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RISK ASSESSMENT USING PREDICTIVE ANALYTICS

Eid Mohammed Alotaibi[A]

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ABSTRACT

Purpose: This research paper uses design science methodology to develop and evaluate a predictive analytics model for audit risk assessment. This research therefore contributes to improving the accuracy and efficiency of audit risk assessment through predictive analytics.

Theoretical framework: This study involved developing and evaluating a predictive analytics model for audit risk assessment, with it being tested during the audit of a publicly listed Saudi company.

Design/methodology/approach: This study adopted the design science research methodology, which is a problem-solving approach that involves the creation of innovative solutions to practical problems. This methodology is particularly relevant for developing and evaluating predictive analytics models for audit risk assessment, because it provides a structured, systematic approach to the problem-solving process. In the context of this research paper, the design science research methodology was used to develop and evaluate a predictive analytics model for audit risk assessment.

Findings: The proposed predictive analytics model for audit risk assessment was found to be an effective tool for helping auditors to make informed decisions based on data analysis. The model accurately identifies high-risk factors associated with an organization, provides valuable insights for decision-making, and highlights areas of potential risk that may require further investigation.

Research, practical & social implications: Future research could explore several areas related to predictive analytics in audit risk assessment. One important area to investigate would be the impact of using predictive analytics on audit quality. The ethical implications of using predictive analytics in audit risk assessment and the potential biases that could affect a model's accuracy are also important areas to explore.

Originality/value: This paper helps improve our understanding of how predictive analytics can be effectively applied to audit risk assessment and how design science methodology can be used to develop and evaluate predictive analytics models. Furthermore, this study provides insights about the effectiveness of predictive analytics for improving audit risk assessment, thus contributing to the existing literature on the topic.

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AVALIAÇÃO DE RISCO USANDO ANÁLISE PREDITIVA

RESUMO

Objetivo: Este trabalho de pesquisa usa metodologia de design science para desenvolver e avaliar um modelo de análise preditiva para avaliação de risco de auditoria. Esta pesquisa, portanto, contribui para melhorar a precisão e a eficiência da avaliação de riscos de auditoria por meio de análises preditivas.
Referencial teórico: Este estudo envolveu o desenvolvimento e avaliação de um modelo de análise preditiva para avaliação de risco de auditoria, sendo testado durante a auditoria de uma empresa saudita de capital aberto.

[A] *PhD in Accounting Information System. Saudi Electronic University. Riyadh, Saudi Arabia.*
E-mail: e.alotaibi@seu.edu.sa Orcid: https://orcid.org/0000-0002-0692-9430

Design/metodologia/abordagem: Este estudo adotou a metodologia de pesquisa design science, que é uma abordagem de resolução de problemas que envolve a criação de soluções inovadoras para problemas práticos. Essa metodologia é particularmente relevante para desenvolver e avaliar modelos analíticos preditivos para avaliação de risco de auditoria, pois fornece uma abordagem estruturada e sistemática para o processo de solução de problemas. No contexto deste trabalho de pesquisa, a metodologia de pesquisa da ciência do design foi usada para desenvolver e avaliar um modelo analítico preditivo para avaliação de risco de auditoria.
Resultados: O modelo de análise preditiva proposto para avaliação de riscos de auditoria foi considerado uma ferramenta eficaz para ajudar os auditores a tomar decisões informadas com base na análise de dados. O modelo identifica com precisão os fatores de alto risco associados a uma organização, fornece informações valiosas para a tomada de decisões e destaca áreas de risco potencial que podem exigir mais investigação.
Pesquisa, implicações práticas e sociais: pesquisas futuras podem explorar várias áreas relacionadas à análise preditiva na avaliação de riscos de auditoria. Uma área importante a ser investigada seria o impacto do uso da análise preditiva na qualidade da auditoria. As implicações éticas do uso de análises preditivas na avaliação de riscos de auditoria e os possíveis vieses que podem afetar a precisão de um modelo também são áreas importantes a serem exploradas.
Originalidade/valor: este documento ajuda a melhorar nossa compreensão de como a análise preditiva pode ser aplicada com eficácia à avaliação de riscos de auditoria e como a metodologia da ciência do design pode ser usada para desenvolver e avaliar modelos de análise preditiva. Além disso, este estudo fornece insights sobre a eficácia da análise preditiva para melhorar a avaliação de risco de auditoria, contribuindo assim para a literatura existente sobre o tema.

Palavras-chave: Tecnologia da Informação, Auditoria, Avaliação de Risco, Análise Preditiva, Ciência do Projeto.

EVALUACIÓN DE RIESGO MEDIANTE ANÁLISIS PREDICTIVO

RESUMEN
Propósito: Este trabajo de investigación utiliza la metodología de la ciencia del diseño para desarrollar y evaluar un modelo de análisis predictivo para la evaluación de riesgos de auditoría. Esta investigación, por lo tanto, contribuye a mejorar la precisión y la eficiencia de la evaluación del riesgo de auditoría a través del análisis predictivo.
Marco teórico: este estudio implicó el desarrollo y la evaluación de un modelo de análisis predictivo para evaluar el riesgo de auditoría, que se probó durante la auditoría de una empresa saudí que cotiza en bolsa.
Diseño/metodología/enfoque: este estudio adoptó la metodología de investigación de la ciencia del diseño, que es un enfoque de resolución de problemas que implica la creación de soluciones innovadoras para problemas prácticos. Esta metodología es particularmente relevante para desarrollar y evaluar modelos analíticos predictivos para la evaluación del riesgo de auditoría, ya que proporciona un enfoque estructurado y sistemático para el proceso de resolución de problemas. En el contexto de este trabajo de investigación, se utilizó la metodología de investigación de la ciencia del diseño para desarrollar y evaluar un modelo analítico predictivo para evaluar el riesgo de auditoría.
Resultados: se encontró que el modelo de análisis predictivo propuesto para evaluar los riesgos de auditoría es una herramienta eficaz para ayudar a los auditores a tomar decisiones informadas basadas en el análisis de datos. El modelo identifica con precisión los factores de alto riesgo asociados con una organización, proporciona información valiosa para la toma de decisiones y destaca las áreas de riesgo potencial que pueden requerir una mayor investigación.
Implicaciones sociales, prácticas y de investigación: La investigación futura podría explorar varias áreas relacionadas con el análisis predictivo en la evaluación de riesgos de auditoría. Un área importante a investigar sería el impacto del uso de análisis predictivos en la calidad de la auditoría. Las implicaciones éticas del uso de análisis predictivos para evaluar el riesgo de auditoría y los sesgos potenciales que pueden afectar la precisión de un modelo también son áreas importantes para explorar.
Originalidad/Valor: este documento ayuda a mejorar nuestra comprensión de cómo se puede aplicar de manera efectiva el análisis predictivo para evaluar el riesgo de auditoría y cómo se puede usar la metodología de la ciencia del diseño para desarrollar y evaluar modelos de análisis predictivo. Además, este estudio proporciona información sobre la efectividad del análisis predictivo para mejorar la evaluación del riesgo de auditoría, contribuyendo así a la literatura existente sobre el tema.

Palabras clave: Tecnologías de la Información, Auditoría, Evaluación de Riesgos, Análisis Predictivo, Project Science.

INTRODUCTION

The accounting and auditing profession has benefited from rapid technological advancements (AICPA, 2017; Alotaibi, 2023; Araz et al., 2020; Brandtner, 2022; Grover et al., 2018; Hirt et al., 2019; Huang et al., 2022; Kogan et al., 2019; Nasir et al., 2021; Qi & Tao, 2018; Samuel et al., 2017; Schlegel, 2014; Shmueli & Koppius, 2011; Søgaard, 2021; Sun, 2018; Susanto & Meiryani, 2019; Vasarhelyi et al., 2015). These advancements have paved the way for new innovative tools, such as predictive analytics, to be used in the industry (Qi & Tao, 2018). Predictive analytics uses data, statistical algorithms, and machine learning techniques to estimate the likelihood of future outcomes based on historical data (Shmueli & Koppius, 2011), and it has many applications ranging from marketing to finance. It is becoming increasingly popular in audit risk assessment, which evaluates an organization's risks as part of its financial reporting and auditing activities. In essence, it involves identifying the potential risks to an organization and assessing the likelihood and degree of their impact on the organization's financial results. Audit risk assessment is therefore a critical component of the audit process, because it helps auditors to identify areas of financial reporting that may be at risk of material misstatements. One of the critical challenges of audit risk assessment, however, is the sheer volume of data that auditors need to analyze. Indeed, such data can include financial, transactional, and other information about the organization's operations. As the volume and complexity of this data increases, it becomes harder for auditors to identify potential risks and evaluate their impact on financial reporting.

Several predictive analytics techniques can be used in risk assessment (Shmueli & Koppius, 2011), such as regression analysis, machine learning algorithms, and time series analysis. Each of these techniques has its strengths and weaknesses, and one is chosen based on the specific needs of the organization and the nature of the data being analyzed. In order to effectively use predictive analytics in risk assessment, organizations must have access to high-quality data and an appropriate model (Araz et al., 2020; Shmueli & Koppius, 2011), which may require investing in data-management systems, analytics software, and other technological solutions. Organizations must also have appropriate personnel with the skills and expertise to effectively analyze and interpret the data generated by predictive analytics techniques. Another important consideration when using predictive analytics in audit risk assessment is the need for appropriate controls and processes. As with any data-driven approach, there is a risk of bias or error in the data analysis, but this risk can be mitigated through appropriate controls and processes, such as by multiple parties validating, testing, and reviewing data. Organizations must also comply with relevant regulations and guidelines when using predictive analytics in risk assessment. Despite the challenges, however, predictive analytics is becoming an increasingly important tool for risk assessment.

An effective predictive analytics model for audit risk assessment requires several vital features:

1. It should be able to handle large volumes of data and analyze complex transactions.
2. It should be adaptable and able to learn from new data, so it will remain relevant over time.
3. It should be transparent and auditable, so auditors can understand how it arrived at its conclusions.

The benefits of using predictive analytics in audit risk assessment include greater efficiency, effectiveness, and accuracy. However, there are also limitations when using predictive analytics. For example, a model's accuracy depends on the quality of the data being used to train it. Additionally, there may be biases in the data or the model that can affect its accuracy, so it is essential that the data being used to train the model is accurate and representative of the population being audited.

This study aims to develop a predictive analytics model for audit risk assessment and test its effectiveness using data collected from a publicly listed Saudi company in the retail sector. Furthermore, this research aims to determine how predictive analytics can be effectively applied to audit risk assessment and identify the critical features of an effective model, as well as explore the benefits and limitations of using predictive analytics for audit risk assessment. When utilizing predictive analytics, we would expect auditors to be better able to assess risks and tailor their audit procedures to mitigate them.

Design science is particularly relevant to this study because it offers a structured and systematic approach for developing and evaluating predictive analytics models for audit risk assessment (David et al., 2002). Design science is a problem-solving approach that involves creating innovative solutions to practical problems, such as by applying predictive analytics to improve audit risk assessment. This methodology involves a cyclical process comprising problem identification, solution design, implementation, and evaluation, and this process is applicable to developing and evaluating predictive analytics models for audit risk assessment. The research questions for this study are as follows:

How can predictive analytics be effectively applied in audit risk assessment?

What are the key features of an effective predictive analytics model for audit risk assessment?

What are the benefits and limitations of using predictive analytics for audit risk assessment?

This paper systematically reviews the existing literature about predictive analytics and audit risk assessment, including material from academic journals, conference proceedings, and other relevant sources. It also presents a case study of a predictive analytics model for audit risk assessment being developed and evaluated using design science, thus highlighting design science's relevance to such efforts.

The developed predictive analytics model for audit risk assessment was tested during an audit of a publicly listed Saudi company for its ability to identify potential financial reporting risks, such as fraud, errors, and omissions. The model's effectiveness was evaluated across a range of metrics, including accuracy, efficiency, and usability. Overall, this research study aims to help enhance audit risk assessment through the use of predictive analytics. Audit risk assessment is a critical component of the audit process, with it identifying potential risks and ensuring the integrity of financial data. The current methods for audit risk assessment are limited in terms of accuracy and efficiency, so predictive analytics has emerged as a promising tool for addressing these limitation. Unfortunately, there is a lack of research on its effectiveness in this context, so this research intends to fill this gap by developing and evaluating a predictive analytics model for audit risk assessment. Previous studies have highlighted the potential of predictive analytics for improving business operations, such as that of Ali, Chang, and Khurram (2018), who found that predictive analytics can significantly improve the accuracy and efficiency of audit risk assessment. Likewise, Aier and Schumann (2015) highlighted the potential of predictive analytics for identifying risks that were previously overlooked by traditional methods for audit risk assessment. These studies demonstrate the potential of predictive analytics for improving business operations, thus emphasizing the need for further research.

In addition to developing and evaluating a predictive analytics model for audit risk assessment, this research contributes to improving our understanding of how predictive analytics can be effectively applied to audit risk assessment and how design science methodology can be used to develop and evaluate predictive analytics models for this purpose. Furthermore, this study builds on the existing literature by providing insights into the effectiveness of predictive analytics for improving audit risk assessment. This study also has practical implications for auditors and organizations when using predictive analytics for audit risk assessment, such as by highlighting the critical features of effective predictive analytics models for audit risk assessment and the practical benefits and limitations. Overall, this study addresses significant gaps in the literature and contributes to developing more accurate and efficient approaches for audit risk assessment.

This paper is structured as follows: First, the literature review provides a comprehensive overview of the existing research on the topic. The second section then describes the methods and procedures used to collect and analyze data, while the results of this are presented in the following section. The fourth section then discusses the findings, with it drawing conclusions and supplying insights. Finally, the conclusion summarizes this study's main findings and implications and makes some recommendations for future research.

LITERATURE REVIEW

Audit risk is the risk of an auditor expressing an inappropriate opinion due to misleading financial statements (Hogan & Wilkins, 2008; Messier et al., 2008). It comprises three components, namely inherent risk, control risk, and detection risk. Inherent risk is the susceptibility of financial statements to material misstatement, regardless of the effectiveness of the organization's internal controls. Inherent risk may be influenced by the complexity of transactions, the industry, the management team's experience, and the size of operations. Control risk reflects the risk that the entity's internal controls will not prevent or detect a material misstatement in the financial statements. It is influenced by the effectiveness of the control environment, which includes the design and implementation of control activities, the monitoring of controls, and the security and integrity of the entity's information systems. Next, detection risk is the risk that an auditor will fail to detect a material misstatement in the financial statements. This may occur due to the nature, timing, and extent of the audit procedure; the sampling methods used; the degree of reliance on internal controls; and the extent that transactions are tested. These three components of audit risk are interrelated, and changes in one component can affect the others. For example, when the inherent risk is high, the auditor may decide to extend the audit procedures performed, potentially increasing the detection risk. Similarly, when the control risk is high, an auditor may decide to increase the testing of controls, thus decreasing the detection risk. Understanding these components of audit risk is critical for planning and conducting an effective audit and expressing an appropriate opinion about the audited entity's financial statements (Messier et al., 2008).

Predictive analytics is a subset of data analytics that uses statistical techniques, machine learning algorithms, and data mining to analyze historical data and predict future events or trends (Shmueli & Koppius, 2011). It involves using various data sources, both structured and unstructured, to build a predictive model that can be used to make informed decisions and take appropriate actions. A predictive analytics model follows a three-step process that comprises data collection and preparation, model building, and deployment. In the data collection and preparation stage, data is gathered from the various sources and cleaned, organized, and transformed into a suitable format for analysis (de Langhe & Puntoni, 2021). In the model-building stage, statistical techniques and machine learning algorithms are employed to build a model for accurately predicting future events or trends. Finally, in the deployment stage, the model is operationalized and used to make predictions that will inform decision-making. Predictive analytics has various applications in a number of industries, such as healthcare, finance, retail, and marketing. It can be used to identify potential fraud, optimize supply chain operations, improve patient outcomes, and predict customer behavior, sales, and costs, to name but a few possibilities (Grover et al., 2018).

Predictive analytics also represents an effective tool for improving audit risk assessment. This section therefore comprehensively reviews the existing literature for using predictive analytics in audit risk assessment, with it focusing on key concepts and theories related to the topic. Traditional methods for audit risk assessment have relied on subjective judgments and internal historical data, which can be a time-consuming process that is prone to error. Predictive analytics, in contrast, leverages advanced data analysis techniques and machine learning algorithms to identify patterns and predict outcomes.

Predictive Analytics for Audit Risk Assessment

Several studies have demonstrated the effectiveness of predictive analytics for detecting high levels of management risk. For example, Brandtner (2022) developed a predictive model for risk management in the supply chain domain, finding that the model achieved greater accuracy than traditional methods. Similarly, Schlegel (2014) developed a model based on machine learning for predicting and managing supply chain risk, again finding that the proposed model was more accurate and efficient than traditional methods. Several approaches and concepts have supported the adoption of predictive analytics in risk assessment (Araz et al., 2020; Brandtner, 2022; de Langhe & Puntoni, 2021; Schlegel, 2014; Shmueli & Koppius, 2011), such as the use of data mining to extract valuable insights from large datasets. Data mining uses machine learning algorithms to identify patterns and relationships within data that can then be used to predict future outcomes. In audit risk assessment, data mining can be used to analyze financial and non-financial data in order to identify risks and potential areas of material misstatement.

Another key concept related to predictive analytics in risk assessment is the use of decision support systems (Samuel et al., 2017; Zhou et al., 2023), which are computer-based tools that help users to make complex decisions by providing relevant information and analysis. In audit risk assessment, such systems can analyze financial data, identify potential areas of material misstatement, and provide recommendations for audit procedures (Al-Refiay et al., 2022). Cognitive computing also supports the effectiveness of predictive analytics in risk assessment (Hirt et al., 2019). More specifically, cognitive computing uses artificial intelligence and machine learning techniques to simulate human cognitive processes, such as perception, reasoning, and learning, and in the context of audit risk assessment, this can help analyze large datasets and identify patterns and trends that would be difficult for humans to detect. Overall, predictive analytics has become increasingly important in risk assessment over recent years as traditional methods have become outdated due to their propensity for error. The effectiveness of predictive analytics in improving audit risk assessment is built upon critical theories and concepts, such as data mining, decision support systems, and cognitive computing. Thus, further research is needed to develop and implement predictive analytics models for audit risk assessment in order to improve the accuracy and efficiency of the auditing process.

The American Institute of Certified Public Accountants (AICPA (2017) says about the subject:

> *"Audit Data Analytics is the science and art of discovering and analyzing patterns, identifying anomalies and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modeling and visualization for the purpose of planning or performing the audit."*

This is particularly important in today's complex business environment, where companies generate and store vast amounts of data, because traditional audit methods may not be sufficient to identify all the potential risks (Abass et al., 2022). Indeed, previous studies have demonstrated the effectiveness of predictive analytics for identifying audit risks. For instance, Huang et al. (2022) used data analytics to develop a full-population testing model for auditing, with them finding that the model correctly tested the full population of transactions with a greater degree of accuracy than traditional audit methods. Similarly, Sun (2018) used machine learning algorithms to predict material weaknesses in internal controls, finding again that the model was more accurate than traditional audit methods.

Previous studies of using predictive analytics in risk assessment have demonstrated benefits in terms of identifying risks and supplementing traditional audit methods, but there are also limitations, such as a reliance on historical data and the need for high-quality data, so these should be considered when designing predictive analytics models for audit risk assessment. Thus, research needs to address these limitations and develop increasingly effective predictive analytics models for audit risk assessment.

Design Science and Accounting Information Systems

Design science has been widely used in information systems research to develop and evaluate innovative and practical systems that address complex real-world problems (David et al., 2002; Hevner et al., 2008; Wieringa, 2014). Accounting information systems (AIS) are no exception to this, with researchers having used design science to create and evaluate AIS technology for supporting the accounting profession (David et al., 2002; Geerts, 2011). We now explore the use of design science in AIS research and discuss its applications, strengths, limitations, and future directions.

Design science is a research methodology for creating and evaluating artifacts that solve specific problems (Wieringa, 2014). It involves several steps, namely problem identification, design and development, demonstration, and evaluation. The main goal here is to develop innovative yet practical solutions that can address real-world problems. In AIS research, design science has been used to develop and evaluate various systems, such as for accounting information, decision support, and business intelligence (David et al., 2002; Hevner et al., 2008). For example, (Søgaard, 2021) used design science to develop a blockchain-enabled platform for VAT settlement in small and medium-sized enterprises (SMEs), with the aim being to improve the accuracy and efficiency of administrative responsibilities. Design science was also used to develop a decision support system for detecting material weaknesses in internal control (Nasir et al., 2021), with this assisting auditors in identifying such weaknesses and providing recommendations. This system was evaluated based on a case study, and this demonstrated that it improved efficiency and effectiveness.

Design science brings several advantages to AIS research (David et al., 2002; Geerts, 2011). First, it provides a structured and systematic approach for developing and evaluating an AIS, thus ensuring a design will meet specific requirements and be effective in solving the identified problem. Second, design science encourages researchers and practitioners to collaborate, leading to a more practical and relevant AIS. Finally, design science provides a framework for disseminating research findings, thus facilitating their adoption and implementation among practitioners. Nevertheless, design science also has some limitations within AIS research. First, it can be a time-consuming and resource-intensive methodology, limiting its suitability in some research contexts. Second, it can be challenging to apply in complex, dynamic environments where problems and requirements change over time. Finally, design science may not be suitable for problems that require exploratory or descriptive research.

Overall, design science has been widely used in AIS research to develop and test innovative and practical solutions that address complex, real-world problems. Indeed, it provides a structured, systematic approach for developing and evaluating AIS artifacts while encouraging collaboration among researchers and practitioners. Nevertheless, its resource-intensive nature and unsuitability for dynamic challenges limit its applicability. In future, AIS researchers will likely apply design science to address more emerging issues, such as cybersecurity, data privacy, and sustainability reporting.

RESEARCH DESIGN

This study followed the design science methodology (David et al., 2002; Hevner et al., 2008; Wieringa, 2014), which is a problem-solving approach for creating innovative solutions to practical problems. It is particularly relevant for developing and evaluating predictive analytics models for audit risk assessment, because it provides a structured, systematic approach for the problem-solving process.

The first step was to identify the problem that needs solving, which in this case is how to improve audit risk assessment through predictive analytics. The second step was to design a solution to the problem, and this involves developing a conceptual predictive analytics model that outlines the key features and components of the solution based on the existing literature for predictive analytics and audit risk assessment, as well as discussions with auditors and other stakeholders. The third step was to implement the proposed solution by building the predictive analytics model and integrating it into the audit process. This involved working closely with auditors and other stakeholders to ensure that the model was effectively integrated into the audit process and that the necessary data was collected and analyzed. The final step was to evaluate the effectiveness of the predictive analytics model by testing it for accuracy, reliability, and usability. These steps are explained in detail below.

Identifying the Problem

Auditing is an essential process for evaluating the accuracy, consistency, and reliability of an organization's financial reports. An important element of this is audit risk assessment, which assesses the potential risks associated with financial data. Identifying problem areas is critical for improving the accuracy and reliability of financial reports.

Several studies have identified various issues with audit risk assessment. First, many audit firms still rely on manual processes and outdated methods for audit risk assessment. This can lead to errors and inconsistencies, such as missing potential risks that could harm the organization. According to Wani et al. (2018), auditors rely heavily on historical data to assess audit risk, and this may not always be relevant to the current situation, potentially leading to inadequate risk assessment and long-term organizational harm. Secondly, a lack of knowledge and expertise for predictive analytics tools is also a significant concern for audit risk assessment. Such tools can help identify potential risks by rapidly analyzing large volumes of financial data, yet many auditors are unaware of these tools or lack the necessary skills to use them effectively. Third, inadequate communication and coordination between auditors and management can also be a concern for audit risk assessment. Auditors must communicate effectively with management to understand an organization's business processes, potential risks, and other critical factors that may impact an audit risk assessment. Finally, inadequate training and development programs for auditors can also be an issue in audit risk assessment. With financial transactions becoming increasing complex and new technologies constantly emerging, auditors need to be equipped with the necessary skills and knowledge to conduct effective risk assessments.

In summary, addressing the above problem areas in audit risk assessment is critical for improving the accuracy and reliability of financial data. These issues could be addressed by incorporating predictive analytics tools, improving communication and coordination, and providing training and development programs for auditors. Through design science, this study aims to develop a predictive analytics tool for audit risk assessment that overcomes the limitations of existing methods and improves the accuracy and reliability of financial data.

The Proposed Model

The proposed risk assessment model is based on using predictive analytics to comprehensively evaluate the risk factors facing an organization. This model is designed to analyze and interpret data from various sources and calculate a risk matrix score to indicate an organization's level of audit risk. The model comprises several sequentially arranged stages to ensure accurate and reliable results. In the first stage, data is collected from various sources, such as financial statements, transactional data, non-financial data, and internal and external audit reports. The data collected at this stage crucially forms the basis for the entire model, and the collection process can help identify key risk factors affecting the audit process. The data is then processed and transformed into a format suitable for analysis.

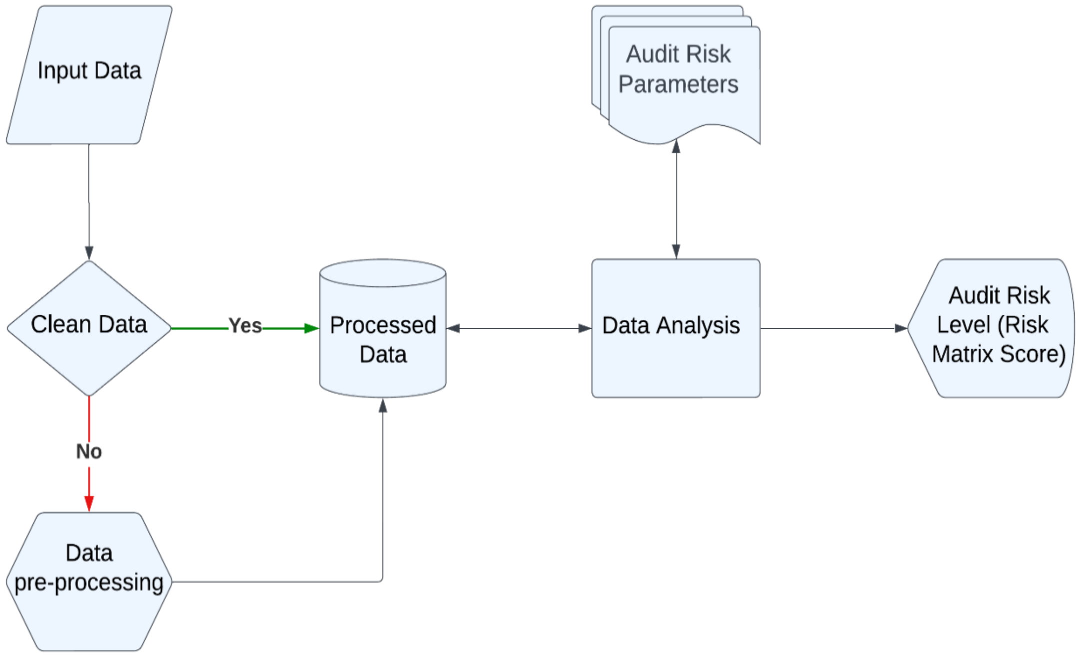
In the second stage, a predictive model is developed to predict the likelihood of financial statement fraud or misstatement. This is achieved using data mining and machine learning techniques, such as logistic regression, decision trees, and neural networks, with the model being trained using historical data and validated with a holdout sample. The final stage involves using the predictive model to assess the level of risk associated with financial statement fraud or misstatement. This risk assessment can be performed at different levels, such as the account level, business unit level, or overall company level. The results of this then inform the audit plan and help prioritize audit procedures.

In summary, 1) data is collected from various sources and cleaned, so 2) a model can be built to predict the likelihood of financial statement fraud or misstatement. Next, 3) the predictive model is used to assess the level of risk associated with financial statement fraud or misstatement. Implementing the proposed model involved:

- developing a data-collection framework,
- developing parameters for risk factors,
- developing the predictive model, and
- evaluating the predictive model using criteria for audit risk assessment.

Figure 1 illustrates the process for using the proposed risk assessment model based on predictive analytics, which is a comprehensive approach for evaluating the risk factors likely to affect an organization. This model analyzes and interprets data from various sources to calculate a risk matrix score that indicates an organization's level of audit risk. Several stages are sequentially arranged to ensure accurate and reliable results.

Figure 1 –The Proposed Audit Risk Assessment Model



Source: Prepared by the Alotaibi, EM (2023)

Once the data is collected, the next stage is to decide whether the data is clean or not. Clean data can proceed straight to the data-processing stage, but unclean data first needs pre-processing, such as by cleaning and filtering the data to ensure its reliability and suitability for accurate analysis. The processed data is then stored in a database for use in the data-analysis process, where predictive analytics techniques, such as regression analysis and decision trees, are applied to identify patterns and trends in the data. This analysis also considers audit risk parameters—such as internal controls, the business environment, and financial performance—to calculate a comprehensive risk matrix score. The final stage is to present the results of this as a risk matrix score that indicates an organization's level of audit risk. The higher the risk score, the greater the likelihood of audit risk, and the matrix is color-coded to make it easier to interpret the results.

The proposed risk assessment model based on predictive analytics represents a robust and reliable approach for evaluating audit risk factors. The model's various stages ensure that the data used for analysis is reliable and accurate, while the use of predictive analytics techniques ensures that the analysis is comprehensive and reliable. Furthermore, the produced risk matrix score clearly indicates the level of audit risk, which is essential for organizations to make informed decisions.

Artifact Creation

In design science research, an artifact is created to achieve the research's goal (David et al., 2002) by addressing the identified problem. In this study, the artifact takes the form of a model that uses predictive analytics to support an audit risk assessment. This model's creation followed a design process over several steps, including requirements analysis, design, implementation, and evaluation. The first step involved defining the requirements for the model, such as the data sources, the input and output data, and the desired functionality based on the identified problem of inaccurate and time-consuming audit risk assessments. The design step involved developing the artifact by defining the data processing and analysis algorithms for the flow, storage, and processing of data. The analysis algorithms were based on machine learning techniques, such as logistic regression, decision trees, and neural networks. The research questions and the identified problem guided the design of a solution to improve the accuracy and efficiency of audit risk assessment. The implementation involved developing the software for the model and integrating the necessary algorithms and architecture. The proposed model was developed in Python with commonly used libraries for data analytics (McKinney, 2011), such that it met the requirements defined in the design stage.

Components of the Predictive Model

The architecture of the predictive model for audit risk assessment involves collecting data from various sources, pre-processing the data, applying machine learning algorithms to identify potential misstatements and risks, and generating a risk assessment score based on the data analysis (de Langhe & Puntoni, 2021), as shown in **Table 1**. The first stage is to collect data from various sources, such as financial data, audit trails, and other relevant information. The data is then pre-processed, such as by cleaning and transforming the data to make it suitable for analysis. This may involve removing duplicates, filling in missing values, and correcting any errors in the data.

Table 1 – Components of the Predictive Analytics Model

Component	**Description**
Data sources	This involves collecting data from various sources, such as financial transactions, account balances, financial ratios, audit trails, and other relevant information.
Data pre-processing	The collected data is prepared using data mining techniques and transformed into a form suitable for analysis. This may involve removing duplicates, filling in missing values, and correcting any errors in the data.

Data analysis	This involves applying data mining and machine learning techniques—such as logistic regression, decision trees, and neural networks—to the pre-processed data.
Risk assessment score	This involves generating a risk assessment score based on the data analysis. This score gives insights about potential misstatements and risks that warrant further investigation by the auditor.

Source: Prepared by Alotaibi, EM (2023)

The data analysis takes pre-processed data and subjects it to machine learning techniques, such as logistic regression, decision trees, and neural networks. This process identifies potential risks in both financial and non-financial data. Finally, a risk assessment score is generated based on the data analysis, with this score providing insights about potential risks. These insights may be used to prioritize elements of the audit plan or identify areas that require additional attention. By using this model, auditors can identify potential risks more efficiently and improve the overall effectiveness of their audit processes.

The evaluation step involved testing the model to assess how well it addressed the research problem (David et al., 2002; Hevner et al., 2008). The model was therefore evaluated using data from actual audit risk assessment processes, with the model's predictions being compared to those of human auditors to assess their accuracy. The evaluation also assessed the model's efficiency in terms of the time taken to complete the audit risk assessment. This model incorporates machine learning algorithms, so it can learn from data and improve its accuracy over time, and it was designed to be scalable, flexible, and adaptable to different audit contexts.

Demonstrating the Model

Table 2 provides a comprehensive list of parameters for audit risk assessment based on the findings of Hogan and Wilkins (2008) and Dusenbury et al. (2000). Auditors often use these parameters to identify and evaluate the risks associated with a company's financial data. The first set of risks are those that are inherent in the company's industry and outside the full control of management or auditors. For example, a slump in market demand for a company's products can significantly impact revenue and profitability, making it a significant risk factor for auditors to consider. The second set of risks are those risks associated with the effectiveness of the company's internal controls. For example, inadequate segregation of duties, weaknesses in IT systems and controls, and a lack of follow-up on control deficiencies are control risks that auditors must consider when determining the extent of the required audit procedures. The third set of risks are those associated with auditors potentially failing to detect material misstatements in financial data. For example, changes in the economic environment, technological changes and disruptions, and shifts in the competitive landscape all present detection risks that auditors must consider.

Table 2 – Parameters for Audit Risk Assessment

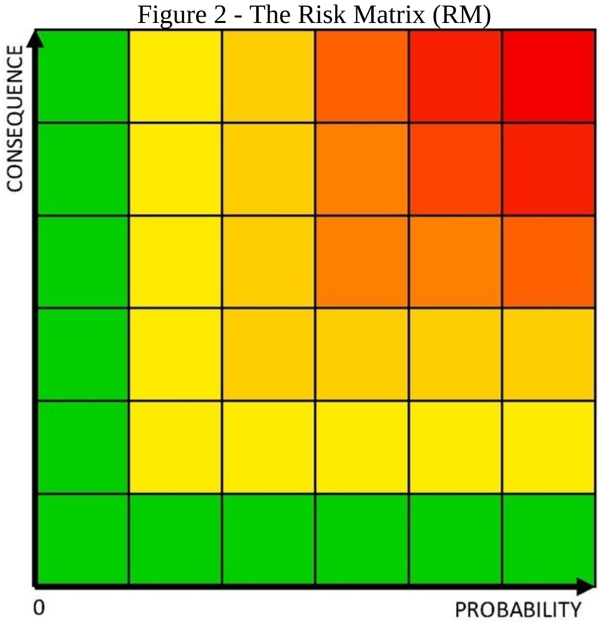
Risk Factor	Type	Description
Industry Risk	Inherent Risk	Risks associated with the industry in which the company operates
Complexity of Transactions		The use of complex derivative instruments
Regulatory Risk		Non-compliance with legal and regulatory requirements
Reputational Risk		Damage to the company's reputation
Segregation of Duties Risk	Control Risk	Inadequate segregation of duties
IT Risk		Weaknesses in IT systems and controls
Security & Integrity		Weak password policies and lack of system access controls
Monitoring		Lack of follow-up on control deficiencies
Economic Risk	Detection Risk	Changes in the economic environment during the audit
Technology Risk		Technological changes and disruptions
Competitive Risk		Shifts in the competitive landscape
Audit Procedures		Extent of audit procedures
Note: These parameters are based on the work of Hogan and Wilkins (2008) and Dusenbury et al. (2000). The actual list of risk factors can vary based on the organization and industry.		

Source: Prepared by Alotaibi, EM (2023)

These parameters were deemed to be the most relevant factors when assessing audit risk, based on the findings of Hogan and Wilkins (2008) and Dusenbury et al. (2000). It is not an exhaustive list that covers all aspects of risk, however, and the actual parameters vary according to the industry and firm size, so auditors tailor their risk assessment procedures accordingly. Nevertheless, this list is representative of common parameters for audit risk assessment in areas like industry-specific issues, the complexity of transactions, regulatory compliance, reputation, economics, IT systems, security and integrity, monitoring, technology, competition, and audit procedures.

The risk matrix (RM) was selected to present the scores for each parameter (Paltrinieri et al., 2019).This tool is used in risk management to easily evaluate and prioritize risks based on their likelihood of occurrence and the potential impact on a project or organization. The schema for this tool is presented in Figure 2, where a two-dimensional matrix shows the probability of an event occurring on one axis and the impact of that event on the other axis. The RM can be used to present the output of the predictive model for audit risk assessment, thus allowing auditors to prioritize certain risks based on their likelihood of occurrence and the potential impact they may have.

Figure 2 - The Risk Matrix (RM)



Source: (Paltrinieri et al., 2019).

The RM is a suitable way to score each parameter in Table 2 because it provides a structured approach to risk assessment, which is essential for audit risk assessment. In the RM model, the likelihood and impact are assessed on a scale of 1 to 5, where 1 represents low likelihood or weak impact, and 5 represents a high likelihood or strong impact. The product of the likelihood and impact scores gives the risk score, which can be used determine the appropriate level of audit effort. For example, a risk factor with a high likelihood and strong impact would receive a high risk score, indicating that it may warrant greater audit attention.

The RM also allows for the inclusion of controls and assessments of residual risk. Controls can be assessed based on their effectiveness and coverage, while the residual risk score can be calculated by subtracting the control score from the inherent risk score. This provides a more accurate way to assess the risk factors, thus allowing auditors to focus their efforts on areas with greater residual risk. Another advantage of the RM lies in its flexibility, so it can be adapted to suit the specific needs of a client or industry by including other additional risk factors. In conclusion, the risk matrix of Paltrinieri et al. (2019) is a suitable way to score each parameter because it provides a structured approach to risk assessment, enables risks to be prioritized based on likelihood and impact, allows for the inclusion of controls and assessments of residual risk, and is flexible enough to meet the specific needs of a client or industry.

Evaluating the Model

Table 3 presents the results of functional (black-box) testing through regression testing on the various components of the predictive model for identifying potential misstatements and risks in an audit (David et al., 2002; Geerts, 2011; Hevner et al., 2008; Wieringa, 2014). Ideally, this will demonstrate that the predictive model effectively identifies potential misstatements and risks and provides insights about the areas that warrant further investigation. The first evaluated component is the adequacy of the data sources, which should be comprehensive and relevant to the audit's objective. The functional testing resulted in a pass, meaning that the evaluation criteria were met. The second evaluated component was the quality of the data, which should be accurate, complete, and reliable. Regression testing was again used, and this component passed, indicating that the collected data met the evaluation criteria.

The data pre-processing component for cleaning and transforming the data in preparation for analysis was evaluated next. This passed the regression testing, indicating that the data were effectively cleaned and transformed. The handling of missing values was also evaluated for the data pre-processing component, such that missing values must be handled effectively to ensure the accuracy of the analysis. The testing revealed that this was indeed the case.

Table 3 – Results of Functional (Black-Box) Testing of the Model

Component	**Evaluation Criteria**	**Evaluation**	**Evaluation Method**	**Results**
Data sources	Adequacy of data sources	The data sources should be comprehensive and relevant to the audit's objective.	Regression Testing	Pass
	Data quality	The collected data should be accurate, complete, and reliable.	Regression Testing	Pass
Data pre-processing	Data cleaning and transformation	The data pre-processing should effectively clean and transform the data ready for analysis.	Regression Testing	Pass
	Handling missing values	The data pre-processing should handle missing values effectively to ensure the accuracy of the analysis.	Regression Testing	Pass
Data analysis	Selection of machine learning algorithms	The selection of algorithms should be appropriate to the audit objective and the type of data being analyzed.	Regression Testing	Pass

	Accuracy of the analysis	The analysis should accurately identify potential misstatements and risks.	Regression Testing	Pass
Risk assessment	Relevance of the risk assessment score	The risk assessment score should be relevant to the audit's objective and provide insights into potential misstatements and risks.	Regression Testing	Pass
	Usefulness of the risk assessment score	The risk assessment score should be useful for prioritizing audit procedures and identifying areas that require further investigation.	Regression Testing	Pass
Note: Pass means that the evaluation criteria were met, while Fail indicates that the evaluation criteria were not met, and Not Applicable means that the evaluation criteria do not apply to that component.				

Source: Prepared by Alotaibi, EM (2023)

RESULTS

A Saudi accounting firm tested the proposed model at the engagement level. **Table 4** presents the results of the predictive analytics model for assessing audit risk when applied to a publicly listed Saudi company in the retail industry. The evaluated parameters include industry risk, the complexity of transactions, legal and regulatory risk, reputational risk, segregation of duties risk, IT risk, security and integrity, monitoring, economic risk, technology risk, competitive risk, and the nature of audit procedures.

Table 4 – The Proposed Model's Results

Parameter	**Result**	**Details**
Industry Risk	Medium	Market is stable but competition is increasing.
Complexity of Transactions	High	Transactions involve multiple parties and complex procedures
Legal and Regulatory Risk	High	There is a high level of government regulations and compliance requirements.
Reputational Risk	Low	Company has a strong reputation and a positive image.
Segregation of Duties Risk	Medium	There is some segregation of duties but opportunities for fraud still exist.
IT Risk	High	IT systems are complex and vulnerable to cyber-attacks.
Security & Integrity	Medium	Security measures are in place but some vulnerabilities still exist.
Monitoring	Low	Monitoring systems are not fully implemented or utilized.
Economic Risk	Medium	Economy is stable but there are some concerns about inflation.
Technology Risk	High	Technology is rapidly changing, and outdated systems may become a liability.

Competitive Risk	High	Competition is intense and market share is under pressure.
Nature of Audit Procedures	High	Audit procedures are complex and require specialized knowledge.
Total Risk Matrix	**High**	Overall risk is high due to multiple high-risk factors.

Source: Prepared by Alotaibi, EM (2023)

The industry risk was evaluated as medium, indicating that the market is stable with increasing competition. The complexity of transactions was found to be high due to multiple parties and complex procedures being involved, while the legal and regulatory risk was also high due to the high level of government regulation and compliance requirements. The reputational risk was deemed low, reflecting the company's good reputation and positive image. The segregation of duties risk was at a medium level, indicating that there is some segregation of duties but also opportunities for fraud. The IT risk was found to be high due to complex IT systems and their vulnerability to cyber-attacks. Security and integrity were rated as medium, indicating that security measures are in place, but some vulnerabilities remain. The low monitoring risk indicates that monitoring systems have not been fully implemented or utilized. The economic risk was rated as medium, indicating that the economy is stable, albeit with some concerns about inflation. The technology risk was high, reflecting the rapidly changing nature of technology and the possibility that outdated systems may become a liability. The high competitive risk indicates that intense competition is putting market share under pressure, while the nature of audit procedures is high, reflecting complex audit procedures that require specialized knowledge. The overall risk is rated as high due to multiple high-risk factors. Based on the above results, the company should take appropriate actions to mitigate the identified risks and thereby minimize their impact on business operations and financial performance.

DISCUSSION

Predictive analytics is a rapidly growing field that has the potential to revolutionize audit risk assessment by allowing auditors to make better decisions with the help of data analysis. The proposed predictive analytics model for audit risk assessment represents a valuable tool for assessing an organization's overall risk and identifying areas of potential risk that warrant further investigation. The model was tested by applying it to a publicly listed Saudi company in the retail industry, with the results showing that this company's overall level of risk is high due to multiple high-risk factors, such as legal and regulatory risk, the complexity of transactions, IT risk, competitive risk, and the nature of audit procedures. These findings highlight the need for the auditors to pay close attention to these areas and recommend appropriate risk-management strategies.

The effectiveness of the proposed model can be evaluated based on its accuracy, reliability, and usefulness. Accuracy refers to the model's ability to correctly predict the level of risk associated with an organization, while reliability refers to the consistency of the model's predictions over time and across different contexts. Usefulness refers to the extent to which the model provides valuable insights that can inform decision-making. In terms of accuracy, the results presented in Table 4 suggest that the model effectively and accurately predicted the level of risk associated with the relevant company. More specifically, the model correctly identified high-risk factors associated with the company, such as legal and regulatory risk, the complexity of transactions, and IT risk. These findings are consistent with the company's industry and market conditions, suggesting that the model is serving its intended purpose.

Regarding reliability, the proposed model faces some challenges, because reliability depends on the quality of the data being used to train and test it, as well as the stability of the underlying factors contributing to audit risk. If these factors change over time, the model may become less reliable and need updating. Moreover, external factors beyond its control may impact the model's reliability, such as changes in the regulatory environment or the emergence of new technologies that pose new risks. In terms of usefulness, the proposed predictive analytics model is helpful for auditors because it provides a comprehensive assessment of an organization's overall risk. The model also highlights potential areas of high risk that may require further investigation, thus allowing auditors to focus on the most critical areas. Moreover, the model can help auditors to identify potential weaknesses in an organization's risk-management strategy and recommend appropriate remedies.

Nevertheless, using predictive analytics for audit risk assessment also has some limitations. The main limitation is that it requires large volumes of data, which can be challenging for smaller companies or those with limited data resources. In addition, it may lead to complacency or an overreliance on technology in the presence of misleading data, leading to auditors overlooking significant risks or failing to identify potential fraud. Despite these limitations, the proposed predictive analytics model for audit risk assessment represents an effective tool for helping auditors to make informed decisions based on data analysis. While the model still faces some challenges in terms of its reliability, its accuracy and usefulness make it a valuable resource for auditors seeking to manage audit risk. By incorporating the model's insights into their audit procedures, auditors can enhance their audits and help organizations to manage their risks more effectively.

Overall, the model accurately identifies high-risk factors associated with an organization, provides valuable insights for decision-making, and highlights potential risk areas that may require further investigation. On the down side, the model's reliability may be impaired by changes in underlying factors that contribute to audit risk or external factors, and its use may lead to complacency or an overreliance on the technology.

CONCLUSION

In conclusion, this study has addressed the research questions of how predictive analytics can be effectively applied in audit risk assessment, the critical features of an effective predictive analytics model for audit risk assessment, and the benefits and limitations of using predictive analytics for audit risk assessment. The objective of the research was to develop and evaluate a predictive analytics model for audit risk assessment using design science methodology, and this research has contributed to improving the accuracy and efficiency of audit risk assessment through predictive analytics.

The proposed predictive analytics model for audit risk assessment represents a valuable tool for assessing an organization's overall risk and identifying areas of potential risk that warrant further investigation. The model's effectiveness was evaluated based on its accuracy, reliability, and usefulness. The results suggest that the model effectively and accurately predicted the level of risk associated with the relevant company. It correctly identified high-risk factors associated with the company, such as legal and regulatory risk, the complexity of transactions, and IT risk. The proposed model is also helpful for auditors as it provides a comprehensive assessment of an organization's overall risk and can identify potential weaknesses in its risk-management strategy, thereby recommending appropriate remedies.

Nevertheless, using predictive analytics for audit risk assessment has some limitations, such as the requirement for large volumes of data and the possibility of overreliance on technology, leading to auditors overlooking significant risks or failing to identify potential fraud. Additionally, changes in underlying factors contributing to audit risk or external factors may impair the model's reliability. Despite these limitations, the proposed predictive analytics model for audit risk assessment is an effective tool for helping auditors make informed decisions based on data analysis.

This study demonstrates that predictive analytics is evolving to become increasingly popular in businesses. The benefits of using predictive analytics include improved efficiency, effectiveness, and accuracy in identifying areas of financial reporting that may be at risk of material risk misstatement. This research adds to the existing literature by providing insights into the effectiveness of a predictive analytics model for audit risk assessment, highlighting its key features, and addressing the benefits and limitations of using predictive analytics for audit risk assessment. Future research could explore several areas related to predictive analytics in audit risk assessment, such as by investigating the effect of predictive analytics on audit quality. The ethical implications of using predictive analytics in audit risk assessment and the potential biases that could affect the model's accuracy are also important areas for further exploration.

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