*Indonesia Accounting Research Journal, 12 (4) (2025), pp. 212-218*

Published by: Institute of Accounting Research and Novation (IARN)

Indonesia Accounting Research Journal

Journal homepage: https://journals.iarn.or.id/index.php/IARJ/index

# Audit transformation through data visualization

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**Article Info**

***Article history:***

Received Jun 12, 2025
Revised Jun 17, 2025
Accepted Jun 24, 2025

***Keywords:***

Accounting Information System;
Audit;
Big Data;
Data Analytics;
Data Visualization.

**ABSTRACT**

The advancement of big data has significantly impacted various areas of business, including accounting and auditing. While numerous studies have examined the influence of big data on audit processes, research that specifically focuses on the role of data visualization remains limited. This study aims to investigate the benefits of data visualization in the context of auditing, using a qualitative approach through a case study method. The participants in this study were final-year undergraduate accounting students who had acquired basic competencies that closely align with the demands of the professional world. The findings indicate that the group supported by data visualization tools achieved higher test scores and completed tasks more efficiently compared to the group without such support. An independent samples t-test revealed a statistically significant difference between the two groups, suggesting that data visualization contributes meaningfully to more effective information processing in auditing tasks. This study contributes to the literature on accounting, accounting information systems, auditing, and the application of big data, while addressing the empirical gap concerning data visualization as a central variable in the audit field.



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## 1. INTRODUCTION

The body of literature concerning the application of big data in the fields of accounting and auditing has expanded considerably in recent years. Nonetheless, there remains a relative paucity of research that explicitly examines the pivotal role of data visualization within the audit domain (Alles & Gray, 2016; D. A. Appelbaum et al., 2018; Earley, 2015; Gepp et al., 2018; Krieger et al., 2021; Manita et al., 2020; F. Tang et al., 2017). These scholars collectively argue that big data, along with its associated technological capabilities, holds substantial potential to fundamentally reshape and enhance auditing practices.

Conceptually, big data offers substantial benefits for the audit process. However, several studies underscore that auditors have yet to fully leverage this potential (Hamdam et al., 2021). A primary challenge lies in the difficulty of extracting meaning from the vast and complex volume of data. In this regard, data visualization serves a strategic function by simplifying information and reducing auditors' cognitive load. By converting data into visual representations, information becomes more accessible and analytically tractable (Alawadhi, 2015; A. Rose et al., 2017). Prior research also indicates that auditors require more time to detect patterns when data is presented in

tabular form, whereas the human brain processes graphical or visual information more efficiently (Lurie & Mason, 2007).

The utility of data visualization in enhancing the efficiency and quality of audit procedures has been increasingly acknowledged by both academic scholars and professional practitioners, including recognized auditing bodies (AICPA, 2015; Brown-Liburd et al., 2015; Chang & Luo, 2021; Richins et al., 2017). Notably, to date, no empirical evidence has identified any detrimental effects associated with the integration of data visualization into audit processes (Chang & Luo, 2021). On the contrary, data visualization is widely regarded as a valuable augmentation to traditional audit methodologies, offering versatile applications across various stages of the audit cycle, including both control testing and substantive testing procedures (A. M. Rose et al., 2021; Yoon et al., 2015).

Mauludina et al. (2024) highlight a range of data visualization capabilities that auditors can leverage throughout the audit process. Among the most salient is its ability to reveal patterns, uncover meaning, detect anomalies, and identify potentially suspicious elements within large datasets. While the theoretical potential of data visualization in auditing has been extensively discussed, its practical implementation remains considerably underdeveloped (Mauludina et al., 2024). Furthermore, the increasing volume of data has yet to yield a clear understanding of its tangible impact on audit execution and outcomes (Hamdam et al., 2021).

Empirical studies that explicitly examine the role of data visualization within the auditing context remain limited. As noted by Mauludina et al. (2024), the volume of such research over the past decade has been relatively low and exhibits a fluctuating trend. This underscores the continued relevance and urgency of further investigation to deepen scholarly understanding in this domain. The present study contributes meaningfully to the auditing field, regardless of specific contextual settings, and serves to complement and strengthen the existing body of literature, particularly in a domain where empirical evidence remains scarce.

In response to this gap, the present study aims to examine the role of data visualization as a complementary element in the audit process, particularly in enhancing auditors' ability to detect patterns, uncover hidden meanings, and identify data anomalies that may support subsequent audit procedures. This research contributes to the broader accounting literature, with specific relevance to the fields of accounting information systems and auditing. The findings are expected to offer valuable insights for practitioners and stakeholders seeking to optimize the use of data visualization as a strategic tool for improving audit effectiveness.

## 2. RESEARCH METHOD

This study adopts a qualitative approach, employing a case study strategy as the primary means to address the research questions. The qualitative approach is grounded in an inductive paradigm, which contrasts with the deductive nature of quantitative research that typically aims to test or confirm existing theories (Mauludina, Azis, et al., 2023; Mauludina, Mulyani, et al., 2023; Sekaran & Bougie, 2016). While quantitative research often relies on advanced and inferential statistical techniques, this study is classified as qualitative, as it does not engage in theoretical deduction but instead utilizes descriptive analysis to explain findings within their contextual settings. Moreover, it qualifies as empirical research, as it seeks to generate in-depth understanding of the observed phenomenon based on actual data.

This study employed a case study design to compare the performance outcomes of two distinct groups of participants. The research sample comprised over 100 final-year undergraduate students majoring in accounting, all of whom had completed competency development programs or certification exams, including modules in data analytics. These participants were considered to possess a foundational level of preparedness for entry into the professional accounting and auditing field. Given that all participants had successfully completed relevant academic subjects and participated in field-specific professional training, their competencies were considered comparable to those of early-career professionals. This assumption serves to minimize potential bias related to generalizability, thereby enhancing the study's applicability to real-world auditing contexts.

Participants were instructed to analyze a standardized dataset representing a company's sales transactions and were required to provide business development recommendations based on their analysis. To mitigate potential bias stemming from differing baseline competencies between groups, all participants received a brief refresher on relevant data analytics principles and a clear explanation of the task prior to its commencement. The evaluation framework focused on two key performance indicators: (1) time efficiency in completing the task, and (2) the accuracy with which patterns and business-relevant insights were identified.

The participants were randomly assigned into two groups. The control group was given only the raw dataset, while the experimental group received the same dataset augmented with data visualizations designed to aid interpretation. The purpose of this design was to evaluate the extent to which the inclusion of data visualization tools influences analytical performance. To ensure comprehensive analysis, an independent-samples t-test was conducted to determine whether the differences in average performance metrics between the two groups were statistically significant.

## 3. RESULTS AND DISCUSSIONS

This study's case implementation took place in a controlled environment specifically prepared for testing purposes. The room was outfitted with computers that had been preconfigured with all necessary data and detailed task instructions. The assessment was fully computerized to emulate real-world professional scenarios. No time constraints were imposed during the test, allowing researchers to assess participants' time efficiency organically as they worked toward identifying accurate patterns. Scoring was based solely on the correctness of the patterns identified—points were awarded for accurate findings, while incorrect responses received no score. Final scores were then computed using a maximum scale of 100 points.

Table 1. Descriptive result

| | Subject 1 | Subject 2 |
|---|---|---|
| Average completion time | 59,6 minutes | 57,7 minutes |
| Standard deviation of time | 0,4 minutes | 5,7 minutes |
| Average test score | 45,1 | 61,3 |
| Standard deviation of test score | 15,6 | 16,9 |

Table 1 presents the descriptive results of the test administered to the two subject groups. Subject Group 2 recorded an average completion time of 57.7 minutes, which is 1.9 minutes faster than Subject Group 1, whose average completion time was 59.6 minutes. In terms of accuracy, Group 2 also outperformed Group 1, achieving an average test score of 61.3—16.2 points higher than the average score of 45.1 recorded by Group 1.

However, Subject Group 2 exhibited a higher standard deviation in completion time—5.7 minutes—compared to just 0.4 minutes in Subject Group 1. Similarly, the standard deviation of test scores in Group 2 was 16.9, slightly higher than the 15.6 observed in Group 1. These findings suggest that although Group 2 generally demonstrated better overall performance in terms of both speed and accuracy, there was greater variability in individual outcomes within the group, particularly in terms of time efficiency. It should be emphasized that the use of visualization tools does not necessarily lead to improved time efficiency. The observed variation is not assumed to stem from inconsistent visualization skills among participants but is more likely due to individual differences in working styles or cognitive preferences. This interpretation is further supported by Group 2's higher average test scores and the relatively small gap in score variability between the two groups.

Table 2. Independent t-test between groups

| Test | *P-value* |
|---|---|
| Independent T-Test for Test Scores | 0,000** |
| Independent T-Test for Completion Time | 0,024* |

Note: ***p-value* < 0,01, **p-value* < 0,05

To ensure that the observed differences between the two groups could be attributed to the intended differentiating variable—namely, the use of data visualization tools—a statistical analysis was conducted using an independent samples t-test. As presented in Table 2, the results indicate that both the differences in test scores and completion times between Subject Group 1 and Subject Group 2 are statistically significant. The p-value for the test score comparison was 0.000 ($p < 0.01$), while the p-value for completion time was 0.024 ($p < 0.05$), both falling below the predetermined thresholds for statistical significance.

These findings suggest that the observed differences were not merely coincidental but were influenced by the presence of data visualization as an intervening factor. Accordingly, the results of this study reinforce prior research that has emphasized the benefits of data visualization in the auditing process, as demonstrated by Alles & Gray (2016), D. A. Appelbaum et al. (2018), Earley (2015), Gepp et al. (2018), Krieger et al. (2021), Manita et al. (2020), and F. Tang et al. (2017). More specifically, the results are consistent with the findings of Chang & Luo (2021) and Yoon et al. (2015), who reported that data visualization adds value at various stages of the audit process, particularly by enhancing the effectiveness and efficiency of decision-making.

A significant p-value in the t-test indicates that the existence of visualization tools is statistically valuable in enhancing audit task outcomes. This suggests that the observed improvements—such as increased accuracy or reduced task completion time—are not due to random chance. In the context of professional auditing environments—such as those found in public accounting firms—these findings underscore the practical relevance of integrating data visualization tools to support more effective decision-making and greater efficiency. Nevertheless, successful implementation requires attention to factors like staff training, compatibility with existing systems, and organizational readiness to ensure the full benefits are realized.

The findings of this study further corroborate the conclusions drawn by Mauludina et al. (2024), who asserted that data visualization serves as a powerful tool for uncovering patterns, detecting anomalies, and extracting meaningful insights from large datasets. In an increasingly data-driven business landscape—where organizations are faced with overwhelming volumes of information generated on a daily basis—the ability to distill relevant insights from complex datasets is critical to informed decision-making.

Data visualization addresses this challenge by transforming raw and often unstructured data into intuitive visual formats, thereby reducing cognitive load and enabling auditors to interpret information more efficiently. This visual simplification facilitates a deeper understanding of the underlying data structure, enhances pattern recognition, and ultimately contributes to the accuracy and speed of audit investigations. As highlighted by Ma (2023), the strength of data visualization lies in its capacity to bridge the gap between data complexity and actionable insight, making it an indispensable component of modern audit methodologies.

Data visualization–supported auditing offers expanded opportunities for identifying outliers, trends, and correlations across both financial and non-financial datasets. Prior studies have even demonstrated the application of data visualization techniques to non-financial information as a means of enhancing audit effectiveness. For instance, Guo et al. (2021) employed topological graph techniques in journal entry analysis, while Werner et al. (2021) utilized process mining to evaluate the effectiveness of internal controls.

Furthermore, data visualization can also be employed within the context of exploratory or unsupervised analysis—an approach in which auditors initiate the analytical process without predefined business questions or hypotheses (Richins et al., 2017). The objective of this method is to uncover hidden patterns and underlying structures in the data without initial guidance, thereby increasing the likelihood of discovering unexpected insights (Li et al., 2021). In contrast to the supervised or explanatory approach, which relies on specific cues and targeted objectives to direct the investigation, exploratory analysis is more open-ended, allowing the data itself to guide the discovery process (Alzamil et al., 2021).

In addition, data visualization can be enhanced through interactive techniques that allow auditors to engage with data in a more flexible and in-depth manner. Table 3 outlines various interactive techniques designed to adapt visualizations according to user preferences. These techniques are categorized into two primary functional groups in data visualization. The first category is representation tools, which enable users to modify how data is displayed to suit their analytical needs. This includes techniques such as Encode (transforming data representations), Reconfigure (rearranging the structure or layout of data), and Connect (illustrating relationships between data points).

The second category is data selection tools, which allow users to isolate and emphasize specific data elements of interest. This category includes techniques such as Select (marking relevant data items), Elaborate/Abstract (adjusting the level of detail shown), Filter (displaying data based on specified conditions), and Explore (navigating or uncovering additional data within the display). In addition, data visualization can be enhanced through interactive techniques that allow auditors to engage with data in a more flexible and in-depth manner. Table 3 outlines various interactive techniques designed to adapt visualizations according to user preferences. These techniques are categorized into two primary functional groups in data visualization.

Table 3. Interactive visualization techniques

| Technique | Explanation | Ilustration |
|---|---|---|
| Representation tools | | |
| *Encode* | Demonstrate various representations of data | Transform tabular format into graphs or vice versa. Convert a pie chart into a histogram. |
| *Reconfigure* | Exhibit different arrangements of data | Modify baselines or axis scales, and reverse attributes displayed on x- and y-axes. |
| *Connect* | Display the related data items | Examine the leveled set of data flow diagrams or entity-relationship diagrams. Emphasize patterns in intricate transaction data. |
| Data selection tools | | |
| *Select* | Mark data items of interest | Highlight selected items in extensive spreadsheets or graphical displays. The highlighted item remains visible, facilitating easy location even after rearranging the display. |
| *Eleborate/abstract* | Present more or less detail | Manuver the cursor over the screen to reveal more or less detailed information, such as data underlying a segment of a graphical display |
| *Filter* | Exhibit data based on specific condition(s) | Utilize query tools embedded in database and spreadsheet products, and enterprise computer programs. |
| *Explore* | Reveal other data | Pan or move the cursor across a graphical display to inspect different segments of a display. Click on hyperlinks to navigate within extensive, complex textual documents. |

*Source: Dilla & Raschke (2015) and Yi et al. (2007)*

The application of data visualization within the auditing domain is closely tied to the nature and scope of the specific audit being performed—whether it be a financial statement audit, internal audit, operational audit, or investigative audit. While these audit types differ in focus, objectives, and procedures, they are all grounded in the same core principle: the systematic collection, analysis, and evaluation of evidence to support professional judgment and decision-making. As noted by Mauludina et al. (2024), the integration of data visualization tools in audit practice has, to date, been predominantly concentrated in the context of financial statement audits, where visual analytics are used to detect anomalies in financial data, highlight trends in account balances, and support risk assessments. However, the potential for broader application across other audit types remains significant. For instance, internal audits could benefit from interactive dashboards for ongoing monitoring of compliance and control effectiveness; operational audits could leverage visualizations to assess process efficiencies and resource utilization; while investigative audits could use network diagrams and flowcharts to trace complex transaction patterns and detect fraud.

This study offers empirical support for the role of data visualization in enhancing audit effectiveness. The results further advocate for the expanded utilization of data visualization

techniques across different audit contexts. Rather than being confined solely to financial statement audits, data visualization demonstrates considerable potential for broader application in internal, operational, and investigative audits. Its ability to improve both efficiency and accuracy in evaluation and decision-making underscores its value as a strategic asset in strengthening audit quality across various domains.

## 4. CONCLUSION

The study affirms that data visualization serves as a valuable supporting component throughout multiple phases of the audit process, particularly in aiding auditors to detect significant patterns, trends, and anomalies that can guide subsequent audit actions. The results indicate notable differences in outcomes between the two groups, with the group utilizing data visualization tools achieving higher scores and demonstrating greater time efficiency compared to the group without such tools. These differences were statistically confirmed using an independent samples t-test, which showed significant results. This provides strong evidence that the variation in performance was influenced by the inclusion of data visualization as a key differentiating factor.

This study makes a significant contribution by advancing the body of knowledge in the areas of accounting, accounting information systems, auditing, and big data application. It addresses the existing gap in empirical research concerning the role of data visualization in audit practice, which has thus far received limited attention. Moreover, the study offers valuable practical insights for auditors, professional bodies, and other stakeholders, highlighting the potential of data visualization technologies—which are now increasingly accessible—for enhancing professional audit practices. To fully leverage these benefits across all stages of the audit process, it is essential to ensure that auditors possess strong digital and data analytics competencies, along with access to the appropriate technological resources.

This research is subject to certain limitations, most notably the restricted subject pool, which consisted solely of final-year accounting students. To improve the generalizability of future findings, subsequent research should involve more diverse and representative participant groups. Furthermore, upcoming research could explore the effectiveness of data visualization in specific audit types with greater procedural complexity, thereby offering a more nuanced and context-specific understanding of its practical benefits. In light of these considerations, key research priorities moving forward include enhancing auditor competencies, integrating visualization into audit workflows, evaluating its impact on professional judgment, comparing its effectiveness across sectors, and addressing ethical and data governance concerns to better realize the advantages of data visualization in auditing.

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