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Data Driven Decision Making: Examining the Role of Data Analytics in Business Performance

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Abstract

The growing availability of digital data has changed the way businesses approach decision-making. Data generated through customer transactions, sales, financial activities, and business operations provides valuable information, but its usefulness depends on how effectively it is analysed and interpreted. This study examines the role of data analytics in transforming business data into meaningful insights that support informed decision-making.

The research focuses on the four major types of data analytics: descriptive, diagnostic, predictive, and prescriptive analytics, and their relevance to different stages of the decision-making process. It explores the application of data analytics in areas such as marketing, sales, finance, operations, customer management, and risk management. The study also considers how data-driven insights can help businesses identify trends, understand customer behaviour, forecast demand, improve resource allocation, and reduce business risks.

The research is based on secondary data, including relevant research literature, reports, and real-world business examples. Along with the benefits of analytics, challenges related to data quality, privacy, security, implementation costs, and availability of skilled professionals are considered.

The study provides an understanding of how data analytics can strengthen business decision-making and contribute to improved organisational performance.

A. INTRODUCTION

The increasing use of digital technologies has changed the way organisations collect, record, process and use financial and business information. Traditionally, accounting mainly focused on recording past transactions and preparing financial statements. However, businesses today generate large volumes of data through sales transactions, customer payments, inventory movements, banking activities, payroll systems and other day-to-day operations. This has increased the importance of data analytics in converting raw financial and operational data into information that can support business decisions.

Data analytics refers to the process of examining data to identify patterns, relationships, trends and useful insights. In the field of accounting, analytics can be applied to financial reporting, budgeting, cost control, cash flow management, profitability analysis, auditing and risk assessment. Rather than relying only on historical reports, organisations can use analytical techniques to understand current financial conditions, identify unusual transactions and estimate possible future outcomes.

The growing availability of accounting and financial data has also changed the role of accounting professionals. Accountants are increasingly expected to interpret data and provide information that supports managerial and strategic decisions. For example, analysing sales and cost data can help management understand product profitability, while

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cash flow analysis can support decisions related to working capital and liquidity. Similarly, audit analytics can assist in identifying unusual transactions and areas that may require further examination.

Data analytics also has an important role in improving business performance. Analytical insights can support better resource allocation, cost management, revenue planning and risk reduction. Predictive techniques can help organisations estimate future sales, expenses or cash requirements, while prescriptive analysis can assist in selecting suitable courses of action based on available information. However, the usefulness of analytics depends on factors such as data quality, technological infrastructure, data security and the availability of skilled professionals.

In this context, data-driven decision-making has become increasingly relevant to modern accounting and business management. The ability to analyse financial and non-financial information allows organisations to move beyond simply recording what has already happened and use data to support future decisions. This paper therefore examines the role of data analytics in business decision-making, with particular attention to its applications in accounting, finance, auditing and business performance.

B. REVIEW OF LITERATURE

Previous research has examined the growing role of data analytics in accounting, finance and business decision-making. As organisations increasingly depend on digital systems, researchers have explored how large volumes of financial and non-financial data can be used to improve reporting, forecasting, auditing, risk management and organisational performance.

Appelbaum et al. (2017) examined the use of business analytics in accounting and management accounting. Their research highlighted that analytics can help accountants move beyond traditional reporting by providing more timely and detailed information for planning and decision-making.

Similarly, **Vasarhelyi, Kogan and Tuttle (2015)** discussed the impact of data analytics and technology on auditing and accounting. Their work showed that the availability of digital transaction data creates opportunities for continuous monitoring and more detailed examination of financial information. Instead of depending only on periodic reviews and limited samples, auditors can increasingly use analytical tools to examine larger sets of transactions and identify unusual patterns.

Warren, Moffitt and Byrnes (2015) also studied the implications of big data for accounting. They argued that the increasing availability of structured and unstructured data is changing the nature of accounting information.

Research by **Alles and Gray (2016)** focused on the role of analytics in auditing and fraud detection. The authors emphasised that analytical techniques can support the identification of unusual transactions, potential errors and areas of financial risk.

Davenport and Harris (2007) examined the strategic use of business analytics and argued that organisations can gain competitive advantages by using data systematically in decision-making. Their work highlighted how analytical capabilities can improve forecasting, customer management, operational efficiency and strategic planning.

Davenport (2014) discussed the increasing importance of analytics in organisations and highlighted the shift from traditional business intelligence towards predictive and prescriptive analytics. The study explained that organisations increasingly use data to predict future outcomes and identify appropriate actions rather than simply analysing historical performance.

Seddon et al. (2017) investigated the relationship between business analytics and organisational performance. The study therefore emphasised the importance of organisational capabilities alongside technology.

Cao, Chychyla and Stewart (2015) examined big data analytics in the accounting and auditing environment. Their research highlighted the potential of big data to improve audit efficiency, risk assessment and the analysis of financial information.

Brown-Liburd, Issa and Lombardi (2015) examined how big data and analytics are changing the auditing profession. Their study suggested that auditors can use large and diverse datasets to identify patterns and anomalies that may not be visible through traditional audit processes.

Earley (2015) studied the implications of data analytics for auditing and discussed how audit analytics can transform traditional audit procedures. The research indicated that analytics allows auditors to examine larger populations of transactions and identify unusual relationships or patterns.

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Gepp et al. (2018) examined the application of data analytics and big data techniques in accounting and finance. Their research demonstrated that analytical methods can support areas such as financial forecasting, fraud detection, risk assessment and performance analysis.

Kokina and Davenport (2017) investigated the impact of automation and artificial intelligence on the accounting profession. Their study suggested that technologies capable of processing large volumes of accounting information can automate routine activities and allow accountants to focus more on analysis and higher-value of decision-making.

Moffitt, Rozario and Vasarhelyi (2018) examined the use of robotic process automation in accounting and auditing. Their research showed that automation can improve the efficiency of repetitive accounting processes, reduce manual work and increase consistency.

Dai and Vasarhelyi (2017) examined the potential impact of blockchain technology on accounting and auditing. Their research suggested that combining blockchain with analytical technologies could improve the availability, transparency and reliability of transaction information.

Overall, the existing literature shows that data analytics has applications across several areas of accounting and business. Previous studies have discussed its role in management accounting, financial analysis, auditing, fraud detection and decision-making. They also indicate that the benefits of analytics depend on the quality of available data, appropriate technological systems and the analytical capabilities of professionals.

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Research Gap / Problem

Although previous studies have examined the role of data analytics in specific areas such as accounting, auditing, fraud detection and financial reporting, these areas are often discussed separately. There is a need to examine how different forms and applications of analytics collectively support the conversion of accounting and business data into useful information for managerial decision-making and business performance.

In addition, the growing use of digital accounting systems has increased the availability of financial and operational data, but the availability of data alone does not guarantee better decisions. Organisations must be able to analyse, interpret and apply the information appropriately. Therefore, this study examines the role of data analytics in business decision-making, with particular emphasis on its relevance to accounting, finance, auditing and overall business performance.

Objectives of the Study

1. To examine the role of data analytics in accounting and business decision-making.
2. To understand the application of different types of analytics in financial and management accounting.
3. To analyse the use of data analytics in areas such as budgeting,Transactional Analysis, Financials Analysis To examine how analytical insights can contribute to improved business performance.
4. To identify the major challenges associated with the use of data analytics in accounting and business.

C. RESEARCH METHODOLOGY

Research Design

The present study is based on a descriptive and analytical research design. The study examines the role of data analytics in business decision-making, with particular emphasis on its applications in accounting, finance, auditing and business performance. The descriptive approach is used to explain the different types and applications of data analytics, while the analytical approach is used to examine how analytical insights can support financial planning, forecasting, fraud detection, risk management, cost control and other business decisions.

Sources of Data

The study is based entirely on secondary data. No primary data was collected from respondents. Information for the study was obtained from published research articles, academic journals, books, professional accounting publications, company reports, investor publications and official company and technology sources.

Particular attention was given to published information relating to the practical use of data analytics by organisations such as Walmart, Apple,Uber, Netflix and Mastercard. These examples were used to understand how analytics is applied in areas such as financial forecasting, customer analysis, fraud detection and inventory management.

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Method of Data Collection and Analysis

Relevant secondary sources were reviewed and organised according to the objectives of the study. The information collected was analysed under major themes, including types of data analytics, applications in accounting and business, financial planning and forecasting, fraud and risk management, inventory and cost control, and challenges associated with the use of analytics.

A thematic approach was used to interpret the information obtained from different sources. The findings from academic literature were compared with practical examples from business organisations to understand both the theoretical and practical relevance of data analytics. Figures and graphical information from selected sources were also examined to explain the role of analytics in forecasting and financial decision-making.

Scope of the Study

The study focuses on the role of data analytics in supporting accounting and business decision-making. It covers descriptive, predictive and prescriptive analytics and examines their relevance to financial planning, revenue analysis, fraud detection, inventory management and credit risk assessment. The study also considers major challenges such as data quality, privacy and security, implementation costs, technological changes and the shortage of skilled professionals.

D. DISCUSSION AND FINDINGS

1. **DELOITTE**

Deloitte uses data analytics in accounting and auditing to examine financial records, assess audit risks, identify misstatements and improve the reliability of financial reporting. Its Deloitte Omnia platform uses advanced analytics, artificial intelligence and automation to analyze large volumes of accounting and financial data.

Descriptive Analytics – Analysis of Past Accounting Data

Deloitte uses descriptive analytics to examine historical accounting information and determine what has occurred in an organization's financial records. It can analyze general ledger data, journal entries, revenue, expenses, accounts receivable, accounts payable and other financial statement accounts.

Accounting example: During an audit, Deloitte can analyze a company's journal entries and general ledger to identify unusual postings, duplicate entries, abnormal account balances or transactions recorded outside normal accounting patterns. For example, an unusually high year-end revenue entry may be identified for further verification.

Tools used: Deloitte Omnia, journal-entry analytics, data visualization and accounting-data dashboards.

Predictive Analytics – Identification of Future Accounting Risks

Deloitte uses predictive analytics to assess the likelihood of future financial risks, accounting errors and potential misstatements by using historical accounting data and statistical or machine-learning models.

Accounting example: Deloitte can analyze historical patterns in accounts receivable, revenue recognition, expense claims and journal entries to identify accounts or transactions that are more likely to contain material errors or misstatements. For instance, unusual changes in receivables compared with revenue may indicate a potential risk requiring additional audit attention.

Tools used: Deloitte Omnia, statistical analysis, regression models and machine-learning techniques.

Prescriptive Analytics – Supporting Accounting and Audit Decisions

Deloitte uses prescriptive analytics to determine what action should be taken after accounting risks or unusual transactions have been identified. It supports auditors in prioritizing high-risk accounts and selecting appropriate audit procedures.

Accounting example: If analytics identifies unusual revenue transactions or a high-risk receivables balance, Deloitte can prioritize these areas for further investigation. Auditors may then perform procedures such as vouching invoices, confirming receivable balances, examining supporting documents or testing revenue recognition.

Tools used: Deloitte Omnia, artificial intelligence, machine learning, risk analytics and automated audit workflows.

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APPLICATIONS:
Deloitte analyzes:
Revenue growth (%)
Expense-to-sales ratio (%)
Receivables ageing
Inventory turnover ratio
Journal-entry values and frequency
Deloitte applies descriptive, predictive and prescriptive analytics collectively in accounting decision-making by analyzing revenue growth, profit margins, expense ratios, receivables ageing, inventory turnover, journal-entry values and account balances. Historical data is used to identify unusual fluctuations and trends, while predictive models help forecast revenue, expenses, cash flows and credit losses and assess the probability of material misstatements. Based on risk scores, materiality thresholds and expected financial impact, prescriptive analytics helps determine which accounts and transactions require detailed audit testing, confirmation or investigation. Thus, analytics supports financial statement analysis, risk assessment, fraud detection, audit planning and evidence-based accounting decisions.
CHALLENGES:
Deloitte faces several challenges while using descriptive, predictive and prescriptive analytics in accounting. These include poor-quality or incomplete accounting data, difficulty in integrating data from different accounting systems, data privacy and confidentiality risks, and the complexity of handling large volumes of financial transactions. Predictive models may also produce inaccurate results when historical accounting data is inconsistent, while AI-based analysis may require human judgment and professional validation. Additionally, implementing advanced analytics involves high technology, training and maintenance costs, and excessive reliance on automated results may create risks in areas requiring professional accounting and audit judgement.

Figure 1:Deloitte Before vs. After Using Accounting Analytics:
Source: Deloitte, 2024. Deloitte audit analytics: Before vs after comparison of transaction-analysis coverage in a traditional sample-based approach and an analytics-enabled approach. [online] Available at: https://www.deloitte.com.



The implementation of accounting analytics significantly changes the audit approach from selective, sample-based testing to broader population-level analysis. Traditionally, auditors may rely on samples of transactions, whereas Deloitte's analytics-enabled approach can analyze up to 100% of relevant transaction populations. This enables earlier identification of unusual journal entries, anomalies and potential material misstatements, while reducing manual effort and improving the focus of audit procedures.

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Deloitte's Omnia specifically supports analysis of large datasets and journal entries, including identifying patterns, risks and outlier.

1. **PwC**

PwC uses data analytics, AI and machine learning in auditing and accounting analysis to examine financial transactions, identify anomalies, assess risks and support audit decisions. Its major audit analytics tools include Halo, Aura, Alteryx and newer AI-enabled platforms.

Descriptive Analytics –

PwC uses descriptive analytics to analyze historical accounting data, including general ledger transactions, journal entries, revenue, expenses, receivables and payables.

Accounting example: Halo for Journals analyzes client journal entries and uses visualizations to identify unusual patterns, relationships and outliers. This helps auditors understand the client's financial transactions and identify areas requiring further examination.

Tools used: Halo, Halo for Journals, Alteryx and data-visualization dashboards.

Predictive Analytics –

PwC uses predictive analytics to identify potential accounting risks and future financial outcomes using historical data, statistical models and machine learning.

Accounting example: PwC has developed a predictive analytics revenue regression tool that uses cloud-based machine learning and advanced statistical models to predict client revenue and support audit procedures. This helps auditors assess whether reported revenue appears consistent with expected patterns and identify areas requiring additional testing.

Tools used: PwC Predictive Analytics for Revenue, machine learning, regression models and advanced statistical models.

Prescriptive Analytics –

PwC uses prescriptive analytics and AI-supported systems to help determine appropriate responses to identified accounting and audit risks.

Accounting example: When analytics identifies unusual journal entries or potential misstatements, PwC's audit technology helps auditors prioritize high-risk transactions and determine where additional testing or investigation is required. Its newer AI capabilities also support risk assessment, data analysis and audit procedures while keeping professional auditor judgement central.

Tools used: PwC's AI-enabled audit technology, Halo, machine learning, AI agents and automated audit workflows.

APPLICATIONS:

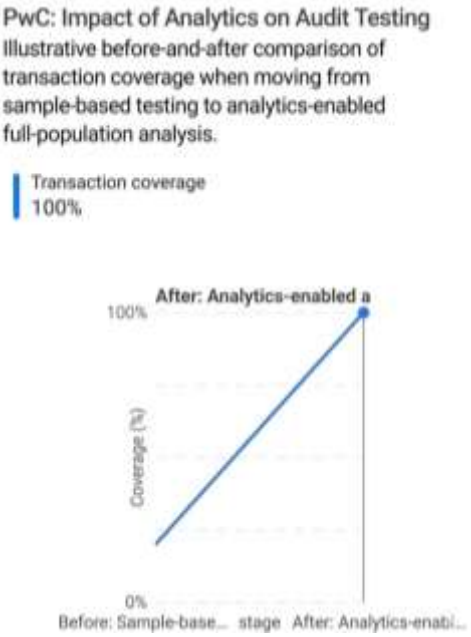
PwC applies descriptive, predictive and prescriptive analytics mainly in auditing and accounting-related financial analysis. These are applied to general ledger and journal entries, revenue recognition, expenses, accounts receivable and payable, financial statement balances, inventory, investments, fraud-risk assessment and internal controls. For example, Halo analyzes large volumes or whole populations of transactions to identify unusual and high-risk entries

CHALLENGES:

PwC faces several challenges in applying descriptive, predictive and prescriptive analytics to accounting and auditing. These include poor-quality or incomplete accounting data, difficulty integrating data from different client accounting systems, data privacy and confidentiality risks, and the high volume and complexity of financial transactions. Predictive models may produce inaccurate results when historical data is unreliable, while AI-based recommendations still require professional auditor judgement and validation. Other challenges include high implementation and maintenance costs, employee training requirements, cybersecurity risks and over-reliance on automated results.

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Figure 2: Illustrative comparison of transaction coverage before and after analytics implementation at PwC.



Source: PricewaterhouseCoopers. (2024). Impact of analytics on audit testing: Illustrative before-and-after comparison of transaction coverage. PwC Global Insights.

The line graph illustrates the change in transaction-analysis coverage when PwC moves from a traditional sample-based audit approach to an analytics-enabled approach.

In the before stage, the graph shows 20% transaction coverage. This represents a simplified illustrative level for a traditional sample-based approach, where auditors examine a selected portion of transactions rather than the entire population. In accounting, this can mean testing selected journal entries, revenue transactions, expense records, receivables or payables. Because only a sample is examined, some unusual transactions outside the sample may not be directly reviewed.

In the after stage, the graph rises to 100% transaction coverage. This represents full-population analysis, where analytics can examine the complete set of relevant transactions. PwC's audit analytics tools, including Halo, are designed to analyze large volumes of financial data and help identify unusual transactions, trends and outliers.

The movement from sample-based analysis to full-population analytics can help PwC auditors:

*Identify unusual journal entries more comprehensively.
*Detect unusual revenue and expense transactions.
*Analyze accounts receivable and payable populations.
*Identify potential material misstatements.
*Perform more effective risk assessment.
*Focus detailed audit procedures on transactions that appear to have higher risk.
*Reduce the amount of manual data analysis required.

1. **EY**

EY uses analytics throughout the audit and financial accounting process, particularly through EY Helix, EY Canvas and EY SAAM. EY Helix includes analyzers for general ledger, inventory, trade payables, revenue and trade receivables, while EY SAAM uses AI and machine learning to automate invoice processing and predict accounting treatments

Descriptive Analytics —

EY uses descriptive analytics to examine historical accounting transactions and financial-statement data. EY Helix's General Ledger Analyzer can analyze journal entries, while its Revenue and Trade Receivables Analyzer examines sales invoices, credit memos and settlement patterns.

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Real-life accounting example: EY can analyze a client's revenue and receivables transactions throughout the year to identify unusual revenue trends, credit-note patterns and outstanding receivables. This helps auditors understand the client's financial performance and identify areas requiring further investigation.

Tools: EY Helix, General Ledger Analyzer, Revenue & Trade Receivables Analyzer, Inventory Analyzer and Trade Payables Analyzer.

Predictive Analytics —

EY applies predictive analytics using AI and machine learning to predict accounting outcomes and identify potential risks.

Real-life accounting example: EY SAAM (Smart Accounting and Analytics Module) uses machine learning to predict the appropriate journal entry/accounting treatment for invoices. EY states that SAAM can process approximately 15,000 invoices per day (5.5 million per year) with more than 95% precision.

Tools: EY SAAM, machine learning, AI and statistical/predictive models.

Prescriptive Analytics —

EY uses prescriptive analytics to support decisions after accounting risks or anomalies have been identified.

Real-life accounting example: If EY's analytics identifies an unusual journal entry or a high-risk revenue or receivables transaction, auditors can prioritize the transaction for investigation and select appropriate audit procedures such as document inspection, confirmation or substantive testing. EY Helix is designed to support auditors from risk assessment through audit execution.

Tools: EY Helix, EY Canvas AI, AI-powered audit tools, risk analytics and automated workflows. EY Canvas AI, for example, can compare a company's key financial ratios with industry peers to support risk assessment.

APPLICATIONS:

EY applies descriptive, predictive and prescriptive analytics mainly across the audit and accounting cycle, using financial and transactional data. Its EY Helix platform covers areas including the general ledger, revenue, trade receivables, purchases, trade payables, inventory, payroll and fixed assets.

Major application areas:

*General Ledger & Journal Entries – analysing account postings and identifying unusual entries.
*Revenue & Trade Receivables – analysing sales invoices, credit notes, collections and receivable balances.
*Purchases & Trade Payables – analysing purchases, supplier transactions and outstanding liabilities.
*Inventory & Cost of Goods Sold – analysing inventory composition and COGS.
*Payroll – analysing payroll-related transactions and expenses.
*Fixed Assets – analysing asset-related accounting data.
*Financial Statement Analysis – identifying trends, anomalies and relationships between financial accounts.
*Risk Assessment & Audit Planning – identifying high-risk accounts and transactions and directing further audit procedures.

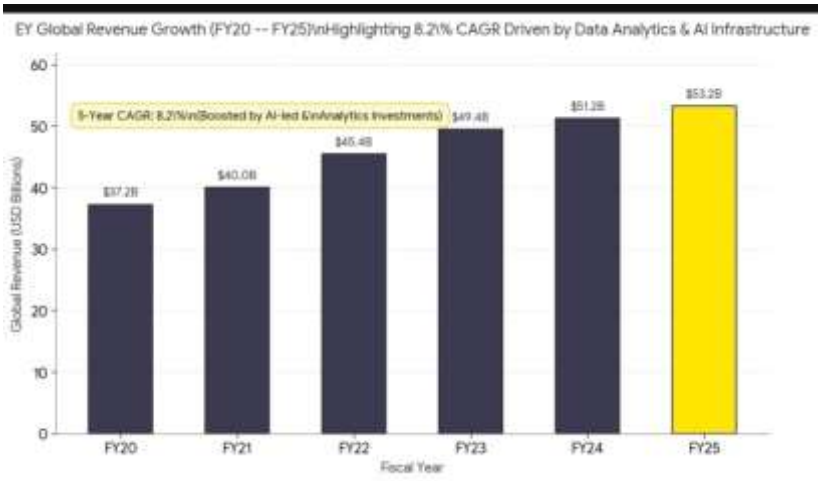
CHALLENGES:

EY faces several challenges in applying descriptive, predictive and prescriptive analytics to accounting and auditing. The major challenges include poor or inconsistent client data, integration of data from different accounting systems, data privacy and cybersecurity risks, and the complexity of large financial datasets. Predictive models may also produce inaccurate results when historical accounting data is incomplete or unreliable. In addition, AI-generated results require professional auditor judgement and validation, particularly when assessing material misstatements or accounting treatments. Other challenges include high implementation costs, employee training, system maintenance and the risk of excessive dependence on automated analysis.

Figure 3: The Quantifiable Transformation: EY's Analytics-Driven Financial Growth and Operational Efficiency

Source :Ernst & Young Global Limited. (2025, October 15). *EY announces global revenue of US$53.2b for fiscal year 2025*. EY Global Newsroom. https://www.ey.com/en_gl/newsroom/2025/10/ey-announces-global-revenue-of-us-53-2b-for-fiscal-year-2025

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The aggressive roll-out of proprietary data analytics platforms directly correlates with EY's massive top-line expansion. By fiscal year 2025, EY reached a record-breaking US$53.2 billion in global revenue, logging a 5-year Compound Annual Growth Rate (CAGR) of 8.2% from FY20 through FY25.A substantial driver of this momentum is the 30% year-on-year growth in AI-related revenue, sustained by a US$1.0 billion annual commitment to AI infrastructure and ecosystem partnerships.

Quantitative Impact & Operational Scales :The scale of EY's shift toward data analytics is best highlighted by three key performance indicators (KPIs):

Data Processing Volume: EY's flagship analytics engine, EY Helix, has scaled exponentially to process over 415 billion lines of financial data annually.

Audit Engagements: EY now deploys its unified AI data platform across more than 160,000 global audit engagements, replacing localized data siloes.

Audit Sample Size: Prior to data-first workflows, audit teams traditionally sampled a fraction of transactions (e.g., manually checking 10 out of 1 million journal entries). With Helix, EY routinely achieves a 100% full-population analysis of a client's general ledger data instantly.

1. **KPMG**

KPMG transforms accounting and financial auditing through its advanced data-driven framework. By pairing global strategic platforms with specialized artificial intelligence (AI) ecosystem partners, KPMG executes comprehensive financial analysis that transitions seamlessly from monitoring historical ledgers to predicting and prescribing enterprise-wide strategies

Descriptive Analytics--

KPMG uses descriptive analytics to synthesize, aggregate, and reconstruct past financial activities across vast enterprise resource planning (ERP) systems. This forms the absolute baseline for standard compliance and regulatory audits.

Real-Life Accounting Example: Instead of traditional statistical sampling (manually inspecting a minor subset of transactions), KPMG performs full-population testing. During a complex procurement or revenue audit, the system visualizes the complete ledger footprint to map out the order of entries, tracking three-way matches (matching purchase orders, receiving reports, and vendor invoices) to capture unauthorized transaction flows, duplicate payments, or broken control chains.

KPMG Tools Used:

KPMG Clara Analytics (KCa): The centerpiece global cloud platform that acts as the descriptive hub, scanning 100% of a client's transactional journal entries to filter operational trends.

Tableau / QlikView: Embedded directly alongside Clara data dumps to render automated KPI tracking, data lineage mapping, and interactive compliance scorecards.

Predictive analytics--

Predictive accounting analytics shifts the dynamic from backwards-looking reviews to establishing dynamic forward-looking baselines. KPMG uses this layer to identify forward risk models and assess asset impairments or revenue projections.

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Real-Life Accounting Example: In predicting Estimated Credit Losses (ECL) for financial institutions or enterprise clients, KPMG inputs accounts receivable aging reports alongside external macroeconomic and microeconomic indices (such as regional inflation rates, customer segment financial health, and historical payment timelines). The predictive algorithms estimate customer defaults, calculate real-time asset degradation curves, and project bad-debt provisions over the next fiscal cycle.

KPMG Tools Used:

KPMG Intelligent Forecasting Solution: A targeted statistical and machine learning (ML) framework engineered to run multi-scenario forecasting models to safeguard financial performance management.

MindBridge AI Integration: KPMG embeds MindBridge's machine learning engine directly into KPMG Clara to process transactions through high-level regression algorithms, predicting which ledger lines exhibit the highest probability of containing material misstatements or fraud markers.

Prescriptive Analytics--

Prescriptive analytics represents the highest tier of execution, mapping statistical forecasts against strict corporate tax, compliance, and accounting rule architectures to provide targeted recommendations.

Real-Life Accounting Example: Corporate financial disclosures and annual regulatory reporting present a massive workflow challenge, requiring hundreds of pages to conform to precise GAAP or IFRS structures. KPMG uses prescriptive processing to instantly cross-analyze a draft financial report against a target checklist. If a note regarding long-term lease liabilities lacks the mandatory maturity scheduling, the engine does not just flag the gap—it explicitly directs the accounting team to the missing quantitative information, references the exact regulatory statute, and drafts the necessary disclosure structural template.

KPMG Tools Used:

KPMG GenAI Disclosure Checklist Solution (built with Databricks): A highly specialized generative AI solution that maps public or private annual financial statements against over 2,000 regulatory disclosure questions, verifying accurate logic paths and instantly delivering page citations and corrective actions.

Alteryx Optimization Modeler: Combined with Python environments to optimize tax restructurings, transfer pricing pathways, and working capital cash deployments based on predictive cash flow simulations.

APPLICATIONS:

Here is how KPMG applies these analytics across its global operations:

Standardized Cloud Ingestion: KPMG extracts raw financial ledger and transactional data from diverse client ERPs (like SAP and Oracle) and ingests it into KPMG Clara, automatically converting fragmented information into a uniform data model.

Big-Tech Ecosystem Alliances: The firm embeds its specialized accounting logic directly onto high-performance partner infrastructures, utilizing Microsoft Azure for scalable cloud processing and Databricks for safe generative AI deployment.

Integrated Machine Learning: KPMG infuses MindBridge AI engine algorithms directly into standard audit paths, allowing automated predictive risk scoring and fraud anomaly detection to occur right alongside traditional verification steps.

Hybrid Accounting Teams: Data engineers and data scientists are embedded side-by-side with Certified Public Accountants (CPAs), ensuring that data-driven findings immediately influence real-world audit actions and client strategic advisory.

Automated Regulatory Calibration: A dedicated compliance team continuously updates the underlying rules engines of platforms like the GenAI Disclosure Checklist to immediately reflect changes made by global accounting boards (FASB and IASB).Human-in-the-Loop Governance: KPMG enforces a mandatory validation protocol where human audit experts must review, cross-examine, and approve all machine-generated cash forecasts, prescriptive tax adjustments, and financial disclosures.

CHALLENGES:

Primary Challenges in Deploying Accounting Analytics

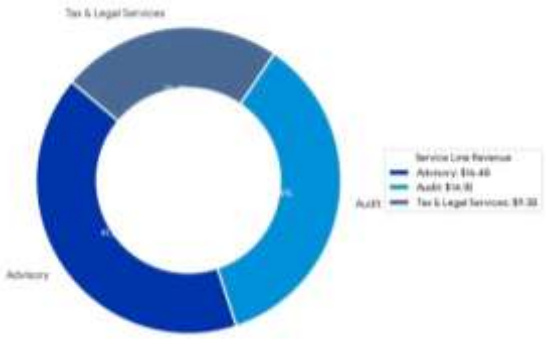
Fragmented Data Ingestion: Extracting data from customized, legacy client ERP systems requires massive manual cleaning because missing fields and mismatched formatting routinely stall automated analytical pipelines.

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The Black Box Dilemma: Complex machine learning models often mask how they calculate fraud or risk scores, leaving auditors unable to clearly explain the mathematical logic to strict public oversight regulators like the PCAOB.
Data Sovereignty Barriers: Strict international privacy frameworks (like GDPR) and cross-border data transfer laws heavily restrict hosting sensitive corporate financial ledgers on centralized, multi-region cloud infrastructures.
The CPA Talent Deficit: A severe global shortage of hybrid professionals leaves traditional accounting teams struggling to interpret complex Python, R, or machine learning outputs without extensive, costly retraining.
Steep Infrastructure Costs: Maintaining massive cloud processing pipelines, paying for high-tier enterprise AI licenses, and executing continuous model calibration creates permanent upward pressure on operational budgets.

Figure 4: KPMG FY25: Global Revenue Composition by Service Line (Total: US$39.8 Billion)

Source: KPMG Delivers 5.1% Rise in Global Revenue." KPMG International, 16 Dec. 2025, kpmg.com/xx/en/media/press-releases/2025/12/kpmg-delivers-rise-in-global-revenue.html.



The pie chart illustrates how KPMG's total global revenue of US$39.8 billion is distributed across its three core service lines following its firm-wide digital transformation:
*Advisory (41.2% / US$16.4 Billion): This is the largest slice of the pie. It reflects massive market demand from corporate clients hiring KPMG to help them build their own data pipelines, cloud architectures, and predictive analytics models.
***Audit (35.4% / US$14.1 Billion):** This represents the core financial statement verification business. It is powered completely by the **KPMG Clara** platform, proving that full-population ledger scanning (100% testing) has become a highly scalable, high-revenue automated product rather than a manual labor expense.
*Tax & Legal Services (23.4% / US$9.3 Billion): While the smallest slice, this division is heavily optimized by prescriptive analytics. Tools like the GenAI Disclosure Checklist automate multi-day document reviews down to minutes, allowing this segment to grow rapidly without needing a linear increase in human staff.The chart proves that Advisory and Audit combined make up over 76% of KPMG's business. By infusing machine learning and cloud analytics into these two massive segments, KPMG has successfully decoupled its revenue growth from pure human billable hours, allowing the firm to scale its operations globally.

1. **Grant Thornton**

Grant Thornton, as one of the world's leading largest professional services networks, relies heavily on data analytics to deliver mid-market and enterprise accounting, advisory, and assurance services. The firm has fundamentally modernized its delivery framework by embedding artificial intelligence (AI) and full-population data tools natively into its systems.

Descriptive Analytics--

Grant Thornton applies descriptive analytics to perform deep financial profiling, aggregating 100% of historical transactions to identify operational trends, transaction peaks, and processing baselines.
Real-Life Accounting Example: In standard annual audits, Grant Thornton completely moves past manual invoice sampling. Instead, they upload a client's entire transaction history into their environment. The engine tracks and visualizes the complete "Procure-to-Pay" or "Order-to-Cash" workflows, instantly uncovering duplicate journal postings, isolated manual ledger adjustments, and out-of-sequence accounting periods.
Grant Thornton Tools Used:

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gtap (Grant Thornton Analytics & Automation Platform): Launched as a core cloud infrastructure, gtap standardizes how raw ERP data is ingested, cleansed, and profiled to create a single, unified descriptive foundation.
Lumen: Grant Thornton's advanced analytics approach that drives "whole ledger" analytics. It is used by teams to capture the entire transactional landscape and quickly profile base operating anomalies.

Predictive Analytics--

Predictive analytics enables Grant Thornton to use historical accounting behaviors combined with real-world macro data to model future outcomes, evaluate potential bad-debt write-offs, and flag structural risks before they impact the financial statements.

Real-Life Accounting Example:During corporate restructurings or capital allocation strategies, Grant Thornton builds intelligent revenue and cash flow forecasting models. By feeding historical accounts receivable logs combined with local inflation indicators, credit score variances, and purchasing trends, the system forecasts precise customer default rates and calculates real-time Expected Credit Loss (ECL) provisions for the next fiscal year.

Grant Thornton Tools Used:

Lumen Predictive Modeling: Combines automated data regression paths with artificial intelligence to spotlight high-risk financial reporting variables, such as potential inventory obsolescence or asset impairment timelines.
gtap Risk Profiler: Utilizes built-in machine learning classification algorithms to match historical bookkeeping irregularities against broader industry trends, predicting which accounting segments possess the highest likelihood of hosting material misstatements or fraud

Prescriptive Analytics--

Prescriptive processing combines predictive outputs with strict regulatory compliance rule engines, enabling Grant Thornton to recommend definitive optimization steps for tax planning, operational accounting workflows, and reporting corrections.

Real-Life Accounting Example: When mid-market clients undergo cross-border expansions, Grant Thornton uses prescriptive models to optimize Transfer Pricing and international tax structures. The analytics platform simulates multi-scenario corporate restructuring pathways, calculates exact potential tax exposures, and directly prescribes the most legally compliant and capital-efficient ledger routing framework to minimize corporate tax leakage.

Grant Thornton Tools Used:

gtap Agentic Workflow Modules: Designed to transition toward an agent-assisted execution model. When an error or risk is detected, the built-in AI agents do not just flag it; they generate automated compliance checklists, write the necessary adjusting journal entries, and draft the required IFRS/GAAP disclosure modifications.
Causal Analytics Suite: An advanced consulting library utilized by their specialized Data and Analytics teams to run optimization simulations, providing clients with strategic resource allocation directives.

APPLICATIONS:

Here is how Grant Thornton applies these analytics across its global operations:

Standardized Cloud Ingestion: Grant Thornton uses the Grant Thornton Analytics & Automation Platform (gtap) to extract financial data directly from mid-market and enterprise ERPs (like NetSuite and Microsoft Dynamics), automatically cleaning and uniforming the datasets

Whole-Ledger Data Profiling: The firm deploys its Lumen platform to run full-population scanning across 100% of a client's transaction history, instantly visualizing end-to-end accounting flows and mapping operational spikes.

Task-Specific AI Agents: Accountants use automated gtap Agentic Workflow Modules that run background checks on financial data to predict misstatement risks and automatically write recommended adjusting journal entries.

Mid-Market Customization: Financial forecasting models are specifically calibrated to handle smaller, tighter mid-market business data structures, focusing primarily on short-to-medium-term working capital preservation.

Automated Regulatory Tuning: Centralized technical accounting teams continuously update the underlying compliance logic within the platforms to immediately reflect changing international GAAP and IFRS reporting laws.

Human-Guided Governance: The firm enforces strict oversight by requiring experienced Certified Public Accountants (CPAs) to manually review, cross-examine, and approve all machine-generated cash forecasts, tax routes, and draft disclosures.

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CHALLENGES:

Core Challenges in Deploying Grant Thornton's Analytics

*Mid-Market ERP Fragmentation: Customized and less mature client ERP software requires extensive data cleaning before platform ingestion

*Data Integrity Constraints: Incomplete transaction tracking and poor client bookkeeping lead to inaccurate machine learning forecasts.

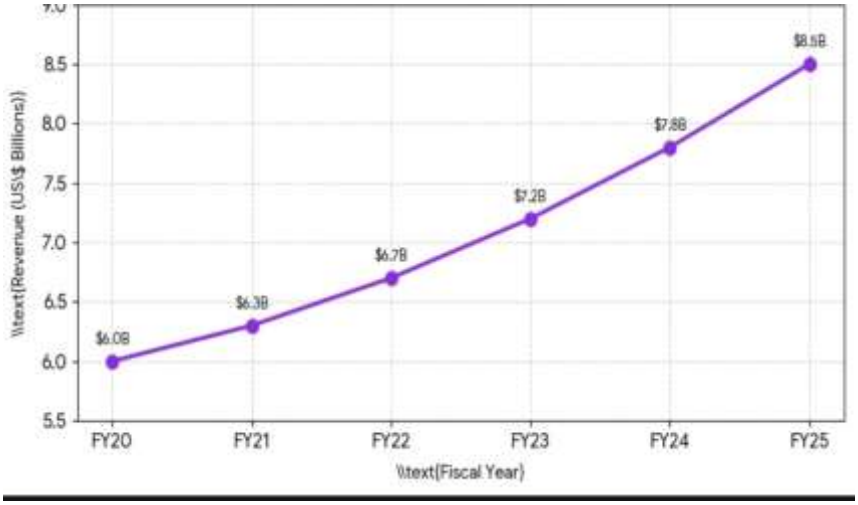
*The Black Box Audit Dilemma: Regulators demand transparent proof for audit decisions, making automated AI risk ratings hard to justify.

*The CPA Tech Talent Gap: Traditional accountants lack the data-science skills required to interpret complex statistical anomalies.

*Rapidly Changing Regulations: Evolving tax codes and reporting standards require continuous, costly manual updates to AI compliance engines.Prohibitive Infrastructure Costs: Maintaining high-performance cloud data pipelines creates massive budgetary pressure for non-Big Four firms.

Figure 5: Grant Thornton Global Revenue Expansion (FY20 – FY25) Driven by gtap and Lumen Platform Implementation

Source: Grant Thornton International Ltd. (2025, December 18). *Grant Thornton grows global revenues to a record USD 8.5 billion*. Grant Thornton International Official Press Room.



The trend line in this chart directly visualizes the financial payoff of Grant Thornton's multi-year technology overhaul and its aggressive focus on the enterprise mid-market:

The Inception Phase (FY20–FY22): The initial growth from $6.0B to $6.7B marks the period when Grant Thornton first introduced its Lumen whole-ledger analysis tool. By moving away from random sampling, audit teams began processing entire transaction pools, which allowed them to win larger, more complex mid-market accounts that previously went exclusively to the Big Four.

The Acceleration Phase (FY23–FY24): The steeper climb from $7.2B to $7.8B reflects the massive scalability gained as the firm integrated automated regression paths and background risk profiling into daily workflows. Instead of billing strictly by human hours spent manual-checking spreadsheets, automated data ingestion allowed the firm to process a much higher volume of audit and tax engagements simultaneously

The Peak Launch (FY25): The surge to a historic $8.5B matches the formal introduction and expansion of gtap (Grant Thornton Analytics & Automation Platform) [□, 1.2.3]. This unified cloud pipeline introduced autonomous AI agents that automatically drafted adjusting journal entries and disclosure compliance checklists

Key Findings

The study found that data analytics plays an important role in accounting and business decision-making by converting financial and operational data into meaningful information. The analysis of Deloitte, PwC, EY, KPMG and Grant Thornton shows that analytics has expanded beyond historical reporting to support transaction analysis, risk identification, forecasting and decision-making.

The findings show that **descriptive, predictive and prescriptive analytics** have interconnected roles. Descriptive analytics helps understand past performance, predictive analytics estimates possible future outcomes, and prescriptive

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analytics supports the selection of appropriate actions. Together, they support accounting and management from analysing past results to planning future decisions.

The study also found that analytics can be applied to **budgeting, financial planning, transaction analysis, forecasting, fraud detection, risk management and business performance**. Analytical tools can help identify unusual transactions, assess financial risks, forecast revenue and cash flows, and analyse costs, inventory and receivables.

The analysis of the selected professional service firms demonstrates the increasing use of specialised analytics platforms in accounting and auditing. However, the effectiveness of these technologies depends on **data quality, system integration, cybersecurity, suitable infrastructure and skilled professionals**. The shortage of professionals combining accounting knowledge with analytical and technological skills remains an important challenge.

Finally, the study found that **professional judgement and human oversight remain essential**. Analytics and AI can support professionals by identifying patterns and risks, but their outputs require interpretation and validation. Therefore, analytics should be viewed as a decision-support tool that strengthens accounting and business decisions rather than replacing professional expertise.

Overall, the findings confirm that data analytics can improve the way organisations analyse information, manage risks, plan finances and make business decisions, while its effectiveness depends on reliable data, appropriate technology and human judgement.

E.CONCLUSION

This study examined the role of data analytics in accounting and business decision-making, with particular emphasis on descriptive, predictive and prescriptive analytics and their applications in financial and management accounting. The study found that the increasing availability of financial and operational data has significantly expanded the role of analytics in modern organisations. Accounting information is no longer used only to record past transactions and prepare financial statements; it is increasingly analysed to understand performance, identify risks, forecast future outcomes and support managerial decisions.

The study demonstrates that descriptive, predictive and prescriptive analytics represent interconnected stages of data-driven decision-making. Descriptive analytics helps organisations understand historical and current performance, while predictive analytics uses available information to estimate possible future outcomes. Prescriptive analytics then supports the evaluation of alternative actions and helps management or accounting professionals determine appropriate responses. Together, these approaches allow organisations to move from simply understanding what happened towards considering what may happen and what action may be taken.

The practical analysis of Deloitte, PwC, EY, KPMG and Grant Thornton further demonstrates the growing importance of analytics in accounting and auditing. Their use of analytical platforms and technologies for transaction analysis, journal-entry analysis, risk assessment, anomaly detection, forecasting and audit planning illustrates how large volumes of accounting data can be examined more efficiently. Analytics can improve the identification of unusual transactions and high-risk areas and allow accounting and audit professionals to focus their attention where further investigation is most necessary.

The study also concludes that data analytics has applications beyond auditing. It can support financial planning, budgeting, revenue analysis, inventory management, cost control, fraud detection, credit risk assessment and business performance analysis. By combining financial information with operational and external data, organisations can develop a broader understanding of the factors influencing financial performance. This can contribute to improved resource allocation, working capital management, forecasting and risk reduction.

However, the study also establishes that advanced analytical technology alone cannot guarantee better decisions. The effectiveness of analytics depends on the accuracy, completeness and consistency of the underlying data. Data integration difficulties, privacy and cybersecurity concerns, implementation costs, changing technology and shortages of skilled professionals can limit successful adoption. In addition, predictive and AI-based systems can produce misleading results when their underlying data or assumptions are inappropriate.

Therefore, the study concludes that **data analytics should be viewed as a decision-support capability rather than a replacement for professional accounting judgement**. The strongest results are likely to be achieved when analytical

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technologies are combined with reliable data, appropriate controls and professionals who understand both accounting and data analysis. Accountants and auditors will increasingly need to develop technological and analytical skills alongside their traditional financial knowledge.

Overall, data analytics has become an important component of modern accounting and business management. Its ability to analyse transactions, identify patterns, assess risks, forecast future conditions and support decisions provides organisations with opportunities to improve financial planning and business performance. At the same time, responsible implementation requires attention to data quality, security, professional judgement and ethical considerations. The study therefore concludes that the future of accounting is not simply about collecting more data, but about **turning reliable data into meaningful insight and using that insight intelligently to make better financial and business decisions.**

F. REFERENCES

Alles, M., & Gray, G. L. (2016). Incorporating big data in audits: Identifying inhibitors and a research agenda to address those inhibitors. *International Journal of Accounting Information Systems, 22*, 44–59. https://doi.org/10.1016/j.accinf.2016.07.004

Appelbaum, D., Kogan, A., Vasarhelyi, M. A., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems, 25*, 29–44. https://doi.org/10.1016/j.accinf.2017.03.003

Deloitte. (2025). *Deloitte expands its global suite of GenAI and agentic AI capabilities in Omnia, advancing the audit experience*. Deloitte.

Deloitte. (2026). *Deloitte Omnia: Digital audit technology*. Deloitte.

Deloitte. (2026). *Deloitte unveils connected agentic intelligence in Deloitte Omnia to advance audit & assurance*. Deloitte.

Ernst & Young LLP. (2025). *Our commitment to audit quality: Ernst & Young LLP's 2025 report*. EY.

EY. (2026). *Digital in systems, processes and analytics*. EY.

EY. (2026). *EY audit technology*. EY.

EY. (2026). *EY Helix – Audit technology*. EY.

Grant Thornton. (2023). *Audit quality & transparency report 2023*. Grant Thornton.

Grant Thornton. (2025). *Audit quality and transparency report 2024*. Grant Thornton.

Grant Thornton. (2026). *Grant Thornton launches gtap to transform audit*. Grant Thornton.

KPMG. (2026). *Data foundation for AI*. KPMG.

KPMG. (2026). *Finance transformation*. KPMG.

KPMG. (2026). *KPMG Clara*. KPMG.

KPMG. (2026). *AI-enabled. Human-led. Audit quality—delivered through KPMG Clara AI*. KPMG.

Mastercard. (2026). *Decision Intelligence for fraud and risk management*. Mastercard.

Mastercard. (2026). *Transaction fraud monitoring*. Mastercard.

Mukherjee, A., Sharma, U., & Liu, J. (2025). Big data analytics role in shaping the work of accounting function and accounting professionals. *Journal of Accounting & Organizational Change, 21*(7), 272–306. https://doi.org/10.1108/JAOC-08-2024-0255

PwC. (2021). *Using technology to ensure quality for clients – PwC's tech-enabled audit*. PwC.

PwC. (2025). *Technology in PwC audit*. PwC.

PwC. (2026). *Audit of General Ledger with Halo*. PwC.

PwC. (2026). *Audit technologies*. PwC.

Smyl, S., & Bell, F. (2018). *Forecasting at Uber: An introduction*. Uber Engineering.

Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. *Accounting Horizons, 29*(2), 381–396. https://doi.org/10.2308/acch-51071

Warren, J. D., Moffitt, K. C., & Byrnes, P. (2015). How big data will change accounting. *Accounting Horizons, 29*(2), 397–407. https://doi.org/10.2308/acch-51069

Webb, C. (2020). *Analytics in finance and accountancy*. Association of Chartered Certified Accountants.

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This article is openly accessible and reusable with proper attribution.

Xiao, S., Kodavanti, P., & Meng, E. (2020). *Building a backtesting service to measure model performance at Uber-scale*. Uber Engineering.

Yoon, K., Hoogduin, L., & Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons, 29*(2), 431–438. https://doi.org/10.2308/acch-51076

Zhang, J., Yang, X., & Appelbaum, D. (2015). Toward effective big data analysis in continuous auditing. *Accounting Horizons, 29*(2), 469–476. https://doi.org/10.2308/acch-51070

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