Current Development of Automation in Accounting

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Automation in Accounting
Current development and difficulties

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Abstract

Automation in Accounting has been developed since the 1980s. From financial data digitalisation to performing professional judgements, IT systems have evolved rapidly. The literature review investigates how major accounting firms are implementing Robotic Process Automation in tax and advisory service and current development of Artificial Neural Networks in financial statement fraud detection.

1 Background

1.1 Computerisation and Expert Systems

Since commercial computers were introduced and accountants became familiar with computers, using a computer for accounting tasks started to increase in the 1980s. Simple numerical data processing, such as typing, was gradually computerised (Collier, 1984; Carr, 1985; Coopers & Lybrand, 1985; Wilson R. A., 1989). Whereas, other areas requiring accountants' professional judgement were believed hard to be replaced by computers (Wilson & Sangster, 1992).

Even though, some areas in accounting began to deploy application software, such as auditing and taxation to help professionals to make professional judgements. Mainly, there are two types of accounting software (Qureshi, Shim, & Siegel, 1998). One type of expert systems collected knowledge from professionals to construct rule-based systems. The ability of this type of expert systems was based on the number of rules programmed into the system (Qureshi, Shim, & Siegel, 1998). The other type of expert systems collected cases and outcomes as a library for users to compare the current problems and historical ones. This type of expert systems relied on the number of cases input into the system (Qureshi, Shim, & Siegel, 1998). Inevitably, both types required substantial resource to develop and were implemented only in large companies (Wilson & Sangster, 1992).

1.2 Robotic Process Automation (RPA)

With the increased complexity of software, a computer's ability to manage itself becomes more and more important. And this ability to configure, heal and optimise itself was defined by IBM as automatic computing (IBM Corporation, 2005). New software which can automate processes across different software systems emerges.

Robotic Process Automation can repeat what human do for specific tasks (Moffitt, Rozario, & Vasarhelyi, 2018). Similar to macros in Excel, activities can be recorded and then the script will be produced accordingly. Furthermore, RPA can be executed across different software and actions can be monitored by users (Moffitt, Rozario, & Vasarhelyi, 2018). Major public practice firms have been developing RPA in their taxation and assurance service, and they believe cost saving will be significant (Cooper, Holderness, & Sorensen, 2019).

1.3 Artificial Neural Network (ANN)

Unlike rule-based expert systems requiring predefined rules, artificial neural network needs a lot of data (Qureshi, Shim, & Siegel, 1998). Artificial Neural Network imitates how human think - avoiding making the mistakes again and repeating what we are good at. In the mathematic expression, it means weights of input will be continuously adjusted based on data. That is, important information will be given more weight and the less relevant information will be given less weight in an equation. With this approach, the artificial neural network can "learn" from the data, and then create and adjust rules (Qureshi, Shim, & Siegel, 1998).

ANN has been developed in risk assessment areas, where the data relationship is unclear, and the gathering information is difficult. For example, ANN helps auditors to find frauds in financial statements (Lin, Hwang, & Becker, 2003). It is difficult to detect misstatement in financial reports because the management of companies might provide fake information to conceal the fraud. In addition, auditors only have limited time to perform audits. With ANN, auditors would be able to know where the risks are and spend their time wisely (Lin, Hwang, & Becker, 2003).

1.4 Financial statement fraud

There are three types of fraud, asset misappropriation, corruption and financial statement fraud. Association of Certified Fraud Examiners (2018) reported that in the Asia-pacific area the financial statement fraud only accounted for 13% of frauds, but the median loss of financial statement frauds is US 700,000, the highest amount between the three types of fraud.

Cressey (1953) developed a theoretical framework of the fraud triangle to detect frauds. This framework argues that three components will signal a fraud is happening, including, opportunity, pressure and rationalisation. Opportunity means the offender has an opportunity to commit a crime. For instance, a cashier has the opportunity to handle cash. For cash misappropriation, this person might be categorized as a high-risk person. Pressure means the offender feel some pressure so the offender will be likely to commit a crime. Financial pressure from the family or performance pressure from shareholders is the examples for this component. Rationalisation means the offender is likely to rationalize the wrongdoing. For example, the offender believes the company is treating employees badly, so that the offender justifies his/her behaviour of stealing money from the company.

2 Methodology

2.1 Discussion topics

The literature review aims to identify the current development of automation in the accounting field. For rule-based areas, this literature review focuses on how RPA is used in major public accounting firms. For professional judgement area, this literature review focuses on the effectiveness of ANN in detecting frauds.

2.2 Paper selection

The papers in this literature review were selected by keywords in Google scholar. No webpages and blogs were considered because they lack in peer reviews and proper citations. Evermore, some of them came from biased or second-hand sources without verification by recognised authorities.

For the area of RPA implementation, the keyword was "Robotic Process Automation" and publish year was "after 2018". And the papers relating to the public accounting firms and audit were chosen.

For the area of effectiveness of ANN in detecting frauds, the keywords were "ANN" and "financial statement frauds".

2.3 Analysis

For RPA implementation, the paper discusses practical aspects of implementation, difficulties and constraints facing accounting firms.

For ANN implementation, the paper discusses inputs and effectiveness of different approaches to detect financial statement frauds.

This paper chose practical issues rather than the theoretical perspectives because theories may not precisely depict real-life situations. A limitation of this approach is lack of theoretical supporting; therefore, the result may not be generalised.

3 Literature review

3.1 RPA in Big 4 Accounting firms

3.1.1 Current use

Big four accounting firms are implementing RPA in those processes where inputs are structured and digital, and where are only related to rule-based without judgements (Cooper, Holderness, & Sorensen, 2019). In short, importing data and exporting data are the main focuses of automation.

They are using RPA extensively in taxation (Cooper, Holderness, & Sorensen, 2019). To provide tax service, accountants need to produce several reports for each tax legal entities. When the numbers of ERP systems increase and each of them used by more than one entity, the task becomes complex (Cooper, Holderness, & Sorensen, 2019). Therefore, the RPA can be used to extract data from multiple ERP systems, allocate data to each entity, check the accuracy of data and transform the data into reports for tax purpose (Cooper, Holderness, & Sorensen, 2019).

Accounting firms also use RPA in advisory service. Rather than deploying RPA in internal processes, this department mainly helps clients identify opportunities of automating processes and program the robot (Cooper, Holderness, & Sorensen, 2019). Although every client has different processes, accounting firms believe they can deliver value by automating finance processes, operational processes, human resource and procurement processes (Cooper, Holderness, & Sorensen, 2019).

Nevertheless, the automation in assurance is still in its early stage because accountants bear more responsibilities for their assurance service (Cooper, Holderness, & Sorensen, 2019). Therefore, only low-risk parts of works are implemented. In addition, automation is run parallelly by a robot and an accountant (Cooper, Holderness, & Sorensen, 2019). For example, they automate a process to extract data from clients' server or compare this year data to last year data and alarm auditors when the difference is significant (Cooper, Holderness, & Sorensen, 2019).

3.1.2 Factors in choosing process

Firstly, a team manager needs to approve this automation. Unlike most digitalisation led by the management, big accounting firms encourage staff to initiate the process automation. Therefore, an implementation needs approval from the team manager to go ahead (Cooper, Holderness, & Sorensen, 2019).

Secondly, the cost-benefit analysis will be evaluated. A participant in the interview provided an example that a process takes only one hour in a week might not worth automating it (Cooper, Holderness, & Sorensen, 2019). On the other hand, the benefit of the RPA application will be assessed. That is, if the RPA application has the potential to attract multiple clients, the process will be more likely automated as the return on investment (ROI) will pass the threshold.

Thirdly, the associated risk will be considered. For example, the main reason for automation is to reduce errors in an output. If the automation cannot minimise errors and even add more uncertainties, the RPA will not be considered (Cooper, Holderness, & Sorensen, 2019).

3.1.3 Difficulties

For simple tasks, accountants can create bots themselves. However, accounting firms need software engineers to design the program for complex tasks (Cooper, Holderness, & Sorensen, 2019). Due to a lack of accounting knowledge, software engineers might not identify use cases to meet the requirements of accountants (Cooper, Holderness, & Sorensen, 2019). In addition, software engineers do not understand the regulatory requirements for accountants (Cooper, Holderness, & Sorensen, 2019). Both make it difficult to automate complex processes.

Some processes can be automated in theory, but then they might turn out to be more time-consuming (Cooper, Holderness, & Sorensen, 2019). For example, the process of comparing the difference between data and then sending out emails to ask the reasons or confirm the figures is automatable. However, this kind of emails generated by the bot can be categorised as a junk email by the recipient's server. As a result, this process requires more efforts to complete (Cooper, Holderness, & Sorensen, 2019).

In the past, when auditors evaluate the effectiveness of internal controls, they select some samples from all transactions. With the help of RPA, now auditors can examine all the transactions to reduce sampling risk. However, auditors are required to investigate those inconsistencies. Therefore, how to differentiate the inconsistent items will need to address (Moffitt, Rozario, & Vasarhelyi, 2018).

3.2 ANN in detecting financial statement frauds

3.2.1 GANNA and ALN

Bell *et al.* (1993) developed a logistic regression model to assess the likelihood of financial statement frauds. In order to improve the efficiency of building models, Fanning *et al.* (1995) proposed two approaches: generalized adaptive neural network architectures (GANNA) and the Adaptive Logic Network (ALN).

The performance of Artificial Neural Network (ANN) heavily relies on the structure of the network. Therefore, to build a good ANN, the designer needs to find the right number of layers and the right number of processing elements in the network. By using GANNA, the neural network can build its structure itself by trial and error (Fanning, Cogger, & Srivastava, 1995).

The main characteristic of ALN is that the network evolves by deleting unnecessary branches. As a result, the ALN can process the data faster and use less computing power (Fanning, Cogger, & Srivastava, 1995).

The result of Fanning *et al.* (1995) shows that both GANNA and ALN are faster and have better accuracy to detect financial statement frauds than the logit model in Loebbecke (1989). In addition, the 47 yes-no questions (regarding attitude, condition and motivation) in Loebbecke 's work (1989) for auditors to identify financial statement frauds can be reduced to 11 questions, suggested by the GANNA approach. This can save a lot of time for auditors.

3.2.2 Fuzzy neural network (FNN)

To increase the prediction accuracy of models, Lin *et al.* (2003) developed an ANN with fuzzy logic in financial statement fraud detection.

The fuzzy model was based on a fuzzy clustering method in Fuzzy Logic Toolbox (Gulley & Jang, 1997), called GENFIS2 function. Then, the model was trained by a backpropagation algorithm, developed by Jang, J. in 1993. And inputs are the financial ratios of two hundred companies charged by the US Securities and Exchange Commission (SEC) from 1980 to 1995.

The study argued that the FNN has 35% hit rate to detect financial statement frauds, which is higher than the 5% hit rate of the logit model. However, FNN's hit ratio for non-frauds is only 86%, lower than the 97.5% of the logit model.

3.2.3 Multilayer feed forward neural network (MLF)

Unlike most studies focusing on large market capitalisation companies (Abbott & Parker, 2000; Klein, 2002; Lin *et al.,* 2006; Lin & Hwang, 2010), Omar *et al.* (2017) developed an MLF model for small market capitalisation companies in Malaysia.

The study selected ten financial ratios to represent three components in the fraud triangle, opportunity, pressure and rationalisation. The data was collocated from 110 companies' data for five years.

The result showed the overall prediction accuracy was as high as 94.87%, which was higher than previous studies. The study argued that the reasons are the chosen variables and the effectiveness an ANN model can deliver more than logistic regression can deliver.

4 Discussion

For accounting firms, legal accountabilities for audit failures hinder the RPA implementation in auditing service. Also, some processes are difficult to be automated due to the lack of people knowing the software engineering, accounting knowledge and associated legal issues in the industry. Lastly, the audit methodologies have not redesigned for the big-data era. With more information available, how to audit and what responsibilities auditors should bear are issues to be addressed.

Regarding the current development of ANNs in financial statement fraud detection, currently, the prediction accuracy of ANNs is high for non-fraud cases, whereas the prediction accuracy for fraud cases is low. The reason might be that ANNs need a lot of data. However, there might not be sufficient and most recent data to train neural networks. As a result, the prediction accuracy for fraud cases is low and the ability to detect future fraud is questionable. In addition, the main drawback of ANNs is that they cannot explain their predictions. Therefore, these predictions cannot be used to initiate investigations or prosecute problematic management.

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