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The use of Artificial Intelligence to determine contingent legal liabilities provisions.

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We suggest how Artificial Intelligence (AI) can help us make more accurate legal liability provisions under International Accounting Standards. International Financial Reporting Standards provide considerable guidance on how uncertain legal events should be recognized on the balance sheet. The process is subjective and, we argue, a more qualitative approach would be beneficial. We recommend the use of Artificial Intelligence to get a tentative outcome and a more reliable liability assessment for use in financial statements. This would provide a more true and fair view of the outcome of disputes. We discuss the theoretical and practical issues raised by using Artificial Intelligence to value provisions and propose a way of applying it to calculations of provisions under IAS 37.

KEYWORDS
IAS 37, Contingent liabilities, Artificial Intelligence in accounting, legal provisions.

1 | INTRODUCTION

This paper proposes a way to improve the true and fair nature of corporate accounts in respect of the way possible legal liabilities are assessed and their provision determined impartially. Contingent liabilities are uncertain obligations that are off-balance sheet whose magnitude depends on a future event. Provisions for contingencies that are recognized on-balance sheet are not contingent liabilities. Legal outcome loss contingencies are covered under International Financial Reporting Standards (IFRS) by IAS 37. This standard is documented and discussed by Hennes (2014). Possible

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amendments were proposed by the International Accounting Standards Board (IASB) in 2005 and 2010 when the IASB called for increased disclosure. We suggest increased disclosure should be provided based on the use of Artificial Intelligence (AI) which, if approached correctly, facilitates greater reliability.

With advances in financial technology, it is possible to use AI to data mine historic legal case outcomes. Hand and Adams (2014) explain that data mining is the identification of structures and patterns in large datasets. In simple words, datamining is bringing AI, or other advanced analytics, into databases. Besides data mining applications, two types of AI can play roles in assessing contingent legal liabilities: expert systems and artificial neural networks (ANN). The use of expert systems in auditing was first proposed by Abdolmohammadi (1987). He suggested that a model of auditors' decision-making process was required. This could be achieved using AI in two different ways, namely using symbolic reasoning systems (SRS), which would directly record the steps of the decision making process and symbolic expert systems (SES), in which a knowledge representation would be developed using a rule-based reasoning system (Buchanan Shortliffe, 1984; Stefik, 1995). Another approach that can be considered is machine learning, that can be implemented either in the form of artificial neural networks (Lippmann, 1987), including deep learning (LeCun et al., 2015), or in symbolic expert systems (Clark Niblett, 1987; Quinlan, 1986). Baldwin et al (2006) detail how AI has been used with varying degrees of success in accounting. We extend this by demonstrating that its usage is applicable to uncertain legal outcomes as recognized on company balance sheets.

Current accounting practice and IFRS direct that provisions be recognized only when they arise and importantly only if the contingency is deemed possible. AI can be applied in the preparation of balance sheets to mimic aspects of cognitive functions used to evaluate the value of disputes. This can be done using knowledge acquisition or machine learning and computational problem solving. In this sense, AI can be regarded as a hybrid set of technologies that supplement existing audit practices. After all, audit procedures are fundamentally dependent on available technologies. Supporting our approach, Elliott (1992) suggests that innovative technology will have to be adopted by the accounting profession.

Several studies, as explained by Quin and Bederson (2011), have found that computers are better than people have issues collecting and processing large amounts of information. They argue that computers can perform the function better across several areas including expert opinions in exceptionally narrow domains, modelling and reinforcement learning. In this respect, the accounting They further suggest that processing large amounts of information is subject to ambiguity and we believe this could lead to a suboptimal audit judgment. AI can help with this by structuring data capture from legal contracts. It has been deployed in identifying the relevant legal clauses in leases, payments and renewals. The output has largely been used in transitions to new standards, such as accounting for leases under IFRS 16 or lease accounting standard ASC 842 where the data requirement for compliance is onerous. We suggest that a similar approach can be used to identify legal cases and outcomes and that IAS 37 should be revised to facilitate this.

Revisiting IAS 37 is important because the concept of “true and fair” is central to accounting standards. This concept is explored by Walton (1993) who suggests that there is a degree of divergence on the interpretation of the meaning of the terms. The intent, however, is unambiguous. Accounting standards are expected to be applied in order to provide a true and fair reflection of financial reality in financial statements. For contingent liabilities, this means a realistic provision in respect of recognition, measurement, presentation and disclosure. We argue, the application of AI to calculation of provisions can increase credibility of financial statements.

2 | PROBLEM STATEMENT

Judgments are a necessary part of working with contingence liabilities, as it is necessary for assessing the uncertain nature of the outcomes of legal disputes. Of course, the judgments are subjective, as all expert knowledge is subjective (Dörfler, 2010). However, the problem is that not all solicitors have achieved the highest level of expertise, when intuitive judgments become reliable (Dörfler Ackermann, 2012; Dörfler Eden, 2019). Goodman-Delahunty et al. (2010) show that solicitors can be poor estimators of legal outcomes which may resultant in disclosure in financial statements requiring subsequent revisions. This is relevant because Lennox and Li (2002) found that auditor litigation is strongly related to alleged accounting deficiencies. This is particularly the case, as Dye (1993) showed, when a company fails when faced with large legal settlements which are not anticipated and provisioned.

IAS 37's objective is to ensure fair recognition of all entities' liabilities. Our interest is in that part of the standard that covers the provisions for contingent liabilities and assets. As observed by Du et al (2016), IAS 37 has ambiguous terminology. It uses terms like probable, more likely than not, and remote; these terms are difficult to calibrate. We observe that increasing the accuracy of probability estimations while getting rid of the ambiguity in the terminology can greatly increase the reliability and therefore the usefulness of estimations.

Our observations on the terminology of IAS 37 also apply to IFRS 3 Business Combinations. The later can take precedent when booking contingent liabilities applied to business combinations. Past events become contingent events when their existence is dependent on an occurrence or non-occurrence of an uncertain future event. The provisioning entity should not have control over such an event. In order to establish a provision there must be a potential obligation and a probability of payment to settle that obligation. The use of probability in determining such a provision is defined where an event is more likely than not to occur. It is not probable if the obligation is remote. Disclosure is required based on the nature of the uncertainties, the timing of any payments, the type of assumptions made, and the breakdown of changes during the period reviewed.

3 | THE OBJECTIVE OF IAS 37

IAS 37 was drafted to ensure recognition and adequate measurement for provisions, contingent liabilities and contingent assets. It requires disclosure of sufficient information in the notes to understand both the timing and amount of these provisions. The key principle is that a provision should be recognised when a potential obligation is likely due to something that occurred in the past. This is therefore only applied in respect of genuine obligations, such as a legal outcome. In this instance, the requirement is for the amount to be estimated reliably. Stated more formally, a provisioning event creates a legal obligation. This means an entity has no alternative but to settle that legal event with a payment.

The distinction between a contingent liability and a provision (for a contingent liability) is salient. Under IAS 37 a contingent liability is a possible obligation. For example, this is the case if a company has guaranteed the borrowings of a subsidiary, but this subsidiary is in good financial condition. This would still need to be disclosed as a note but would have no impact on either the statement of financial position or the statement of profit or loss. Although it may be sometimes possible to quantify the possible obligation in financial terms it would have no impact on the reported financial performance of the company. A provision, however, will impact the reported position. There is a limited amount of literature on contingent liabilities and their provisioning. At the government level, this is typified by Brixi and Schick (2002) commentary on International Public Sector Accounting Standard IPSAS 19 "Provisions, contingent liabilities and contingent assets" which is primarily drawn from IAS 37. There is also a respectable amount of literature

TABLE 1 Provision for setting lawsuit determined by traditional advice.

April 2, 2020- Company derived provision for settling lawsuit:

	Balance	Debit	Credit
Expenses on provisioning	Income statement	9,326,000	
Provision	Balance sheet		9,326,000

on contingent liabilities for corporate accounting, drawn from IAS 37 directly. Most of this is descriptive. Vyas et all (2015), however, highlight that contingent liabilities and provisions are an area where financial statements are at risk of creative accounting.

Provisions for a contingent liability are made using a probability-weighted expected value [IAS 37.39]. These amounts should consider the discounted present value [IAS 37.45 and 37.47]. In reaching this value, the entity is expected to consider the risks and of the potential obligation materializing [IAS 37.42].

4 | EXAMPLE OF AN AI-DERIVED LEGAL LIABILITY PROVISION

Consider two scenarios, both pertaining to the same case. Scenario 1 The entity has legal case with an uncertain outcome. The directors assert that there is a probability of a successful award. They make a partially informed call as to the magnitude and record that the likelihood is 75 percent or greater.

Scenario 2 The entity has legal case with an outcome that can be estimated using prior case data. The directors have a probabilistic estimate induced by AI that suggests a greater than 75 percent likelihood of a successful award. They make an informed call as to the magnitude, assuming past precedents hold.

The difference between the two scenarios is simply the different estimation of possible outcomes. The first is partially informed the second is informed. A 75 percent likelihood would suggest a provision, not a contingent liability disclosed in the notes in both scenarios under IAS 37. It can be read to suggest that the most likely outcome is in fact the estimate of the liability that should be selected.

We caveat our observations on the process in both scenario 1 and 2 as we want to be mindful of the use of the term objective. If there are past cases, there are many different ways of processing them, and is a subjective judgment which method is chosen. Furthermore, the relevance of the past legal outcome is limited, as things may have changed since their occurrence. In fact, we can be sure that things did change, the question is how much and therefore how relevant still various instances of past experience may be. This is exactly why AI can work better than statistical frequencies.

For sake of illustration, let us assume in scenario 1 that they decide to settle the case out of court. According to IAS 37, a provision should be set up by the entity to reflect this as they do plan to settle. As such, a note in the accounts is not sufficient. Let us assume the directors expect a USD 15m payment to be required within in two years. They settle on this sum based on a discussion. With this time horizon, the time value of money must be taken into account. This would suggest risk adjusted interest rate in respect of the realization of the liability. In this respect, let us assume the auditors are being more prudent than the directors and apply 24 percent annually, or 2 percent per month. This equates to a present value of USD 9,326,000. This would be presented in table 1 thus:

Under scenario 2, the AI predicted estimate of USD 30m based on a reliability output. This would, in our opinion, be a better provision based on actual past outcomes, provided that we work with relevant past cases. Notice the use of statistical outcomes results in a different number from that chosen based on a discussion. In this scenario, the

TABLE 2 Provision for settling the lawsuit determined by Artificial Intelligence.

April 2, 2020 – AI derived provision for outcome lawsuit:

	Balance	Debit	Credit
Expenses on provisioning	Income statement	18,652,000	
Provision	Balance sheet		18,652,000

required booked provision presented in table 2 would be twice that of the prevision under scenario one, namely USD 18,625,000.

The purpose of this illustration is to show two statistical outcomes. One is the probabilistic outcome identified by the traditional method in Table 1 and the other is that determined by AI in Table 2. If past outcomes are relevant, the latter would have resulted in a more accurate assessment of the liability on the original April 2nd 2020 balance sheet. We suggest, this illustrates the how AI can achieve a fairer representation of the entity's situation, assuming the caveat on past experience being relevant holds.

5 | DISCUSSION

Exploring how AI can be deployed in accounting, and in IAS 37 in particular, is important because human judgement is prone to error, which can result in an inaccurate reflection of assets and liabilities on a company's balance sheet. Although the research specifically drills down into one specific area of accounting standards, the lessons learnt and conclusions reached will have widespread implications across the profession, not just in the compilation of reports and accounts. As the auditing moves into the digital age, as Broby and Paul (2017) demonstrate, it will have to adopt greater use of financial technology.

Provisions for contingent liabilities in IAS 37 are distinguished from those in other standards because they cannot be generated using a current market price. Were that the case, there could be a more accurate estimation of value than could be obtained by either human inference or AI or any other technology. There is no exchange transaction, as is the case with for example IFR 9, which has previously muted as a standard in which AI might have applications (Deloitte, 2016). Chief amongst these applications is impairment modelling. Indeed, some models have been developed by auditors to produce granular forecasts of Probability of Default, Exposure at Default and Loss Given Default.

IAS 37 is helps with relevance and processes. It can be used to deliver a better expected probability weighted estimate. However, for a single legal case, the likely outcome is not based on prior case outcomes, merely a 'best' estimate, and it is unclear what that estimate is based on. A dispassionate assessment of prior outcomes may lead to a better probabilistic estimate and more accurately predict outcome probabilities, if relevant past experience is used. This is the key to our proposed solution, namely to use AI to find the relevant past experiences for the estimation.

6 | APPROACH AND INNOVATION

We argue AI will generate better outcomes in reported accounts, as also suggested by Omoteso (2012). However, in our approach AI is not adopted with the purpose of removing the human element from information-intensive processes, but with the purpose of supporting humans, and ultimately to get the best of both worlds, the superior performance from smart people using smart technology (Dörfler, forthcoming). As this can lead to mixed views on outcomes, the starting point of our reasoning is that humans and machines are good at different things. Machines can easily record and handle large amounts of data, they do not make mistakes, and can perform at extremely large speeds. In contrast, humans are good at making judgements in shortage and even complete absence of data, creating new alternatives, imagining what has not happened yet (cf Dörfler, 2020). All the machine attributes are applicable to a large dataset of legal outcomes, but many of them also include soft attributes, judgments, etc. in their descriptions.

In the following we outline our approach avoiding the technical details. These can be found described at a generic level in Russell Norvig (2020). Instead, we build our discussion from using AI in management generally (Csaszar and Steinberger, 2021), specifically focusing on analytics (Davenport, 2018) and more narrowly focusing on O'Leary's (2010) explanation of the contributions of AI to accounting, finance and management in Intelligent Systems in Accounting, Finance and Management.

Our approach is, in principle, easy to explain but hard to implement. It is an extension of financial technology (Broby, 2021). Instead of eliminating the human element, we recommend making the best use of the time as well as expertise of humans, supporting them with AI. By way of caveat, auditors and accountants often have insights from highly nonlinear and arguably non-algorithmic cognitive processes that machines cannot reproduce. Furthermore, conflicts of interest and differences of value systems can bring confusion and lack of transparency to human decision processes. In contrast, if the arguments of experts are recorded in knowledge bases, we get full transparency, while the essential intuitive qualities of expertise are preserved.

Although AI tools are ubiquitous, these are very rarely used to their full potential and are constrained by their perceived limitations. While we do not get into the over-enthusiastic world of thinking machines and artificial general intelligence (AGI), we do believe that cleverly set up AI solutions can be extremely beneficia, such as the recent success of DeepMind with Alphafold (Hickin Bechtel, 2021). Success will be determined not by the specific technology (more precisely, technologies, as we suggest using more than one) but by how technology is used. Essentially, there are two approaches to AI, the connectionist and the symbolic (Minsky, 1991). The most widespread AI implementations today the Artificial Neural Networks (ANN), belong under the connectionist category. Coakley and Brown (2000) provide a good discussion of ANN applications in accounting and finance; for more general introduction into ANN see (LeCun et al., 2015; Lippmann, 1987). ANN are incredibly efficient in reproducing the statistical frequencies of the learning examples – but they cannot do much more than that and face significant scalability problems (Mocanu et al., 2018).

In contrast, Symbolic AI (SAI) typically uses 'if… then' rules, they provide a knowledge representation in a specific narrow domain. Symbolic Reasoning Systems (SRS) are based on acquiring the steps of problem solving; they are rarely used today, but this approach produced the first working AI (Newell Simon, 1956, 1961; Simon Newell, 1958). Symbolic Expert Systems (SES) work on the basis of knowledge representations (Buchanan Shortliffe, 1984; Feigenbaum, 1992; Feigenbaum et al., 1988); typically they either rely on explicitly defined rules (deductive reasoning) or learn the rules from a limited number of cases utilising a symbolic machine learning algorithm; the two basic algorithms are the AQ (Clark Niblett, 1987) and the ID3 (Quinlan, 1986, 1993). ANN and SAI can be used in combination for solving the previously described problem according the following logic:

1. The deductive reasoning of SAI can be used to achieve transparency of the decision makers' reasoning. This will not by itself remove any biases, conflicts of interest, power plays or value collisions but will make them transparent for consideration.

2. ANN can be used, in conjunction with the inductive reasoning of SAI to narrow down the search space to the relevant cases. This is the hard part of the above-described problem; see more details below.

From the AI perspective the main research result will be to create this superior solution; currently we have a conceptual model but we do not have a working implementation yet. In figure 1, we detail our suggested approach. This data mines the outcome of prior legal cases to create training examples for a learning algorithm.

In making a provisioning decision of the sort we propose, the main problem is the size of the historic legal outcomes solution space and the questionable relevance of the particular cases. This means that there are many examples of cases that are somewhat similar, but figuring out which ones are relevant to the particular decision at hand requires a search process that is computationally unfeasible. This problem is normally addressed with using faster tools; this is achieved by simplified algorithms that can run faster and thus process larger amounts of data in the same time, and running software on faster hardware. This led to conceptualising what has become known as big data analytics. The biggest implementation issue of the proposed method is the ability to read different formats of report and accounts, tables, columns and rows.

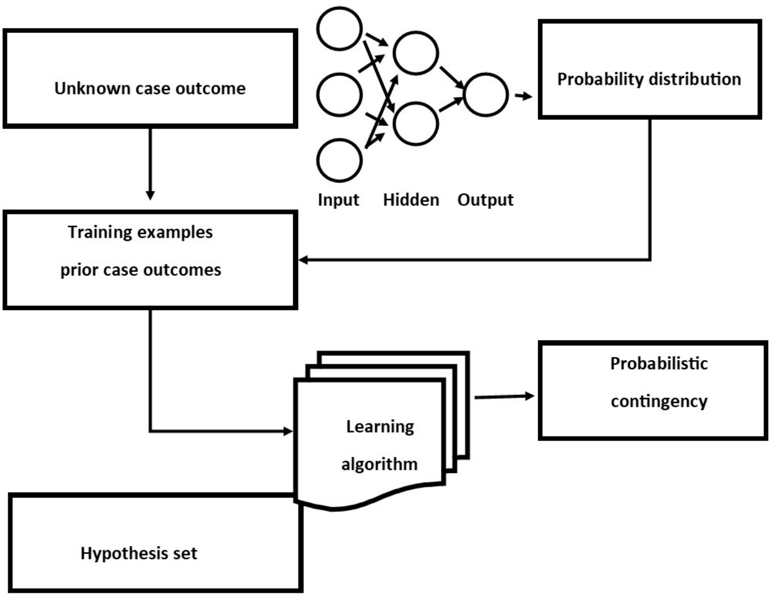
It is obvious that human experts could choose the relevant cases, particularly as at least some of the material is in free text format. However, human experts will not be able to process the available volume of cases, particularly not in a relatively short amount of time. Therefore, we suggest a solution, combining the ANN with the inductive reasoning of SAI will radically narrow down the solution space. In other words, to figure out a very small subset of cases that the auditors should have a look at. In order to achieve this we can use the data stored about the cases in the databases, and a combination of keywords that can be assigned to cases when they are created. Then for any new case we can set new keywords, and this can initiate the process of searching for relevant cases in the case base.

The significance of using this type of processing, as opposed to more conventional data analytics tools, is that the algorithm can find nonlinear patters in the case sets, while analytical tools typically focus on linear relationships. Once the nonlinear patterns are found, these can be further elaborated sophisticated statistical methods, typically omitted in data analytics, as they would be prohibitively time consuming if we were looking for nonlinear relationships generally. However, if focused on the patterns identified by SAI these more complex statistical tools can be very useful.

The proposed AI solution will be able to handle the routine cases, and therefore the focus of the human experts can shift towards more unique cases, which is where the strength of the human cognition lies. At the same time, more and more of the cases can be handled by machines, as cases are becoming routine. The reduction of the number of cases to be handles by human experts reduces the chance of error, at the same time having the most interesting cases to deal with helps increasing the attention. Therefore, both the time and the expertise of the human experts is put at better use, and their work is made more convenient by AI doing most of the processing. Of course, this may also lead to less of human work being needed at lower levels of expertise; but that problem is outwith the scope of this paper. Using AI will not lead to elimination of accountants or auditors, these can be used as opportunities for learning and improvement, potentially leaving space for career relationships to be developed within the discipline. Furthermore, the constructed knowledge bases can be used as learning tools for the newcomers. This is what we mean by smart people being supported by smart technology.

We believe the applications of AI in accounting will lead to productivity improvements. In situations where the financial statements are relied on to make decisions on these outcomes, such as in the provision and pricing of legal liability risk, an improved method of estimation will have commercial implications. It will also have implications for the accuracy of financial valuations based on audited accounts that incorporate IAS 37. Research into its use will also lead to similar investigations into other accounting areas such as the contentious IAS 39, The Recognition of Financial Instruments, which covers derivatives.

FIGURE 1 A stylised Artificial Neural Networks to determine legal probability distributions.



7 | CONCLUSION

In conclusion, AI can be used to evaluate outcomes of new legal cases on the basis of relevant historic legal cases and we propose that IAS 37 be adapted to facilitate this in its provisioning guidance. The aim is to use AI to identify financial outcomes more accurately than company management. Current assessment of such outcomes is based on the judgement of company management, which presents a conflict of interest. The use of potentially biased estimates compromises the “true and fair” nature of the accounts.

AI is likely to be used more frequently in audit. Such technology could result in more accurate outputs, freeing up accountants for cognitive and professional tasks. Our proposed use of AI shows how such technology can be used to make a more accurate estimate for provisions based on a large dataset of legal outcomes. We therefore recommend the use of AI to provision for likely legal liabilities.

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