# KEY DETERMINANTS OF GOVERNMENT AUDITOR'S BEHAVIOUR TO ADOPT BIG DATA ANALYTICS IN AUDIT PRACTICE

**Ahmad Ikhlasul Jiwandono [1*], Hafiez Sofyani [2]**

**Affiliation:**
[1,2]Accounting Study Program, Faculty of Economics and Business, University of Muhammadiyah Yogyakarta

**Article Process:**
Received 07-26, 2024
Revised 08-08, 2024
Accepted 08-08, 2024

*** Correspondence:**
ahmad.ikhlasul.fe21@mail.umy.ac.id

**DOI :**
10.30813/jab.v17i2.6000

## Abstract

**Background**: Despite the increasing adoption of big data and Big Data Analytics (BDA) in the business world, the accounting and audit profession is considered slow in taking advantage of these innovative developments. Government auditors play an important role indirectly in improving good governance. The use of BDA in government audits has been carried out in Indonesia since 2020. However, because its use is not mandatory, not all government auditors use the application.

**Objective**: This research investigates the key determinants that drive government auditors' behaviour to adopt BDA technology in audit practice, especially in the Indonesian context, with a focus on the Indonesian Supreme Audit Agency (SAA).

**Research Method:** This study was conducted through a questionnaire survey involving 126 government auditors in Indonesia. Meanwhile, research data was analyzed using the Structural Equation Modelling - Partial Least Square method (SEM-PLS).

**Research Results**: Research findings show that performance expectancy and effort expectancy have a direct influence on auditors' intentions to use BDA techniques at SAA. Meanwhile, the auditor's intention to use BDA techniques has a significant effect on Actual Use.

**Originality/Novelty of Research:** This research addresses the gap about factors that encourage auditors' behaviour to adopt BDA technology in audit practice, especially in public sector context.

**Keywords**: Auditor; Supreme Audit Agency; Big Data Analytics, Intention to Use, Performance Expectation, Effort Expectation; Actual Usage

## Introduction

In recent years, much academic research and practitioner literature has focused on the benefits of Big Data Analytics (BDA) (Agostini et al., 2022). BDA is now used in almost all aspects of decision-making and business strategy of big corporations (Sihombing et al., 2023). The accounting profession and audit are slow in the utilization of the development of these technology. This is despite the fact that the role practice of accountants and auditors is undergoing paradigm transformation (Ayu Putri et al., 2024). BDA is an analysis method that examines the entire process of receiving big data that can help to find errors and fraud as well as opportunities that are useful for companies when making decisions (Deniswara et al., 2020).

According to Ayu Putri (2024) based on the results of a fraud survey by The Association of Certified Fraud Examiners (ACFE) in Indonesia, ACFE states that Indonesia is a country with the most fraud in 2022 which amounts to 23 (twenty -three) cases dominated by 64% corruption cases. As an independent institution given a single authority by Law Number 15 of 2004, the Indonesian Supreme Audit Agency (SAA) must carry out its duties to assess how the implementation of the responsibilities and management of state finances is carried out. In accordance with SAA's 2020-2024 strategic plan, BDA will continue to be developed and optimized in audits to minimize fraud in the Indonesian government.

BDA is one component of the digitalization revolution 4.0 which has become a topic of conversation in various countries at the end of this year. BDA has been widely applied in various countries such as the health industry in Russia (Widya Sulaiman et al., 2023), government in Malaysia (Putra et al., 2023a), finance in Italy (Dagilienė & Klovienė, 2019), construction in England (Alaka et al., 2018), and the manufacturing industry in China. (Meinal et al., 2024). Meanwhile in Indonesia, BDA is applied to financial information systems for auditors in various sectors (Pratama & Komariyah, 2023). Although the initial appearance of BDA was only used for a few modern companies in Indonesia, BDA has begun to be implemented in the government, namely BDA on auditee documents implemented by the SAA. The use of BDA technology has also been applied in various countries in conducting audits of Government Financial Reports. In this way, it is hoped that BDA can increase government accountability and transparency in serving the public.

The use of BDA can also assist top management in important decision-making processes (Shabbir & Gardezi, 2020), requests and interest in forensic accounting data analysis (Rozi, 2023), and audits (De Santis & D’Onza, 2020). Based on previous research said that the reason a person to use BDA is because the technology can improve performance optimally and also reduce efforts in solving a problem(Hasan et al., 2020). Developments in BDA technology also influence audit procedures and accounting approaches during the audit process (Rahmadhani et al., 2023). Sihombing (2023) pointed out BDA can help auditors improve audit quality. Therefore, the implementation of BDA can make it easier for auditors to obtain data on the audited party so that it will influence auditor judgment.

Since 2020, BDA with the aim of improving auditor performance has been used in the Indonesian government, especially at the Indonesian SAA, but there are still several auditors who have not used this technology since the usage is not mandatory. In fact, according to the 2023 SAA annual report, it shows that SAA's performance is still not optimal. Considering the significant role of the BDA in audits (see: Sihombing et al., 2023; Dagilienė & Klovienė, 2019), the use of BDA should be a solution to the still not optimal performance of SAA auditors at this time.

There are several studies that discusses and analyzes BDA roles in audits. For example, research by Hamdam (2022) which states that the use of BDA has been proven to improve the quality of audit assessments and also improve auditor judgment. Tang and Karim (2019) also found similar study results, namely that adopting BDA techniques was effective in detecting fraud early. It is also known that through research by Putra (2023) there is no negative influence significant negative effect between audit quality variables on the examiner's ability to detect fraud. However, there is still a research gap regarding the factors that influence auditors' intentions and behaviour to use BDA in audit To cover this research gap, this research aims to determine the factors that influence the intention and behaviour of SAA auditors to use BDA techniques in audit practice.

This research uses the Unified Theory of Acceptance and Use of Technology (UTAUT) which explains the acceptance of new technology (Venkatesh et al., 2003). So this study uses the main factors of the UTAUT theory, namely performance expectancy and effort expectancy in testing the factors that influence the intention and behavior of SAA auditors to use BDA techniques in audit practice. Performance expectancy and effort expectancy are the strongest predictors in influencing the intention to use a technology (Abu Afifa et al., 2023). Likewise, intention to use is a significant predictor of actual behavior, including in the context of technology acceptance (Ajzen, 1991). With the existence of good performance expectancy and efforts towards BDA techniques, auditors will intend to use BDA techniques in audit practices that can improve the quality of the audit system.

However, research that examines these factors in influencing the intention to use BDA techniques in audit practice is still limited. This is the reason the author conducted this study in order to prove whether these factors can influence the auditor's intention to use BDA techniques in audit practice. This research contributes theoretically and practically. Theoretically, this research is an expansion of the literature for researchers who want to conduct research on technology acceptance by adopting UTAUT theory. Practically, this research can produce new solutions that the use of BDA can improve audit quality and early fraud prevention that can be applied to solve problems related to the reluctance of SAA auditors to use BDA technology in their audits.

## Literature review

### Theoretical Underpinning

Various theories have been developed for research on individual acceptance and use of information technology (IT). One of these theories is the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is a comprehensive theory that provides an overview of the variables that need to be measured to assess technology adoption (Srivastava et al., 2024). This theory aims to evaluate the acceptance and use of new technology, which allows one to explain the acceptance of technology by employees in various industries. The UTAUT concept, which has been used for many years, is a strategic framework that provides a comprehensive understanding of the drivers of new technology adoption.

UTAUT has discovered important components related to the estimation of intentions in technology use, especially in organizational environments. UTAUT has four main determining factors, namely performance expectancy, effort expectancy, social influences, and facilitating conditions which influences intentions in using technology . Although research considers UTAUT to have reached its practical limits in explaining individual technology acceptance and usage decisions in organizations, UTAUT-based research has grown rapidly. UTAUT theory has been proven to be a valid tool and instrument for research and is a predictor of adoption behavior and intention to use with a focus on performance expectancy and effort. As a result, UTAUT has developed into the most widely used theory in research (Tarhini et al., 2016).

Performance Expectancy are how much people believe that using a system will help achieve goals and improve performance (Venkatesh et al., 2003). Meanwhile, Yan (2023) they argue that performance expectancy indicate users' beliefs that adopting technology will improve their performance and efficiency. Research Rahi (2019) has proven that performance expectancy have a positive impact on intentions to use a technology. These results are strengthened by research Srivastava (2024) that has tested empirically which found a strong impact of performance expectancy on technology users' adoption intentions. Performance Expectancy are also considered the most accurate predictor for determining how willing a person is to use technology. Therefore, based on the discussion above we hypothesize that:

**$H_1$** : Performance expectancy have a positive effect on intention to use BDA on audit implementation at SAA

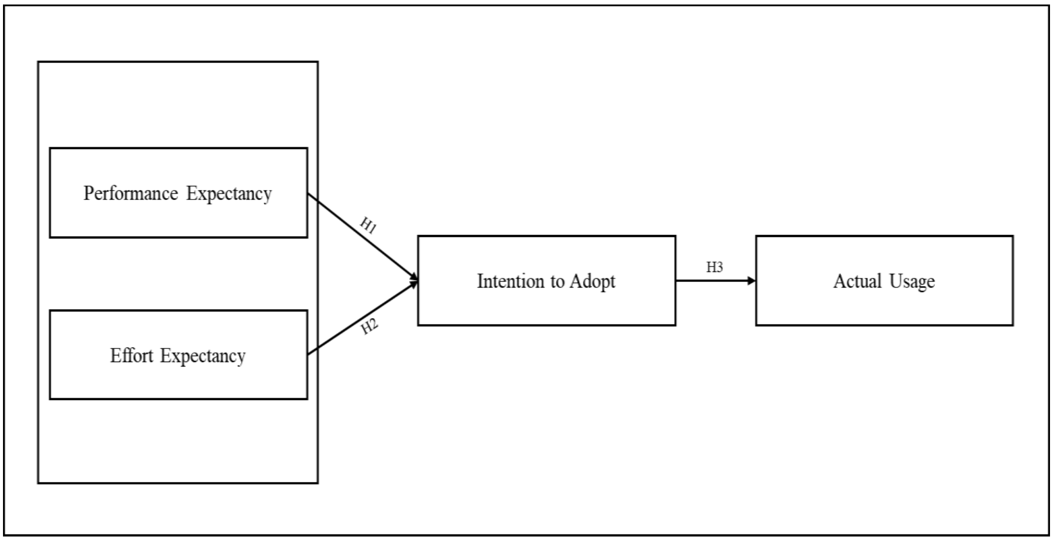
Effort Expectancy is the level of comfort and convenience offered by the latest technology (Venkatesh et al., 2003). According to Yan (2023) users, they tend to adopt technology that facilitates them to achieve their goals which as a result can reduce the time and energy spent when working on a task. Research from Sugiharto (2021) found that effort expectancy contribute directly and significantly to intention to use a technology. These findings are in line with research conducted by Esawe (2022) those who found that Effort Expectancy has a significant impact on interest in using a technology. Technology that is user friendly will make users comfortable when adopting the technology. Therefore, based on the narrative above, the following hypothesis can be concluded:

**$H_2$** : Effort expectancy has a positive effect on intention to use BDA on audit implementation at SAA

Intention to use is often considered a predictor of actual use. Gupta & Dogra (2017) states that intention to use significantly impacts actual use with intention to continue using, predicting to use, trying to use and planning to use. In research Alleyne & Lavine (2013) it has been empirically proven that the intention to use has a positive direct impact on the actual use of a technology. These results are consistent with previous literature Ajzen, (1991) arguing that the theory of planned behavior proposes a positive relationship between intentions and actual behavior. Thus, this study concludes the following hypothesis:

**H** $_3$ : Intention to use BDA the implementation of audits at SAA has a positive effect on actual use

Based on the explanation above, the research model is depicted as Figure 1.




Source: Data processed by researchers, 2024

**Figure 1.** Research Model

## Research methods

This research will be carried out at SAA in indonesia using associative quantitative methods. This research uses a data collection method with a questionnaire survey given directly to respondents. This study also involved 126 auditors from several SAAs in Indonesia who would be respondents. This research presents the antecedent variables performance expectancy and effort expectancy, intention to use is the independent variable while Actual Use is the dependent variable to test the effect of actual use of audit big data on auditor performance.

According to Memon (2020) researchers, they must determine the sample size through power analysis. This research conducted power analysis with G* Power 3.1.9.7 software. Based on the analysis carried out, the minimum sample size obtained from this research was 68 respondents. The sampling method for this research is the purposive sampling method. The respondents used as samples were all SAA auditor employees.

### Operational Definition of Variables

Performance expectancy is the level of confidence a person has in the extent to which the use of technology can help users improve performance (Venkatesh et al., 2003). The research predicts how user expectancy will be due to increased performance from using BDA in the audit process at SAA . The indicators in measuring these variables were adopted from research Abu Afifa (2023) with a modified questionnaire from Ferri (2020).

Effort Expectancy defines as the Effort that is expected by considering how easy it is for someone to apply the technology (Ali et al., 2024). The research investigates how users' expectancy are due to the ease of use of BDA in the audit process at SAA. Indicators in variable measurement were adopted from research Abu Afifa (2023) with a modified questionnaire from Esawe (2022).

Intention to use is described as a person's willingness to engage in a particular usage behavior (Gupta & Dogra, 2017). This research investigates how someone intends to use technology. Indicators in variable measurement were adopted from research Ali (2024) with a modified questionnaire from Srivastava (2024).

According to Rattanaburi and Vongurai (2021) Actual Use, it is defined as whether a person actually uses technology and refers to the frequency of technology use and the time of use. This research describes how the actual use of technology is. The indicators in their measurements adopt research Anouze & Alamro (2020) with a modified questionnaire from Al-Mamary (2023).

### Measurement and Scale

The measurement technique for this research is to use a 5 point Likert scale. The purpose of using this scale is to assess a person's attitudes, opinions and views on a particular matter (Sugiyono, 2015). Measurement will be carried out by giving a value of 1-5 to each alternative respondent's answer with the condition that Strongly Disagree (STS) = value 1; Disagree (TS) is worth 2; Neutral (N) is worth 3; Agree (S) is worth 4 and Strongly Agree (SS) is worth 5.

### Data analysis technique

This research uses Partial Least Square (PLS), which is an evolution of the Structural Equation Model (SEM), with the SmartPLS test tool . PLS-SEM was used in this research because of its more exploratory context. In contrast to CB-SEM, which aims to confirm a theory by testing how well the model used is, PLS-SEM aims to compare hypotheses with previously developed theories (Hair et al., 2022). This data analysis method makes it possible to reject or support previous theoretical or research findings. PLS-SEM can handle social science problems such as abnormal data and complex models.

# Results and Discussion

## Results

This research obtained data from 126 respondents who had filled out the questionnaire and met the criteria. Next, the questionnaire was processed using the Smart PLS test tool to test descriptive statistics, validity, reliability and path coefficient .

**Table 1.** Respondent Demographics

| Criteria | Frequency | % |
|---|---|---|
| **Educational background** | | |
| Non IT and Non Accounting | 35 | 27.8 |
| I.T | 11 | 8.7 |
| Accounting | 80 | 63.5 |
| **Level of education** | | |
| Doctor | 1 | 0.8 |
| Masters | 46 | 36.5 |
| Bachelor | 79 | 62.7 |
| **Gender** | | |
| Man | 75 | 40.5 |
| Woman | 51 | 39.5 |
| **Age** | | |
| 20-35 | 69 | 54.8 |
| 36-50 | 49 | 38.9 |
| > 50 | 8 | 6.3 |
| **Certification** | | |
| Certified | 82 | 34.9 |
| Not yet certified | 44 | 65.1 |
| **Total** | **126** | **100.0** |

Source: Research Data, 2024

Table 1 shows the demographic information of the respondents used for this research. Based on educational background, the majority of respondents have an educational background in accounting. Based on educational level, the majority of respondents were undergraduates and only 1 respondent had an educational level of Doctorate. Based on gender, the majority of respondents were male. Meanwhile, based on age, the majority of respondents were 20-35 years old. Based on the certification grouping, the majority of respondents in this study are certified.

**Table2.** Descriptive Statistics Test Results

| Variable | Min | Max | Mean | Std. Deviation |
|---|---|---|---|---|
| Performance Expectancy | 2.0 | 5.0 | 4,352 | 0.5470 |
| Effort Expectancy | 1.0 | 5.0 | 3,817 | 0.7138 |
| Intent to Use | 2.0 | 5.0 | 4,185 | 0.5956 |
| Actual Use | | | 3,892 | 0.6137 |

Source: Research data, 2024

In table 2, as a result of descriptive statistical testing, the average value (mean) of all variables has a nominal value that is close to the maximum value (max). This means that respondents have high levels of effort expectancy, performance expectancy, intention to use, and actual use. Then based on the standard deviation value, all variables show a nominal value that is less than the average value (mean) , this indicates that this research data is distributed evenly so that the majority of SAA auditors have a tendency to expect effort, expect performance, intend to use, and homogeneous or the same actual use.

**Table 3.** Convergent Validity

| Code | Indicator | Loading |
|---|---|---|
| PE1 | I hope that using BIDICS will improve my performance | 0.932 |
| PE2 | I hope that the use of BIDICS will make it easier to provide the necessary audit information | 0.971 |
| PE3 | I hope that using BIDICS will improve my work efficiency | 0.956 |
| EE1 | My interactions and navigation with the BIDICS app were clear and understandable | 0.926 |
| EE2 | It was easy for me to become skilled in using the BIDICS application | 0.940 |
| EE3 | I would find it easy to use the BIDICS app to do what I want | 0.945 |
| IT1 | I will use BIDICS | 0.877 |
| IT2 | I have always intended to use BIDICS in my audit work | 0.885 |
| IT3 | I feel comfortable with the use of BIDICS | 0.900 |
| AU1 | I have a preference for using BIDICS | 0.814 |
| AU2 | Using BIDIC gives me satisfaction | 0.916 |
| AU3 | So far, I am satisfied with the experience of using BIDICS | 0.861 |

Source: Research Data, 2024

Based on Table 3, all instruments meet the requirements. In accordance with input from Hair (2019), if there is a loading value <0.5, it is deleted and not included in further testing. Based on the results in table 3, the AVE values for all constructs have met > 0.5 so that all variables are declared valid.

**Table 4.** Adjusted R-square value ($R^2$)

| **Endogenous Variables** | **Adjusted $R^2$** |
|---|---|
| Intent to Use | 0.487 |
| Actual Use | 0.475 |

Source: Research Data, 2024

Table 4 shows that the Adjusted R-squared value of the intention to use variable is 0.487. This shows that the performance expectation and effort expectation variables can explain their impact on the intention to use variable by 48.7%, while the remaining 51.3% is explained by other variables not included in the research model. Meanwhile, the Adjusted R-squared value of the actual usage variable is 0.475. This shows that the intention to use variable can explain its influence on the actual usage variable by 47.5% and the remaining 52.5% is described by other variables outside this research model.

**Table 5.** Discriminant Validity Criteria-Fornell-Lacker

| **Variable** | **Actual Use** | **Effort Expectancy** | **Intent to Use** | **Performance Expectancy** |
|---|---|---|---|---|
| Actual Use | 0.865 | | | |
| Effort Expectancy | 0.711 | 0.937 | | |
| Intent to Use | 0.692 | 0.513 | 0.887 | |
| Performance Expectancy | 0.510 | 0.292 | 0.610 | 0.953 |

Source : Research Data, 2024

Table 5 presents the results of the discrimanant validity test using the Fornell-Lacker Criteria. According to Ab Hamid (2017) Each structure must have a square root AVE that is greater than its correlation with other latent constructs. The results in Table 4 show that all variables have the highest value for the correlation of their own construct with other variables , so that all variables are declared valid (the variables meet discriminant validity).

**Table 6.** Results Reliability Test

| **Variable** | **Cronbach's alpha** | **Composite reliability** |
|---|---|---|
| Actual Use | 0.830 | 0.899 |
| Effort Expectancy | 0.931 | 0.956 |
| Intent to Use | 0.865 | 0.917 |
| Performance Expectancy | 0.950 | 0.968 |

Source : Research Data, 2024

Table 6 presents the results of the Reliability Test with assessments obtained from the use of Cronbach's alpha coefficient values and composite reliability values. According toSarstedt (2017) A minimum score cutoff or score cutoff of 0.6 is recommended for Cronbach alpha and composite reliability. The results of the reliability test, as shown in Table 5, explain that each construct has met the required criteria and has good reliability.

Table 7 shows the results of hypothesis testing or direct influence testing carried out using the bootstrapping method on the SmartPLS application. Based on the results of hypothesis testing, the performance expectation variable is the intention to use the BDA application has a coefficient value for the original sample, namely 0.504 and a t-statistic value of 5.632 > t-table 1.66 and a p value of 0.000 < 0.05.

**Table 7.** Direct Effect Test Results ( Path Coefficient )

| Variable | Original Sample | T Statistics | P Values | Information |
|---|---|---|---|---|
| Performance Expectancy → Intention to Use (H1) | 0.504 | 5,632 | 0,000 | Supported |
| Effort Expectancy → Intention to Use (H2) | 0.366 | 3,837 | 0,000 | Supported |
| Intent to Use → Actual Use (H3) | 0.692 | 12,669 | 0,000 | Supported |

Source: Research Data, 2024

Thus, it can be concluded that $H_1$ is accepted and shows that performance expectancy have a positive effect on the intention to use the BDA application.

Results of testing the effort expectation variable on intention to use the BDA application has a coefficient value result on the original sample , namely 0.366 and a t-statistic value of 3.837 > t-table 1.66 and a p value of 0.000 < 0.05. The test results conclude that $H_2$ is accepted and shows that effort expectancy have a positive effect on intention to use the BDA application.

Results of testing the intention variable to use the BDA application in actual use, the coefficient value for the original sample is 0.692 and the t-statistic value is 12,669 > t-table 1.66 and the p value is 0.000 < 0.05. These results show that $H_3$ is accepted and proves that the intention to use the BDA application has a positive effect on actual use.

**Discussion**

Based on the test results, $H_1$ states that performance expectancy have a positive effect on the intention to use BDA, because users believe that using this technology will improve their performance.

Thus, when BDA can help auditors to improve performance efficiently, the greater the auditor's intention to use BDA. These results are in line with research from Tarhini (2016), Adebo (2024), and Ferri (2020) who found that performance expectancy positively and significantly influence the intention to use a technology. Gupta & Dogra (2017) reinforces this by revealing that the greater the perceived benefits of technology, the greater the intention to use the application. Based on these results, it shows that when users believe that BDA can significantly improve their performance, they will be more motivated to adopt the technology. In the context of the study, this means that BDA that is proven to improve work efficiency and effectiveness will be more attractive to auditors. Auditors who feel that BDA technology can bring significant improvements in their performance will be more likely to be willing to use it.

Based on the test results, $H_2$ explains that effort expectancy have a positive effect on the intention to use BDA because of the ease of using BDA which can reduce a person's effort in doing their work. Convenience is the main consideration factor because users tend to choose to use a system that makes it easier to operate. This research proves that auditors have considered BDA easy and effective to use. The results of this study support previous research conducted Al-Mamary (2023), Sugiharto (2021) which argued that effort expectancy have a positive effect on intention to use a system. Alleyne & Lavine (2013) also found that effort expectancy are a significant determinant of a person's intention to adopt a technology. When technology users feel that the technology is easy to use and does not require extra effort, they tend to be more motivated to use it. Therefore, it is important for BDA developers to focus on user-friendly design and implementation that minimizes the difficulty of use. In this way, they can increase adoption intention because ease of use directly contributes to the intention to use the technology.

Based on the results of the $H_3$ test, it shows that the intention to use BDA has a positive effect on actual use. Behavioral intention is a probability or measure of strength if someone intends to carry out a certain behavior or use. Therefore, high behavioral intentions reflect a high propensity for technology adoption. This supports the argument Ajzen (1991) that intention is a strong predictor of actual use. These results also align with, and support research conducted by Rattanaburi & Vongurai (2021), Ali (2024), and Deby Cahyani Pramesti & Gst Ayu Eka Damayanthi (2023) which argues that the intention to use a system has a positive and significant impact on actual use. Based on these results, high user intention to use BDA reflects a strong tendency to adopt the technology. This emphasizes the importance of understanding and influencing user intention as a key strategy in driving technology adoption. By identifying factors that influence intention, such as performance expectancy and effort expectancy, SAA Indonesia can design effective interventions to increase actual use of BDA.

### Theoretical Implications

The current study results provide empirical support for the UTAUT constructs in the context of BDA-based auditing. It confirms that performance expectancy and effort expectancy are significant predictors of auditors' intention to use these technologies, aligning with UTAUT's proposition that these factors are critical in determining technology acceptance. Further, by applying UTAUT to the auditing domain, this study contributes to extending the applicability of the model beyond traditional technological contexts. This extension enriches our understanding of how technology acceptance theories can be adapted to specialized professional fields like auditing. The findings also prompt further exploration into how other UTAUT constructs (such as social influence, facilitating conditions, and behavioral intention) influence the adoption and usage of BDA in auditing, thereby refining existing technology adoption theories.

### Practical Implications

Based on the study result, some implications are also presented. First, SAA needs to focus on providing training programs that emphasize the benefits of BDA in improving audit quality (performance expectancy) and ensure that auditors are proficient in using these technologies (effort expectancy). This can enhance auditors' confidence and competence in utilizing analytics tools effectively. Second, designing user interfaces that are intuitive and easy to navigate can further enhance auditors' perceptions of effort expectancy. This includes simplifying workflows, providing clear instructions, and integrating user feedback to continually improve usability. Third, recognizing the importance of performance and effort expectancy can inform change management strategies aimed at promoting the adoption of big data analytics in auditing practices. Addressing auditors' concerns about the benefits and usability of these technologies through effective communication and support can facilitate smoother transitions. Finally, SAA can develop policies and strategies that incentivize and promote the use of big data analytics in auditing, leveraging the perceived benefits highlighted in your study. This may include establishing clear objectives for incorporating analytics into audit processes and allocating resources for technology implementation and maintenance.

## Conclusion

This research aims to test and collect empirical evidence about the components that can influence auditors' intentions to use BDA techniques in audit practices at SAA. The results of this research indicate that performance expectancy and effort expectancy influence auditors' intentions to use BDA techniques at SAA. Meanwhile, the auditor's intention to use BDA techniques at SAA influences the actual use of these techniques. Use of BDA techniques to improve suboptimal performance and audit quality is very important. This research will provide theoretical and practical benefits. Theoretically, this research contributes to UTAUT by presenting literature regarding elements that can influence auditors' intentions to use BDA techniques in audit practice. Practically, this research provides suggestions and input to the SAA to encourage the intention and behavior of their auditors to use BDA techniques in audits.

This research has limitations. First, this research applies a quantitative survey method which forces respondents to respond with certain answers. Future research can use qualitative methods by conducting interviews to obtain respondents' opinions and feelings regarding the issue under study. Second, this research obtained a relatively small sample, so it does not provide generalizations to a wide population. Future research is expected to obtain a larger sample. In addition, we note that this research is a first step in uncovering the factors that influence auditors' intentions to use BDA techniques in audit practice. Future research should seek to explore more variables.

## References

Ab Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of Physics: Conference Series*, *890*(1). https://doi.org/10.1088/1742-6596/890/1/012163

Abu Afifa, M. M., Vo Van, H., & Le Hoang Van, T. (2023). Blockchain adoption in accounting by an extended UTAUT model: empirical evidence from an emerging economy. *Journal of Financial Reporting and Accounting*, *21*(1), 5–44. https://doi.org/10.1108/JFRA-12-2021-0434

Adebo, A. I., Aladelusi, K., & Mohammed, M. (2024). Determinants of e-pharmacy adoption and the mediating role of social influence among young users. *Journal of Humanities and Applied Social Sciences*. https://doi.org/10.1108/jhass-12-2023-0164

Agostini, M., Arkhipova, D., & Mio, C. (2022). Corporate accountability and big data analytics: is non-financial disclosure a missing link? In *Sustainability Accounting, Management and Policy Journal* (Vol. 14, Issue 7, pp. 62–89). Emerald Publishing. https://doi.org/10.1108/SAMPJ-02-2022-0110

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Bilal, M., Ajayi, S. O., & Akinade, O. O. (2018). A framework for big data analytics approach to failure prediction of construction firms. *Applied Computing and Informatics*, *16*(1–2), 207–222. https://doi.org/10.1016/j.aci.2018.04.003

Ali, M. B., Tuhin, R., Alim, M. A., Rokonuzzaman, M., Rahman, S. M., & Nuruzzaman, M. (2024). Acceptance and use of ICT in tourism: the modified UTAUT model. *Journal of Tourism Futures*, *10*(2), 334–349. https://doi.org/10.1108/JTF-06-2021-0137

Alleyne, P., & Lavine, M. (2013). Factors influencing accountants' behavioural intentions to use and actual usage of enterprise resource planning systems in a global development agency. *Journal of Financial Reporting & Accounting*, *11*(2), 179–200. https://doi.org/10.1108/jfra-11-2011-0017

Al-Mamary, Y. H. S., Siddiqui, M. A., Abdalraheem, S. G., Jazim, F., Abdulrab, M., Rashed, R. Q., Alquhaif, A. S., & Aliyu Alhaji, A. (2023). Factors impacting Saudi students' intention to adopt learning management systems using the TPB and UTAUT integrated model. *Journal of Science and Technology Policy Management*. https://doi.org/10.1108/JSTPM-04-2022-0068

Anouze, A. L. M., & Alamro, A. S. (2020). Factors affecting intention to use e-banking in Jordan. *International Journal of Bank Marketing*, *38*(1), 86–112. https://doi.org/10.1108/IJBM-10-2018-0271

Ayu Putri, D., Nizarudin, A., & Julia. (2024). *Peran Big Data Analytics dan Kualitas Audit dalam Memperkuat Kemampuan Auditor Mendeteksi Kecurangan Laporan Keuangan*. *10*(3), 1551–1561. https://doi.org/10.35870/jemsi.v10i3.2350

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

De Santis, F., & D'Onza, G. (2020). Big data and data analytics in auditing: in search of legitimacy. *Meditari Accountancy Research*, *29*(5), 1088–1112. https://doi.org/10.1108/MEDAR-03-2020-0838

Deby Cahyani Pramesti, P., & Gst Ayu Eka Damayanthi, I. (2023). *Analisis Perilaku Penggunaan Mobile Banking Dengan Model TAM dan Keamanan*. https://doi.org/10.24843/EJA.2024.v34.i06.p16

Deniswara, K., Handoko, B. L., & Mulyawan, A. N. (2020). Big data analytics: Literature study on how big data works towards accountant millennial generation. *International Journal of Management*, *11*(5), 376–389. https://doi.org/10.34218/IJM.11.5.2020.037

Esawe, A. T. (2022). Understanding mobile e-wallet consumers' intentions and user behavior. *Spanish Journal of Marketing - ESIC*, *26*(3), 363–384. https://doi.org/10.1108/SJME-05-2022-0105

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

Gupta, A., & Dogra, N. (2017). Tourist adoption of mapping apps: A UTAUT2 perspective of smart travellers. In *Tourism and Hospitality Management* (Vol. 23, Issue 2, pp. 145–161). University of Rijeka. https://doi.org/10.20867/thm.23.2.6

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). Emerald Group Publishing Ltd. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Tomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. https://www.researchgate.net/publication/354331182

Hamdam, A., Jusoh, R., Yahya, Y., Abdul Jalil, A., & Zainal Abidin, N. H. (2022). Auditor judgment and decision-making in big data environment: a proposed research framework. *Accounting Research Journal*, *35*(1), 55–70. https://doi.org/10.1108/ARJ-04-2020-0078

Hasan, M. M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-020-00291-z

Meinal, G., Ginting, S. B., & Hasibuan, A. (2024). *ANALISIS BIG DATA INFORMASI DALAM PROSES MANUFAKTUR INDUSTRI 4.0*. https://ejournal.warunayama.org/kohesi

Memon, M. A., Ting, H., Cheah, J. H., Thurasamy, R., Chuah, F., & Cham, T. H. (2020). Sample size for survey research: Review and recommendations. *Journal of Applied Structural Equation Modeling*, *4*(2), i–xx. https://doi.org/10.47263/jasem.4(2)01

Pratama, F. W., & Komariyah, E. F. (2023). Examining the Auditors� Acceptance of Big Data Analytics Technology Platform: Evidence from Government Auditors in Indonesia. *The Indonesian Journal of Accounting Research*, *26*(02). https://doi.org/10.33312/ijar.714

Putra, N. S., Ritchi, H., & Alfian, A. (2023a). Hubungan Big Data Analytics terhadap Kualitas Audit: Penerapan pada Instansi Pemerintah. *Jurnal Riset Akuntansi Dan Keuangan*, *11*(1), 57–72. https://doi.org/10.17509/jrak.v11i1.55139

Putra, N. S., Ritchi, H., & Alfian, A. (2023b). Hubungan Big Data Analytics terhadap Kualitas Audit: Penerapan pada Instansi Pemerintah. *Jurnal Riset Akuntansi Dan Keuangan*, *11*(1), 57–72. https://doi.org/10.17509/jrak.v11i1.55139

Rahi, S., Othman Mansour, M. M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *Journal of Research in Interactive Marketing*, *13*(3), 411–435. https://doi.org/10.1108/JRIM-02-2018-0032

Rattanaburi, K., & Vongurai, R. (2021). Factors Influencing Actual Usage of Mobile Shopping Applications: Generation Y in Thailand. *Journal of Asian Finance, Economics and Business*, *8*(1), 901–913. https://doi.org/10.13106/jafeb.2021.vol8.no1.901

Rozi, F. (2023). *93-Article Text-386-1-10-20230907*.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 1–40). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1

Shabbir, M. Q., & Gardezi, S. B. W. (2020). Application of big data analytics and organizational performance: the mediating role of knowledge management practices. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-020-00317-6

Sihombing, R. P., Narsa, I. M., & Harymawan, I. (2023). Big data analytics and auditor judgment: an experimental study. *Accounting Research Journal*, *36*(2–3), 201–216. https://doi.org/10.1108/ARJ-08-2022-0187

Srivastava, S., Mohta, A., & Shunmugasundaram, V. (2024). Adoption of digital payment FinTech service by Gen Y and Gen Z users: evidence from India. *Digital Policy, Regulation and Governance* , *26*(1), 95–117. https://doi.org/10.1108/DPRG-07-2023-0110

Sugiharto, B., Tinggi, S., & Sutaatmadja, I. E. (2021). APPLICATION OF UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT) MODEL TO THE INTENTION TO USING MOBILE BANKING SERVICE. *Article in ACCRUALS (Accounting Research Journal of Sutaatmadja)*. https://doi.org/10.35310/accruals.v5i02.885

Tang, J., & Karim, K. E. (2019). Financial fraud detection and big data analytics – implications on auditors' use of fraud brainstorming session. *Managerial Auditing Journal*, *34*(3), 324–337. https://doi.org/10.1108/MAJ-01-2018-1767

Tarhini, A., El-Masri, M., Ali, M., & Serrano, A. (2016). Extending the utaut model to understand the customers' acceptance and use of internet banking in lebanon a structural equation modeling approach. *Information Technology and People*, *29*(4), 830–849. https://doi.org/10.1108/ITP-02-2014-0034

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Widya Sulaiman, T., Bagas Fitriansyah, R., Rafif Alaudin, A., Hasyim Ratsanjani, M., & Negeri Malang, P. (2023). *LITERATURE REVIEW: PENERAPAN BIG DATA DALAM KESEHATAN MASYARAKAT*. *1*(3). https://publish.ojs-indonesia.com/index.php/SATUKATA/index

Yan, C., Siddik, A. B., Akter, N., & Dong, Q. (2023). Factors influencing the adoption intention of using mobile financial service during the COVID-19 pandemic: the role of FinTech. *Environmental Science and Pollution Research*, *30*(22), 61271–61289. https://doi.org/10.1007/s11356-021-17437-y