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THE ADOPTION OF BIG DATA ANALYTICS IN THE EXTERNAL AUDITING: Bibliometric and Content Analyses

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Abstract: *Purpose* – This study reviews the literature on adopting big data analytics (BDA) in external auditing. This goal is divided into several sub-goals. First, we aim to find the most productive and cited authors, documents, and sources concerning this research discipline. Second, we aim to organize and summarize prior literature to reveal the areas that have been studied and the gaps that require further investigation.

Design/methodology/approach – This study uses a systematic approach in reviewing literature. We utilized bibliometric and content analyses to provide a comprehensive and updated image of the current state of the literature and potential areas that need further research. Ninety-eight articles published between 2011 and 2021 extracted from 38 journals indexed in the Scopus database were included in our review.

Findings – The United States is the most productive country of research related to BDA in auditing, with 34 articles. The research trend flourished in 2015 to reach its peak in 2021 with 27 pieces. It is worth noting that the University of New Jersey (Rutgers University) is the most productive affiliation with 18 contributions. The most productive and cited journal was Accounting Horizons, with 16 articles. In addition, the most cited paper is "Big data in accounting: An overview" by Vasarhelyi,

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Kogan, and Tuttle (2015). Our analysis grouped the literature into three main research themes:1) BDA in auditing process; 2) BDA diffusion; and 3) BDA in auditing curricula. In addition, seven future research areas are developed: 1) research scope and methodology, 2) BDA and components of the audit process, 3) BDA and interactions with stakeholders, 4) new theories, 5) reasons for adopting BDA, 6) impact of BDA on audit firms, 7) BDA and auditing education.

Implications – This analysis provides valuable insights for audit academics, practitioners, and educators on using BDA in external auditing. The results of this study will inform academic researchers of potential future research opportunities. Moreover, this study presents the academic community's insights that benefit audit practitioners and educators.

Originality/value – This study contributes to the literature by combining bibliometric and content analyses to provide a comprehensive and updated picture of the current state of BDA and the external auditing literature.

Keywords: Big Data, Big Data Analytics, Data Analytics, Audit Data Analytics, External Auditing, Audit Process, Audit Quality, Bibliometric Analysis, Content Analysis.

1. INTRODUCTION

Big data (BD) and big data analytics (BDA) are expected to disrupt and change the assurance industry (Earely, 2015; Cao *et al.*, 2015; Appelbaum *et al.*, 2018; Salijeni *et al.*, 2019). In response to this technology, audit firms have invested extensively in integrating BDA tools into the audit process (Gepp *et al.*, 2018; FRC, 2017; 2020a; 2020b). Such efforts have been made to enhance the quality of financial statement audits (KPMG, 2017; FRC, 2020b). Additionally, regulatory agencies have begun exploring the potential consequences of adopting BDA in external auditing (auditing hereafter). For instance, the International Auditing and Assurance Standards Board (IAASB) established a data analytics working group to evaluate the influence of BDA on auditing standards (IAASB-DAWG, 2016). Also, the Rutgers AICPA Data Analytics Research (RADAR) Initiative was established at the end of 2015 (Rozario and Vasarhelyi, 2018). Moreover, the Financial Reporting Council (FRC) has issued many reports showing how adopting BDA can affect the audit process and quality (FRC, 2017; 2020a; 2020b).

BD depicts the nature of the data, while BDA points to analytics tools that collect, analyze, and make sense of BD data (Chen *et al.*, 2012; Brown-Liburd *et al.*, 2015; Earley, 2015; Joshi and Marthandan, 2018). Many terms have been used interchangeably to refer to BDA in the literature and practitioners' reports. Some studies have used the term data analytics (DA) (IAASB-DAWG, 2016; ACCA, 2019; Rozario and Issa, 2020; Koreff *et al.*, 2021; Austin *et al.*, 2021). Others have used audit data analytics (ADA) (FRC, 2017; 2020a; Michael and Dixon, 2019; Kim *et al.*, 2020; Lee *et al.*, 2021). Some studies have used the term BDA (Salijeni *et at.*, 2019; Kend and Nguyen, 2020; De Santis and D'Onza, 2021). All these terms were approximately defined the same way, which was initially developed by AICPA in 2014 and adopted by the IAASB Data Analytics Working Group in 2016, which is "*The science and art of discovering and analyzing patterns, deviations, and inconsistencies and identifying anomalies, and extracting other useful information in data underlying or related to the subject of an audit through analysis, modeling, and visualization for planning or performing the audit*" (AICPA, 2014, p.5; IAASB-DAWG, 2016, p.7). BDA is transforming the audit process from complete dependence on financial and accounting, structured, and internal data to non-financial and non-accounting, unstructured, and exogenous data (IAASB-DAWG, 2016; FRC, 2017; 2020a; Eilifsen *et al.*, 2020).

Several studies have been conducted over the past ten years to examine the integration of BDA into auditing. However, the BDA adoption in auditing is still in its early stages and is considered a "black box" (Alles, 2015; Gepp *et al.*, 2018; Eilifsen *et al.*, 2020). The main objective of the research is to analyze and offer an updated image of the recent literature on the adoption of BDA in auditing to illustrate the areas covered by prior literature and determine the potential areas that need further research. This goal is divided into several sub-goals. First, we aim to find the most productive and cited authors, documents, and sources concerning this research discipline. Second, we want to understand the conceptual structure of this research discipline (the relationship between BDA and different audit topics). Third, we aim to organize and summarize prior literature to reveal the areas that have been studied and the gaps that require further investigation. To achieve our goal, we performed bibliometric and content analyses of 98 articles produced between 2011 and 2021 in journals that are indexed in the Scopus database.

The contribution of this research is evident in using a combination of bibliometric and content analyses to offer a comprehensive and updated picture of the current state of BDA and the auditing literature. Pizzi *et al.* (2011) stated that the bibliometric approach adds two new functions to literature analysis: performance and mapping. We use performance analysis to determine the pioneers in this research topic (authors, documents, and journals). Additionally, the content analysis presents prior literature in an organized and summarized form to determine the covered areas and those needing further investigation.

This study is beneficial to different financial reporting stakeholders. Our results will inform academic researchers of areas that represent potential future research opportunities. It also provides new researchers with information about the most important pioneers (authors, documents, and journals). Moreover, this study presents some insights that may benefit audit practitioners and educators.

The remainder of this paper is organized as follows. Section 2 reviews the BDA literature in the context of auditing. Section 3 discusses the methodology used in the study. Section 4 presents the results of this study. Section 5 illustrates the gaps that need to be addressed in future research. Finally, Section 6 concludes the paper.

2. BACKGROUND

This section analyzes and discusses the review papers conducted concerning BDA and auditing (Table *I*). We categorized these studies into three main themes: (1) emerging technologies in auditing (Lamboglia *et al.*, 2020), (2) emerging technologies in accounting (Richines *et al.*, 2017; Gepp *et al.*, 2018; Atayah and Alshater, 2021), and (3) BDA in auditing (Appelbaum *et al.*, 2017; Appelbaum *et al.*, 2018; Ahmad, 2019). The first group discussed using emerging technologies (AI, blockchain, BDA, IoT, and continuous auditing) in auditing using a systematic literature review to know the evolution of the conceptual structure of this research area. The second group discussed emerging technologies in branches of accounting and finance (i.e., financial, management, tax, auditing, and finance). One study in this group used the systematic review approach, whereas the remaining used the traditional literature review approach. A common aspect of the first and second groups is the inclusion of BDA in the emerging technologies discussed.

The third group focuses exclusively on BDA and auditing. Appelbaum *et al.* (2017) used a traditional literature review approach to synthesize the challenges that auditors may encounter due to using BD and complicated analytical tools by audit clients. Appelbaum *et al.* (2018) reviewed 301 concerning the use of analytical procedures in auditing. They developed a framework (external audit analytics) to categorize the prior literature by techniques, engagement phases, research methods, and the orientation of analytical tools (descriptive, predictive, and prescriptive). Ahmad (2019) followed the systematic approach to examine the literature on the impact of BDA on auditors' cognitive errors, memory, judgment, and decision-making.

The findings of those review papers can be summarized in the following clauses: "BDA is a game changer in external auditing," "BDA in external auditing is still in its early adoption stages," "BDA in external auditing is still -to some extent- a "black-box" from researchers' viewpoint," "using BDA in auditing is dependent on the evolution of auditing standards," "there is a growing academic interest in the BDA in external auditing," and "BDA and auditing prior research is fragmented and not organized in a systematic way." Our research complements and extends previous review papers by using bibliometric and content analyses to review 98 articles extracted from the Scopus database between 2011 and 2021 about using the BDA in external auditing.

Table I: Summary of Literature Review Papers

		Richins et al. (2017)	*Appelbaum et al. (2017)*	*Gepp et al. (2018)*	*Appelbaum et al. (2018)*	*Ahmad (2019)*	*Lamboglia et al. (2020)*	*Atayah & Alshater (2021)*
Emerging Technologies Discussed	Big Data Analytics	✓	✓		✓	✓	✓	✓
	Artificial Intelligence						✓	✓
	Blockchain						✓	✓
	Continuous Auditing							
	Internet of Things						✓	
Accounting Branches Discussed	Auditing		✓	✓	✓	✓	✓	✓
	Financial Accounting							
	Management Accounting							
	Tax Accounting							✓
	Finance/Accounting	✓		✓				
Type of Literature		TLR*	TLR	TLR	SLR**	SLR	SLR	SLR
No. of Studies Reviewed		N/A***	N/A	N/A	301	136 (75 BDA & 61 Cognitive)	256	154 (31 BDA)
Time Covered		N/A	N/A	N/A	1970-2015	1970-2018	1988-2019	1986-2020

* TLR: Traditional Literature Review[1] ** SLR: Systematic Literature Review *** N/A: Not Applicable (The literature paper did not mention this item)

3. METHODOLOGY

This review study uses quantitative bibliometric and qualitative content analyses. We used the two methods to offer more focused research, thereby contributing to the knowledge related to BDA in the external audit field. The bibliometric analysis approach can be viewed as a quantitative tool for analyzing published contributions and bibliographic units (Lamboglia *et al.*, 2020). The content analysis aims to systematically review and summarize the prior literature to identify research gaps that need further research (Seuring and Gold, 2012). In reviewing the literature, the selection process is crucial to ensure the validity and consistency of the subject to be analyzed (Pizzi *et al.*, 2021). Also, the content analysis should be conducted using a predetermined process (Seuring and Gold, 2012).

This study defined specific criteria for developing a research protocol, as shown in Figure (1). According to Massaro *et al.* (2016), defining a research protocol for literature analysis ensures the reliability of the study, leads to a structured literature review, and allows academics to reproduce the research. We follow the methodologies of recent review studies that critically analyze the use of technologies in the audit domain (Lamboglia *et al.*, 2020; Kotb *et al.*, 2020; Pizzi *et al.*, 2021; Atayah and Alshater, 2021). The following section describes the procedures used to collect data and the tools used to conduct this research.

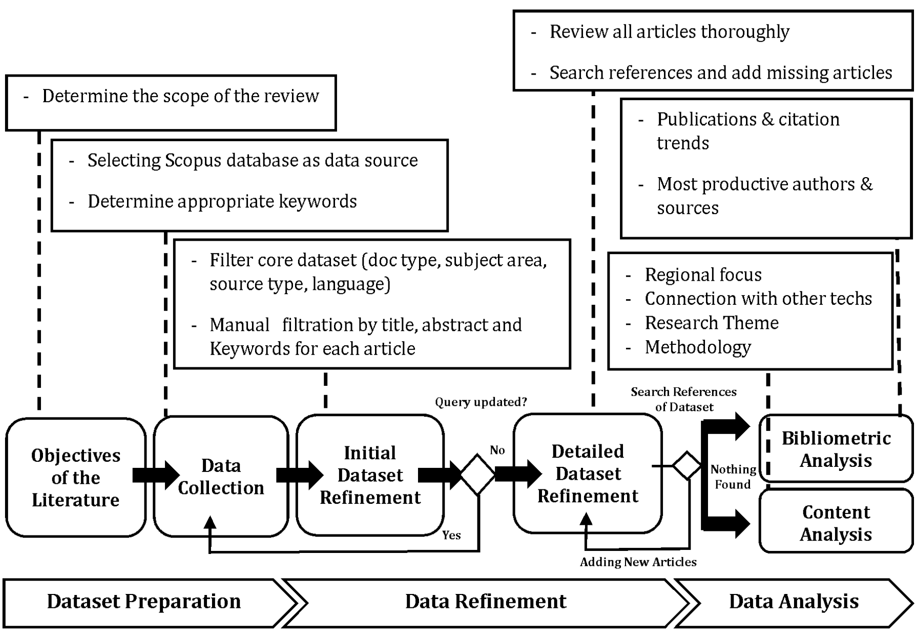

Figure 1: Research Protocol (adapted from Lamboglia *et al.*, 2020)

3.1. Data Sources and Data Collection

The Scopus database was selected for a comprehensive search because of its broad coverage and reliability (Pizzi *et al.*, 2021). We used the search query of (TITLE-ABS-KEY (audit*) AND ("data analytics" OR "bigdata" OR "big data" OR "audit data analytics" OR "big data analytics")). Table (*II*) shows the criteria for including and excluding articles. The excluded papers were not directly related to auditing (covering internal auditing, financial accounting, management accounting, and customer service). Two authors have manually screened each article's title, abstract, and keywords to remove irrelevant articles. An in-depth review of each article's introduction, methodology, results, and conclusions was conducted by the same two

Table II: Search Query Description

Description	*Exclusion criteria*	*Remaining articles*
TITLE-ABS-KEY(audit*) AND ("data analytics" OR "bigdata" OR "big data" OR "audit data analytics" OR "big data analytics") AND (LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"DECI") OR LIMIT-TO (SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"ECON") OR LIMIT-TO (SUBJAREA,"MULT")) AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"re")) AND (LIMIT-TO (SRCTYPE,"j")) AND (LIMIT-TO (LANGUAGE,"English"))		3,247
Access	All types were included, whether open access or others	3,247
Years	Including years from 2008 to 31 October 2021	3,247
Subject Area	(Business, Management and Accounting, Economics, Econometrics and Finance, Social Sciences, Decision Sciences, and Multidisciplinary) were kept, and other subject fields were excluded	1,156
Document Type	Only articles and review papers were kept, and other types were excluded	742
Publication Stage	Final documents and articles in the press were kept	742
Source Type	All sources were excluded except journal	727
Language	All languages were excluded except English	712
Total remaining publications before manual filtration		**712**
Manual Filtration	Screening every article's title, abstract, and keywords	158
	Thoroughly reviewing each article	84
	Searching the references and adding missing articles	98
Total relevant publications		98

authors. The results reached were reviewed by the other two authors. During the content analysis process, the articles' references were manually reviewed, and other related articles were identified and added to the dataset. This study employed Excel, VosViewer, and Biblioshiny to conduct bibliometric and content analyses.

3.2. Content Analysis

According to Neuendorf (2002, p. 141), the content analysis seeks to "identify and record relatively objective characteristics of messages." Therefore, we used content analysis to provide a thorough literature analysis. One of the authors has developed an analytical framework to analyze the collected dataset based on prior accounting and auditing literature (Lamboglia *et al.*, 2020; Kotb *et al.*, 2020; Pizzi *et al.*, 2021; Atayah and Alshater, 2021). Then, other authors checked it for appropriateness and suitability. This check led to some modifications in the selection criteria (Table III). The final dataset was manually coded by two authors and carefully reviewed by the remaining two authors to ensure reliability, accuracy, and consistency. The authors were keen to continually discuss debatable issues as soon as they came to the surface to ensure agreement on all research steps.

Table III: Analytical Framework

Group	*Criteria*	*Attributes (Coding Scheme)*	*Results no. (%)*	*Adapted from*
1	**Regional Focus**	1 North America (USA)	32 (32.80%)	Guthrie *et al.* (2012)
		2 Europe	17 (17.30%)	
		3 Oceania (Australia & New Zealand)	3 (3%)	
		4 Rest of the world	6 (6.10%)	
		5 Global (Mix between 1,2,3 &4)	4 (4.10%)	
		6 Not geography-specific	36 (36.70%)	
2	**Research Theme**	1 BDA in Auditing Process	54 (62.20%)	Kotb *et al.* (2020)
		2 BDA Diffusion	29 (29.60%)	
		3 BDA in Auditing Curricula	15 (15.31%)	
3	**Research Method**	1 Questionnaire	8 (8.20%)	Guthrie *et al.* (2012)
		2 Interviews	11 (11.20%)	
		3 Experiment	5 (5.10%)	
		4 Case / Field Study	8 (8.20%)	
		5 Secondary Data	7 (7.10%)	
		6 Simulation	7 (7.10%)	
		7 Conceptual	41 (41.80%)	
		8 Mix Between More Than One Method	11 (11.20%)	

Group	*Criteria*	*Attributes (Coding Scheme)*	*Results no. (%)*	*Adapted from*
4	**Theory**	1 No Theory Used	84 (85.70%)	Kotb *et al.* (2020)
		2 Organizational Theories (Agency, Stakeholders, Contingency, Institutional, Legitimacy)	4 (4.10%)	
		3 Psychological Theories (Cognitive, Cognitive Load, Cognitive Fit)	3 (3%)	
		4 Information Systems Theories (Diffusion Innovation, Technological Process Reframing, Concept of Black Box)	4 (4.10%)	
		5 Sociological Theories (Concept of Affordance)	1 (1%)	
		6 Mix Between Different Theories (Concept of Power, Algorithmic Decision, Socio-technical systems)	2 (2%)	

4. RESULTS

The bibliometric analysis covered literature growth patterns, most abundant sources, important authors, and citation analysis. Then, a coding analysis is presented with a detailed explanation of the research groups and the dataset's attributes.

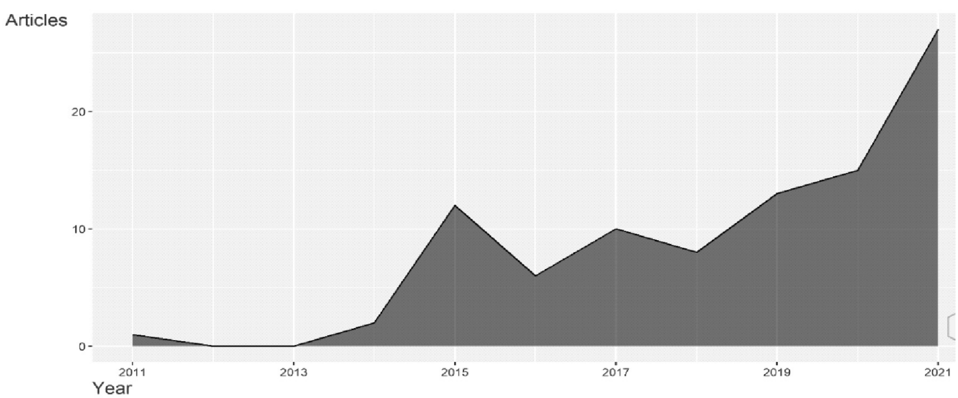

Figure 2: Number of Annual Publications

4.1. Bibliometric Analysis

Ninety-eight articles were published between 2011 and 2021 from 38 different sources, indicating the lack of a centralized outlet focusing on this specialized research area. Documents are limited to either articles (approximately 97%) or review papers (3%) because these types are peer-reviewed. Moreover, 215 authors authored these documents, but single-authored documents represent about 12% (11 articles). The discussion about BDA in auditing began in 2011 in the United States with a paper published by Thiprungsri and Vasarhelyi, in which they examined using clustering technique to automate fraud detection in audit engagements. BDA in auditing received considerable attention in 2015; since then, there has been an upward trend in publications in that research discipline (Figure 2). In 2021, academic attention to this area has exponentially increased to reach 27 articles. This area witnesses an annual growth rate of 50.98%.

4.1.1. Analysis of Sources

Table (IV) shows that research related to BDA and auditing is concentrated in specific sources. Approximately 63% of the total articles (62) were published by 26% of sources. Nine of the top ten sources were among the top-ranking journals, reflecting the quality of these articles. Additionally, the American Accounting Association (AAA) has four of the top ten productive sources with 36 pieces, reflecting the attention given to this topic in the USA. The remaining sources are from the United Kingdom (Emerald) and the Netherlands (Elsevier), indicating the attention and support of most developed countries dedicated to this topic.

Table IV: Analysis of Sources

Most Productive Sources				*Most Cited Sources*		
Sources (Publishers)	*NP*	*TC*	*PY_ Start*	*Sources (Publishers)*	*NP*	*TC*
Accounting Horizons (AAA)	16	704	2015	Accounting Horizons	16	704
Journal of Emerging Technologies in Accounting (AAA)	12	103	2015	Journal of Information Systems	5	142
International Journal of Accounting Information Systems (Elsevier)	7	97	2014	Journal of Accounting Education (Elsevier)	6	120
Journal of Accounting Education (Elsevier)	6	120	2017	Journal of Emerging Technologies in Accounting	12	103
Journal of Information Systems (AAA)	5	142	2015	International Journal of Accounting Information Systems	7	97
International Journal of Digital Accounting Research (Rutgers University)	4	95	2011	International Journal of Digital Accounting Research	4	95

Most Productive Sources				*Most Cited Sources*		
Managerial Auditing Journal (Emerald)	4	90	2016	Journal of Accounting Literature	2	94
Meditari Accountancy Research (Emerald)	4	4	2020	Managerial Auditing Journal	4	90
Accounting Research Journal (Emerald)	3	0	2020	Accounting Review	1	72
Current Issues in Auditing (AAA)	3	9	2015	Business Horizons	1	45

4.1.2. Analysis of Authors

The 98 articles consist of 87 multi-authored documents by 204 authors and 11 authors contributed by 11 single-authored papers. Table (*V*) presents the most productive and cited authors. Vasarhelyi leads the list with 10 articles representing about 10% of the total production in the research area from 2011 to 2021. Appelbaum then comes in second place with six contributions.

Table V: Most Productive Authors

Most Productive Authors				*Most Cited Authors*		
Authors	*NP*	*TC*	*PY_Start*	*Authors*	*NP*	*TC*
Vasarhelyi, M. A.	10	484	2011	Vasarhelyi, M. A.	10	484
Appelbaum, D.	6	196	2015	Kogan, A.	4	281
Kogan, A.	4	281	2015	Appelbaum, D.	6	196
Jans, M.	4	95	2014	Alles, M.G.	3	151
Alles, M.G.	3	151	2014	Brown-Liburd, H.	2	150
Werner, M.	3	35	2015	Tuttle, B.M.	1	149
Sun T. S.	3	23	2018	Lombardi, D.	2	110
Brown-Liburd, H.	2	150	2015	Cao, M.	1	110
Lombardi, D.	2	110	2015	Chychyla, R.	1	110
Issa, H.	2	110	2015	Issa, H.	2	110

4.1.3. Citation Analysis

Citation analysis is an indicator of the influence of a specific scientific actor in any research field (Atayah and Alshater, 2021). Table (*VI*) below shows the ten articles with most citations. Seven of the ten most cited documents were published in the special issue issued by Accounting Horizon; the Accounting Horizons Forum Big Data in 2015. These articles –conceptually– introduced BD and BDA to the audit community and are the pioneers in this research area. Vasarhelyi *et al.* (2015) indicated the potential impact of incorporating

BD into accounting and audit analytics. Krahel and Titera (2015) discussed the effects of BD on auditing standards. The study of Cao *et al.* (2015) has discussed the BD characteristics and implementation in financial statement audits. Additionally, Yoon *et al.* (2015) revealed the impact of BD on audit evidence and challenges. Alles (2015) identified drivers, facilitators, and hindrances to adopting BD in the audit process. Brown-Liburd *et al.* (2015) highlighted the potential cognitive obstacles auditors may suffer when using BD in audit processes. Zhang *et al.* (2015) discussed the possible integration of BD to support continuous auditing techniques. Hence, this "Accounting Horizons" issue is considered a valuable and essential reference for researchers interested in studying the association between BD and BDA from one side and accounting and auditing on the other.

Table VI: Most Cited 10 Documents

Authors	*Title*	*Source*	*TC*
Vasarhelyi, Kogan & Tuttle, 2015	Big data in accounting: An overview	Accounting Horizons	149
Cao, Chychyla & Stewart, 2015	Big data analytics in financial statement audits	Accounting Horizons	110
Brown-Liburd, Issa & Lombardi, 2015	Behavioral implications of Big Data's impact on audit judgment and decision making and future research directions	Accounting Horizons	110
Appelbaum, Kogan & Vasarhelyi, 2017	Big Data and analytics in the modern audit engagement: Research needs	Auditing	90
Alles, 2015	Drivers of the use and facilitators and obstacles of the evolution of big data by the audit profession	Accounting Horizons	79
Yoon, Hoogduin & Zhang, 2015	Big data as complementary audit evidence	Accounting Horizons	76
Krahel & Titera, 2015	Consequences of Big Data and formalization on accounting and auditing standards	Accounting Horizons	73
Jans, Alles & Vasarhelyi, 2014	A field study on the use of process mining of event logs as an analytical procedure in auditing	Accounting Review	72
Zhang, Yang & Appelbaum, 2015	Toward effective big data analysis in continuous auditing	Accounting Horizons	70
Sledgianowski, Gomaa & Tan, 2017	Toward integration of Big Data, technology and information systems competencies into the accounting curriculum	Journal of Accounting Education	64

4.2. Content Analysis

Content analysis was conducted to identify topics that have been investigated and other topics that require more attention from further research. Table *III* shows the analytical framework used to perform the content analysis with a summary of the results.

4.2.1. Regional Focus

Most studies did not belong to a particular geographical area with 34 articles. Then, 51 articles emerged from the USA, Europe, Australia, and New Zealand, indicating the dominance of developed countries in creating, developing, and adopting innovations, which then transferred to the rest of the world. According to Yapa *et al.* (2017), developed countries (the USA and Western countries) are leading the auditing profession for more than one reason: (1) all international organizations responsible for setting either accounting or auditing standards (IAASB, IASB, IFAC, and FRC) are located in these countries; (2) using advanced complex technologies in auditing needs extensive investments that are available with big audit firms that are headquartered in those countries; and (3) audit firms in those countries are governed by strict regulations; thus, they adopt audit innovations to achieve the highest possible audit quality and avoid legal litigations. There is a need to study and explore the current state of integrating BDA into external auditing in less developed and developing countries. This need stems from the argument of Lukka and Kasanen (1996, p. 755), who stated that "accounting research can be viewed as a local discipline by nature," indicating that there are still too many unknowns about the adoption of BDA in auditing.

4.2.2. Research Themes

We categorize the literature into three main research themes: BDA in the auditing process, BDA diffusion, and BDA in the auditing curricula.

4.2.1. BDA in Auditing Process.

The "BDA in audit process" is the most researched theme with 57 articles. This category can be classified into the following subgroups.

4.2.2.1.1. BDA and the Future of the Audit Profession. Early studies have examined practitioners' expectations concerning the audit profession in the context of BD and BDA (Vasarhelyi *et al.*, 2015; Krahel and Titera, 2015; Lombardi *et al.*, 2015; Tiberius and Hirth, 2019). Krahel and Titera (2015) expected drastic shift in the level, nature, timing, and audit frequency. Lombardi *et al.* (2015) predicted that some routine audit tasks would be automated, but audit judgment and decision-making processes would not be automated. Tiberius and Hirth (2019) presented German respondents' expectations of the audit profession over the next five to ten years. They revealed that respondents expect no significant changes in the audit profession during the foreseeable future and that technology will support auditors rather than replace them. Finally, Vasarhelyi *et al.* (2015), Krahel and Titera (2015), and Lombardi *et al.* (2015) indicated that current auditing standards are not ready for the expected paradigm shift that will occur in auditing. Most studies of this group expected no major modifications in the audit process due to BD and BDA in the foreseeable future.

4.2.2.1.2. BDA and audit evidence. This group has investigated the effect of using BD and BDA on audit evidence's nature, reliability, and quality (Yoon *et al.*, 2015; Brown-Liburd and Vasarhelyi *et al.*, 2015; Appelbaum, 2016; Newman *et al.*, 2021; Wadesango *et al.*, 2021). BD provides auditors with new sources of information that can be used as complementary evidence in addition to conventional evidence (Yoon *et al.*, 2015; Wadesango *et al.,* 2021). Brown-Liburd and Vasarhelyi (2015) highlighted new data that auditors can use when integrating BD into auditing, such as RFID, GPS, and IoT recordings. Newman *et al.* (2021) assert that adopting BDA in auditing would positively affect audit evidence. According to KPMG (2017), new supplementary evidence enhances auditors' ability to better understand the business and industry of the client; thus, a better risk assessment is expected. However, Wadesango *et al.* (2021) revealed that auditors depend only on traditional analytical tools to analyze voluminous traditional accounting data. Brown-Liburd and Vasarhelyi (2015) and Appelbaum (2016) asserted that integrating new external BD evidence into auditing requires auditors to validate the reliability and quality of this new BD evidence. Hence, using BD and BDA could represent a complement to the traditional audit evidence if reliability is assured. However, it is not stated how to assure the reliability and quality of the external BD.

4.2.2.1.3. BDA and audit judgment. This group of studies has emphasized how BD and BDA affect audit judgments (Rose *et al.*, 2017; Backof *et al.*, 2018; Hamdam *et al.*, 2021; Chang and Luo, 2021; Koreff *et al.*, 2021; Holt and Loraas, 2021). Backof *et al.* (2018), No *et al.* (2019), and Hamdam *et al.* (2021) revealed the positive impact of visualizations and the entire population investigation on auditor judgment and decision-making processes. Conversely, the study of Rose *et al.* (2017) indicated that using BD visualizations would bother senior auditors in recognizing patterns, resulting in negative effects on audit planning and effectiveness when those visualizations are viewed before the traditional audit evidence. In addition, Chang and Luo (2021) reveal that integrating data visualizations into auditing can expand cognitive biases, which may negatively affect auditor judgment and decision-making. Also, Koreff *et al.* (2021) found that adopting BDA can lead to unintended and adverse effects on audit judgments. Finally, Holt and Loraas (2021) stated that using unstructured data (visualizations, email, press releases) as audit evidence adversely affects auditor judgment and decision-making.

4.2.2.1.4. BDA and audit procedures. Other studies have researched the potential impact of BDA on audit procedures (Rozario and Issa, 2020; Kend and Nguyen, 2020; Appelbaum *et al.*, 2021; Christ *et al.*, 2021; Salijeni *et al.*, 2021). Rozario and Issa (2020) found that using BDA enhances the efficiency and effectiveness of auditing large amounts of payment transactions and identifying duplicate payments. Kend and Nguyen (2020) and Salijeni *et al.* (2021) revealed that BDA positively impacts auditing because it automates routine manual tasks and frees them to spend more time in critical areas. In addition, Christ *et al.* (2021) reveal that using BDA to execute inventory counts increases efficiency, improves effectiveness, and improves audit documentation. Appelbaum *et al.* (2021) discussed the BDA tools available to auditors and the required knowledge and skills that auditors should acquire to deal with such an ever-changing environment. Kend and Nguyen (2020) and Christ *et al.* (2021) highlighted the necessity of modifying audit standards to guide the adoption of BDA in audit processes because lack of guidance represents a significant obstacle to adopting such technologies.

Other studies have investigated the role of specific analytical tools in the audit field, such as process mining (Werner and Gehrke, 2015; Jans, 2019; Jans and Hosseinpour, 2019; Werner *et al.*, 2021), blockchain (Rozario and Vasarhelyi, 2018; Tušek *et al.*, 2021), statistical techniques (Rezaee *et al.*, 2018; Derks *et al.*, 2021), deep learning techniques (Sun and Vasarhelyi, 2018; Zhaokai and Moffitt, 2019; Sun, 2019; Li and Liu, 2020), machine learning (Li *et al.*, 2020; Zhang and Wang, 2021), and continuous auditing (Feung and Thiruchelvam, 2020). This group of studies highlights that using BDA and other technologies will eventually lead to more effective and efficient auditing processes.

Werner and Gehrke (2015), Jans (2019), Jans and Hosseinpour (2019), and Werner *et al.* (2021) concluded that process mining improves financial statement audits. Rozario and Vasarhelyi (2018) and Tušek *et al.* (2021) claimed combining blockchain and BDA (smart audit procedures) would be the next generation of audit analytics, ADA 3.0. However, successful adoption of such technologies requires auditors with excellent technological knowledge and skills. Rezaee *et al.* (2018) introduced time-series analysis as an analytical tool that auditors can use to transform semi-structured and unstructured data into structured ones. Derks *et al.* (2020) claimed that using Bayesian statistics positively affects substantive testing and audit sampling. However, the auditor can benefit from this tool if data quality is validated before analysis and a statistician is involved in the audit team. Sun and Vasarhelyi (2018) and Sun (2019) introduced deep-learning techniques as additional audit evidence. They highlighted the ability of these techniques to analyze semi-structured and unstructured datasets (contracts, earnings announcements, emails, news articles, data extracted from social media, and analyst reviews). They also emphasized the potential of introducing deep learning techniques into all audit phases to support auditors' judgment and decision-making processes.

Zhaokai and Moffitt (2019) and Li and Liu (2020) focused on text analytics. They demonstrated the feasibility of using natural language processing (NLP) and other text-mining techniques to analyze the entire population of contracts. Zhaokai and Moffitt (2019) indicated that text analytics provides auditors with additional data to determine audit risks better and provide supplementary audit evidence. They highlight the role of such techniques in automating routine contract examination tasks and directing saved time to more critical areas. Li and Liu (2020) stated that NLP improves the effectiveness of brainstorming sessions conducted by auditors throughout the audit process. They proposed that using NLP in auditing enhances risk identification, risk assessment, and auditor judgment. In addition, Li *et al.* (2020) found that using an artificial neural network (ANN) approach improves risk assessment during the planning phase through providing fewer Type II errors than analytical procedures (ratio and regression analysis).

4.2.2.1.5. BDA and fraud detection. Fraud detection is a crucial function of modern financial auditing (Gray and Debreceny, 2014). This group of studies concentrated on using different BDA tools (clustering, text analytics, data visualizations, and other machine-learning algorithms) to detect fraud in financial statements. Mongwe and Malan (2020) indicated that financial ratio analysis is the most common fraud-detection technique in the literature, and the use of automated fraud detection is minimal. Thiprungsri and Vasarjelyi (2011) and Byrnes (2019) claimed that clustering techniques are promising in audit practice because they help auditors cluster transactional data and identify outliers. Singh and Best (2016) advised auditors to use visualization techniques in addition to conventional analyses to improve their ability to recognize patterns and identify deviations. Finally, Hoelscher and Shonhiwa (2021) highlighted the role of Excel's conditional formatting and fuzzy lookup in discovering data entry errors and common types of employee fraud.

4.2.2.2. BDA Diffusion

This theme focuses on the drivers, barriers, and adoption rates of BDA in auditing practice. Some studies attempted to determine the most critical factors affecting BDA adoption in auditing. Wang and Cuthbertson (2015) indicated that the adoption of BDA depends on providing guidance regarding its application in audit engagements and understanding its use in different audit phases. Dagilienė and Klovienė (2019) found that large clients using BD were the main drivers of BDA adoption in auditing. Consistent with these findings, De Santis and D'Onza (2020) found that clients' digital immaturity is a significant obstacle to legitimizing BDA within the Italian audit market. Oyewo *et al.* (2020) found that organizational factors (firm size, affiliation to international audit firms, and operations' scope) significantly affect the BDA adoption rate. Consistent with these results, Krieger *et al.* (2021) indicated that adopting BDA relies on the active role of audit firms (establishing technological infrastructure, attracting competent auditors, and providing proper training). Thus, Big-4 audit firms are leading the adoption of BDA. Also, the clients' use of BD and providing guidance are significant factors.

Other studies have determined the benefits of integrating BDA into auditing. Werner (2017) and Chiu and Jans (2019) listed the benefits of using process mining as an analytical tool in the audit process, such as examining the entire population, detecting potential risks, and identifying ineffective controls and processes. Gambetta *et al.* (2016) found that using BDA and CAATs improves detection risk assessment. Michael and Dixon (2019) revealed that using BDA in audit engagements satisfies stakeholders' needs and expectations, leading to a decreased audit expectation gap. Manita *et al.* (2020) determined five main benefits of automated auditing: more value added, new services are offered; enhanced audit quality; improved auditor profile and creating a culture of innovation within audit firms. Brown-Liburd *et al.* (2015), Earely (2015), Wang and Cuthbertson (2015), and Manita *et al.* (2020) indicated that there is a high probability that BD will improve audit judgment and audit quality if significant obstacles are removed. Werner (2017) claimed that BDA improves the overall audit of financial statements.

Another line of research attempted to identify the most common barriers to BDA adoption. Salijeni *et al.* (2019) indicate that many challenges must be addressed before fully adopting BDA in auditing. Al-Htaybat and von Alberti-Alhtaybat (2017) and Krieger *et al.* (2021) argued that a lack of BDA professionals and specialists in audit firms inhibits BDA adoption. Cao *et al.* (2015) indicated that using BD analytics is complex due to the need for skilled experts and suitable hardware and software. Brown-Liburd *et al.* (2015) revealed that BDA could produce voluminous false positives that require careful examination, resulting in issues concerning information overload, irrelevant information, and recognition of patterns; leading to negative effect on audit judgments. Alles (2015) and Austin *et al.* (2021) highlighted the role of auditing standards in slowing BDA adoption. Zhang *et al.* (2015) claimed that the real challenge in adopting BDA in auditing is the attributes of BD itself (4Vs). The BD attributes lead to the following gaps: data consistency, integrity, identification, aggregation, and confidentiality. Alles and Gray (2016) reported that adopting BDA requires direct access to client's data and cannot deal with messy, non-financial data. They also highlight that auditors perceive BDA as an end, not a means, and do not understand that BDA's success depends on their choices.

Some studies have attempted to examine the adoption level of BDA in auditing. Alles (2015) expected that using BDA in auditing would be a must, not just an option. Earely (2015) and Buchheit *et al.* (2020) reported that, although audit firms make substantial investments in developing audit-related data analytics, the integration of BDA into audit engagements is still lagging. In addition, Aboud and Robinson (2020) found that BDA as a fraud detection tool is underutilized. De Santis and D'Onza (2020) found that BDA is more accepted by Italian auditors than other stakeholders (standard setters, oversight bodies, and clients). Eilifsen *et al.* (2020) concluded that auditors use advanced BDA scarcely. However, Cristea (2021) reported that the use of BDA by auditors is average in Romania. Thus, BDA is adopted in different contexts, however, the adoption rate varies from one country to another.

Other studies sought to determine how stakeholders perceive the use of BDA. Kim *et al.* (2020) found that shareholders are more satisfied with the prospective returns of audit clients adopting BDA. In addition, Ballou *et al.* (2021) revealed that investors, jurors, and peer reviewers appreciate using BDA in audit procedures. Also, Austin *et al.* (2021) reported that stakeholders (managers, standard-setters, auditors, data specialists, and audit committee members) agreed on the vital role played by BDA in auditing. Ibrahim *et* *al.* (2021) indicated that BD adopters are expected to provide high-quality financial reporting, manage their risks better, and experience fewer budgeting variances.

4.2.2.3. BDA in Auditing Curricula

Prior literature has attempted to respond to the calls of practitioners and academics regarding the need to update the accounting and auditing curriculum to generate an auditor with proper skills in the BD era (Salijeni *et al.*, 2019). Yoon *et al.* (2015) indicated that the auditing curriculum should provide more content regarding advanced analytics and address the changing nature of the audit evidence. Enget *et al.* (2017), Sledgianowski *et al.* (2017), and Qassim and Kharbat (2020) indicated that the accounting and auditing curriculum should be modified to reflect the changes that have occurred in the accounting and auditing professions.

Some studies have introduced educational content (instructional class cases) to help academics provide up-to-date accounting and auditing curricula and teach BDA to undergraduate and graduate students (Chan and Kogan, 2016; Weirich *et al.*, 2017; Fay and Negangard, 2017; Enget *et al.*, 2017; Weirich *et al.*, 2018; Cunningham and Stein, 2018; Negangard and Fay, 2020; Lee *et al.*, 2021; McKee, 2021). Chan and Kogan (2016) and McKee (2021) taught students how to employ R software and cluster analysis to execute risk analysis and audit planning. Negangard and Fay (2020) used text analytics to detect fraud indicators from Enron's financial statements. Cunningham and Stein (2018) and Weirich *et al.* (2018) indicated how to use visualizations to implement different audit procedures. Weirich *et al.* (2017) and Fay and Negangard (2017) taught students how to use CAATs (ACL and IDEA) to execute different analytics in auditing tasks. Lee *et al.* (2021) provided MSc accounting students with a case study to strengthen their database and SQL skills by introducing the AICPA's proposed audit data standards, general ledger testing, and journal entry testing.

Other studies discussed the gap between what academics provide and what practitioners expect regarding the knowledge, skills, and abilities of accounting graduates (Ballou *et al.*, 2018; Andiola *et al.*, 2020; McBrides and Philippou, 2021). Ballou *et al.* (2018) found a gap between academics (educators) and practitioners (employers), as academics gave more weight to traditional technical accounting knowledge than practitioners. Practitioners have suggested a balance between knowledge, skills, and abilities. Andiola *et al.* (2020) examined the implementation of the guidance proposed by Standard A7 in the accounting curricula of AACSB-accredited accounting programs. They revealed that only 23% of faculty members fully implemented their changes, reflecting the slowness of the curriculum changes. McBrides and Philippou (2021) stated that four skills students should have to use BDA effectively: questioning and skepticism, critical thinking, comprehending and analyzing, and communicating results. They claimed that the accounting master's courses don't fully cover these skills.

Another group of studies investigated the accounting and auditing curriculum and provided suggestions regarding its modification to keep up with new market needs (Sledgianowski *et al.*, 2017; Qassim and Kharbat, 2020; Blix *et al.*, 2021). Sledgianowski *et al.* (2017) developed an accounting curriculum using educational resources to introduce BDA to their students. Blix *et al.* (2021) analyzed seven well-known audit textbooks and concluded that every audit textbook should cover BDA in an independent chapter, provide a comprehensive case study, and attach exercises to practice the BDA skills. Qassim and Kharbat (2020) presented a framework for accounting educators to include materials related to blockchain, BDA, and artificial intelligence in their accounting classrooms. The studies of this group can be used as a baseline when developing a double-major curriculum to address both traditional accounting skills and up-to-date analytics skills.

4.2.3. Research Methods and Nature of Research

Table (*VII*) [Panel A] illustrates the research methods utilized by articles in the collected dataset. The conceptual research method is the most employed one, with 41 articles (41.80%). Under this broad method, there are three main research study groups: literature, conceptual, and commentary. The conceptual papers (29 articles) discussed conceptually how to integrate BDA tools into audit processes (such as Cao *et al.*, 2015 introduced BDA; Sun, 2019 introduced deep learning and textual analytics; Jans and Hosseinpour, 2019 introduced process mining; Derks *et al.*, 2021 introduced Bayesian statistics). Aa well, other conceptual studies presented researchers' viewpoints -based on prior literature and their own experience– regarding the impact of BDA on the audit practice (Gray and Debreceny, 2014; Yoon *et al.*, 2015; Vasarhelyi *et al.*, 2015; Brown-Liburd and Vasarhelyi, 2015; Richins *et al.*, 2017; Ahmad, 2019; Ibrhim *et al.*, 2021).

Interviews came second, with 11 articles published between 2017 and 2021. Third, 11 articles used mixed research methods. Five articles used a mix between questionnaires and case studies to collect their data (Weirich *et al.*, 2017; Fay and Negangard, 2017; Engent *et al.*, 2017; Negangard and Fay, 2020; Andiola *et al.*, 2020) which are to some extent related to the theme of "BDA in auditing curricula." Ballou *et al.* (2018), Eilifsen *et al.* (2020), and Newman *et al.* (2021) used questionnaires and interviews. The remaining three articles used mixed research methods such as interviews, case studies, questionnaires, and secondary data.

More than 60% of the research articles were qualitative. These numbers provide evidence that there is still a space for more empirical quantitative studies because too many articles were conducted using qualitative methods (discussions, literature, interviews, and case studies), with few articles adopting quantitative methods (experiments or questionnaires). According to Ledgerwood *et al.* (2017, P.45), using qualitative research methods is suitable for exploratory research that seeks to collect knowledge about a new scientific area that is not fully understood. This is likely the case in most articles in our dataset that seek to understand the outcomes of embedding BDA in the auditing profession. However, these qualitative-based articles may reflect the low adoption rate of such new technologies among audit firms on a large scale.

Table VII: Research Methods and Theories Employed

Panel A: Research Methods Employed by Dataset									
Research Themes	*Questionnaire*	*Interview*	*Experiment*	*Case/Field Study*	*Secondary Data*	*Simulation*	*Conceptual / Theoretical*	*Mix Methods*	*Total*
BDA in the auditing process	3	4	4	2	6	6	25	4	54
BDA diffusion	5	7	1	1	1	1	12	1	29
BDA in auditing curricula	-	-	-	5	-	-	4	6	15
Total	**8**	**11**	**5**	**8**	7	7	**41**	**11**	**98**
Panel B: Theories Employed by Dataset									
Theories	*Questionnaire*	*Interview*	*Experiment*	*Case/Field Study*	*Secondary Data*	*Simulation*	*Conceptual / Theoretical*	*Mix Methods*	*Total*
No Theory	6	6	3	8	7	6	38	10	84
Organizational Theories	1	1	-	-	-	-	1	1	4
Psychological Theories	-		2	-	-	-	1	-	3

Information Systems Theories	1	1	-	-	-	1	1	-	4
Sociological Theories	-	1	-	-	-	-	-	-	1
Mix Between Different Theories	-	2	-	-	-	-	-	-	2
Total	**8**	**11**	**5**	**8**	**7**	**7**	**41**	**11**	98

4.2.4. Theories Used

We identified and categorized the theories employed by the dataset into four main groups: organizational, psychological, information systems, and sociological (see Table *VII*/Panel B). Then, we added two other categories: "no theory used" to indicate no explicit theory is used and "mix between theories" to reflect the use of mixed theories from the different groups indicated above. Although a large proportion of the articles in the dataset were developed to theorize and conceptualize the integration of BDA in the auditing domain, approximately 85% did not use any theory. Only 13 articles used a theory-based methodology where organizational and information systems theories were most frequently used, with four pieces each. The organizational group has been employed to explain the use of BDA in auditing (Dagilienė and Klovienė, 2019; Michael and Dixon, 2019; Eilifsen *et al.*, 2020; Ibrahim *et al.*, 2021). The information systems group was used to reveal how BDA is being adopted and accepted by audit firms and the factors affecting its adoption (Appelbaum, 2016; Zhaokai and Moffitt, 2019; Buchheit *et al.*, 2020; Krieger *et al.*, 2021). Other studies have used psychological theories to explain the potential impact of BDA on audit judgment and skepticism (Bakof *et al.*, 2018; Hamdam *et al.*, 2021; Holt and Loraas, 2021). Salijeni *et al.* (2021) used the concept of affordance to study the recent evolutions in audit technologies. Furthermore, Kroeff *et al.* (2021) used a combination of the concepts of power and algorithmic decision-making theory to explain auditors' abuse of power due to using algorithmic tools. Finally, Austin *et al.* (2021) used the socio-technical systems version of the diffusion innovation theory to examine the driving factors affecting BDA adoption in financial reporting.

5. AREAS FOR FUTURE RESEARCH

This section details the potential research gaps that need to be addressed in the future. In this section, we illustrate the possible future research gaps extracted from the insights derived from bibliometrics and content analyses. Future research areas can be categorized into the following classes:

5.1. Research Scope and Methodology

After analyzing the geographical areas covered by the dataset, it was found that more than 60 articles were conducted in most developed countries (the USA, Europe, and Oceania), with little or no information about other less developed and developing countries. Hence, there is a need to know the adoption rates, drivers, facilitators, and obstacles to the BDA adoption in developing countries. This need stems from the argument provided by Lukka and Kasanen (1996, p. 75), stating that research in accounting can be viewed as "a rather local discipline by nature." The auditing profession operates in a strict regulatory environment in developed countries but not in less developed and developing countries. Therefore, what is the state of BDA adoption by audit firms in developing countries with no litigation risk, such as Egypt?

Further, empirical studies conducted to investigate the adoption of BDA in audit firms have concentrated on interviewing auditors belonging to the Big-4 audit firms, with no attention paid to smaller audit firms (Gambetta *et al.*, 2016; Rose *et al.*, 2017; Backof *et al.*, 2018; Kend and Nguyen, 2020; Krieger *et al.*, 2021; Salijeni *et al.*, 2021). Thus, the adoption of BDA in audit firms needs to be investigated in non-Big-4 audit firms with limited financial and technological resources compared to other large audit firms to provide a holistic picture of the adoption process among auditors of different sizes.

An analysis of the research methods revealed that more than 60 studies were conducted using qualitative research methods (literature review, conceptual, interviews, and process observations), reflecting the novelty of this research area. According to Ledgerwood *et al.* (2017, p.45), using qualitative research methods is suitable for exploratory research in which researchers seek to collect knowledge about a new scientific area that is not fully understood. Despite the tremendous benefits received by practitioners from analytical research, little analytical research using modeling, applications, case studies, and simulations has been conducted. Further empirical and analytical research is required to fill this gap.

5.2. BDA and Components of the Audit Process

There are no conclusive results regarding the impact of BD and BDA on audit judgment. Some studies indicate that such tools allow auditors to understand business data more thoroughly and efficiently determine anomalies (Backof *et al.*, 2018; ACCA, 2019), thus helping them improve judgments. However, others have indicated that such tools have unintended and negative impacts on auditors' judgments and decision-making (Rose *et al.*, 2017; Chang and Luo, 2021; Koreff *et al.*, 2021; Holt and Loraas). For instance, the results of Koreff *et al.* (2021) open the door for further research to be done to determine the actual impact of using algorithms on audit behavior (abuse of power) and judgment (the tendency to rely on the results of algorithms without judging them). These results highlight the potential negative impact of BDA on auditor objectivity, judgment, and skepticism. Thus, the overall audit quality is questionable.

Although adopting BDA leads to more comprehensive audit evidence (IAASB-DAWG, 2016(, it is difficult for auditors to ensure the sufficiency and appropriateness of the evidence obtained using an algorithm (FRC, 2020b). In addition, Wadesango *et al.* (2021) indicate that auditors still depend on traditional analytics tools (Excel) to analyze traditional accounting data with no use of other data types. Such findings make the question of Salijeni *et al.* (2019) still valid; Does BDA use conventional analytic tools with greater processing power to analyze a larger sample of traditional evidence or use new analytical techniques to analyze new diverse audit evidence? Hence, there is an urgent need for investigating the use of BDA and its effects on the audit evidence's type, source, and quality.

Another point that requires further research is the composition of the audit teams. The IAASB audit quality framework of 2014 emphasized the importance of properly structured engagement teams in conducting high-quality audits. In the context of BD and BDA, it is necessary to answer the following questions: Will the number of data analytics specialists in audit teams increase? If most routine audit tasks are automated, will the number of financial auditors decrease? Will non-auditors (IT auditors and data analytics specialists) play a broader role in the audit process?

5.3. BDA and Interactions with Stakeholders

The IAASB audit quality framework of 2014 states that full and timely access to inside and outside relevant information is necessary to gather appropriate audit evidence. Also, to effectively adopt BDA, auditors need full access to high-quality data (IAASB-DAWG, 2016; FRC, 2020a). Salijeni *et al.* (2019) reported the potential impacts of using BDA on the relationship between auditors and their clients, but the direction and magnitude of this relationship are still unrevealed. However, audit clients may be resistant to provide auditors with a sufficient access to their systems to execute audit analytics; therefore, the inability of auditors to collect "all" data needed to reach an accurate conclusion; thus, audit quality is negatively affected (ACCA, 2019). This may negatively affect the relationship between management and auditors. On the other side, it is supposed that BDA will provide auditors with previously unavailable insights (such as trends and patterns related to customer behavior, critical business operations, and predictive analytics). Providing these insights to the client management would enhance their relationships. So, what could be the impact of adopting BDA on the relationship between auditors and management?

5.4. New Theories

Although integrating BDA into auditing is still a new research topic in its early stages, only 11 articles have based their analyses on theories. Thus, a theory that interprets the relationship between BDA and external auditing needs to be explored and developed. Further research can use other theories (e.g., regulation, signal, information, and measurement theories) to explain the adoption, non-adoption, and impact of BDA on components of the audit process. The theories that have already been introduced (agency, stakeholder, contingency, technology innovation, and technological process reframing theories) should be thoroughly investigated in different contexts to provide a deeper understanding of using BDA in auditing.

5.5. Reasons for Adopting BDA

After analyzing articles related to the research theme of "BDA diffusion," there is a need to know the key reason or rationale behind adopting BDA by audit firms, whether to enhance audit quality, add value to clients, gain more revenues, satisfy audit regulators, or to enhance the audit firm's image and appear as a technological pioneer? Audit firms may adopt automated tools in their audit practices with other concealed intentions. For instance, audit firms adopted Business Risk Auditing (BRA) in the 1990s under the pretext of deeper understanding of clients and enhanced audit quality. However, Knechel (2007) indicated that BRA was adopted to reveal areas where potential consulting work might be provided; thus, increasing their revenues. There is consensus in the literature that auditors adopt BDA to strengthen audit quality (Cao *et al.*, 2015; Krahel and Titera, 2015; IAASB-DAWG, 2016; Salijeni *et al.*, 2019; Dagiliene and Kloviene, 2019; Manita *et al.*, 2020; FRC, 2020a; 2020b). However, most of these articles are conceptual with no empirical evidence and recent empirical studies provide opposing evidence (Rose *et al.*, 2017; Chang and Luo, 2021; Koreff *et al.*, 2021; Holt and Loraas, 2021). These recent results refute the assumption of the positive impact of BDA on audit quality; hence, there is a need for more research to examine the actual reasons behind adopting BDA.

5.6. Impact of BDA on Audit Firms

If the adoption of BDA in auditing flourishes in the coming years, several audit tasks will be automated and there will be a paradigm shift in the scope of the profession beyond the traditional audit of financial statements to satisfy stakeholders' needs (Michael and Dixon, 2019). Thus, further research is needed to examine how audit firms can handle the impact of BDA on future auditor roles and skills, and the impact on recruitment policies. Another challenge is that a small number of audit team members know and can perform data analytics. There is a need to deploy software in client systems, access high-quality client data, and perform data management tasks (organize, clean, and analyze data) to reach a reliable and consistent format (FRC, 2020b). Such tasks might change the composition of the audit team. Thus, more research is needed to examine whether audit firms will add technically qualified members to audit teams, audit firms will train existing traditional auditors to deal with such new tasks, or audit firms will outsource such tasks.

According to the IAASB audit quality framework of 2014, audit firms should provide auditors with appropriate training on new accounting, auditing, and regulatory requirements. Using BDA in auditing changes the tasks performed; thus, training sessions should be provided continuously. Further research is needed to understand what auditors should be taught to keep up with the current changes. Also, it is required to know how to balance data analytics and IT training from one side with training on updates related to accounting and auditing issues. Moreover, with the adoption of BDA in auditing, changes in audit pricing need to be investigated; whether audit firms would increase audit fees due to significant investments incurred (argued by Austin *et al.*, 2021) or decrease due to cost savings achieved (claimed by Krieger and Drews, 2018)?

5.7. BDA and Auditing Education

The 2018 AACSB Standard A5 states that accounting and auditing curricula should include data analytics skills. The standard provides guidelines for accounting and auditing curriculum developers to help them produce employable accounting graduates with the proper knowledge and skills[2]. However, most studies in "BDA in auditing curricula" have either provided opinions concerning integrating BDA into the accounting curriculum or introduced some teaching notes that academics can use in their classes. To the best of our knowledge, no study, except Andiola *et al.* (2020) and McBride and Philippou (2021), has examined the level of integration of such analytics skills into the accounting curriculum. Such studies found minimal changes in accounting programs and that the speed of change is slow. Further research should assess the current curriculum provided in business schools.

Further research should focus on comparing the required knowledge, skills, and abilities in the audit market with those provided by business schools to identify gaps and how to decrease such gaps. To our knowledge, only Ballou *et al.* (2018) have taken practical steps to determine the skills needed by accounting graduates from the practitioner's viewpoint. Additionally, Earley (2015) argued that accounting education and training were traditionally far from BD and analytics techniques. Thus, further research should focus on how to integrate BD and what content to integrate into professional certificates (CPA, CIA, CMA, CFA) to make auditors knowledgeable and able to deal with BD and BDA.

6. SUMMARY AND CONCLUSIONS

This conceptual study presents an updated picture of the current state of literature concerning the use of big data and analytics (BDA) in external auditing and proposes future research opportunities. To achieve this objective, we used bibliometric and content analyses to offer a more focused analysis, thereby contributing to the knowledge related to BDA in the audit area. This study collected and analyzed 98 articles published in 38 journals from the Scopus database. The study examined the most productive and cited sources, authors, and important documents. The United States is the most productive country for research related to BDA in auditing, with 34 articles. The research trend flourished in 2015 but declined again to start rising again in 2018 to reach its peak in 2021 with 27 pieces. It is worth noting that the University of New Jersey (Rutgers University) is the most productive affiliation with 18 contributions. The most productive and cited journal was Accounting Horizons, with 16 contributions. In addition, the most cited paper is "Big data in accounting: An overview" by Vasarhelyi, Kogan, and Tuttle (2015).

Content analysis was used to organize, summarize, and analyze 98 articles published between 2011-2021. The content analysis examined four main features: regional focus, research themes, research methods, and theories employed. We categorized the prior literature into three main research themes. Research in this discipline has been transforming from conceptual to empirical. From 2011 to 2018, the literature attempted to theorize and provide conceptual frameworks regarding the meaning, nature, characteristics, and potential factors affecting the adoption of BD in auditing. However, since

2019, empirical research in this discipline has witnessed a turning point. The audit profession is still lagging in adopting new technologies, especially the BDA. Emerging audit technologies are concentrated in the Big-4 audit firms and their networks.

Although this study makes numerous contributions to literature, it has several limitations. First, our dataset depended on the search query we employed, as other studies that examined the same topic using different terms may not have been included in our dataset. Second, the use of the Scopus database may have introduced some level of bias. Other studies on BDA and auditing may have been published in journals not indexed in the Scopus database. However, this database is considered one of the most reputable for accounting and auditing. Third, the study focused only on articles and review papers, leading to the investigation of only a small dataset. Fourth, although a structured literature review methodology was followed, there could be some subjectivity in the data collection, filtration, analysis, and interpretation.

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Notes

1. Massaro *et al.* (2016, p. 769) defined the traditional literature review as being conducted approximately with no rules and systematic literature review as being conducted with Rigid rules. Also, Denyer and Tranfield (2006, p. 216) stipulated that "the most common technique in management research is the traditional literature review in which the researcher summarizes and interprets previous contributions in a subjective and narrative fashion".
2. Standard A5 stated that data analytics include, not exclusive to, "*statistical techniques (mean, median, or mode of a data set, ratio analysis, Benford Analysis, ANOVA and Regression analysis), clustering (search for anomalies, abnormalities, or patterns), data management (store and transfer data within and between systems), (data) modeling (modeling and visualization techniques), data analysis (methods or tools used to obtain a deeper understanding of a data set), text analysis (to extract information from written data), predictive analytics (use past information about clients to predict current and future events), learning systems, or visualization*" (AACSB, 2018, p. 27).

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