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Review

The application of artificial intelligence in auditing: Looking back to the future

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ABSTRACT

ICT-based decision aids are currently making waves in the modern business world simultaneously with increased pressure on auditors to play a more effective role in the governance and control of corporate entities. This paper aims to review the main research efforts and current debates on auditors' use of artificial intelligent systems, with a view to predicting future directions of research and software development in the area. The paper maps the development process of artificial intelligent systems in auditing in the light of their identified benefits and drawbacks. It also reviews previous research efforts on the use of expert systems and neural networks in auditing and the implications thereof. The synthesis of these previous studies revealed certain research vacuum which future studies in the area could fill. Such areas include matching the benefits of adopting these intelligent agents with their costs, assessing the impact of artificial intelligence on internal control systems' design and monitoring as well as audit committees' effectiveness, and implications of using such systems for small and medium audit firms' operations and survival, audit education, public sector organisations' audit, auditor independence and audit expectations-performance gap.

1. Introduction

Accounting is arguably the first area of business in which Information and Communications Technology (ICT) tools and techniques have been applied. Although the application of ICT was first undertaken on the basic accounting systems, financial modelling packages soon proved highly beneficial in the analytical aspects of accounting (Carr, 1985; Clark & Cooper, 1985). Barras and Swann (1984) were of the view that the pace of ICT adoption by accounting as a profession was considered slow due to the conservative approach of its practitioners. However, by the late 1990s, the profession had been compelled to computerise its operations as a way of promoting efficiency, withstanding competition and reducing expenses (Manson, McCartney, & Sherer, 1997, 2001).

ICT tools are now commonly used in a range of tasks, from simple assignments such as arithmetic calculations to complex ones such as flowcharting and statistical analysis. Such tools include audit toolkits (comprising standard software packages and purpose-written software), checklists, logit models, audit enquiry programs (capable of analysing and testing data in-depth), integrated audit monitor modules (programmed routines that continuously monitor real data and processing conditions), expert systems and internal control templates commonly utilised for identifying the strengths and weaknesses of a system. Examples of these templates are PricewaterhouseCoopers (PwC)'s Risk Control Workbench and Deloitte's Visual Assurance.

Due to the steady advancement in computer technology, most of the large accounting firms have introduced the use of artificial intelligence in making audit judgements as part of their integrated audit automation systems. As earlier predicted by Abdolmohammadi (1987) and Bell, Knechel, Payne, and Willingham (1998), ICT devices such as Electronic Data Interchange (EDI), Electronic File Transfer (EFT) and image processing are gradually replacing traditional audit trails thereby completely changing the entire audit process.

In spite of the metamorphosis the audit profession has experienced in the last one and half centuries, the central theme of auditing remains providing an independent third party expert opinion on the truth and fairness of financial information being presented by the management and the compliance of these information with applicable accounting standards and relevant legislation. Thus, auditing is considered to comprise an information-intensive set of activities involving gathering, organising, processing, evaluating and presenting data with a view to generating a reliable audit opinion (decision). This final audit opinion is usually an amalgam of the audit judgements (based on pieces of relevant, appropriate, adequate and convincing audit evidence) on different aspects of the financial statement.

As ICT-based decision aids continue to make waves in the modern business world simultaneously with increased pressure on auditors to play a more effective role in the governance and control of corporate entities, this paper aims to review the main research efforts and

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current debates on the use in auditing of a class of computerised decision aids, artificial intelligence systems. This is with a view to suggesting future directions of research and software development in the area. This review is necessary due to the recent developments in artificial intelligent systems at the turn of a new decade of this young millennium. Besides, most of the existing studies on IT-Audit either consider decision aids generally or an aspect of artificial intelligence, whereas, this study focuses on the use of the two main types of artificial intelligence – experts systems (ES) and neural networks (NN), in auditing. The next section sheds more light on the use of different artificial intelligence-based systems in auditing.

2. Auditing and artificial intelligence-based systems

According to Carlson (1983) as cited in Abdolmohammadi (1987), a typical decision process should necessarily encompass three basic iterative phases. These are: intelligence (which involves gathering data, identifying objectives, diagnosing problems, validating data and structuring problems), design (which comprises manipulating data, quantifying objectives, generating alternatives and assigning risks or values to alternatives) and choice (which involves generating statistics on alternatives, simulating results of alternatives, explaining alternatives, choosing among alternatives and explaining choice). Artificial intelligence is therefore an integral part of the decision aids family that continue to be developed and adopted in both technical and managerial operations of modern businesses and professions including auditing.

Dalal (1999, p. 1) had earlier observed that:

> *"With the world's population likely to increase to unimaginable levels and due to the complexity in the nature of transactions, applying audit procedures will be increasingly dependent on software. Artificial Intelligence and Expert Systems are therefore useful and perhaps, inevitable in the conduct of the present day audit".*

To confirm Dalal's observation, over the last two decades, there has been a sustained effort in the development of highly complex artificial intelligence-based systems (in the forms of expert systems and neural networks) to assist auditors in making judgements (Abdolmohammadi & Usoff, 2001). The objective of these systems is to assist auditors to make better decisions by taking care of potential biases and omissions that could have ordinarily occurred in purely manual decision making processes. While it is widely believed that these systems should be used as mere aids or inputs into the auditor's final determination of audit results due to the degree of versatility and sensitivity such judgements require (Abdolmohammadi & Usoff, 2001; Elliott & Jacobson, 1987; Manson et al., 1997), some empirical results indicate that auditors sometimes over-rely on these systems' output (Glover, Prawitt, & Spilker, 1996; Swinney, 1999). However, regardless of the nature of tools and techniques an auditor utilises before arriving at a particular decision (opinion), he/she is ultimately responsible for the judgement. As it is the case with auditors relying on other experts (such as Estate Valuers and Solicitors) for establishing audit evidence as bases for audit opinions, artificial intelligence tools adopted by auditors are considered as mere "agents" being hired for the accomplishment of a particular task. The onus is on the auditor to ensure the relevance, reliability and effectiveness of such tools for his/her purpose. Furthermore, the use of artificial intelligence-based systems in arriving at a judgement is like a double-edged sword. An auditor may be liable for not adequately using a modern decision aid in arriving at a judgement that turns out to be erroneous just as he may be liable for basing his judgement solely on an expert system to make an incorrect judgement (Ashton, 1990; Sutton, Young, & McKenzie, 1994).

Various benefits have been identified as accruable to the audit from auditors' use of artificial intelligence-based systems for audits. These include efficiency and effectiveness (Abdolmohammadi & Usoff, 2001); consistency (Brown & Murphy, 1990); structure for audit tasks (Pieptea & Anderson, 1987); improved decision making and communication (Brown & Murphy, 1990); enhanced staff training (Elliott & Kielich, 1985); expertise development for novices and shorter decision time (Eining & Dorr, 1991). Nevertheless, the following have been identified as possible drawbacks of adopting artificial intelligence-based systems: prolonged decision processes as a result of exploring more alternatives (Mackay, Barr, & Kletke, 1992); the huge cost of building, updating and maintaining systems (Pieptea & Anderson, 1987); the inhibition of novices' knowledge base (Murphy, 1990); the inhibition of developing professional judgement skills (Yuthas & Dillard, 1996); the risk of the tools being transferred to competitors and the possibility of their being used against the auditor in a court of law for having over-relied on the evidence of decision aids (Abdolmohammadi & Usoff, 2001).

Having looked at the development in and the impact of artificial intelligence on auditing, in the light of current literature, from a general perspective, it will be necessary to examine auditors' adoption of its specific components (that is, expert systems and neural networks) in more details.

2.1. Expert systems

One of the earliest efforts at expounding the meaning of expert systems was made by the British Computer Society Specialist Group on Expert Systems. The group defined an expert system thus:

> "*An expert system is regarded as the embodiment within a computer of a knowledge-based component, from an expert skill, in such a form that the system can offer intelligent advice or take an intelligent decision about a processing function. A desirable additional characteristic, which many would consider fundamental, is the capability of the system, on demand, to justify its own line of reasoning in a manner directly intelligible to the enquirer. The style adopted to attain these characteristics is rule-based programming*" (As quoted in Connell, 1987, p. 221).

Arnold, Collier, Leech, and Sutton (2004) defined expert systems as software-intensive systems that combine the expertise of one or more experts in a specific decision area in order to provide a specific recommendation to a set of problems which assists the user in making a better decision than when unassisted. An expert system (ES) is a combination of system and process designed to imitate the judgements of experts. It is different from other computerised systems because it possesses peculiar attributes such as focus and application (Baldwin-Morgan & Stone, 1995).

In the words of Eining, Jones, and Loebbecke (1997, p. 5),

> *"Expert systems differ from more traditional decision aids in two fundamental ways. First, they place emphasis on knowledge, typically generated as rules, rather than algorithmic solutions. Second, they provide access to this knowledge base to the user of the decision aid. In addition, sophisticated expert system software gives numerous capabilities for enhancing the dialogue between the user and the system".*

As far back as the 1930s, early applications of artificial intelligence had centred around the manipulations of physical objects by program-controlled machines but these had few commercial or practical benefits. These limitations were addressed by governments of different countries through certain collaborative efforts of both academics and industrialists. Examples are the Japanese Institute for New Generation Computer Technology and the British Alvey Programme both in 1982. The Alvey Programme focused on

four broad research areas which included software engineering, very large-scale integration, man–machine interfaces and intelligent knowledge-based systems (Connell, 1991). This leading research into intelligent knowledge-based expert systems enlisted the participation of large banks and accounting firms in developing an expert system, ALFEX (ALvey Financial Expert System). Although the efforts on the Alvey Programme were truncated half way through, the experience and exposures gained by participating accounting firms proved useful for the European Community initiatives such as ESPIRIT. This initial experience also spurred these firms into developing in-house expert systems for different aspects of their professional practice (Connell, 1991).

An effective ES is expected to provide several benefits to the audit profession. These include understanding of task processes, increased knowledge and knowledge transferability. These explain why most accounting firms, particularly the large ones, are increasingly adopting ES in several areas of their operations (Brown, 1991). Moreover, a research into the use of expert systems by accountants in the UK, USA and Canada showed that audit had the highest number of expert systems developed by accounting firms (Edwards & Connell, 1989). ES used in auditing have been identified as encompassing systems that support audit planning, compliance testing, substantive testing, opinion formulation, reporting and audit client engagement decisions (Gray, McKee, & Mock, 1991; Greenstein & Hamilton, 1997). Other studies on auditors' use of ES are discussed in the following three sub-sections.

2.1.1. Models for assessing the impact of auditors' use of expert systems

Baldwin-Morgan and Stone (1995) proposed a two-dimensional framework (matrix model) to address the possible multiple impacts of ES on accounting firms. This matrix comprised the levels of impact (industry, organisation, individual and task) on the one hand and the categories of impact (efficiency, effectiveness, expertise, education and environment) on the other. The rationale for choosing different levels of impact was the fact that each type of task or industry might have unique effects caused by ES. Baldwin-Morgan and Stone's study therefore provides a useful framework for studying ICT's impact on accounting practice as it takes into consideration some necessary peculiar contingency factors (task, industry, environment and size).

Baldwin-Morgan and Stone's study was able to present a model to assess the impacts of ES on organisations and individuals that use them and this is totally unlike what is found in most prior studies which only discussed how ES works and why they have been developed or at best their potential impacts on audit. The model was grounded in previous empirical studies on the impact of audit expert systems and management accounting expert systems available in the literature as at then (Baldwin-Morgan, 1993; Brown & Phillips, 1990; Yamasaki & Manoochehri, 1991). The study therefore combined a sound theoretical model with empirical insights.

More recently, Dillard and Yuthas (2001) introduced an entirely new perspective to the impact of expert systems use in auditing by considering ethical issues inherent in the application of ES in audit practice. The study adopted Niebuhr's theory of "the responsible self" to underpin the scope of what constitutes an ethical issue and as a framework for identifying responsible action – to always consider ongoing interactions among the stakeholder groups affected by the implementation of expert systems. The study also suggested that the framework should be used to evaluate the actions of stakeholders before the development of the system side by side with the potential consequences for the system.

2.1.2. Benefits of expert systems' use in audits

Arnold et al. (2004) assessed the impact of decision aids on experts' and novice decision-makers' judgement. The study indicates that an appropriate combination of user and aid may improve the expert decision-maker's decision quality but the novice decision-maker may be susceptible to poorer decision-making if intelligent decision aids are more expert than the user. The research adopted an experimental approach on two groups of expert and novice insolvency practitioners using a decision aid called INSOLVE (See Leech, Collier, & Clark, 1998).

Eining and Dorr (1991) conducted an experiential learning research using 191 upper level students of accounting to serve as novice audit decision makers in evaluating the adequacy of an internal control system with a view to investigating the impact of an ES on experiential knowledge acquisition. The study revealed that of the four groups to which research subjects were classified for the exercise (no decision aid, questionnaire, ES with no explanatory capability and ES with explanatory capability), participants allocated to the two expert system groups performed significantly better than the other two groups.

Eining and Dorr's study was based on a sound theoretical framework famous in educational psychology, the Cognitive Learning Theory. This was combined with an appropriate methodology, controlled laboratory experiment and the result of the research provided one of the earliest insights for practising firms venturing into the use of expert systems for novice auditors. Changchit and Holsapple (2004) developed and evaluated a similar ES that could be useful for evaluating internal control effectiveness.

2.1.3. Assessments of expert systems' impact on different types of audits

Eining et al. (1997) suggested using decision aids in the complex decision process of assessing the risk of management fraud. The study adopted a laboratory experiment approach on ninety-six auditors to examine the use of an expert system to enhance the engagement of the user. Compared to the use of checklists and a logit statistical model which provides only a suggested assessment, the study's results indicate that the use of expert systems enhances auditors' ability to better discriminate between circumstances with different levels of management fraud risk. Therefore, expert systems appear, from this study, to be the most technologically advanced and provide a higher level accuracy device in assessing such a risk.

Eining et al.'s study is one of the few that compared the impact of three decision aids (checklists, statistical models and expert systems) in auditors' assessment of the risk of management fraud. Also, while the study's incorporation of a constructive dialogue mechanism in using expert systems further advances knowledge in the area, its use of a laboratory experiment might not have presented a realistic perspective of the phenomenon being studied especially since it was a one off exercise. In addition, the use of a single highly structured firm of a "big6" status might not form an adequate basis from which to generalise the study's results. Using a similar mechanism within a specific industry, insurance, Pathak, Vidyarthi, and Summers (2005) combined fuzzy mathematics with ES technology to design a system that can identify elements of fraud in insurance claim settlements.

Swinney (1999) examined the reliance on expert systems developed to assist auditors in evaluating loan reserves by one of the then "big6" accounting firms. The research was grounded in previous studies, which had "*reached decidedly contrary conclusions supporting both under-reliance and over-reliance on expert systems*". Therefore, Swinney's (1999) research addressed two research questions within the social context of the accounting firm. These are:

i. Do auditors over-rely on expert system output in forming their own loan loss reserve judgements?

ii. Do auditors over-rely more on negative expert system output than on positive expert system output in forming their own loan loss reserve judgement?

Swinney drew from relevant theoretical and empirical arguments about organisational social context and factors that might lead to under/overreliance on expert systems by accounting firms. Two hypotheses were developed from the arguments. In the first hypothesis, Swinney sought to examine how "*the loan loss reserve judgements made by auditors following consideration of erroneous negative system output are the same as the loan loss reserve judgements made by auditors following consideration of erroneous positive expert system output*". The second hypothesis examined how the loan loss reserve decisions by auditors following consideration of mistaken negative expert system output, the loan loss reserve decisions made by auditors following consideration of incorrect positive expert system output and the loan loss reserve decisions made by auditors who do not consider any expert system output are all very similar.

The study made use of a laboratory experimental research method to collect empirical evidence to test the hypotheses in a small case study sample while data collected were analysed using non-parametric statistical tests. The findings support overreliance on expert system output and greater influence of negative expert system output. The study shows sufficient grasp of the issues involved in the study by drawing parallels between the theoretical and empirical debates and the findings of the study. However, as identified by the author, the study's sample size of just 29 auditors appears rather limited for a study of this importance. Besides, since actual output from a working expert system developed by one of the then "big6" accounting firms was used for the participants in the study (from three different firms), there is a chance that some of the participants were already familiar with the expert systems used in the research. This raises a possibility of bias and may have affected the results. Nonetheless, the study was able to blend practice with relevant technological and social theory to fulfil the modest aim it set out to achieve. However, an investigation of real life decision-making using INSOLVE would have been closer to reality than the experimental techniques used in gathering data.

Added to the foregoing studies, some previous works studied ES applications in other areas of auditing. For example, Rosner, Comunale, and Sexton (2006) demonstrated how a fuzzy logic ES could allow auditors assess materiality, taking relevant qualitative factors into consideration. Zebda and McEacham (2008) advocated fuzzy logic as a possible solution to the identified deficiencies of probabilistic logic being used in ES for treating uncertainty while Murphy (2008) introduced, based on cases from financially distressed US companies, decision rules that correspond to an ES for auditors' assessment of an entity's going-concern status.

As financial audit is essentially a series of linked decisions each requiring professional judgement, it would be a complex and difficult task to develop one complete financial auditing expert system with current technological capabilities. Therefore, accounting firms and researchers are compelled to develop expert systems for various narrowly defined audit domain tasks. Nevertheless, Gray et al. (1991) predicted a composite meta-level expert system with the aid of emerging technologies such as the blackboard system to share information between the individual expert systems given the ongoing evolutionary advancement in technology. The next section discusses studies relating to the second form of artificial intelligence (as identified in the introduction section above), neural networks.

2.2. Neural networks

A neural network (NN) is a form of artificial intelligence (AI) that attempts to mimic human brains. It comprises a set of interconnected units (processing elements) that respond individually to a set of input signals sent to each. Neural networks are useful in making predictions based on a large database of past events and trends. As audit judgements (decisions) are based on evidence extracted from historical accounting records, the applicability of NNs in assessing trends and patterns with a view to making audit judgements cannot be over-emphasised. Below is a review of studies in IT-Audit that are related to NNs.

To assess the risk of management fraud, Green and Choi (1997) developed a neural network fraud classification model using endogenous financial data through the evaluation of analytical procedure expectations. This model was designed to prompt the auditor to carry out substantive testing as soon as any financial statement is classified as fraudulent. However, none of the currently accessible literature substantiates the proposed model.

Using a sample of 77 fraud engagements and 305 non-fraud engagements, Bell and Carcello (2000) developed a logistic regression model that predicts the possibility of fraudulent financial reporting for an audit client based on certain fraud risk factors such as weak internal control environment, rapid company growth, inconsistent relative profitability and management lying to the auditors or being covertly evasive among others. The results of the study indicate that the model was significantly more accurate than practising auditors in assessing risk for the 77 fraud engagements while there was no significant difference for the non-fraud samples. Although the model is likely to be effective given its incorporation of the fundamental risk factors, its use would be more relevant in large organisations than small and medium enterprises as a result of its complexities. Similarly, Lin, Hwang, and Becker (2003) evaluated the efficacy of an integrated fuzzy neural network for assessing the risk of fraudulent financial reporting as an alternative to the existing statistical models and artificial neural networks. The study was able to achieve the objective for which it was carried out, that is, to investigate the effectiveness of information technologies such as an integrated system of neural networks and fuzzy logic in fraud detection. Apart from the fact that the model was more complex than ordinary statistical models or artificial neural networks, its acceptability to practising firms remains uncertain.

Koh (2004) assessed the usefulness of data mining methodologies such as neural networks, decision trees and logistic regression in predicting an entity's going concern status through the analysis of complex non-linear relationships. The study concluded that such methodologies could save auditors the embarrassment of issuing an unqualified opinion to companies about to fold up.

It can be observed from the foregoing review that of the previous studies identified in the literature as being related to the use of NNs in audit, three are focused on designing and evaluating NN models for auditors' assessment of the risk of management fraud. This suggests that NNs could be helpful in reducing control and detection risks while enhancing auditors' ability to predict and uncover financial statements fraud. The consequence of these is an enhanced role for auditors in corporate governance.

3. Suggested areas for future research and software development

The foregoing review reveals that the current body of literature on the use of artificial intelligence in auditing have been examined from three broad perspectives. Some of the studies focussed on the applicability of some proposed artificial intelligence-based models to specific types of audit assignments (e.g. Eining et al., 1997; Swinney, 1999; Lin et al., 2003), some concentrated on examining theoretical frameworks that could be adopted for understanding the impact of artificial intelligence on auditing (Baldwin-Morgan

& Stone, 1995; Dillard & Yuthas, 2001) while others investigated the relative benefits and drawbacks of using these systems in audits (Arnold et al., 2004; Eining & Dorr, 1991). However, the current body of literature so far is yet to cover some crucial areas. These are assessing the financial costs and benefits of artificial intelligent systems in audit particularly in this current economic climate, practical litigation implications of using such systems based on real past experiences of audit firms; and implications of using such systems for small and medium audit firms' operations and survival, audit education, public sector organisation's audit, auditor independence and audit expectations-performance gap. These gaps are therefore suggested for future research in the area.

Further research efforts are also needed to explore how the current trend in auditors' use of artificial intelligence could affect auditors' training from the points of view of professional examinations and continuous professional development. The area of the trend's implications for auditing standards with particular reference to audit evidence could also be explored by future research. Other areas for consideration could also include assessing the current level of internal auditors' use of artificial intelligence in designing and monitoring internal control systems in computerised business systems. Finally, future research can assess the implications of auditors' use of artificial intelligence on audit committees' effectiveness – can the audit committee understand and challenge auditors' judgements when such judgements are underpinned by artificial intelligent systems?

In the light of the foregoing suggested areas of future research, it is being predicted that audit firms particularly the large ones will continue to invest in expert systems and neural networks that are industry-specific and audit task-specific in order to reduce their audit risks. Also, large multinational corporations could develop their internal audit function to the level of using such systems to strengthen their internal control systems and reduce business risks. Furthermore, intelligent systems are being predicted to be developed for enhancing up-coming auditors' education and training.

4. Conclusion

This paper maps the development process of artificial intelligent systems in auditing in the light of their numerous benefits and some drawbacks identified in the current body of literature. It also discussed the significance of auditors' use of artificial intelligent systems in arriving at audit judgements. Specifically, it reviewed research efforts on the use of expert systems and neural networks in auditing and the implications thereof. The previous studies were reviewed and synthesised in a way that revealed certain research vacuum which future research in the area could fill. Such areas include matching the benefits of adopting these intelligent agents with their costs, assessing the impact of artificial intelligence on internal control systems' design and monitoring as well as audit committees' effectiveness, and implications of using such systems for small and medium audit firms' operations and survival, audit education, public sector organisation's audit, auditor independence and audit expectations-performance gap. It is based on these identified areas for future research that suggestions were made for future software developments in the area.

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