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Artificial Intelligence in Accounting and Finance: Meta-Analysis

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Abstract

The use of the traditional system is declined greatly and with a modernization of the accounting and finance process there have been a great deal of change, and these improvements are beneficial to the accounting and finance industry. Adopting Artificial Intelligence applications such as Expert systems for audit and tax, Intelligent Agents for customer service, Machine Learning for decision making, etc. can lead a great benefit by reducing errors and increasing the efficiency of the accounting and finance processes. To keep ensuring a transparent and replicable process, we have conducted a meta-analysis. The database search was between the years 1989-2020 and reviewed 150 research papers. As meta-analysis results show, the majority of researches illustrate a positive effect of the impact of AI systems in the accounting and finance process.

Key points:

- Meta-Analysis has been applied for emphasizing positive results of the impact of Artificial Intelligence systems in the Accounting and Finance process.
- Implementing Artificial Intelligence systems in Accounting and Finance process can increase the efficiency of the process.
- Artificial Intelligence technology has been influential in all the areas of accounting, which are especially concerned with knowledge

Keywords—Artificial Intelligence, Literature Review, Meta-Analysis, Accounting, Finance, Positive Impact.

Paper Type—Literature Review

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1.0. Introduction

Many industries are turning to Artificial Intelligence (AI) to perform tasks that were previously performed by humans. When it comes to processing massive amounts of data, finding fraud by identifying unusual operations, communicating with customers online, and performing other essential functions, the financial services industry has embraced AI. For example, in the facial reorganization, voice recognition, or Machine Learning (ML), there are several excellent use cases. In addition to enhancing customer value propositions, new technologies also improve efficiency and effectiveness in the organization. Financial Stability Board Study has established the use of Artificial Intelligence technology for regulatory enforcement, oversight, evaluation of data quality, and identification of fraud by organizations both public and private (FSB, 2017). The accounting systems and processes are converted into computer formats from the arena of paper journals and booklets with the advent of computers that have pushed artificial intelligence into methods of self-management, self-configuration, self-diagnosis, and self-healing that ensure maximum accounting performance. The evolution of accounting software and the new artificial intelligence development have fully changed accounting systems. Extent studies have shown that the efficiency of accounting operations is positively affected by Internet computers, software/expert systems, and more recent developments in Artificial Intelligence (Ballada, 2012).

It has been a hot topic in recent years to predict the AI applications that will be available in the financial services sector soon. Especially as blockchains and cryptocurrency acceptance expands, there is a high probability that transactional security and account security will improve. Due to the reduction or elimination of transaction costs, the need for an intermediary is eliminated. All types of digital assistants and applications will continue to improve themselves through cognitive computing. From the payment of bills to the preparation of tax returns, intelligent machines can plan and carry out short- and long-term activities. VR's advanced auto-assistance technologies can also predict better customer service as NLP progresses and learns more from previous experiences. A greater level of transparency will result from more detailed, accurate client reporting and more comprehensive due diligence checks, which would take too many hours to be performed by humans (Bachinskiy, 2019).

During the era of Artificial Intelligence, conventional accounting staff would leave the accounting program to complete a few more complex tasks. These would significantly boost working performance, minimize errors, increase companies' productivity, and also allow the accounting industry to further transforming the accounting field (Chaoyi et al., 2020). The accounting industry has a long history of applications for artificial intelligence (AI), mainly for financial reporting and auditing, dating back 25 years (Giudici, 2018). Artificial intelligence (AI), particularly in connection with the accounting profession, has recently improved significantly from paper and pencil entry to software and computer entry. The most recent invention of AI products has contributed to the development of robots and a stronger infrastructure of experts in accounting software. This emerging technology phenomenon has therefore induced much change in the market climate and affected the activity of the business. The evolution of accounting software and the new artificial intelligence development have fully changed accounting systems. Extent studies have shown that the efficiency of accounting operations is positively affected by Internet computers, software/expert systems, and more recent developments in artificial intelligence.

Artificial Intelligence Algorithms with higher sophistication can meet the need for new power in the financial field as computer computing power increases. AI is widely used in investment management, algorithm trading, fraud detection, loan, and insurance underwriting, to name just a few. Regulators will be able to determine illegal compliance using artificial intelligence. This is an evolution of the experience based on the supervision of transactions and the analysis of massive amounts of data, while new required skills and knowledge for regulators will be discussed.

When it comes to stock investments on the financial market, the public is always eager to understand the underlying rules, which can be used for analysis and prediction (Huang, 2009). To maximize the profit, investment experts from around the world are applying different methods of investment analysis and data mining to the vast amounts of publicly available stock market data. Market and non-market factors interact with each other, making it difficult to establish an accurate model of internal interaction (Preis, 2012). A "black box" model prediction using machine learning is increasingly used in stock market forecasting.

2.0. Terminology

The science and technology behind the robot design, development, and deployment as an Artificial Intelligence technology (Graetz, 2017). In other words, it is concerned with the construction, design, function, and use of robots. The robots are similarly matched to the human interface, which removes the need to change programs (e.g., ERP, software store, accounting, payroll), or the basic infrastructure of information technology Each robot is logged and monitored to satisfy audit requirements and guarantee the integrity of the data. In every category of business management activity, RPA has become a very useful and important method. Software robots can conduct traditional work processes: opened, read, and sent emails, scanned, retrieved, modified, validated, data entered through different applications, opened, read and sent emails, processed, and formatted data, and make decisions.

Expert systems are artificial intelligence programs introduced during the 1980s that achieve a degree of competence that can replace human expertise in a given decision-making area. Artificial intelligence technology is quickly applied and most commonly used by expert systems. They provide computer programs that simulate expert thought in a specific area. They also come with machine shells of expert experts. A system shell by an expert is a software programming system that allows expert or information-based systems to be built. Therefore, where a person/group has special knowledge that others need, a field for an expert system is possible (Taghizadeh et al., 2013). Academic auditors were interested in the study of the functions of expert audit systems. One of the initial attempts was to use artificial intelligence technology in an auditing sense. TICOM (the internal control model) (Bailey et al., 1985). Although TICOM is not an expert system framework, it is an analytical method focused on the principle of artificial intelligence of the representation of information and simplified diagrams. TICOM is designed to help the auditor plan, analyse and review internal control systems for the Decision Support Assistance system.

The auditor will use TICOM to model the information system and then test the internal control system using the querying functionality. Hansen and Messier also developed one of the first expert auditing programs, EDP-EXPERT. The framework was developed to provide the EDP auditor with decision support, an environment that is appropriate for the development of the expert system due to the complex and diverse nature of the audit systems and the small number of experienced and professional EDP auditors. A computer audit professional was the expert and provided the system with weights and suggestions (Hansen and Messier Jr., 1987). Expert systems have made an enormous contribution to the accounting profession over the past fifteen years. Due to the high cost of developing these systems, only large accounting companies have been active in developing most expert accounting systems.

Advances in IT are quickly entering the daily business operations, enhancing production performance, increasing the quality of information, and changing the essence of business processes, including financial reporting One such innovation is computerized intelligent agents (IA), independent software companies which employ their know-how to achieve user's aims (Gao et al., 2007). Companies are looking forward to implementing IAs to reduce the costs of this innovative technology and increase production. The research conducted by Huaiqing et al., (2007), has included lightweight Intelligent Agents in financial surveillance systems. The intelligent agents can have an efficient way of systematically tracking corporate financial transactions, identification, and reporting of any financial irregular transactions that could lead to unhedged threats, fraud, and other financial contradictions. They also suggested an ontological structure focused on a detailed review and an abstraction of UML-based financial transactions. These ontologies provide all information correspondence within the system with a single vocabulary. The use of ontologies will contribute to an unequivocal comprehension of the concepts and the potential source of misunderstanding. Moreover, such models provide a uniform structure in terms of their strengths and limitations, where different systems can be compared. The intelligent agent is ideal for a particular company situation. The selection of the system would depend on the size of the organization, the production process, cost classification, and other elements.

In the future of the auditing and accounting professions, artificial intelligence is important. The use of artificial intelligence applications in accounting goes back decades. Greenman (2017) acknowledged that numerous artificial intelligence systems and techniques have been used by the domain of accounting researchers, and successfully performed in basic financial and analytical reports and audit reassurance tasks. The auditor, who recognizes, monitors, and improves the analytical and cognitive structures and processes, will therefore prosper. Fogel et al., (2017) see the implementation of expert systems as being of greater interest to the accountant than the displacement of technology. He says that in the past business owners and their accountants will make choices based on statistics which are often out of date, but expert systems and the automation of the data processes always include up-to-date details concerning the business that makes it possible to take much informed decisions (Fogel et al., 2017).

Chukwudi et al. (2018) gave some insights into the gains made by AI and their positive effects on accounting. They pointed out that accuracy and speed will increase, outside and intern reporting will be improved, paper use will be decreased, usability and usefulness will be increased, as will an improved database system. This would transform AI into an effective consulting service, which would be boring and painstaking. In the world of industry 4.0, accounting companies must remain competitive and constructive. They must react, take and adjust their choices continuously to optimize profitability and services and drive business process improvements (Barta, 2018). In conventional accounts, the jobs of the accounting department are not split, this is often seen in small and medium-sized enterprises. All financial staff can access both bookkeeping and cash-flow, which is why the organization is missing, and this can lead to financial theft, as it allows themselves access to self-serving criminals. However, by integrating artificial intelligence, computers can do a significant portion of the accounting and other related work, accounting staff only have to provide guidance and review them. At the end of the time, the machine settles the bill and performs the test balance automatically. Each accountant has unique rights in the accounting system (scanner, retina scanner, etc.) and has different passwords and accounting, simple division of responsibility, thereby minimizing financial fraud to some levels.

3.0. Related Work

According to the research of Greenman (2017), The future of accounting and auditing careers relies on artificial intelligence. AI is an important tool for providing these professionals with the resources they need to improve their careers' effectiveness and productivity. In addition to the high-value specialties that indicate professional judgment, routine bookkeeping or process-based activities tend to be substituted by automated technology. Many agree that the younger generation must understand artificial intelligence and be prepared to work with it.

Yin and Xiaoni (2019) aimed to analyse the application of intelligent technology in forecasts of bankruptcy to measure development and explain research patterns in the last fifteen decades through bibliometric review. The quest for literature included journal papers and reviews published during 1968-2018 on Web of Science. After screening duplicates and reports, 413 foreign academic papers are the final results obtained. Initial research was performed by using a series of keyword combinations as search criteria to classify foreign academic papers related to the research subject. Results show that, while the number of publications has risen considerably since the financial crisis of 2008, authors' collaboration, particularly in the global region, is small.

The results also provide a detailed review of interdisciplinary research in the fields of financial, market, and computer research on bankruptcy modelling. The consequences of this paper highlight the identification of underexplored research fields and provide insights into the holes present in future studies (Saggese et al., 2016). It indicates that certain AI techniques are not properly studied in bankruptcy prediction studies. Such techniques can however outperform when dealing with massive data, which is currently critical for corporate management and decision-making. Indeed, as a research method, artificial intelligence is increasingly popular in many fields, allowing researchers and practitioners to view the use of intelligent techniques as alternative research and decision-making analyses.

4.0. Methodology

This paper aims to provide a meta-analysis of literature review that involves a detailed and qualitative method to search and examine the literature on the source material, such as the impact of Artificial Intelligence applications on accounting and finance process. Glass (1976) first defined meta-analysis in the social science literature as "The statistical analysis of a large collection of analysis results from individual studies to integrate the findings". Meta-analysis is an epidemiological, quantitative, and formal research design used to analyse the outcomes of previous research systematically to extract results from the research organization. The results from a meta-analysis can be more accurate than any individual research adding to the combined studies' estimation of the impact of medication or risk factors for disease or other findings.

Identifying causes of variance in reactions may contribute to the more efficient treatment or management changes, that is, analysing the heterogeneity of a group of studies and generalized reaction. The heterogeneity evaluation is probably the biggest challenge in meta-analysis. This study as a first objective has conducted a meta-analysis of literature review and involved around 150 research from different sources. All papers were reviewed and selected properly for further analysis. The gathered data were composed of 5 different tables which illustrate the variety of results from the selected literature. The Cochrane (2008) collaboration has been a long-standing, rigorous, and innovative leader in developing methods in the field. Major contributions include the development of protocols that provide structure for literature search methods and new and extended analytic and diagnostic methods for evaluating the output of meta-analyses. The use of the methods outlined in the handbook should provide a consistent approach to the conduct of meta-analysis.

4.1. Search Strategy

The centre of the systematic review is a well-constructed search technique and is stated in the methodology section of the paper. The search strategy recovers a large number of studies for eligibility & inclusion that will be reviewed. The search technique consistency also influences what items were missing. In this method, informant staff may be collaborators. All research papers for this study were searched properly for the subject AI in accounting and finance and collected from different academic sources such as Researchgate, Journal of Computing, Emerald, Elsevier AI&Society, Heliyon, Review of Economics & Business Studies, etc.

Other databases, such as ACM or IEEE, should also be supported in a similar depth. But we have actively opted for reducing the number of databases, as with Buchanan and Bryman (2009) and also the academics and scientists Amorim and Melão (2018) to increase transparency and simple replication of findings. We chose the systemic literary review because it is "a method of identification, assessment, and synthesis of the existing previous work performed and recorded by researchers, academics and practitioners that is systems, explicit and replicable" (Fink, 2010). The writers have conducted systematic literature following the diagram method to ensure a consistent and replicable procedure. This approach allows researchers to sum up current evidence according to a step-by-step procedure that is explicit, comprehensive, and clear.

4.2. Identification of Sources

A job may be made better if the type of information corresponds appropriately to the context. Each source has benefits and inconveniences. During the "Find Sources" stage in the research process, it is important to know what you are searching for. The large search query has been designed: 'Artificial Intelligence and 'Accounts &Finance.' The search for a database took place in December 2020 and resulted in over 200 hits. By restricting the searches to names, abstracts, and keywords we have limited the number of publications for the Scopus Journal review. We have also included foreign publications in English, which avoided misunderstandings and contributed to international scientific discourse in these publications. As it comes from the quest itself, we did not pick a particular time frame. To guarantee scientific rigor, the criteria of inclusion focused on the type of document, i.e., peer-reviewed publications, conference papers, and full-text availability. This search resulted in the first number of 155 references after duplicates have been eliminated. We omitted 1 article which was not available in full text and two others that focused on technical aspects in the second level. There were 69 academic papers, 58 scientific papers, and 23 papers in the remaining 150 references.

5.0. Findings and Discussion

The research quality is assessed based on the validity, scope, and completeness of the research. The study population must be adequately identified by researchers in their protocols. First of all, the target population has the attributes that allow the research to achieve its goal. The researcher must define requirements for inclusion and exclusion in a sample. Defining parameters of inclusion and exclusion increases the probability of accurate and reproductive outcomes, decreases the likelihood of damage to subjects, and avoids abuse of vulnerable subjects. All papers selected for this review have an overall structure that incorporates all key elements of a study, and (Table1). As criteria were identified document type, date of selected papers, the language of publishing, participants type which research was conducted, and participant's characteristics. Of the general picture were distributed inclusions and exclusions as well. Inclusions of document type are research articles and academic books, respectively Exclusion consists of presentation, Abstracts, and non-academic sources. The date of selected articles is between the years 1989 and 2020. Before the year 1989 is an Exclusion. The language of publications is language. Participants in the conducted researches are professionals as an accountant, financial managers, auditors, etc., also students in accounting and finance-related module, accounting and finance companies and their customers as well. Non-professionals were excluded. Participant characteristics are people in age average 18 and 65 years old, and health conditions are healthy as well. The generation 18 and below, elderly people above 65 and disabled, and health compromised people are excluded.

In the documents collected, factors that contribute to AI volatility, as well as ES hedging ability, have been analysed. In addition to references from some experts, such as articles and university papers in the fields under consideration, this paper mainly incorporates the findings of research papers. The results of such analysis are summarized in the preceding section. (Table 2).

Criteria	Inclusion	Exclusion
Document type	• Research articles • Academic books	• Presentations/Abstracts • Non-academic sources
Date	≥ 1989-2020	< 1989
Language	English	Non-English
Participant's type	• Professionals • Students • Companies/customers • Finance Executives	Non-professional
Participant's characteristics	• Age: Adults (≥ 18 years ≤ 65 years) • Healthy	* < 18 (Children/infants) > 65 (elderly) * disabled/ health compromised persons

Table 1.
Specific Criteria of a Literature Review

As it shows in the below-given table, the majority of research papers are published on the platform Researchgate. The second group an Others which include various research sources such as the Journal of Computing, AI and Society, Heliyon, Review of Economics & Business Studies, etc. Other resources as Emerald and Elsevier consist of sufficient research papers as well. Authors of all these papers are from different countries and done in different time lining. The articles numbered and the full name of authors, date of publications, resources will be shown in the References part of this paper.

Sources	No. of articles
Emerald Elsevier	[7], [8], [9], [10], [32], [61], [72], [88], [90], [91], [92], [93], [94], [95], [96], [108], [109], [114], [116], [28], [33], [35], [37], [38], [40], [42], [44], [45], [46], [47], [48], [50], [54], [64], [66], [68], [71], [101], [135],
ResearchGate	[1], [6], [15], [21], [25], [30], [34], [36], [51], [52], [53], [65], [69], [73], [78], [81], [82], [83], [84], [85], [86], [87], [98], [99], [100], [102], [103], [104], [106], [111], [112], [115], [117], [121], [122], [123], [125], [129], [138], [139], [140], [141], [143], [144], [146], [147], [148], [149], [150],
Pergamon Press Plc	[2], [4], [5], [18], [20], [24], [26], [29], [31], [56]
Atlantis Press	[41], [79]
Scientific Research Publishing	[3], [17], [19], [39], [57], [59], [63]
Others	[11], [12], [13], [14], [16], [22], [23], [27], [43], [49], [55], [58], [60], [62], [67], [70], [74], [75], [76] [77], [80], [89], [97], [105], [107], [110], [113], [118], [120], [124], [126], [127], [128], [130], [131], [132], [133], [134], [136], [137], [142], [145],

Note: For the above-shown references (numbers) kindly refer to Appendix A.

Table 2.
Article's Sources

5.1. Qualitative Data

Analysing classified by three main criteria's as "Analysing method", "Analysis period" and "Participants" by Positive, Negative and Neutral impact of AI in accounting and finance process. 150 research articles about the impact of Artificial Intelligence on accounting and finance process were selected and reviewed. In general, the "Analysing method" results consist of seven methods such as qualitative, quantitative, statistical, analytical, systematic methods, and literature review. The methodological approach is presented in Table 1. Summarized results of the meta-analysis are given in Table 3. The qualitative data were collected from previous research projects and presented in this paper in meta-analysis.

Results are identified next: the qualitative research method indicates the highest positive impact which are 26 papers of 30, 4 of 30 papers of the current method have a neutral impact of AI and only 3 papers are with a negative impact. Quantitative method features are on average 19 papers of 20 with a positive impact, only 1 is neutral and 2 are with negative impacts. Analytical and systematic methods have a similar feature with a high positive impact of AI in the accounting and finance process. By literature review method positive features are on the top with 17 research papers of 20. Overall, by Analysis Method the positive impact of AI in the accounting process is the highest feature. Literature has generally shown that AI dynamism is one of the most disruptive technology in the banking, accounting industry, retail, travel, and media, while the adoption of AI in various industries has on a global level have been studied.

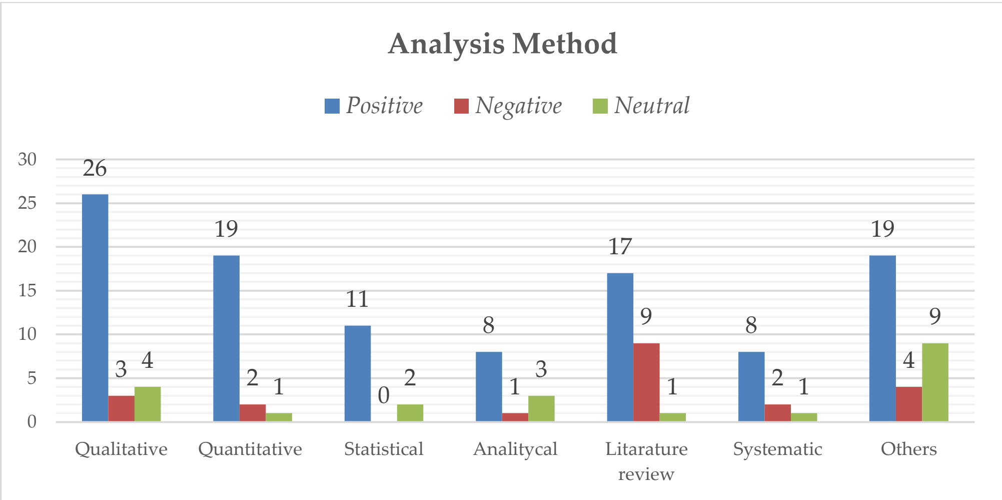


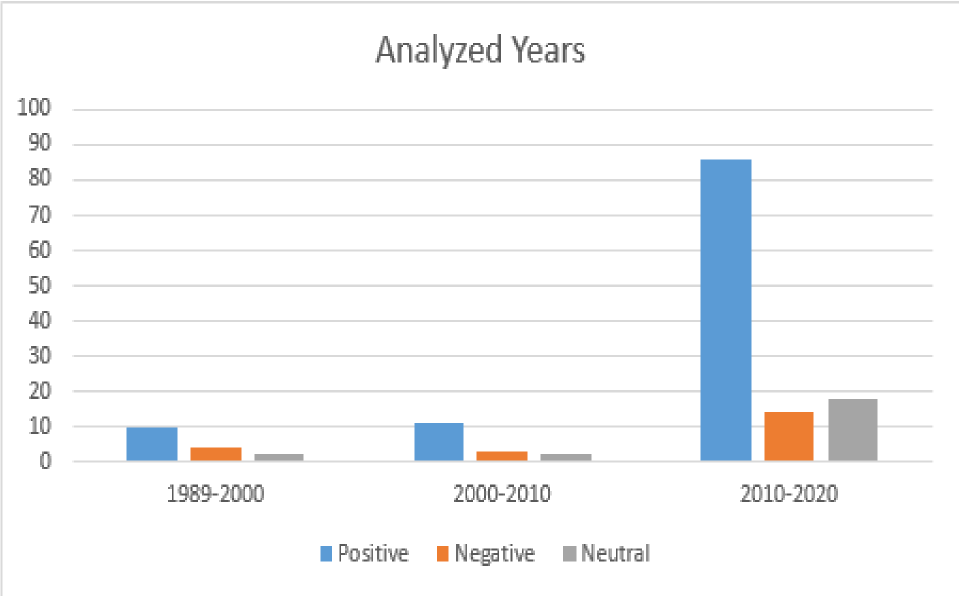
Table 3. *Results of Analysed Methods.*

5.2. Research Timeline

For the current meta-analysis were selected 150 research papers were between the years 1989-2020. Below in Table 4 are given detailed results of reviewed articles by analysed years. As it is shown in the above diagram the majority of research papers were selected from the years 2010-2020 November periods. The highest result here with positive impact with a number 86 articles. Neutral impact of AI in accounting and finance process between the years 2010-2020 November has a middle place with an average of 18 research papers and only 14 researches are negatively impacted in these periods.

At the beginning of the XX century, the positively impacted research papers are also on the top which indicates 11 papers, negative and neutral cases are almost the same with 2-3 articles. Only in the period 1989-2000 years all three features are low which means the research about the impact of AI in accounting and finance process was done in a small amount. 10 papers with a positive impact, 4 with negative, and only 2 research articles have a neutral impact of AI in the accounting and finance process. Shortly, in comparison with 3 time-table results of the period 2010-2020 November have the highest features.

Table 4.
Results of Analysed Years



5.3. Participants

This part of the results illustrates the participants and elements of gathered data for certain research. Table 5 below shows the type of participants which are Professionals, students, different financial and finance companies, and their customers as well. Moreover, the scientist papers are also included. The leader among the objectives is a research paper with a high indicator. By science articles about the impact of AI in accounting and finance, the positive feature is at the top with 45 papers. Although 12 of these papers have negative and 11 neutral impacts of AI in the accounting and finance process. Accounting and finance companies and their customers indicate nest results: 41 positive, 4 negative, and 8 are neutrally impacted with AI in accounting and finance processing. Hence, by professionals, the features have fluctuated. The positively impacted researches are sharply high and negative case is 1, neutral impacted papers are only 4. Regarding students is the almost same indicator with only 1 research paper for positive, negative, and neutral criteria. In other words, by sorting out criteria among the participants, on the top is scientific papers, after taking a place accounting and finance companies and their customers. Professionals indicate more positive impact and students are remaining stable with the number of impacted cases of AI in accounting and finance.

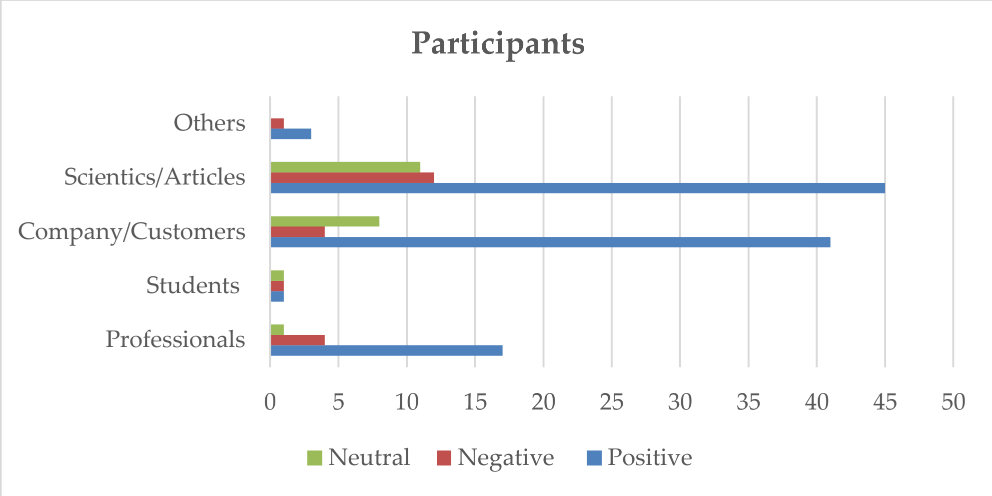


Table 5. *Results of Participants*

6.0. Future Research

For future research, we plan to explore a systematic review of the Deep Learning method for forecasting Crude Oil Market Bankruptcy in Malaysia. In recent years, though ML has become a major subject, the principle of machine learning has already been present for decades (Bratko and Michalski, 1998). Rooted in the idea that machines can be programmed automatically by experience, in the late 1950s, Artificial Intelligence (AI) pioneers developed techniques to teach computers how to play games to improve (with a technique called alpha-beta pruning and a minimum algorithm) Stockman (1979) to classify images (with a technique called perception) (Widrow and Lehr, 1990). Crude oil as a major source of energy plays a crucial role in economic development.

As Malaysia's capital market evolves, more corporate characteristics are to be revealed. The study will pick more Deep Learning indicators on this pattern to forecast bankruptcy in the Oil &Gas industry. In addition, more small and medium-sized investment corporations in Malaysia will be involved in this approach. For energy investors, predicting crashes in oil prices may help minimize risk and ensure proper investment in and distribution of capital. Saggu and Anukoonwattaka (2015), suggest that economic development in Asia-Pacific's least developed and landlocked developing countries is at serious risk of crashes in commodity prices. Jianfeng et al., (2012) estimated crude oil prices based on vector machinery supports. There are several algorithms and methods in the field of Deep Learning used to answer a wide range of questions. Some techniques have solid mathematical foundations, while others, like climbing on the Hill, or evolutionary methods, use heuristic approaches (Jules and Wattenbergy, 1994).

7.0. Conclusion

The future of the accounting and finance professions relies on Artificial Intelligence. AI is an important tool for offering these professionals the resources they need to improve their work productivity and effectiveness (Baldwin et al., 2006). Regarding the results of the conducted research, AI applications have a strong positive impact on the accounting and finance process, especially an Expert System and Intelligent

Agent by reducing errors, increasing efficiency of the audit process, cost-saving, and time-saving by training inexperienced accounting staff. As meta-analysis results show, the majority of research papers between the years 1989-2020 illustrate a strong positive effect of AI systems in the accounting and finance process. Through their analysis conclusions, most authors agreed about increasing efficiency in the accounting process by adopting AI systems. The study found a positive effect on accounting performance with the use of artificial intelligence. AI systems will in the next few decades take increasing decisions from people. While accountants have been using technology for a long time to enhance their actions and give businesses more value, this provides the ability to restore, refurbish and substantially improve company standards and investment decisions, which are the ultimate goals of the profession. In 10 years, time, the accounting profession will look markedly different from now. Contributing to emerging innovations, including AI, would survive and prosper by further specialization, delivering advisory services, and helping clients incorporate the AI technology, rather than relying solely on financial data calculations (Ovaska-Few, 2017). Training and in some cases, retraining will be required. The construction costs must be prepared to be picked up by organizations.

Overall, in the accounting and financial industry, the implementation of Artificial Intelligence is motivated by demand factors such as requirements of financial regulation, competition with other firms, and profitability and supply factors such as access to the infrastructure and the data sector and technical advances. Several breakthroughs in finance are being made in the process of Artificial Intelligence, including the development of software that can disrupt the industry. Therefore, the premise is that AI can not only partially or completely replace human resources, it can also boost efficiency beyond the thresholds of humans. The effect of this growth on accounting and financial stability must be taken into account in determining better results.

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No.	Author (s)	Year	Title
1.	O. Chukwudi	2018	Artificial Intelligence in Accounting firms. Nigeria
2.	S.Varghese	1990	A Conceptual framework: The Network Approach to Expert Systems Development in Auditing
3.	Y. Li	2018	Machine Learning Methods of Bankruptcy Prediction Using Accounting Ratios
4.	Michael D.	1991	A Survey of the Current Uses of Expert Systems in the Modern Accounting Environment
5.	E.Brown	1991	Expert Systems in Public Accounting: Current Practice and Future Directions
6.	R. Sariçiçek	2019	Transformation in Accounting and Artificial Intelligence
7.	J. Paule-Vianez	2019	Prediction of financial distress in the Spanish banking system: An application using artificial neural networks
8.	T. Feng, et.al	2019	Smart contract model for complex reality transaction
9.	D. Belanche et. al.	2019	Robots or frontline employees? Exploring customers' attributions of responsibility and stability after service failure or success
10.	M. Fahim	2018	Improving administrative decisions through expert systems: empirical analysis
11.	Ali Alagoz	2014	With Data Mining as an Enterprise Intelligence Technology: Accounting Information System Relationship
12.	Mates D., Iancu E.	2010	Expert System Models in the Companies' Financial and Accounting Domain
13.	C. Greenman	2017	Exploring the Impact of Artificial Intelligence on the Accounting Profession
14.	Y. Zhang	2020	The Impact of Artificial Intelligence and Blockchain on the Accounting Profession
15.	N. Soni	2018	Impact of Artificial Intelligence on Business
16.	M. Busuioc	2017	Accountable Artificial Intelligence: Holding Algorithms to Account
17.	Z. Huang	2017	Discussion on the Development of Artificial Intelligence in Taxation
18.	E.Boritz	1991	An Expert Systems Approach to Substantive Audit Planning
19.	J. Luo	2018	Analysis of the Impact of Artificial Intelligence Application on the Development of Accounting Industry
20.	D. Murphy	1991	The Effects of Expert System Use on Entry-Level Accounting Expertise: An Experiment
21.	V. Chukwuani	2020	Automation of Accounting Processes: Impact of Artificial Intelligence

Appendix A
Table 1.
Fundamental data about the papers

22.	J. Currie	1990	The Development and Use of an Expert System to Interpret an Accounting Standard
23.	M. Vasarhelyi	2019	The Application of Expert Systems in Accounting
24.	J.Abdolmohammadi	1991	Identification of Tasks for Expert Systems Development in Auditing
25.	K. Jarek	2019	Marketing and Artificial Intelligence
26.	R. McDuffie	1994	Validation of an Accounting Expert System for Business Combinations
27.	Ch. Saw Lee et al.	2019	Usage and Impact of Artificial Intelligence on Accounting: Evidence from Malaysian Organizations
28.	F. Königstorfer	2020	Applications of Artificial Intelligence in commercial banks – A research agenda for behavioral finance
29.	R.Michaelsen	1994	A Test of the Usefulness of Surveys in Identifying Potential Expert Systems Applications in Tax Planning
30.	N. Noponen	2019	Impact of Artificial Intelligence on Management
31.	R. Ye	1995	The Value of Explanation in Expert Systems for Auditing: An Experimental Investigation
32.	M. Fahim	2018	Improving administrative decisions through expert systems: empirical analysis
33.	D. Bayraktar	1998	A knowledge-based expert system approach for the auditing process of some elements in the quality assurance system
34.	D. O'Leary	2014	The Use of Artificial Intelligence in Accounting
35.	B. Sheehan	2020	Customer service chatbots: Anthropomorphism and adoption
36.	D. Üçoğlu	2020	Effects of artificial intelligence technology on accounting profession and education
37.	D. Wall	2018	Some financial regulatory implications of Artificial Intelligence
38.	J. West	2016	Intelligent financial fraud detection: A comprehensive review
39.	I. Bahia	2013	Using Artificial Neural Network Modeling in Forecasting Revenue: Case Study in National Insurance Company/Iraq
40.	A. Faúndez-Ugalde,	2020	Use of artificial intelligence by tax administrations: An analysis regarding taxpayers' rights in Latin American countries
41.	Z. Li	2018	The Impact of Artificial Intelligence on Accounting
42.	R. Nishanta	2020	Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda
43.	P. Seth et al.	2019	Impact of Artificial Intelligence & Service Automation on Service Quality and Service Management in Maintenance of Standard Sustainability

44.	C. Yan	2020	Improved adaptive genetic algorithm for the vehicle Insurance Fraud Identification Model based on a BP Neural Network
45.	M. Bräuning	2017	Lexicographic preferences for predictive modeling of human decision making: A new machine learning method with an application in accounting
46.	N. Melao	2019	Impacts of Artificial Intelligence on Public Administration: A Systematic Literature Review
47.	X. Luo	2020	Accounting for model errors of rock physics models in 4D seismic history matching problems: A perspective of machine learning
48.	P. Wagner	2002	Knowledge acquisition for expert systems in accounting and financial problem domains
49.	S. Kondo	2020	Machine learning against accounting fraud
50.	F. Ryman-Tubb	2018	What an Artificial Intelligence and machine learning research impacts payment card fraud detection: A survey and industry benchmark
51.	J. Gillham	2017	The macroeconomic impact of artificial intelligence
52.	Hsueh-Ju Chen	2009	Using the artificial neural network to predict fraud litigation: Some empirical evidence from emerging markets
53.	M. Serçemeli	2018	Artificial Intelligence in Digital Transformation of Accounting and Auditing Professions
54.	E. Kim	2019	Champion-challenger analysis for credit card fraud detection: Hybrid ensemble and deep learning
55.	C. Gou	2020	Analysis on the Impact of Financial Intelligence on Requirements for the Quality of Accounting Information
56.	J. Akoka	1996	Logistics Information System Auditing Using Expert System Technology
57.	H. Yan,	2019	New Trend in Fintech: Research on Artificial Intelligence Model Interpretability in Financial Fields
58.	J. Akoka, et al,	1996	An Expert System for Financial and Accounting Information System of Auditing
59.	J. Luo	2018	Analysis of the Impact of Artificial Intelligence Application on the Development of Accounting Industry
60.	L. Letourneau-Guillon et al.	2020	Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics
61.	T. Duho	2019	Bank diversification strategy and intellectual capital in Ghana: an empirical analysis
62.	M. Arboleda	2019	Fraud detection-oriented operators in a data warehouse based on forensic accounting techniques
63.	A. Elsharif	2019	The Elements of Accounting Information Systems and the Impact of Their Use on the Relevance of Financial Information in Wahda Bank—Benghazi, Libya

64.	I.Sadgali	2019	Performance of machine learning techniques in the detection of financial frauds
65.	R. Lopes da Costa	2020	"The impact of artificial intelligence on commercial management"
66.	N. Noora	2019	Whistleblowing Practice of the Internal Auditors in Malaysia
67.	K. Borzova	2018	The problem of the relation of human factors and artificial intelligence algorithms in economics and finance
68.	P. Leonov	2020	Visual analysis in identifying a typical indicator of financial statements as an element of artificial intelligence technology in the audit.
69.	S. Mohammad et al.	2020	How Artificial Intelligence Changes the Future of Accounting Industry
70.	J. Wyrobeka	2020	Application of machine learning models and Artificial Intelligence to analyze annual financial statements to identify companies with unfair corporate culture
71.	Ch. Li	2020	Research on the Impact of Artificial Intelligence Technology on Accounting
72.	S Askari	2020	IFDTC4.5: Intuitionistic fuzzy logic-based decision tree for E-transactional fraud detection
73.	Sh. Sunder	2017	Statistical studies of financial reports and stock markets
74.	G. Swankie	2019	Examining the Impact of Artificial Intelligence on the Evaluation of Banking Risk
75.	A. Sangster	1991	Expert System in the Accounting Curriculum: A Textbook Review
76.	E. Daniel	1997	The Impact of Artificial Intelligence in Accounting Work: Expert Systems Use in Auditing and Tax
77.	E. Dadashev	2019	Impact of Artificial Intelligence on the Economy
78.	A. Gacar	2019	Artificial Intelligence and the Effects of Artificial Intelligence on Accounting Profession: Opportunities and Threats Towards Turkey
79.	N. Dečman	2020	The Impact of Artificial Intelligence on the Accounting Process
80.	Z. Li	2018	The Impact of Artificial Intelligence on Accounting
81.	N. Kaigorodova	2018	Directions of improving information system of the insurance company
82.	M. Giovanni	2015	A Fuzzy Expert System for Evaluating the Responsiveness of Italian Insurance Companies to the “Solvency 2 Storm”
83.	B. Medetoğlu	2020	The Use of Artificial Intelligence in Finance and Banking System: An Application on Users
84.	M. Homayouni	2011	The role of intelligent agents in customer knowledge management

85.	D. O'Leary	2014	A Framework for Taxation-Based Computer Decision Systems
86.	D. O'Leary	1989	An Accounting Prototype Expert System
87.	B. Patrut	2006	Intelligent Agents in Accounting and Finance
88.	S. Karlinsky	2017	Tax-Based Expert Systems: A First-Principles Approach
89.	N. Zhang	2018	Alignment of business in robotic process automation
90.	A. Smoudy	2019	The Role of Artificial Intelligence on Enhancing Customer Experience
91.	M. Jullum	2020	Detecting money laundering transactions with Machine Learning
92.	M. Lokanan	2018	Detecting anomalies in financial statements using machine learning algorithm: The case of Vietnamese listed firms
93.	A.Verhage	2016	Great expectations but little evidence: policing money laundering
94.	A. Rantanen	2018	Classifying online corporate reputation with machine learning: a study in the banking domain
95.	A.Krichene	2016	Using a naive Bayesian classifier methodology for loan risk assessment Evidence from a Tunisian commercial bank
96.	D. Ge	2019	Intelligent site selection for bricks-and-mortar stores
97.	D.Vasconcellos de Paula	2018	Estimating credit and profit scoring of a Brazilian credit union with logistic regression and machine-learning techniques
98.	X. Guo	2019	Research on the Transition from Financial Accounting to Management Accounting under the Background of Artificial Intelligence
99.	W. Elkelish	2020	The impact of artificial intelligence on corporate control
100.	P. Dzhaparov	2020	Application of Blockchain and Artificial Intelligence in Bank Risk Management
101.	I.Sadgali	2018	Performance of machine learning techniques in the detection of financial frauds
102.	P. Monelos	2013	Bankruptcy Prediction Models in Galician companies. Application of Parametric Methodologies and Artificial Intelligence
103.	K. Ray	2018	Artificial Intelligence and Value Investing
104.	I. Wiafe et al.	2020	Artificial Intelligence for Cybersecurity: A Systematic Mapping of Literature
105.	Y. Shi	2019	A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms

106.	Kyung-shik Shin	2014	A GA-based Rule Extraction for Bankruptcy Prediction Modeling
107.	K. Patil	2019	Artificial Intelligence in Financial Services: Customer Chatbot Advisor Adoption
108.	M. Lokanan and V.Tran	2018	Detecting anomalies in financial statements using a machine learning algorithm
109.	M. Jullum	2020	Detecting money laundering transactions with machine learning
110.	K. Shaffer	2019	Artificial intelligence products reshape accounting: time to re-train
111.	A. Tariq	2019	Machine Learning-Based Detection of Credit Card Fraud: A Comparative Study
112.	N. Tadapanen	2020	Artificial Intelligence in Finance and Investments
113.	L. Mirgaziyanovna	2020	Artificial Intelligence and Its Use in Financial Markets
114.	P. Yeoh	2019	Artificial intelligence: accelerator or panacea for financial crime?
115.	K. Kumar	2014	Artificial Intelligence in Financial Distress Prediction
116.	E. Payne	2018	Mobile banking and AI-enabled mobile banking
117.	H. Nobanee	2020	Artificial Intelligence in Financial Industry
118.	P. Yigit	2011	Artificial Neural Networks and an Application on Evaluation of Loan Demands
119.	B. Medetoğlu	2020	The Use of Artificial Intelligence in Finance and Banking System: An Application on Users
120.	S. Abukhader	2018	The extent of artificial intelligence into accounting and auditing work – An analytical attempt of job and duties
121.	A. Ramezanzadeh	2016	Designing Bankruptcy Prediction System Using Artificial
122.	Ch. Engel	2020	Towards Closing the Affordances Gap of Artificial Intelligence in Financial Service Organizations
123.	M. Rodríguez	2020	Explainable AI for bankruptcy prediction using XBRL filing
124.	Y. Zhang	2019	Fairness Assessment for Artificial Intelligence in Financial Industry
125.	A.Garcia-Almanza	2010	Understanding Bank Failure: A Close Examination of Rules Created by Genetic Programming
126.	Ch. Chimonaki	2014	Identification of financial statement fraud in Greece by using computational intelligence techniques
127.	P. Giudici	2018	Fintech Risk Management: A Research Challenge for Artificial Intelligence in Finance

128.	K. Randhawa	2017	Credit card fraud detection using AdaBoost and majority voting
129.	K. Patel	2018	Artificial Intelligence in Finance
130.	R. Vedapradha	2018	Application of Artificial Intelligence in Investment Banks
131.	N. Muñoz-Izquierdo	2019	Is the External Audit Report Useful for Bankruptcy Prediction? Evidence Using Artificial Intelligence
132.	M. Ate	2017	Artificial intelligence in banking
133.	Golovachev	2014	Forecasting profitability in the stock and foreign exchange markets based on models of artificial neural networks
134.	Sh.Ranjan	2020	Artificial Intelligence in Financial Acumen: Challenges and Opportunities
135.	I.Sadgali	2019	Performance of machine learning techniques in the detection of financial frauds
136.	P. Li	2019	Research on the application and security of artificial intelligence in the financial industry
137.	W. Elijah	2018	Role of artificial intelligence in financial reporting
138.	S. Samtani	2020	Trailblazing the Artificial Intelligence for Cybersecurity Discipline: A Multi-Disciplinary Research Roadmap
139.	B. Alareeni	2020	A Review of Auditors' GCOs, Statistical Prediction Models and Artificial Intelligence Technology
140.	V. Soni	2020	Challenges and Solution for Artificial Intelligence in Cybersecurity of the USA
141.	M. Taddeo	2020	On The Risks of Trusting Artificial Intelligence: The Case of Cybersecurity
142.	M. Abdulrahman,	2019	The impact of Artificial Intelligence (AI) in detecting fraud in the UAE
143.	R. Yampolskiy	2020	The Intersection and Governance of Artificial Intelligence and Cybersecurity
144.	M. Taddeo	2019	Three Ethical Challenges of Applications of Artificial Intelligence in Cybersecurity
145.	A. Lauterbach	2019	Artificial intelligence and policy: quo Vadis?
146.	M. Rafee	2020	A Study on Impact of Artificial Intelligence in Financial Services Of Private Banks In Bangalore
147.	W. Elkelish	2020	The impact of artificial intelligence on corporate control
148.	D. Desai	2012	Expert system design for credit risk evaluation using neuro-fuzzy logic
149.	M. Mahmoud	2008	Expert System for Banking Credit Decision
150.	D. O'Leary	2000	Value Creation from Expert Systems: An Economic Approach with Applications in Accounting, Auditing, and Finance