]. According to [27], if someone does not achieve the desired goal, then technology is wrong and not following the goals to be achieved. It can be concluded that the Task Technology Fit model is used to measure the suitability of technology with task characteristics. It can also be used to measure the continuance use of this technology system.

2.4 Initial Trust Model

This Model can predict the behavioral intentions of adopting Big Data Analytics. This Model is a belief theory model developed by Mc Knight (1998), where this theory is based on an individual's position to believe or allow individuals to trust other people [9]. A person's desire to meet a constituted need without experience and relevant information could imply the meaning of an Initial Trust [28]. Initial Trust becomes essential when a technology user does not have experience accepting the new technology[29].

The Initial Trust Model is divided into two categories. The categories are factors that affect the Initial Trust of a person. The first category is the tendency of Trust [30]. The second category is Structural Assurance, where Trust is focused on

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the beneficial outcome of future actions by another party [31]. Based on the description above, it is found that there is a positive impact of Trust and structured power of information systems regarding behavioral intentions of adopting Big Data Analytics.

2.5 Performance Expectation

Performance Expectation is one construct from the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT was developed by [11]. Performance Expectation is predicted to influence one's adoption intentions. There is a cognitive social theory with eight integrated models based on research on technology acceptance information [32]. The emphasis of this Model is Performance Expectation which can affect the Intention to adopt Big Data Analytics. Assessment of success can be analyzed through performance, so performance expectations are one of the variables in UTAUT that significantly affect success.

Furthermore, the literature reviewed in this study consistently highlights Performance Expectation as a critical determinant of an individual's Intention to adopt a particular innovation relative to other constructs within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The research [33] discusses how many students in Thailand can receive E-Learning and how they respond to it. The results show a very positive relationship between performance and expectations. It is evidenced by the statements given by students that their parents are happy for their child to be enrolled in an online course. E-Learning acceptance is also related to the new school year taught. Senior students tend to be more responsive to E-Learning.

2.5.1 Behavioral intention

Behavioral Intention is a person's subjective possibility of achieving a specific behavior [34]. Someone who has a liking attitude towards something, then the person's actions tend to be doing behaviors that lead to that liking [35]. Suppose someone is already fond of the expectation of excellent performance from Big Data Analytics. In that case, that person will take actions that lead to adopting Big Data Analytics. Various factors can determine a person's Behavioral Intention, thus making someone want to adopt something. Various factors exist, such as the benefits that can be obtained, the satisfaction felt, and others.

2.6 Related Research

Research [30] [36] explains how the Personal Propensity to Trust variable can affect a person's Initial Trust. It takes Trust arising from one's natural mind to increase an Initial Trust, which will later affect adopting a technology.

Research [37] [38] explains the significant influence created by a technology's Structural Assurance on a person's Initial Trust. The higher the Structural Assurance of a technology given to a user, the more it will increase the Initial Trust of that user in the technology used.

The study [37] [39] explains the significant influence of the Initial Trust variable on Behavioral Intention. Initial Trust formed on the variables of Personal Propensity to Trust and Structural Assurance will make someone want to adopt technology in daily work.

Research [40] [41] explains the influence of Technological Features on Task Technology Fit. From the results of these two studies, it was found that there was a significant influence created by Technological Features on Task Technology Fit. Technology features will be adapted to the Task at hand to create Task Technology Fit.

The study [42] [41] explains how Task Features affect Task Technology Fit. This study found a significant influence of Task Features on Task Technology Fit. The characteristics of a task will be adjusted to the features of technology to create Task Technology Fit.

Research [39] [41] was conducted to determine whether there is an influence of Task Technology Fit on Behavioral Intention. One needs to adapt technology features to work being done to match the Task and the technology, which will affect one's interest in adopting Big Data Analytics.

The study [40] [43] was conducted to explain how Performance Expectation affects Behavioral Intention. From these two studies, it was found that there was a significant effect of Performance Expectation on Behavioral Intention. The higher the performance expectations, the higher the Intention to adopt someone.

Based on the results of previous research, it can be seen that there have been many studies discussing the variables in this study. Some of the studies above only present a few variables with at least a combination of each existing approach model, so they are less able to provide various perspectives. While in the results of this study, combining several approach models that make the results of this research can be a reference by Accounting Firms in adopting Big Data Analytics during the audit process, they carry out using several approach models so that there are many perspectives that are used as references in adopting Big Data Analytics.

3. RESEARCH METHODOLOGY

3.1 Hypothesis Development

The hypothesis is formulated as follows:

H1: Personal Propensity to Trust has a positive influence on the Initial Trust

Personal Propensity to Trust, a person's natural mind, can increase one's Initial Trust in adopting something. Several studies support this argument, where a well-considered predictor of Initial Trust is a person's trust tendency [30]. In addition, there is a personal tendency to believe directly in adopting blockchain technology [36]. It can be said that Personal Propensity to Trust Big Data Analytics in the audit process will affect the auditor's Initial Trust in Big Data Analytics.

H2: Structural Assurance has a positive influence on the Initial Trust

An Initial Trust can be created when there is a guarantee that the technology is suitable for use. Structural Assurance posits that maintaining a robust technological infrastructure and protective measures can foster user trust. It also assures the security and privacy of data processed via Big Data Analytics. Such trust-building mechanisms are crucial in establishing Initial Trust among users of these technologies [37]. In addition, Structural Assurance in E-Service will create Initial Trust from the data owner [38]. The underlying hypothesis posits that providing a comprehensive and sophisticated level of Assurance can effectively mitigate concerns among government auditors regarding the use of Big Data Analytics. Therefore, it will enable the emergence of Initial Trust.

H3: Initial Trust has a positive influence on Behavioral Intention

Initial Trust variables can influence a person's behavioral motives in adopting mobile payments [42]. A person's Intention to adopt an E-Wallet is influenced by the Initial Trust variable [39]. So it can be said that the stronger the auditor's Initial Trust in Big Data Analytics, the higher their Intention to adopt Big Data Analytics in audit activities. Improving the auditor's Initial Trust using Personal Propensity to Trust and Structural Assurance is necessary. Hence, auditors can consider their intentions in adopting Big Data Analytics.

H4: Technological Features have a positive influence on Task Technology Fit

Features in technology can be run simultaneously by technology practitioners and the process of Big Data Analytics itself. There is an influence created that the Task Technology Fit adoption model is influenced by the Technological Features variable of Big Data Analytics [40]. Technology features must match a job's characteristics to create intentions in adopting Big Data Analytics. This study predicts that the Technological Features used by government auditors will positively affect Task Technology Fit in the adoption of Big Data Analytics by auditors.

H5: Task Features have a positive influence on Task Technology Fit

This study assumes the task characteristics will be adjusted to the technology to be used so that it will cause a match between the tasks of the auditor and the technology in complete work by auditors. Government auditors will adjust to the new technology system when the technology system is suitable and can complete the job tasks of government auditors. This argument is supported by previous research, where companies must see which Task characteristics require cloud computing technology to help the company achieve goals [44]. This hypothesis predicts that government auditors' tasks will positively affect Task Technology Fit.

H6: Task Technology Fit has a positive influence on Behavioral Intention

The match created between a technological feature and the characteristics of a task will determine someone to adopt a technology system.

Journal of Theoretical and Applied Information Technology
31st July 2023. Vol.101. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

If the tasks to be completed follow technology, it will make one's Intention towards a technological system high. The match between the Task and the technology used will significantly affect the behavioral Intention of adopting Big Data Analytics in the healthcare industry [29]. In addition, the compatibility between technology and Task proved to be significantly influential in adopting cloud computing [41]. Previous research [29], [41] indicates that the Task Technology Fit will positively affect the Intention to adopt Big Data Analytics in the audit process by government auditors.

H7: Performance Expectation has a positive influence on Behavioral Intention

Performance Expectation is the degree to which a person believes using a technological system will help improve performance [11]. The expected performance will go hand in hand with adopting a technology. The higher one's performance expectations, the higher one intends to adopt a technology system. Performance Expectation from using M-Payment in Persian Gulf countries has significance to Behavioral Intention [43]. In this study, government auditors expect to reduce financial statement fraud. Hence, they intend to adopt Big Data Analytics in their audit process.

3.2 Research Model

This study employs the Initial Trust, Task Technology Fit, and Performance Expectations frameworks to establish relationships between key variables and formulate a comprehensive research model (Figure 1).

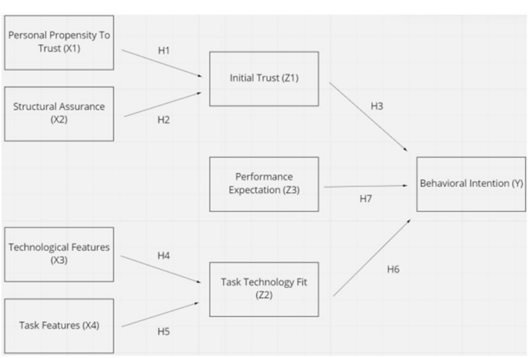

Figure 1. Research Model

Figure 1 shows that Personal Propensity to Trust exerts a significant positive influence on Initial Trust. Similarly, Structural Assurance is expected to impact Initial Trust positively. Technological Features positively affect Task Technology Fit, and Task Features positively influence Task Technology Fit. Further, Figure 1 indicates that Initial Trust positively influences Behavioral Intention. The Task Technology Fit is also predicted to affect Behavioral Intention positively, and Performance Expectation is positively associated with Behavioral Intention.

The variable measurements are presented in Table 3.

Table 3. Variable and Number of Items

No	Variable	Number of Items	References
1	Behavioral Intention	I as an auditor, intend to manage audit activities using a platform based on Big Data Analytics	[45] and adjusted to the context
		I am interested in knowing more about Big Data Analytics based platform	
		Organizations such as the Audit Board need to make changes to	
		The potential use of Big Data Analytics-based platforms is reviewed based on the benefits and decisions of an organization	
		I intend to use Big Data Analytics in the future for auditing	
2	Personal Propensity to Trust	I tend to use Big Data Analytics technology in the audit process carried out	[36] and adjusted to the context
		I tend to use data analytics in the audit process carried out	

No	Variable	Number of Items	References
		I would consider adopting Big Data Analytics in my decision-making as an auditor	
		I have a high tendency to trust Big Data Analytics in the audit process	
3	Structural Assurance	Indonesian laws and regulations keep users away from Big Data Analytics, thus making me safer in using Big Data Analytics products	[36] and adjusted to the context
		The guarantee of Big Data Analytics products makes me feel fine to use	
		As an auditor, I feel fine using Big Data Analytics products because the vendor of the product can protect its products	
4	Initial Trust	I believe in Big Data Analytics	[36] and adjusted to the context
		I do not doubt Big Data Analytics	
		I feel confident that the legal structure, as well as the technology, is enough to protect me from Big Data Analytics related problems	
5	Technological Features	The technology of our Big Data Analytics is well computerized using LAN (Local Area Network) and WAN (Wide Area Network)	[36] and adjusted to the context
		The Big Data Analytics technology we use provides real-time (instant) services	
		Our Big Data Analytics technology provides a safe and secure service	
		Our Big Data Analytics technology system is easy to use	
6	Task Features	Big Data Analytics can be used to find hidden patterns in audit job services	Adapted from [46] and adjusted to the context
		Big Data Analytics can provide insight into data analysis along with a platform for decision making	
		The processing feature of Big Data Analytics involves gathering an organization's raw data to generate meaning	
		Big Data Analytics is already suitable for better decision-making in the work I do	
7	Task Technology Fit	Big Data Analytics is already suitable for better decision-making in the work I do	[47] and adjusted to the context
		Big Data Analytics is aimed at reducing the costs of the Audit Board	
		Big Data Analytics is suitable to be tailored to the services I provide to clients	

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

No	Variable	Number of Items	References
		The operation of Big Data Analytics is beneficial in the work I do every day	
8	Performance Expectation	In my opinion, Big Data Analytics is beneficial in the work I do every day	[48] and adjusted to the context
		By adopting Big Data Analytics, it will increase my chances of being able to complete my essential tasks	
		I believe that the implementation of Big Data Analytics can optimize the audit work I do	
		I believe that with the implementation of Big Data Analytics, it can help reduce the level of financial statement fraud, provide audit evidence support in fraud cases, and can help me in Analyze unstructured data	

3.3 Population and Sample

In finding out how many samples are needed in this study, this research uses Slovin's Formula with the following calculations:

$n = N / (1+Ne)^2$

$n = 103 / (1+ (103 \times (0.05)^2))$

$n = 103 / 1.2575 = 82$

Based on the calculation above, the target sample of respondents is 82 respondents with a population of 103. With the target respondents to be achieved, it can be determined that the data collection technique used is a questionnaire. The questionnaire will be distributed to the auditor of BPK in Jakarta. A questionnaire is a data collection technique that presents a series of questions or written statements for respondents [49]. The questionnaire in this study was adopted through previous research [36] [45] [46] [47] [48]. The measurement of this questionnaire uses a Likert scale of 1 – 4 points with the provisions that 1 = Strongly Disagree, 2 = Disagree, 3 = Agree, and 4 = Strongly Agree. Questionnaires use the Likert scale to measure attitudes and evaluate social phenomena. After the researcher collects the data, the next stage is analysis. Data analysis uses Structure Equation Modeling (SEM) with Smart PLS software. Analysis using the SEM model is carried out to describe the Outer Model, Inner Model, and the results of hypothesis testing.

3.3.1 Outer Model

The Outer Model in this study conducted several tests consisting of the following:

a. Convergent Validity

Convergent Validity is contained in PLS using reflective indicators assessed based on the correlation between item and construct scores. This reflective measure can be considered high if it correlates more than 0.70.

b. Discriminant Validity

Discriminant validity relates to a principle based on a measure of low correlation with other instruments that can be used to measure other constructs.

c. Reliability Test

This test can be an instrument used as a measurement tool for a level of consistency used in research to measure symptoms, where the higher the reliability coefficient, the more reliable the research can be.

3.3.2 Inner Model

The Inner Model in this study conducted several tests consisting of the following:

a. Coefficient of Determinant (R^2)

In this test, the value of R^2 is assessed with a degree of variation consisting of 0.67 so that it can be said to be substantial; 0.33 is classified as moderate, and if the value is 0.19

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

is classified as a weak value. This test is carried out to assess the degree of variation in changes in the independent variable to the dependent variable.

b. Predictive Relevance (Q^2)

Q^2 testing has a condition, if the value of $Q^2 > 0$, then shows the value in the Model has predictive relevance, and vice versa, where the value of $Q^2 < 0$, then the test value has less predictive relevance value.

c. Effect of Size (F^2)

Measurements of F^2 are made to measure how much influence exogenous variables have on endogenous variables in structural models. It is found that if the value of F^2 gets a value of 0.02, then the category of an influence can be said to be weak. If the value of F^2 is 0.15, it can be considered medium. If the value of F^2 is 0.35, then the category can be a significant influence.

d. Goodness of Fit

The goodness of Fit is a single measure to validate a combined performance between measurement and structural models. The value of this indicator is obtained from the average AVE value multiplied by the value of R^2. If the Goodness of Fit value has a value of 0.1, then the feasibility of the Model is small. Whereas if the value of Goodness of Fit is 0.25, then the feasibility of the research model is medium. If the value of Goodness of Fit is 0.36, then the feasibility of the Model is extensive.

4. ANALYSIS AND DISCUSSION

In the process of data processing, it was found that 77 respondents filled out a questionnaire from auditor BPK, where the results of this questionnaire were still less than the target respondents, as many as 82. This phenomenon can be attributed to the limited time available during the peak season for auditors when the questionnaire was distributed. There was also the reluctance of particular BPK auditors to participate in the study by responding to the questionnaire. This questionnaire data was processed using the SEM with Smart PLS software. The following is an illustration of the SEM approach.:

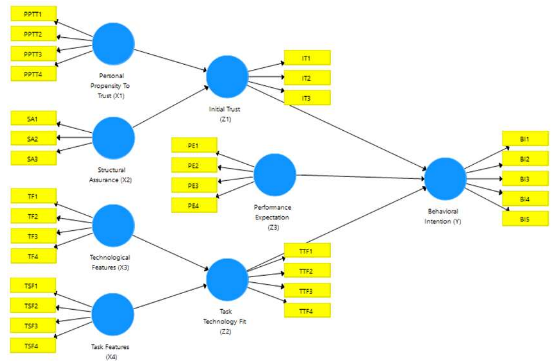

Figure 2. Structural Equation Modelling

4.1 Respondent Demographics

This section describes the results of respondents' demographics based on gender, age, job title, and time of work experience. The following are the results of respondent demographics:

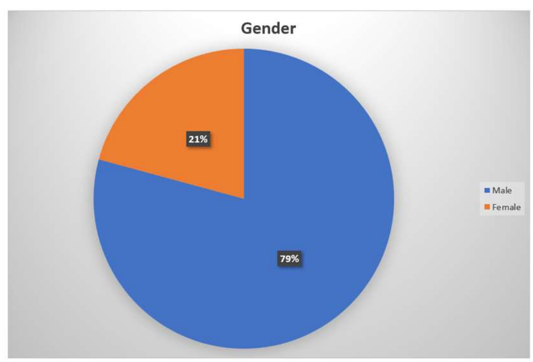

Figure 3. Demographic - Gender

Based on the diagram above, there were 77 respondents. The questionnaire was filled out by 79.2% (61 people) who were men, and as many as 20.8% (16 people) were filled in by women. It can be concluded that there are more male respondents than the number of female respondents.

Journal of Theoretical and Applied Information Technology
31st July 2023. Vol.101. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

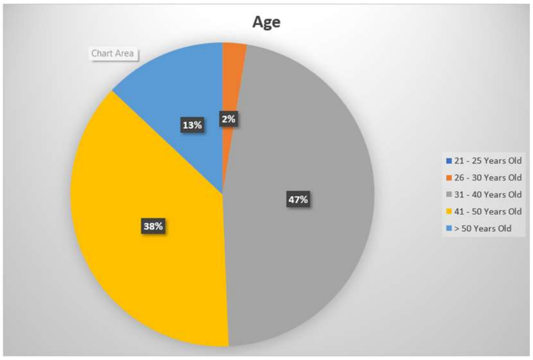

Figure 4. Demographic – Age

Figure 4 shows that the number of respondents with the highest frequency is between the ages of 41 and 50, with 29 respondents (38%). In comparison, respondents with the lowest frequency are between the ages of 26-30 years, with the number of respondents 2 (2%).

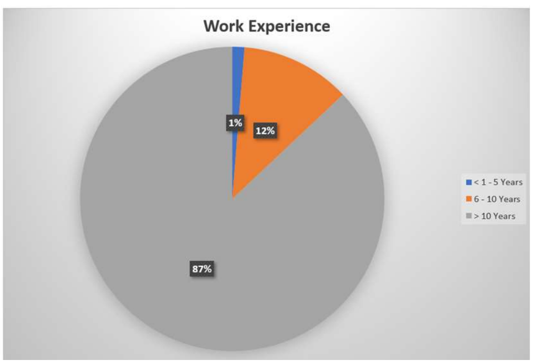

Figure 5. Demographic – Time of Work Experience

Based on the figure above, it can be concluded that the number of respondents with the highest frequency has a work experience time of > 10 years, with 87% of respondents (67 people). Then the lowest frequency has work experience time of < 1 – 5 years with the number of respondents 1 % (1 person).

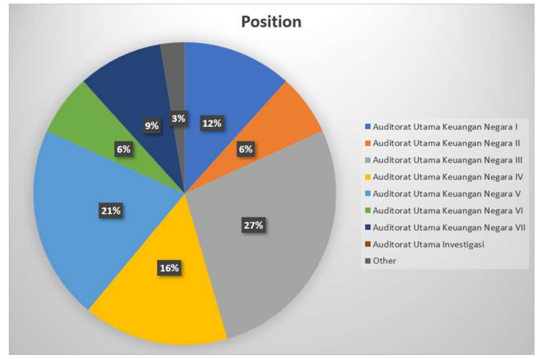

Figure 6. Demographic – Position

As illustrated in Figure 6, the questionnaire was completed by nine individuals (12%) holding the position of Financial Main Auditor I. It is followed by five individuals (6%) holding the Financial Main Auditor II position and subsequently by other positions.

4.2 Outer Model Analysis

This analysis model has been formed for a long time, where the Outer Model or Measurement model is used to measure the constructs' validity and reliability [50].

a. Convergent Validity:

Convergent validity is performed using reflective indicators assessed based on the correlation between item and construct scores. A reflective measure may be highly reliable if its correlation coefficient with the intended construct exceeds 0.70. Table 4 exhibits that each indicator within the variables holds a value surpassing 0.70, signifying the usability of all the indicators in the analysis. The lowest loading value is found in IT indicator 3, in the Initial Trust variable. The task Features variable finds the highest loading value in the TSF 3 and TSF 4 indicators.

Table 4. Outer Loading

Variable		Indicator	Loadings
Behavioral Intention		BI 1	0,922
		BI 2	0,844
		BI 3	0,915
		BI 4	0,925
		BI 5	0,941
		PPTT 1	0,916

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Variable		Indicator	Loadings
Personal Propensity to Trust		PPTT 2	0,803
		PPTT 3	0,887
		PPTT 4	0,842
Structural Assurance		SA 1	0,841
		SA 2	0,897
		SA 3	0,852
Initial Trust		IT 1	0,908
		IT 2	0,903
		IT 3	0,793
Technological Features		TF 1	0,906
		TF 2	0,831
		TF 3	0,892
		TF 4	0,894
Task Features		TSF 1	0,929
		TSF 2	0,928
		TSF 3	0,959
		TSF 4	0,959
Task Technology Fit		TTF 1	0,913
		TTF 2	0,816
		TTF 3	0,933
		TTF 4	0,875
Performance Expectation		PE 1	0,917
		PE 2	0,938
		PE 3	0,927
		PE 4	0,930

b. Discriminant Validity:

Discriminant Validity is determined based on the low correlation measure with other instruments that can measure other constructs. The Fornell-Larcker Criterion is utilized in the present test. Discriminant validity is established if the square of each construct's average variance extracted (AVE) is greater than the inter-construct correlations in the Model, as per the Fornell-Larcker calculation. Table 5 below is the result of testing Discriminant Validity using the Fornell–Larcker Criterion:

Table 5. Fornell – Larcker Criterion

	BI	**IT**	**PE**	**PPTT**	**SA**	**TSF**	**TTF**	**TF**
BI	**0,910**							
IT	0,739	**0,869**						
PE	0,905	0,726	**0,928**					
PPTT	0,852	0,773	0,815	**0,863**				
SA	0,531	0,720	0,576	0,614	**0,864**			
TSF	0,843	0,695	0,923	0,789	0,540	**0,944**		
TTF	0,810	0,780	0,855	0,817	0,654	0,826	**0,885**	
TF	0,690	0,800	0,724	0,824	0,723	0,707	0,809	**0,882**

The above table reveals that the square root of the average variance extracted (AVE) of each indicator within the research variable exceeds the inter-construct correlation values with other constructs in the Model. Thus, this research model can be said to be discriminantly valid.

c. Reliability Test:

This test aims to assess the reliability of symptom measurement by evaluating the level of consistency. The higher the coefficient, the more reliable. This research uses two testing methods: Cronbach Alpha and Composite Reliability. Cronbach Alpha is used to measure a limitation of reliability values to a construct. While Composite Reliability is used to help measure the value obtained on a construct. An indicator in the research variable can be said to be reliable if the value of Cronbach Alpha and Composite Reliability is > 0.70. The following are the results of Cronbach Alpha and Composite Reliability tests:

Table 6. Cronbach Alpha

Variable	Cronbach Alpha
Task Features	0,959
Behavioral Intention	0,948
Performance Expectation	0,946
Task Technology Fit	0,907
Technological Features	0,904
Personal Propensity to Trust	0,886
Initial Trust	0,837
Structural Assurance	0,830

Table 6 shows that all indicators in this research variable are reliable because the value above shows a > number of 0.70. The Task Features variable is reliable because it reaches a Cronbach Alpha value 0.959.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 7. Composite Reliability

Variable	Composite Reliability
Task Features	0,970
Behavioral Intention	0,960
Performance Expectation	0,961
Task Technology Fit	0,935
Technological Features	0,933
Personal Propensity to Trust	0,921
Initial Trust	0,902
Structural Assurance	0,898

Table 7 asserts that the indicators within each research variable are deemed reliable, with all indicators displaying a Composite Reliability value exceeding 0.70.

4.3 Inner Model Analysis

a. Coefficient of Determinant (R^2)

This indicator has a division of the variation level above 0.67, classified as substantial. It is said to be moderate if it is between 0.33 to 0.67; if the value is between 0.19 to 0.33, it is classified as weak. The following is the calculation result of the Coefficient of Determinant:

Table 8. Coefficient of Determinant

Variable	R-Square	R-Square Adjusted
Behavioral Intention	0,833	0,826
Initial Trust	0,694	0,686
Task Technology Fit	0,784	0.778

Based on Table 8 above, it can be seen that the value of the R^2 constructs Behavioral Intention is 0.833 and can be said to have a substantial relationship. In addition, it explains that Initial Trust, Task Technology Fit, and Performance Expectations explain 83% of behaviors that want to adopt. Initial Trust has a value of 0.694. It suggests a substantive relationship, where 69% of Initial Trust behavior is explained by Personal Propensity to Trust and Structural Assurance. Task Technology Fit with a value of 0.784, so it can be said to be a substantial relationship, where Task Features and Technological Features explain 78% of the match between tasks and technology.

b. Predictive Relevance (Q^2)

The results of Q^2 require > 0, indicating that the value in this research model has Predictive Relevance—the closer to 1, the better the Model. If the value of $Q^2 \leq 0$, then the test value has less Predictive Relevance.

Table 9. Predictive Relevance

Variable	Q^2
Behavioral Intention	0,680
Initial Trust	0,504
Task Technology Fit	0,600

Table 9 presents the number of Q^2, where each variable has a value of > 0, so it can be concluded that each variable can describe accurate predictive relevance.

c. Effect of Size (F^2)

This test is carried out in several levels of assessment. The influence category can be considered weak if the value is 0.02 to 0.15. Suppose the value of F2 is between 0.15 - 0.35. In that case, the category of influence can be considered moderate. If the value shows > 0.35, the category of an influence can be considered a significant influence.

Table 10. Effect of Size

	BI	IT	PE	PPT	SA	TSF	TTF	TF
BI								
IT	0,057							
PE	0,883							
PPT		0,576						

Journal of Theoretical and Applied Information Technology
31st July 2023. Vol.101. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

SA		0,315						
TSF							0,598	
TTF	0,002							
TF							0,471	

Table 10 suggests that Performance Expectation significantly affects Behavioral Intention. Initial Trust is influenced by Personal Propensity to Trust: the Technological Features and Task Features impact Task Technology Fit. Regarding the impact of Size, Structural Assurance displays a medium effect on Initial Trust. In contrast, the effect of Initial Trust on Size can be regarded as weak. Conversely, Task Technology Fit substantially affects size concerning Behavioral Intention.

d. Goodness of Fit

The goodness of Fit indicates the last stage in conducting an Inner Model Analysis. The value of this indicator is obtained from the average AVE value multiplied by R^2. If the Goodness of Fit value is 0.1, then the feasibility of the research model is small. Meanwhile, suppose Goodness of Fit has a value of 0.25. In that case, the feasibility of the research model is medium. Moreover, if the Goodness of Fit value is 0.36, then the feasibility of this research model is excellent. Table 11 is the calculation of Average AVE:

Table 11. Average Variance Extracted

Variable	AVE
Behavioral Intention	0,829
Initial Trust	0,756
Performance Expectation	0,861
Personal Propensity to Trust	0,745
Structural Assurance	0,746
Task Features	0,891
Task Technology Fit	0,784
Technological Features	0,777
Average AVE	0,798

Average R^2:

$$= \frac{(0{,}833+0{,}694+0{,}784)}{3} = 0{,}770$$

The Goodness of Fit:

$$= \sqrt{\overline{AVE} x\, \overline{R - Square}}$$

$$= \sqrt{0{,}798}\, x\ 0.770 = 0.687$$

From the calculation above, it can be seen that this research model has a value of 0.687, so the outer and inner models in this study are declared valid and have great feasibility.

4.4 Hypothesis Analysis

The hypothesis testing results are considered through the path coefficient, which shows that the significance level and hypothesis are accepted if the P-Value value < 0.05. The following are the results of bootstrapping in hypothesis testing:

Table 12. Path Coefficients

	Sample Mean	Standard Deviation	T Statistic	P Values
IT > BI	0,154	0,095	1,677	0,047
PE > BI	0,730	0,134	5,588	0,000
PPTT > IT	0,533	0,099	5,353	0,000
SA > IT	0,395	0,095	4,156	0,000
TSF > TTF	0,490	0,128	3,979	0,000
TTF > BI	0,070	0,161	0,272	0,393
TF > TTF	0,470	0,131	0,343	0,000

From the results of the path coefficient above, it was found that of the seven variables, six had a positive influence with a P-Values value of < 0.05. The end of each variable culminates in the auditor's Intention to adopt a Big Data Analytics technology in assisting the audit process carried out.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.5 Discussion

Based on the previous table, it was found that six variables have a positive influence on seven variables.

a. **H1: Personal Propensity to Trust has a positive influence on the Initial Trust**
Personal Propensity to Trust positively influences the Initial Trust with a significance level 0.000. The higher the level of Trust that comes from the natural mind of an auditor, the higher the Initial Trust is owned. One of the questionnaire statements, "I tend to use Big Data Analytics technology in the audit process carried out," shows confidence that arises from a person auditor. These two variables go hand in hand with previous research results. One predictor variable considered suitable for forming an Initial Trust is the tendency of Trust obtained from within a person [30]. The personal inclinations given by one can add an Initial Trust to blockchain technology [36]. The initial Trust of a government auditor will increase in line with the tendency of Trust given by auditors in the audit process they carry out on Big Data Analytics technology. However, this study has different results from the study [51], which said there was no positive effect of Personal Propensity to Trust on Initial Trust password managers. Personal Propensity to Trust does not have a good influence on the object studied, so it does not positively influence the Initial Trust. While in this study, the adoption of Big Data Analytics is significantly based on a person's inner Trust in adoption, so Personal Propensity to Trust positively impacts Initial Trust.

b. **H2: Structural Assurance has a positive influence on the Initial Trust**

Structural Assurance positively influences the Initial Trust with a significance level of 0.000. The more complex the structure and the higher the security assurance of the technology will increase the Initial Trust of auditors to use Big Data Analytics technology in the audit process. Based on the questionnaire statement distributed to respondents, the auditors feel confident in the security assurance of Big Data Analytics. Many things need to be done when undergoing the audit process, especially state audits so that guarantees can help auditors increase their Trust. The results of this study are supported by several studies that have been done before. By ensuring the protection of user data and privacy through its structural and technological measures, Structural Assurance enhances the Initial Trust of various users in Big Data Analytics [37]. Structural Assurance will also increase the Initial Trust of data owners [38]. No studies have provided insignificant results between Structural Assurance and Initial Trust. Structural Assurance is a variable that significantly determines the creation of a person's Trust, and this is the same as the results of this study. Based on the results of several previous studies, this argument convinced government auditors to increase their initial confidence with assurances over the protection of technology.

c. **H3: Initial Trust has a positive influence on Behavioral Intention**

The results of hypothesis testing show a number slightly beyond 0.05, where the P-Values of this hypothesis is 0.047. However, there is a positive influence exerted from Initial Trust on Behavioral Intention. With many positive responses to the Personal Propensity to Trust and Structural Assurance, it will create an Initial Trust in government auditors. The questionnaire statement "I believe in Big Data Analytics" implies that the extent of Initial Trust in Big Data Analytics serves as an initial step towards its adoption by government auditors. This argument is supported by research [52], where the Initial Trust is a variable used by individuals to decide whether to adopt or not. Initial Trust can influence a person's behavioral motives in adopting mobile payments [42]. This study's results differ from the study [53], where there is no significant effect of Initial Trust on Behavioral Intention from the implementation of Big Data in Malaysian Public Agencies. The absence of significance between Initial Trust and Behavioral Intention is created because Initial Trust is very abstract and cannot be used as a focus in adopting Big Data Analytics. However, the results of this study emphasize Initial Trust, which has an important influence on the creation of BPK Behavioral Intention in auditing. Initial Trust formed from various factors is considered essential by BPK auditors in adoption because, according to them, the initial Trust is the basis for adoption. Based on the research results and support from the various studies above, it has been confirmed that the government's Initial Trust in auditors will positively influence their Intention to adopt Big Data Analytics.

d. **H4: Technological Features have a positive influence on Task Technology Fit**

The P-Value of testing this hypothesis is 0.000, and this number is < 0.05, so there is a positive influence created from the features that are in technology with Task Technology Fit. The result suggests that a user-friendly technology system with adequate features will facilitate BPK in completing the audit process. It can be done by ensuring the appropriate utilization of tasks and technology. The adoption of Task Technology Fit is significantly influenced by the variable technology features of Big Data Analytics [40]. In addition, other research conducted by [29] said that technology's features significantly affect the Task Technology Fit model. Various studies have always provided significant results between Technological Features and Task Technology Fit, so it can be said that Technological Features are critical variables that can match tasks and technology.

e. **H5: Task Features have a positive influence on Task Technology Fit**

The results of hypothesis testing on P-Value are 0.000 and < 0.05, so it can be concluded that there is a positive influence between Task Features on Task Technology Fit. A characteristic of a task will be divided into levels based on the level of complexity and technology that supports the Task. This study aims to align the duties of government auditors with the usage of Big Data Analytics. It can be done by ensuring a suitable match between tasks and technology for optimal completion of work by government auditors. The results of this hypothesis are supported by research conducted by those who [44] state that companies need to see the characteristics of which tasks require cloud computing technology. In this hypothesis, various existing studies provide significant results between Task Features and Task Technology Fit. There are still no studies that provide insignificant results, so it can be said that Task Features are essential variables that can form a match between tasks and technology. In this research, government auditors must assess the task characteristics to identify the ones that necessitate the usage of Big Data Analytics. It would lead to a positive impact of Task Features on Task Technology Fit.

f. **H6: Task Technology Fit has a positive influence on Behavioral Intention**

Task Technology Fit does not positively influence Behavioral Intention because it has P Values of 0.393 and > 0.05. This study's results differ from previous studies, where Task Technology Fit should influence Behavioral Intention. However, some studies support the results of this hypothesis, where Task Technology Fit has a negative effect on interest in using Smart Home Health Care Services in South Korea [54].

Koreans agree that Smart Home Health Care Service technology can improve home healthcare services. However, the public thinks technology cannot be popularized in health care services. This study had no positive influence because BPK focused more on the quality of audit evidence (findings), which was very influential against performance expectations expected by auditors. In addition, the data analysis process is processed through the research department so that the auditor only uses the data processing results produced by the department. It can be said that the auditor does not feel that the match between a task and technology (Task Technology Fit) will affect their Intention to adopt Big Data Analytics.

g. **H7: Performance Expectation has a positive influence on Behavioral Intention**

This last hypothesis positively influences Performance Expectation on Behavioral Intention with a P-Value of 0.000 and < 0.05. Government auditors have high-performance expectations, which go hand in hand with adopting Big Data Analytics. The expected performance expectation of a government auditor is to reduce financial statement fraud and provide objective evidence. There is a direct relationship between performance expectations and behavioral intentions to adopt Big Data Analytics [55]. The higher the performance expectations of government auditors, the higher their Intention to adopt Big Data Analytics to support the audit process. No research results show an insignificant influence between Performance Expectation and Behavioral Intention. The importance of an expected performance expectation largely determines sustainability intentions in adoption. That way, the results of this study have the same results and are supported by many studies that have been done before.

5. LIMITATIONS AND CONCLUSION

5.1 Limitations

There are two limitations of this study. The minimum sample is not reached due to external factors (peak season) auditors, and some auditors' unwillingness to answer questionnaires to make the central BPK sample less represents the actual result. It is hoped that further research can cover a broader BPK to be used as respondents, including existing BPK in the regions. In addition, this study only researches the object of BPK (government auditor). Therefore, the results of this study cannot be generalized to external points of view and internal auditors. In subsequent research, it is necessary to conduct testing in the external and internal context of auditors using the same approach factors.

5.2 Conclusion

Adopting Big Data Analytics presents numerous benefits to BPK. Therefore, auditors must first address the complexities associated with its adoption before fully leveraging this technological system's potential value. The method of implementing Big Data Analytics consists of interrelated variables that can affect the activities carried out by the auditor. It requires Trust from auditors and a secure network system to use Big Data Analytics so that auditors can trust Big Data Analytics and want to adopt the technology. A need for auditors to be able to control auditors' data and activities in real time also makes task features enter into task technology. Auditors' high-performance expectations increase interest in adopting Big Data Analytics. Big Data Analytics can present accurate data as audit findings securely. It is supported by computer processing to understand and see good patterns to aid in decision-making and problem-solving. Accounting Firms can adopt Big Data Analytics to produce more accurate audit results and present various strong data-driven findings. Accounting Firms can consider several variable approaches in this research as a basis, which can help them make decisions on adopting Big Data Analytics.

REFERENCES

[1] U. Sivarajah, M. M. Kamal, Z. Irani, and V. Weerakkody, "Critical analysis of Big Data challenges and analytical methods," *J Bus Res*, vol. 70, pp. 263–286, Jan. 2017, doi: 10.1016/j.jbusres.2016.08.001.

[2] E. F. Ahmad, D. Rizal, and S. Aliyudin, "PENGARUH IMPLEMENTASI BIG DATA TERHADAP AUDITDI LEMBAGA PEMERINTAH (STUDI PADA KANTOR INSPEKTORAT KABUPATEN MAJALENGKA)," vol. 5, no. 5, 2020.

[3] Badan Pemeriksa Keuangan, "Apa Tugas dan Wewenang BPK?," Jan. 31, 2018. https://sumbar.bpk.go.id/apa-tugas-dan-wewenang-bpk/ (accessed Feb. 09, 2023).

[4] Badan Pemeriksa Keuangan, "BPK TERAPKAN BIG DATA ANALYTICS DALAM PEMERIKSAAN," Dec. 07, 2020. https://www.bpk.go.id/news/bpk-terapkan-big-data-analytics-dalam-pemeriksaan (accessed Feb. 09, 2023).

[5] M. Cao, R. Chychyla, and T. Stewart, "Big Data Analytics in Financial Statement Audits," 2015.

[6] K. Yoon, L. Hoogduin, and L. Zhang, "Big data as complementary audit evidence," *Accounting Horizons*, vol. 29, no. 2, pp. 431–438, Jun. 2015, doi: 10.2308/acch-51076.

[7] R. C. Mayer, J. H. Davis, and F. David Schoorman, "An Integrative Model of Organizational Trust," 1995. [Online]. Available: https://www.jstor.org/stable/258792?seq=1&cid=pdf-

[8] D. Harrison McKnight, V. Choudhury, and C. Kacmar, "The impact of initial consumer trust on intentions to transact with a web site: a trust building model," *The Journal of Strategic Information Systems*, vol. 11, no. 3–4, pp. 297–323, Dec. 2002, doi: 10.1016/S0963-8687(02)00020-3.

[9] D. H. McKnight, L. L. Cummings, and N. L. Chervany, "Initial Trust Formation in New Organizational Relationships," *The Academy of Management Review*, vol. 23, no. 3, p. 473, Jul. 1998, doi: 10.2307/259290.

[10] D. L. Goodhue and R. L. Thompson, "Task-Technology Fit and Individual Performance," *MIS Quarterly*, vol. 19, no. 2, p. 213, Jun. 1995, doi: 10.2307/249689.

[11] Venkatesh, "User acceptance of information technology: Toward a unified view," 2003.

[12] R. Online *et al.*, "Application of the task-technology fit model to structure and evaluate the adoption of e-books by academics Publication Details," 2013. [Online]. Available: http://ro.uow.edu.au/commpapers/3189

[13] M. K. J. A. Sani, M. K. Zaini, N. Z. Sahid, N. Shaifuddin, T. A. Salim, and N. M. Noor, "Factors influencing intent to adopt big data analytics in Malaysian government agencies," *International Journal of Business and Society*, vol. 22, no. 3, pp. 1315–1345, 2021, doi: 10.33736/ijbs.4304.2021.

[14] C. L. Philip Chen and C. Y. Zhang, "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data," *Inf Sci (N Y)*, vol. 275, pp. 314–347, Aug. 2014, doi: 10.1016/j.ins.2014.01.015.

[15] X. Wu, X. Zhu, G. Q. Wu, and W. Ding, "Data mining with big data," *IEEE Trans Knowl Data Eng*, vol. 26, no. 1, pp. 97–107, Jan. 2014, doi: 10.1109/TKDE.2013.109.

[16] A. Manshur, "Satu Data, Big Data dan Analitika Data: Urgensi Pelembagaan, Pembiasaan dan Pembudayaan," *Bappenas Working Papers*, vol. 4, no. 1, pp. 30–46, Mar. 2021, doi: 10.47266/bwp.v4i1.82.

[17] Y. Riahi and S. Riahi, "Big Data and Big Data Analytics: concepts, types and technologies," *International Journal of Research and Engineering*, vol. 5, no. 9, pp. 524–528, Nov. 2018, doi: 10.21276/ijre.2018.5.9.5.

[18] N. Elgendy and A. Elragal, "Big data analytics: A literature review paper," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer Verlag, 2014, pp. 214–227. doi: 10.1007/978-3-319-08976-8_16.

[19] J. Sun, W. Xu, J. Ma, and J. Sun, "Leverage RAF to find domain experts on research social network services: A big data analytics methodology with MapReduce framework," *Int J Prod Econ*, vol. 165, pp. 185–193, Jul. 2015, doi: 10.1016/j.ijpe.2014.12.038.

[20] T. Kude, H. Hoehle, and T. A. Sykes, "Big data breaches and customer compensation strategies," *International Journal of Operations & Production Management*, vol. 37, no. 1, pp. 56–74, Jan. 2017, doi: 10.1108/IJOPM-03-2015-0156.

[21] Z. Wang and H. Zhao, "Empirical Study of Using Big Data for Business Process Improvement at Private Manufacturing Firm in Cloud Computing," in *2016 IEEE 3rd International Conference on Cyber Security and Cloud Computing (CSCloud)*, IEEE, Jun. 2016, pp. 129–135. doi: 10.1109/CSCloud.2016.11.

[22] G. * Salijeni, A. Samsonova-Taddei, and S. Turley, "Big Data and Changes in Audit Technology: Contemplating a Research Agenda." [Online]. Available: https://ssrn.com/abstract=3148904
[23] O. M. Zragat, "The Moderating Role of Business Intelligence in the Impact of Big Data on Financial Reports Quality in Jordanian Telecom Companies," *Mod Appl Sci*, vol. 14, no. 2, p. 71, Jan. 2020, doi: 10.5539/mas.v14n2p71.
[24] M. Kend and L. A. Nguyen, "Big Data Analytics and Other Emerging Technologies: The Impact on the Australian Audit and Assurance Profession," *Australian Accounting Review*, vol. 30, no. 4, pp. 269–282, Dec. 2020, doi: 10.1111/auar.12305.
[25] L. Dagilienė and L. Klovienė, "Motivation to use big data and big data analytics in external auditing," *Managerial Auditing Journal*, vol. 34, no. 7, pp. 750–782, Jul. 2019, doi: 10.1108/MAJ-01-2018-1773.
[26] S. Vongjaturapat, "Application of the task-technology fit model to structure and evaluation of the adoption of smartphones for online library systems," *Science and Technology Asia*, vol. 23, no. 1, pp. 39–56, Jan. 2018, doi: 10.14456/scitechasia.2018.6.
[27] T. Zhou, Y. Lu, and B. Wang, "Integrating TTF and UTAUT to explain mobile banking user adoption," *Comput Human Behav*, vol. 26, no. 4, pp. 760–767, Jul. 2010, doi: 10.1016/j.chb.2010.01.013.
[28] K. K. Kim and B. Prabhakar, "Initial Trust and the Adoption of B2C e-Commerce: The Case of Internet Banking."
[29] M. Shahbaz, C. Gao, L. L. Zhai, F. Shahzad, and Y. Hu, "Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change," *J Big Data*, vol. 6, no. 1, Dec. 2019, doi: 10.1186/s40537-019-0170-y.
[30] S. Kaabachi, S. Ben Mrad, and B. O'Leary, "Consumer's initial trust formation in IOB's acceptance: The role of social influence and perceived compatibility," *International Journal of Bank Marketing*, vol. 37, no. 2, pp. 507–530, Mar. 2019, doi: 10.1108/IJBM-12-2017-0270.
[31] T. Zhou, "An empirical examination of continuance intention of mobile payment services," *Decis Support Syst*, vol. 54, no. 2, pp. 1085–1091, Jan. 2013, doi: 10.1016/j.dss.2012.10.034.
[32] A. G. Downe and A. A. Taiwo, "The theory of user acceptance and use of technology (UTAUT): A meta-analytic review of empirical findings," *Article in Journal of Theoretical and Applied Information Technology*, vol. 10, no. 1, 2013, [Online]. Available: www.jatit.org
[33] A. Ngampornchai and J. Adams, "Students' acceptance and readiness for E-learning in Northeastern Thailand," *International Journal of Educational Technology in Higher Education*, vol. 13, no. 1, Dec. 2016, doi: 10.1186/s41239-016-0034-x.
[34] N. Ramli, N. A. Rashid, and K. M. Kassim, "Eco-Labeling Perspectives amongst Malaysian Consumers LES PERSPECTIVES DE L'ECO-ETIQUETAGE CHEZ LES CONSOMMATEURS MALAISIENS Kamaruzaman Jusoff (Corresponding author) 2," 2009.
[35] V. C. S. Yeo, S.-K. Goh, and S. Rezaei, "Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services," *Journal of Retailing and Consumer Services*, vol. 35, pp. 150–162, Mar. 2017, doi: 10.1016/j.jretconser.2016.12.013.
[36] H. Heidari, M. Mousakhani, M. Alborzi, A. Divandari, and R. Radfar, "Evaluating the Factors Affecting Behavioral Intention in Using Blockchain Technology Capabilities as a Financial Instrument," 2017.
[37] K. Abouelmehdi, A. Beni-Hessane, and H. Khaloufi, "Big healthcare data: preserving security and privacy," *J Big Data*, vol. 5, no. 1, Dec. 2018, doi: 10.1186/s40537-017-0110-7.
[38] P. McCole, E. Ramsey, A. Kincaid, Y. Fang, and H. LI, "The role of structural assurance on previous satisfaction, trust and continuance intention: The case of online betting," *Information Technology and People*, vol. 32, no. 4, pp. 781–801, Sep. 2019, doi: 10.1108/ITP-08-2017-0274.
[39] J. Saintz, "ANALISA PENGARUH INITIAL TRUST TERHADAP ACTUAL USAGE MELALUI BEHAVIORAL INTENTION DALAM APLIKASI DIGITAL PAYMENT OVO."
[40] S. L. Wang and H. I. Lin, "Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system," *Behaviour and Information Technology*, vol.

38, no. 9, pp. 974–985, 2019, doi: 10.1080/0144929X.2019.1626486.

[41] W. S. D. W. A. Ghani, N. Z. Khidzir, T. T. Guan, and M. Ismail, "Towards Modelling Factors of Intention to Adopt Cloud-Based M-Retail Application among Textile Cyberpreneurs," *Journal of Advances in Information Technology*, pp. 114–120, 2017, doi: 10.12720/jait.8.2.114-120.

[42] T. Zhou, "The effect of initial trust on user adoption of mobile payment," *Information Development*, vol. 27, no. 4, pp. 290–300, Nov. 2011, doi: 10.1177/0266666911424075.

[43] W. A. Alkhowaiter, "Use and behavioural intention of m-payment in GCC countries: Extending meta-UTAUT with trust and Islamic religiosity," *Journal of Innovation and Knowledge*, vol. 7, no. 4, Oct. 2022, doi: 10.1016/j.jik.2022.100240.

[44] S. Tripathi and N. Jigeesh, "Task-Technology Fit (TTF) Model To Evaluate Adoption of Cloud Computing: A Multi-Case Study," 2015. [Online]. Available: http://www.ripublication.com

[45] M. M. Queiroz and S. Fosso Wamba, "Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA," *Int J Inf Manage*, vol. 46, pp. 70–82, Jun. 2019, doi: 10.1016/j.ijinfomgt.2018.11.021.

[46] Adair, "Features of Big Data Analytics and Requirements. ," 2019. https://www.selecthub.com/big-data-analytics/big-data-analytics-requirements/ (accessed Mar. 17, 2023).

[47] A. Bere, "Applying an Extended Task-Technology Fit for Establishing Determinants of Mobile Learning: An Instant Messaging Initiative," *Journal of Information Systems Education*, vol. 29, no. 4, pp. 239–252, 2018.

[48] A. A. Alalwan, Y. K. Dwivedi, and N. P. Rana, "Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust," *Int J Inf Manage*, vol. 37, no. 3, pp. 99–110, Jun. 2017, doi: 10.1016/j.ijinfomgt.2017.01.002.

[49] B. Oktavia, "ASSESSING THE USE OF E-PAYMENT IN CULINARY BUSINESSES DRIVEN BY THE TRUST FACTOR IN TECHNOLOGY ACCEPTANCE MODEL," *J Theor Appl Inf Technol*, vol. 15, no. 11, 2022, [Online]. Available: www.jatit.org

[50] W. W. Chin, "The Partial Least Squares Approach to Structural Equation Modeling The Proactive Technology Project Recovery Function: A Methodological Analysis View project Research Methods View project." [Online]. Available: https://www.researchgate.net/publication/311766005

[51] A. Farooq, A. Dubinina, S. Virtanen, and J. Isoaho, "Understanding dynamics of initial trust and its antecedents in password managers adoption intention among young adults," in *Procedia Computer Science*, Elsevier BV, 2021, pp. 266–274. doi: 10.1016/j.procs.2021.03.036.

[52] L. Sbaffi and J. Rowley, "Trust and credibility in web-based health information: A review and agenda for future research," *Journal of Medical Internet Research*, vol. 19, no. 6. JMIR Publications Inc., 2017. doi: 10.2196/jmir.7579.

[53] N. Z. Sahid, M. K. J. A. Sani, S. A. Noordin, M. K. Zaini, and J. Baba, "Determinants factors of intention to adopt big data analytics in malaysian public agencies," *Journal of Industrial Engineering and Management*, vol. 14, no. 2, pp. 269–293, 2021, doi: 10.3926/jiem.3334.

[54] H. J. Kang, J. Han, and G. H. Kwon, "The Acceptance Behavior of Smart Home Health Care Services in South Korea: An Integrated Model of UTAUT and TTF," *Int J Environ Res Public Health*, vol. 19, no. 20, Oct. 2022, doi: 10.3390/ijerph192013279.

[55] J. P. Cabrera-Sanchez and Á. F. Villarejo-Ramos, "Factors affecting the adoption of big data analytics in companies," *RAE Revista de Administracao de Empresas*, vol. 59, no. 6, pp. 415–429, Nov. 2019, doi: 10.1590/S0034-759020190607.