PERSPECTIVES ON BIG DATA AND BUSINESS INTELLIGENCE TECHNOLOGIES IN THE CONTEXT OF AUDIT TASKS

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Abstract
The process of the audit of annual financial figures and other financial information of a company (financial data) primarily relates to the examination of vouchers. Also, the assessment of organizational aspects of the audited company and its competitiveness and stability in total marks essential elements of a financial audit. The growing extent of the vouchers to be examined, the stronger pressure by shorter reporting deadlines, the pervasive character of organizational aspects of the company and, in the end, declining audit fees lead to an increasing demand for modern IT-supported audit tools to enhance the audit process.
In this paper, essential aspects of the audit process will be elaborated. In the next step, the application of bulk processing of data (Big Data) as well as company data analysis techniques (Business Intelligence) in the audit area will be further outlined. The objective of this paper is to elaborate different perspectives for the application of Big Data and Business Intelligence- Technologies in the domain of financial data auditing.

Keywords
Audit; Big Data; Business Intelligence; Audit Process.

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Introduction

The audit of the financial report or other financial data of a company is challenged by the rapid development in IT scenery in two different ways. First, the auditor is obliged to assess the functionality and effectiveness of the client´s IT structures upon conduction of the audit. The second question is, whether the auditor himself is capable of applying sophisticated IT-tools to increase both efficiency and effectiveness throughout the audit process.
Besides the widespread IT-application in administrative and productive areas, the use of IT-driven analytical tools for decision making processes via Business Intelligence (BI) solutions has gained in importance in recent years. Moreover, with enhanced tools to extract and analyze bulk data from various sources (Big Data), the question arises, whether

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combined Big Data- /BI-Technologies can be used to detect general risk and economic patterns of an entity. This information can be used by both the entity and the auditor.
Therefore, it is crucial to elaborate which areas are suitable for the application of Big Data- /BI-Technologies either as an audit objective or as a tool for auditing financial data.
Business Intelligence as well as Big Data are phenomena of more current origin. While BI systems have historically developed from Decision Support Systems (DSS) and lie in the tradition of processing and analyzing internal enterprise data, Big Data-technologies with their focus on external data are still emerging. For the last three years, this field has emerged as the new frontier in the wide spectrum of IT innovations. The creation of massive data sets through an extensive array of several new data generating sources (e.g. point of sale, mobile phones, automobiles etc.) has prompted organizations, and their auditors to focus their attention on how to utilize and analyze big data.
The application of Artificial Intelligence (AI) applications in the accountancy or audit domain has a long tradition (Abdolmohammadi, 1987; Bailey et Al., 1987). This mainly aimed at using IT tools for solving specific problems based on data that is provided by the end user (Expert Systems). However, this approach failed due to the lack of user neutrality, as explained from O'Leary (2003).
A more general overview about possible ranges of application offers Baldwin, et Al. (2006) matching audit tasks with existing solutions in specific audit areas. Furthermore, Ul-Huq (2014) differentiates between structured, semi-structured and unstructured audit tasks focusing the application of AI- technologies in developed and developing countries. Regarding Data Analytics as a specialized AI technology for audit engagements, a lot of publications concentrate on the usage of Big Data- /BI-Technologies in risk management (Hu et al., 2012;), going-concern- assumptions (Tsai and Hsu, 2013) or fraud (Murthy, 2010; Whiting et al., 2012).

1. Purpose and Approach in the Audit of Financial Data

An audit aims at reaching audit assertions as e.g. the completeness or correctness of the audit subject (invoice, asset, contractual obligation etc.). Naturally this leads to the risk of giving a positive audit judgment in spite of misstatements in the financial data. The risk of reaching a false positive audit assertion is called “audit risk”. The audit risk itself is divided into Inherent Risk, Control Risk and Detection Risk (Botez, 2015). *Inherent Risk* is the susceptibility of an audit area to the appearance of misstatements, while *Control Risk* expresses the danger that mistakes are not uncovered by the internal control system of the entity generating the financial data. Finally, *Detection Risk* shows the risk that the auditor does not recognize misstatements in the financial data through conducting audit procedures. The relation of these components is as follows:

$$Audit\ Risk = Inherent\ Risk * Control\ Risk * Detection\ Risk$$

The relation is called “multiple model”, meaning that a high Inherent Risk leads to high Audit Risk, given the premises that Control and Detection Risk remain constant. Accordingly, an effective internal control system of a company generating the financial data can lead to a lower Control Risk which reduces Audit Risk.
Therefore the prevailing “risk oriented audit approach” governs an initial risk assessment of the whole entity followed by an estimation of Control Risk through an audit of design (“are the controls appropriate?”) and effectiveness (“have the controls been processed?”) of the entity’s internal control system. With substantive audit procedures (checking invoices,

inspection of contracts and assets, recalculation of valuations etc.) the remaining inherent and detecting risks have to be minimized. For guidance on essential elements of the audit process, refer to ISA, 2012.

2. The Application of Information Technology on Mass Data Capture and Evaluation in the Business Environment for Decision Making and Controlling Purposes

BI Technologies are a major technology when using IT-driven methods for decision making and controlling purposes. Based on the fact of a stronger growing need and demand for processing mass data the integration of additional Big Data functionalities in BI architectures and BI methods is to be expected.

Business Intelligence is not a single application, but rather an architecture of integrated systems for decision making and learning based on existing enterprise resource planning (ERP), supply chain management (SCM), customer relationship management (CRM) or other data. The purpose of BI is to transform the raw, massive data that is collected by various internal or external sources into useful information. A typical BI architecture is set up by connected servers and databases used commonly in an enterprise for data gathering, storage, processing, evaluation and presentation. Essential features of BI systems are their capability of integrating and standardizing data of various sources through Extract-Transform- Load (ETL) tools and the evaluation of the standardized data using mid-tier servers that provide specialized functionality for different BI scenarios, e.g. filtering, drill-down, report rendering, searching, data analysis and building predictive models (Chaudhuri et. al, 2011). The possibilities to extend searches and data analytics across various (internal) sources like product catalogs, emails, survey responses, research reports etc. indicate the potential of a powerful BI solution. Together with data mining abilities, that go well beyond what is offered in traditional relational database management systems, it is possible to generate decision trees, regression models, market based analyses and more.

Regarding the increasing amount of internal or external data sources and the enhanced possibilities of their use, Big Data technologies comes into play especially for data gathering, processing and evaluation. Big Data are high volume, high velocity, and/or high variety information assets (including ‘unstructured data‘) that require new forms of processing to enable enhanced decision making, insight discovery and process optimization (Chua 2013). The new aspect which justifies the term ‘Big‘ is not just because it involves data that is much more likely to lack ‘form’ and to fall outside traditional relational databases; it is also because it has been accompanied by the development of advanced analytics that allow organizations to unlock insights from data with previously unachievable speed and accuracy.

According to Chua (2013), the main implications of Big Data for the accountancy and finance profession consist in the valuation of data assets and the use of big data in decision making as well as in the management of risk. The data valuation challenge relates to the problem that the value of old data can quickly decay as new data becomes available. Regarding the use of such data in decision making and management risk processes, Big Data technologies may lack effectiveness in this domain.

Regarding the BI architecture, it can be reasonably assumed, that Big Data is another evolutionary step towards a better usage of mass unstructured data from multiple sources which can enhance current and future BI solutions. The relation between BI and Big Data solutions can be characterized as follows:

Business intelligence is one possible objective of data analysis. Big Data analysis is one possible means of achieving that objective. One can possibly obtain business intelligence without doing Big Data analysis. On the other hand, Big Data analysis can be used to achieve different objectives, not just business intelligence. Furthermore, Big Data is an extension of the current analytic set of databases. Because of its volume and dynamic characteristics, it creates an entire new set of technical challenges.

3. Information technologies in the audit process

Concerning the application of these technologies in the audit domain the following questions for structuring arise:

- To what extent can these technologies be used to generate audit assertions?
- Which Big Data/BI technologies are available to support the respective audit tasks?
- Which requirements exist for the proper application of these technologies?

Taking into account these questions, perspectives of the application of Big Data/BI Technologies arise concerning their assurance character, solutions and usage.

3.1. Perspective Evidential Character

Regarding their evidential character, it is appropriate to focus on Big Data technologies because of their extensive use of external data from various sources. Traditional BI solutions, on the other hand, rely on internal data from the entity and its immediate environment, which are broadly considered as ”traditional” audit evidence, if they satisfy the following principles. According to applicable audit professional standards, audit evidence needs to be “sufficient and appropriate”, where “appropriate” refers to ”reliable” and ”relevant” (SAS No. 106, AICPA 2004).

Big Data contributes to the “sufficiency” requirement because of its volume and the variety of data provided on a real-time basis (velocity). “Sufficiency” itself depends on the risk of misstatement and the appropriateness (i.e., reliability and relevance) of the audit evidence collected where more evidence from Big Data is needed when it has lower reliability and relevance (SAS No. 106, AICPA 2004).

Regarding” sufficiency”, the scope and quality of collected audit evidence are mainly affected by technology (i.e. computerized vs. manual evidence) and cost/benefit constraints. With Big Data technologies the major disadvantage of information abundance provided from traditional data analytic/BI-tools in massive quantities can be addressed with advanced data analytics which are powerful enough for processing larger data sets and are compliable to unstructured data (Russom, 2011). In fact, the ability the collect and analyze data which does not automatically fit a formal data structure is one major advantage of Big Data technologies in contrast to the widely used database schemes in traditional databank management solutions.

The major concern regarding reliability of Big Data-/BI-generated audit evidence relates to their probabilistic nature (e.g. auditor’s predictive model is 3 percent below management’s numbers). However, this nature of Big Data-generated assertions calls for a proper application of those technologies in the audit process and their respective interpretation and do not contradict the requirement of reliability.

With reference to relevance, Big Data/BI- Technologies can generate evidence that is more timely and specific to the audit objectives compared to the traditional audit approach. The

major challenge lies here as well their appropriate application and interpretation, as Big Data analytic results regularly suggest association, not causation (Cao et al. (2015).
To sum it up, in assessing the evidential character of audit evidence generated by Big Data or Big Data- enhanced BI technologies, it is crucial to point out applicable audit tasks and data sources and necessary skills and restrictions when using the results in order to reach a conclusion.

3.2. Perspectives on Solutions

Regarding perspectives on solutions, it is reasonable to differentiate between focusing on certain tasks processed by Big Data/BI- Technologies (task perspective) or an certain data to be processed (data perspective).

a) Task Perspective

With reference to the approach and essential elements in the audit of financial data (Section 1) and to typical BI architecture including Big Data technologies, the following table depicts existing/ probable Big Data/BI- solutions, databases, and their possible application in the major elements of the audit process to support audit objectives (Table no. 1).

b) Data Perspective

Going one step further, the mapping of Big Data/BI- solutions to audit tasks can lead to the general question, whether data collected and processed via Big Data/BI- Technologies for non-audit purposes can be used in the auditing domain as well. Such an approach can be enabled by the prevailing implementation of those technologies in the entity's production, marketing and administration processes (e.g. embedded chips in inventory, production site cameras). For auditing purposes, there will generally be many uses for the data collected, e.g. Table no. 2:

Table no. 2 Usage of Big Data sources for audit purposes

Data	Use 1	Use 2
Security Videos	Receipt and exit confirmation	Shipping Costs Confirmation
News Videos	Overall market position	Product/ service problems
Social Networks	Customer satisfaction	Fraud Detection
RFID	Inventory Confirmation	Pricing of Goods
Web hits	Predict Purchases	Predict Revenue

Source: Adapted from Vasarhelyi et. al, 2015

Table no. 1 Mapping of Big Data/ BI- Solutions to Audit Tasks

Solutions	Database	Examples in the Audit Area				
		Pre-Engagement Risk Assessment	*Initial Risk Assessment*	*Audit of Controls*	*Audit of financial Data*	*Forming Overall Conclusion*
Prediction of daily fluctuations of the Dow Jones Industrial Average Index (Bollen et al., 2011))	Twitter Data (Google's Profile of Mood States)	Unusual stock price fluctuation of entity	Fraud Risk evaluation; overall financial state of a firm	Risk Management controls	Financial instruments revaluation	Return on investments on financial instruments
Prediction of Customer Behavior to personalize landing pages or management inventories (Cao et al., 2015)	-IP-Addresses of User -US Census data -Transactional Data -Weather Data	Customer Complaints regarding entity	Focusing resources on more risky parts of the business.	Controls on Stock Management	Inventories valuation	Overall analytical procedures
Prediction of optimal drilling sites in oil and gas exploration (Cao et al., 2015)	-Geographical Data -Weather Data	Impact of geographical operation sites	Focusing resources on more risky parts of the business.	Budgeting or Risk Management controls	Valuation of drilling rights	Earnings Return
Predictive Policing: Prediction of the most likely timing and location of crimes on a day to deploy forces most effectively (REF)	-Police Data Base -Existing "Prediction Boxes"	Entity's past activities or outcomes of past audits	Frau Risk Evaluation	Assessment of failure Controls	Sample Selection based on past experience	Overall analytical procedures
Monitoring of market events, seek out financial statement fraud, and identification of audit failures by SEC (Arnold and Wong, 2014)	-Regulatory Filings and other reportings to SEC -Databases on MicroCap Securities	Failures according to public reportings	Fraud Risk and Bankruptcy Risk Evaluation	Financial Statements preparation controls	Sample Selection based on current information	Overall analytical procedures
Improving community health regarding restaurant hygiene (Public CIO, 2015)	Database on restaurants (operation time, history of critical violations, complaints. etc.)	Past audits and customer complaints	Evaluation of bankruptcy risk	Assessment of production controls	Sample Selection based on risk characteristics	Going Concern Assumption

Text Analysis regarding news articles, product discussion forums, and social Networks (Yoon et. al, 2015)	Public Information	Customer and other complaints	Understanding of production volume and inventory levels	Assessment of general controls	Use as hypothesis in analytical procedures	Performance prediction
Automated text mining to identify emails of disgruntled employees (Holton, 2009)	Emails of employees	Evaluation of business practices	Evaluation of bankruptcy risk	Assessment of fraud detection controls	Identifying a person's motivation and probable rationalization for Fraud	Financial damage prediction
GPS Data for Localization of Shipments (Yoon et. al, 2015)	Available GPS Data	Operating Areas	Assessment of obsolescence Risk	Assessment of shipping controls	Verifying shipping documents	Financial damage prediction
Automated text mining to identify deceptive language (Larcker and Zakolyukina, 2012)	Conference Call and other Minutes	Evaluation of external pressure	Assessment of high-level fraud	Risk Management controls	Revaluation on business operations	Going Concern assumption

Source: Own elaboration

3.3. Perspective Usage

Regarding the usage of Big Data/BI Technologies, challenges regarding auditor qualification, design of appropriate audit tools and usage standards have to be addressed.

With respect to a necessary domain- specific training of auditors it is not only necessary to educate on technological aspects of these new audit technologies. Also, the appropriate use of Big Data/BI Technologies can depend on behavioral factors like the individual ambiguity tolerance level. Therefore, it is crucial to be aware of subjective factors hindering the proper use of those new audit tools.

Also, another important factor will be the adoption of appropriate data analytic tools. In fact, deciding which tool to use will play an important role in the usefulness of Big Data. While traditional data analytic tools, such as Computer Assisted Audit Techniques (CAATs) are essentially data extraction tools focused on entity- internal data that allow auditors to perform data analysis using queries and do not consider the vast amount of external, unstructured and/ or non-financial data which is specific for Big Data Technologies.

Regarding the appropriate usage standards, the traditional audit standards largely provide guidance related to internal or documented audit evidence. However, they have to deal with the fact, that the quantity of the audited population is not an issue anymore with Big Data. Focus will shift to the auditor's use of various data analytic tools as mentioned before. Traditional approaches regarding relevance and reliability can also not apply without significant adaptions to the specifics of Big Data/BI-Technologies. Many tests will be formalized using algorithmic procedures which require standards for their design, appropriate use and incorporation in the general audit process. Guidance is also necessary for the probabilistic, unstructured nature of this new audit evidence and their corroboration by traditional audit techniques. Eventually, manually made judgments must be integrated into the new Big Data/ BI- driven audit, including a feedback system.

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Conclusions

In order to benefit from the new opportunities provided by Big Data/BI-Technologies, the traditional audit process has to be adjust profoundly, which requires further research regarding the outlined perspectives. In view of the general principles regarding sufficiency, reliability and relevance, the new technologies have to be incorporated in a new audit framework which supports the auditor in the appropriate use, interpretation and judgment on additional traditional audit procedures.

Main features of this new audit framework should relate to the fact that beyond traditional approaches aiming to identify causation relations, it is now possible to identify and make use of (audit-related) correlations. Furthermore, it will be possible to analyze the whole set of data rather than just a small subset or sample. A Big Data/BI- driven audit also needs to consider using a hierarchy of audit procedures with Big Data analytics to identify general business patterns, risks and trends, supplemental traditional manual or computer-assisted audit techniques to conduct a more detailed analysis of potential issues and lastly the audit judgment to determine the impact of findings on financial reporting.

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