The significance of claims fraud in microinsurance and a statistical method to channel limited fraud identification resources

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ABSTRACT
In the past decade, the topic of microinsurance has received much attention from researchers around the world as the drive to alleviate persistent global poverty intensifies. Although microinsurance is a powerful tool that can be used to assist in the fight against poverty by acting as a safety net for policyholders, the problem of claims fraud is a serious threat to its long-term sustainability. Analysis of the existing literature reveals a severe shortage of research into the problem of microinsurance claims fraud, even though we have found that it poses a greater threat in microinsurance than regular insurance. In this paper we highlight the problem of claims fraud in low-income markets and we explain how fraud makes microinsurance unsustainable. After establishing that action is needed to combat fraud in microinsurance we briefly present a number of fraud mitigation techniques that have been successful in conventional insurance. However, certain characteristics that differentiate microinsurance from regular insurance reveal that most of these fraud combating approaches are not appropriate to microinsurance; for example, the proportionately higher costs of identifying claims fraud relative to policy size, the lack of data and the lack of resources experienced by microinsurers render these methods impractical and unaffordable in the context of microinsurance. We proceed to demonstrate the workings of a statistical method known as Principle Component Analysis of RIDIT Scores (the PRIDIT method) which has been shown to effectively identify fraudulent claims without the need for a training sample. The method can thus be easily applied by microinsurers to assist in the detection of claims fraud. While the method of fraud detection that we propose in this paper is not without limitations, it may provide a pragmatic and cost-effective way for microinsurers
to begin tackling claims fraud. Furthermore, the method is clearly explained by means of a worked example to help microinsurers implement the method by themselves at low cost.

KEYWORDS
Microinsurance; fraud identification; practical; cost effective; PRIDIT; unsupervised

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1. INTRODUCTION
1.1 Against the backdrop of a difficult political past and the failure of the current government to successfully combat poverty, an overwhelming percentage of the South African population is poor. As of August 2009, approximately 52% of the South African population was living below the upper-bound poverty line, which is defined as R577 per month, in March 2005 figures (Lehohla, unpublished), approximately the equivalent of R942 in March 2014 terms. These vulnerable members of society battle to make ends meet on a daily basis, let alone have measures in place to cope with the risks that they face (Karla, 2010). Unexpected events such as the sudden death of a family breadwinner or damage to property can push these members of society further into poverty (ibid.).

1.2 Microinsurance products have the ability to provide protection to low-income households against such unexpected events, thus allowing them to focus their limited resources on escaping from poverty (Cohen, Mccord & Sebstad, 2005). Microinsurance is the term used to define insurance arrangements aimed at protecting low-income members of society against specific perils in exchange for premium payments, which are proportionate in size to the likelihood and cost of the risk involved (Churchill, 2007). Essentially, microinsurance is based on the same principles as regular insurance, however, the needs of the target market are significantly different (Biener & Eling, 2012). From the above definition, it is clear that microinsurance is extremely relevant to South Africa, as more than half of the South African population is classified as low-income. However, it is suggested that it is often the low-income segment of society that has the least access to insurance (Karla, op. cit.).

1.3 For microinsurance to be successful in combating poverty, it must be both economically viable for insurers to offer and affordable to the low-income market (Karla, op. cit.). In order for these conflicting objectives to be achieved, the costs associated with microinsurance need to be minimised (ibid.).
1.4 Fraud committed by policyholders increases the costs of providing insurance. Cohen, McCord & Sebstad (op. cit.) thus suggest that the sustainability of microinsurance is fully dependent on control systems that limit fraud, amongst other costs.

1.5 The International Association of Insurance Supervisors defines insurance fraud as an act or omission intended to gain a dishonest advantage for the fraudster or other related parties (Yusuf & Babalola, 2009). In the context of insurance, five categories of fraud are defined as follows (ibid.):

- **Internal fraud** Fraud committed against the insurer by an employee in his/her own capacity or in collusion with other parties that are either internal or external to the insurer;
- **Policyholder fraud** Fraud committed against the insurer by a policyholder in the purchase of an insurance product through the provision of false information or non-disclosure of relevant information;
- **Policyholder claims fraud** Fraud committed against the insurer by a policyholder in obtaining wrongful coverage or payment at claim stage;
- **Intermediary fraud** Fraud committed by intermediaries against the insurer or policyholders; and
- **Insurer fraud** Fraud committed by the insurer against the insured through policy churning or mis-selling.

1.6 The focus of this research was on policyholder claims fraud, specifically in the field of microinsurance. In the subsequent sections of this paper, we will use the word ‘fraud’ to refer exclusively to policyholder claims fraud. Policyholder claims fraud can manifest itself in a variety of ways, ranging from a complete fabrication of losses, to the exaggeration of loss amounts (Tennyson, 2008). In addition, fraud can be as a result of premeditation or opportunism on the part of the policyholder (ibid.). Premeditation refers to a situation in which a person seeks insurance with the primary intention of committing fraud, whereas with opportunism, committing fraud is not the primary purpose of seeking the insurance, but fraud is committed as an opportunity presents itself.

1.7 This research had four aims:

- first, to determine whether the problem of fraud is more significant in microinsurance than regular insurance;
- second, to investigate some of the approaches used by regular insurers to detect and deter fraud and to determine whether these approaches can be used in microinsurance;
- third, if these approaches were deemed to be unsuitable in a microinsurance context, to identify an alternative statistical approach that will assist in the detection of fraud; and
- fourth, to demonstrate the workings of the statistical approach if found.
Sections 2 and 3 which follow, deal with each of the first two aims in turn. In section 4 we explain in more detail a statistical method known as Principle Component Analysis of RIDIT Scores (PRIDIT) for fraud classification, which we identified in the literature and which appears to be a suitable statistical method for detecting fraud in microinsurance. In this section we have aimed to clearly lay out the steps so that microinsurance companies can follow these steps to implement the method themselves. We then proceed in sections 5 and 6 to apply the method to claims data from two microinsurance products sold in the South African market as an illustration of how the method may be applied in practice. This is followed by a discussion and conclusion in section 7 and finally, in section 8, we leave the reader with ideas for further research into this topic.

2. THE PROBLEM FRAUD POSES IN MICROINSURANCE

2.1 In this section we will start by discussing the business model that microinsurance companies follow, and then proceed to explain how fraud interferes with this model. We will then explain why fraud is such a significant problem in microinsurance and why it is also particularly challenging to combat it. We will then give an example of the consequences of fraud in the agricultural microinsurance industry, before briefly discussing an approach to combating fraud in microinsurance.

2.2 The Microinsurance Business Model

2.2.1 Why Scale is Essential to Microinsurers

2.2.1.1 For insurance providers to be willing to target the low-income segment of the market, there needs to be a sufficient profit motive. Key to creating this is achieving large enough business volumes (Churchill, op. cit.). Unit profits may be small in an attempt to make microinsurance affordable to the target market, but when multiplied across a large number of policies, the overall profit figure may be attractive (ibid.).

2.2.1.2 Large policy numbers are also desirable for insurers because as the size of the risk pool increases, the variance of the average claim amount decreases – a principle known as the Law of Large Numbers (ibid.). This translates into increased stability and predictability of future claims experience (ibid.).

2.2.1.3 The increased stability (or lower variability of results) has the potential to result in lower premiums and hence microinsurance being more affordable to the poor. The reduction in premiums is possible for two related reasons: first, the cost of capital is reduced as providers of the capital require a lower return; and second, less (risk-based) capital is required to guard against claims uncertainty. Both of these consequences result in smaller contingency/profit margins being required by the insurer and thus the ability to charge lower premiums without compromising their solvency position or profitability (ibid.).

2.2.1.4 A further reduction in premiums may be possible as the fixed expenses of the insurer are spread across more policies. This benefit applies only to fixed expenses because per-policy expenses are directly related to business volumes.
2.2.1.5 In theory, the increased affordability should once again lead to increased business volumes, more stable results and even more affordable premiums. A visual representation of this cycle is provided in Figure 1 below.

2.2.2 Keeping Costs Low

2.2.2.1 A condition to the above formula of scale resulting in profit is that the per policy expenses should be lower than the per policy income so that a profit is experienced on each policy. If each policy is loss-making, selling a larger number of policies will simply result in a larger loss to the insurer. Furthermore, fewer policies would be required for the business to be economically viable if the per policy profit was maximised by increasing premiums and/or reducing expenses.

2.2.2.2 However, transaction costs involved in getting microinsurance products to consumers are a major obstacle facing insurance providers (Churchill, op. cit.). These transaction costs include substantial expenses incurred in marketing to a client base that is perceived to have a low degree of insurance awareness, collecting premiums from policyholders that don’t have bank accounts and investigating claims (ibid.).

2.2.2.3 It can thus be seen that it is a challenge for microinsurance companies to keep costs low. This is the case even when fraud is not present. We will now explain how fraud makes it even more difficult to reduce premiums due its effect of increasing claims volatility and increasing claims costs.

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**Figure 1** Cycle of increasing volumes and decreasing premiums
2.3 How Fraud interferes with the Business Model

2.3.1 The first and most obvious way that fraud interferes with the microinsurance business model is that it increases the average cost of providing insurance because more claims are paid. Hence, there is a need for insurers to charge higher premiums to meet this increased cost (ibid.), which in turn hampers the cycle shown in Figure 1.

2.3.2 Furthermore, claims fraud reduces the stability and predictability of the claims experience because it distorts the random statistical process underlying the claims experience, making it more difficult to model claims. This is a result of the level of fraud being uncertain.

2.3.3 Modelling techniques could potentially be used to continue to price accurately in the presence of fraud if fraud was constant over time. However, fraud levels are usually not constant over time as they tend to fluctuate with the state of the economy (ibid.), making modelling more challenging.

2.3.4 This means that when fraud is present, the reductions, due to larger business volumes, in the cost of capital and associated risk margins guarding against claims volatility are not as large as they would be in the absence of fraud. These reductions are essentially offset by the increased volatility and cost caused by fraud.

2.3.5 The increased premiums that result from larger/more frequent claim pay-outs and increased risk margins due to the uncertain level of fraud lead to a reversal of the cycle shown in Figure 1.

2.4 An Example of the Consequences of Fraud in Microinsurance

2.4.1 Approximately half of the world’s poor population rely on agricultural activities as their primary source of income (Barnett & Mahul, 2007). For this reason, poor households are extremely susceptible to the financial consequences of weather related events (ibid.).

2.4.2 Barnett & Mahul (ibid.) explain that crop insurance allows poor households that depend on agricultural activities for their livelihoods to transfer the risks of weather-related events to insurers.

2.4.3 Barnett & Mahul (ibid.) are, however, quick to highlight that crop insurance markets in rural areas of many low- and middle-income countries are underdeveloped. One of the many reasons given for this underdevelopment is the problem of fraudulent behaviour, which they believe is prevalent in these markets (ibid.). The availability of insurance is reduced as the fraudulent behaviour increases the cost of offering insurance and jeopardises solvency of insurers (Hoyt, Mustard & Powell, 2006).

2.4.4 The consequence of fraud is clear. Not only does it make business less profitable for insurers, but it also stunts the development of microinsurance, thus reducing the ability of low-income earners to transfer risk. Minimising claims fraud will thus help overcome the challenges involved in providing insurance to the poor. The next question we will answer is that of why claims fraud is common in microinsurance.
2.5 Why is Fraud more common in Microinsurance relative to Regular Insurance?

Fraud is more common in microinsurance relative to regular insurance for four main reasons:
— policyholders are more accepting of fraud when premiums are financially onerous;
— a negative attitude towards insurers results in widespread acceptance of fraud;
— lack of education about the value of insurance increases fraud incidence; and
— compulsory/forced cover encourages policyholders to want their money’s worth.

These reasons are explored in further detail below.

2.5.1 Financially Onerous Premiums

2.5.1.1 Tennyson (1997) found that individuals who find paying insurance premiums financially onerous are likely to be more accepting of fraudulent behaviour than those who do not.

2.5.1.2 As microinsurance generally deals with low-income individuals, it is highly likely that the insurance premiums that they pay make up a significantly higher portion of their income compared to higher income individuals. For example, an individual earning R2000 per month will find an insurance premium of as low as R20 per month financially onerous. Churchill (op. cit.) confirms this presumption by stating that in many situations, low-income individuals view even the smallest of insurance premiums as unaffordable.

2.5.1.3 Relating this to Tennyson’s (op. cit.) findings, the low-income segment of society (those people to whom microinsurance products are generally sold) may be more accepting of fraudulent behaviour when it comes to insurance than the higher-income segments of society. This has the potential to result in relatively higher fraud levels compared to regular insurance markets.

2.5.2 Negative Attitude towards Insurers

2.5.2.1 Tennyson (op. cit.) also found that individuals who have a negative perception of insurance are more accepting of fraud than those who do not, thus resulting in them being more likely to commit fraud.

2.5.2.2 We will draw on this idea in the following paragraph and ¶2.6.2.4 below.

2.5.3 Lack of Education about Insurance

2.5.3.1 Churchill (op. cit.) identifies educating the target market about the value of microinsurance as a further obstacle to serving the low-income segment of society.

2.5.3.2 The problem mentioned in section 2.5.1 above of premiums being onerous is accentuated by policyholders not understanding that they are not guaranteed to receive a payment from the insurer every year. Policyholders may feel “cheated” if no claims are made. This creates a negative attitude towards insurers and according to...
Tennyson’s (op. cit.) finding discussed above in section 2.5.2 will cause policyholders to be more accepting of fraud.

2.5.3.3 The fact that the low-income market is synonymous with low levels of education makes the task of educating policyholders more difficult (Churchill, op. cit.). As such, convincing these members of society of the value in paying premiums for a benefit that may never be received is an unenviable task and failure to do so exacerbates the negative perception of the insurance industry referred to in §2.5.3.2 (ibid.).

2.5.4 Compulsory Cover

2.5.4.1 Tennyson (op. cit.) found that individuals who are compelled to take out insurance are more accepting of fraud than those who are not. The explanation given by Tennyson is that in such situations, individuals often feel that the insurance is unnecessary. As a result they are more likely to commit fraud in order to justify paying the insurance premiums (ibid.).

2.5.4.2 This finding is relevant and perhaps more significant to the field of microinsurance than regular insurance as Churchill (op. cit.) highlights that microinsurance products are most commonly distributed through microfinance institutions. Many of these institutions require the borrower to have an insurance contract in place that will settle the debt if an insured event takes place (ibid.). For this reason, situations in which insurance cover is made compulsory are likely to be more prevalent in microinsurance than in regular insurance (ibid.).

2.5.4.3 Note that compulsion in this context does not refer exclusively to compulsion by law, but also to any transaction where insurance is required but it is not the primary purpose of the transaction; for example, where property insurance is required to back goods purchased on credit.

2.6 Why is combating Fraud particularly difficult in Microinsurance?

We have seen why fraud is more common in microinsurance than regular insurance. Logically, this would call for more thorough fraud combating approaches. However, combating fraud in microinsurance is particularly difficult for the following reasons:

— it is costly to verify claims;
— repudiating claims may lead to a lack of trust in the insurance industry, resulting in a ‘fraud spiral’; and
— inadequate justice systems.

The above reasons are explored in further detail below.

2.6.1 Costly to assess Claims resulting in an Environment conducive to Fraud

2.6.1.1 As we saw in Section 2.2.2 it is essential for microinsurers to minimise costs. In order to achieve this, microinsurance institutions often have minimal claims
verification systems and processes in place, thus producing an environment conducive
to claims fraud (Yusuf & Babalola, op. cit.).

2.6.1.2 Furthermore, the benefit of identifying fraudulent claims may be outweighed by the small sums insured in microinsurance relative to the sums insured in regular insurance (Churchill, op. cit.). All else being equal, a fraud identification strategy adopted by a microinsurer would need to identify a larger number of fraudulent claims for the benefit to outweigh the cost compared to the same strategy adopted by a regular insurer (Biener & Eling, op. cit.).

2.6.2 Repudiating Claims may result in Lower Levels of Trust in the Insurance Industry

2.6.2.1 It is suggested by Churchill (op. cit.) that in order to gain the trust of the low-income target market, insurers should go to great lengths to avoid repudiating claims.

2.6.2.2 Particularly when policyholders lack understanding of insurance, they may not distinguish between claims correctly repudiated to protect the risk pool (such as fraudulent claims) and valid claims being incorrectly repudiated. Instead, they may view all claims that are repudiated as being incorrectly repudiated. Thus, insurers who repudiate claims risk losing the fragile trust of this market.

2.6.2.3 So even if the insurer is able to identify fraud, it must be careful about whether or not it repudiates claims and the manner in which it does so. Adopting an aggressive approach to combating fraud may lead to an increased proportion of claims being repudiated, thus exacerbating the low-income market’s negative perception of insurance and making the challenge of gaining acceptance by the poor even more difficult.

2.6.2.4 A ‘fraud spiral’ begins as policyholders’ perceptions of the insurer continue to get worse as claims are repudiated, resulting in an increased likelihood of fraudulent claims. We will henceforth refer to this spiral as ‘The Insurance Fraud Spiral’. The Insurance Fraud Spiral refers to a situation in which individuals, having a negative attitude towards insurance (see Section 2.5.2), are found to be more accepting of fraudulent behaviour. In an environment conducive to fraud (see Section 2.6.1), this is likely to result in higher levels of fraud. In response to higher levels of fraud, more and more claims are repudiated by insurers, which could further fuel negative perceptions of insurance and reduce trust in insurers (see 2.6.2.2). This in turn leads to an increasing tolerance of fraud. This cycle can be viewed in Figure 2.

2.6.2.5 The Insurance Fraud Spiral has an additional implication for microinsurers that relates to the microinsurance business model explained in section 2.2 above. Insurance companies that aggressively combat fraud are exposed to the risk of potential clients being less willing to purchase insurance. Thus, it becomes more difficult for microinsurers to achieve the business volumes necessary for economies of scale and reductions in the cost of capital and associated risk margins to prevail. The Insurance Fraud Spiral contributes to the reversal of the cycle depicted in Figure 1 above.
2.6.2.6 Furthermore, Churchill (op. cit.) suggests that the target market of microinsurance is perceived to be sceptical about insurance to a greater extent than the target market of regular insurance. The low-income segment of the market is synonymous with low levels of education and hence the understanding of insurance by its members is modest compared to higher income individuals (ibid.). It can thus be argued that the Insurance Fraud Spiral described above is more pertinent to microinsurance than regular insurance.

2.6.3 **Inadequate Justice Systems**

2.6.3.1 Roth (2001) states that funeral insurance is extremely common in South Africa especially amongst low-income earners. The Association of Savings and Investment South Africa (ASISA) states that the total value of known fraudulent funeral insurance claims amounts to an estimated R131,7 million for 2011 alone (IFAnet, unpublished). This is approximately 3.2% of the written premium for the South African funeral insurance industry in 2011 (ibid.). It is suggested that the known cases of fraud are just the tip of the iceberg and that the total cost of fraud could be as high as 12% of the written premium (ibid.).

2.6.3.2 Between September 2010 and April 2013, Censeo, a company that provides investigative resources to some of the biggest insurance companies in South Africa, prevented the pay-out of R55 million in fraudulent funeral insurance claims alone (Barry, unpublished).

2.6.3.3 Len Coetzee, founder of Censeo, claims that less than 3% of the fraudulent claims reported to authorities in South Africa secure convictions (ibid.).
Coetzee further suggests that in the case of a conviction, the sentences passed against such crimes do not act as a deterrent to claims fraud as Censeo has not seen any reduction in the proportion of claims it identifies as fraudulent over time (ibid.).

2.6.3.4 This suggests that the limitations of the South African justice system with regard to economic crimes are a significant factor contributing to the problem of fraud in microinsurance (ibid.).

2.7 Steps in combating Fraud in Microinsurance

2.7.1 The Insurance Fraud Spiral explained above shows how challenging it is to combat fraud in microinsurance. But that does not mean that fraud should simply be accepted, because we have seen how allowing the problem of fraud to fester can interfere with the microinsurance business model and contribute to microinsurance being unavailable for insurers.

2.7.2 If insurers continue to naively pay fraudulent claims, the problem will likely only get worse as fraudulent behaviour becomes widely accepted in lower-income markets and increasing numbers of perpetrators repeatedly commit fraud.

2.7.3 Thus, the question is not whether fraud combating should be done, but how it should be done in a way that overcomes the abovementioned problems of high cost of claims assessment, policyholders’ acceptance of fraudulent behaviour and lack of trust in the insurance industry.

2.7.4 We have chosen to focus this paper on the task of identifying fraudulent claims because we believe this to be the starting point before any action can be taken against fraudsters. We recognise that even if fraudulent claims can be easily identified, it is a tricky task to repudiate claims in a manner that enhances the reputation of the insurer; a task that will involve educating all policyholders about the benefit of repudiating fraudulent claims. We also recognise that the identification and subsequent repudiation of fraudulent claims and other actions against fraudsters is not all that is involved in fraud combating. For example, educating policyholders about the value of insurance (even when no claims are paid) is another approach that will likely contribute to a higher perceived value of insurance and reduced fraud. However, these topics are beyond the scope of this paper.

2.8 The evidence presented above, which has been extracted from the existing literature relevant to the topic of insurance fraud, indicates that there is no hard-and-fast way of addressing the problem of claims fraud. The characteristics of microinsurance that distinguish it from regular insurance in fact exacerbate the problem of fraud. The Insurance Fraud Spiral suggests that any attempt to combat claims fraud in microinsurance needs to be exercised with caution as failure to do so could seriously threaten the long-term sustainability of microinsurance.

2.9 In the next section we present an overview of techniques that have been used to reduce fraud in conventional insurance. As we will see, many of these techniques
are either not possible or practical to implement in microinsurance. Once we have established this, in section 4 we present a statistical method for fraud identification known as PRIDIT that overcomes many of the problems involved in applying traditional fraud identification methods in microinsurance.

3. INVESTIGATING SOME OF THE METHODS CURRENTLY IN USE TO DETECT AND DETER CLAIMS FRAUD AND DETERMINING WHETHER THESE METHODS CAN BE USED IN MICROINSURANCE

3.1 Existing literature on the topic of insurance fraud reveals that past approaches used to address the problem of claims fraud can roughly be divided into two categories. The first category referred to as ‘ex-ante approaches’ involves preventing fraud from happening, the second category referred to as ‘ex-post approaches’ involves the detection of fraud once committed. These categories will be discussed in sections 3.2 and 3.3 respectively.

3.2 Ex-ante Approaches – Prevent Fraud from Happening

3.2.1 Ex-ante approaches refer to any fraud combating approaches that are aimed at preventing fraud from taking place in the first place. Three of these approaches will be discussed below, namely weather-index crop insurance, contract design features and consumer education.

3.2.2 Weather-index Crop Insurance

3.2.2.1 Barnett & Mahul (op. cit.) define weather-index crop insurance as insurance that pays indemnities not based on actual losses sustained by crop farmers, but rather on realisations of a weather-index, measured at a specific weather station in a given location, that is highly correlated with the actual losses sustained.

3.2.2.2 It is suggested by Barnett & Mahul (op. cit.) that weather-index crop insurance goes a long way in protecting poor rural households from the financial consequences of weather-related risk events. As such, weather-index crop insurance for small-scale farmers satisfies the definition of microinsurance (ibid.).

3.2.2.3 Weather-index crop insurance is an innovative way of providing insurance to the poor and although it has many other advantages, which are not highlighted here, it has proven to be a successful approach in combating fraud in crop insurance (Skees, 2008). As Turvey (unpublished) explains, the policyholder is unable to manipulate the amount of a claim or falsify a claim as the payout from weather-index insurance is independent of the policyholder’s actions (Barnett & Mahul, op. cit.).

3.2.2.4 Perhaps the only scope for fraud in the context of weather-index crop insurance is the possibility of the equipment used to measure the relevant weather metrics being tampered with (ibid.). This scope for fraud is larger in lower- and middle-income countries as often the weather stations in these regions are not well secured (ibid.).
3.2.3 **Contract Design Features**

3.2.3.1 The purpose of indemnity type insurance contracts is to restore the policyholder to the same financial position as before the insured risk event took place.

3.2.3.2 Yusuf & Babalola (op. cit.) suggest that the introduction of limits on indemnity type insurance contracts could act as fraud deterrence both in the case of exaggerating loss amounts and staged claim event. In the latter case, it is hypothesised by Yusuf & Babalola (ibid.) that in the presence of limits on indemnity pay-outs, the insured would be afraid to stage a claim event in fear that the resulting loss would be greater than the limit. In the former case, any legitimate claim event that has resulted in a financial loss at or slightly below the limit would not present an opportunity for the insured to inflate the actual amount of the loss (ibid.).

3.2.3.3 The danger with this contract design feature is that it is likely to result in microinsurance products providing inadequate coverage and hence being less successful in meeting the needs of the target market, resulting in a loss of trust in insurers (Karla, op. cit.).

3.2.3.4 Moreno, Vázquez & Watt (2006) suggest that if an insured’s future premiums are increased each time they make a claim then they will be less willing to file fraudulent claims. This type of insurance contract is referred to as a bonus-malus contract (ibid.). This contract design feature is however only relevant to insurance contracts where multiple claims are possible (ibid.). As a large portion of microinsurance products are for single claim events, for example funeral and micro-life products, this contract design feature is unlikely to be as effective in combating fraud in microinsurance as it is in regular insurance (Biener & Eling, op. cit.).

3.2.3.5 In addition, increasing future insurance premiums when dealing with the low-income segment of the market is inappropriate. In section 1.3 above, it was highlighted that one of the requirements for microinsurance to be sustainable is that it made affordable to its target market; hence the introduction of bonus-malus systems in microinsurance is inappropriate if affordability is already a major concern (Karla, op. cit.). An alternative approach would be to grant a premium discount to a policyholder if no claims are made. However, this would mean that the initial premium, before discounts, would be less affordable.

3.2.3.6 Cash-back rewards programmes have traditionally been used by insurers to promote good behaviour and create incentives for policyholders to not claim (Yusuf & Babalola, op. cit.). Such an arrangement provides the policyholder with a reimbursement after a specified period of time over which the policyholder has not submitted a claim (ibid.). Although this contract feature was not originally or solely designed to deter claims fraud, fraud deterrence has proven to be a favourable consequence (Marzen, unpublished).

3.2.3.7 In section 2.5.4, it was highlighted that individuals who are compelled to take out insurance are more likely to be tolerant of claims fraud as they often feel that the insurance is unnecessary (Tennyson, op. cit.). In such situations cash-back reward programmes may prove to be even more successful in deterring fraud as policyholders
no longer feel that they have to make a claim in order to justify the existence of the insurance.

3.2.3.8 The danger with introducing cash-back rewards programmes is once again premium affordability as these programmes are ultimately funded via increased premiums. However, there is the potential for the benefit of the reduction in fraud to offset the increased costs of providing cashbacks.

3.2.4 Consumer Education

3.2.4.1 Yusuf & Babalola (op. cit.) state that the majority of insurance providers, particularly in low- and middle-income countries, have done an extremely poor job of educating consumers about the menace of insurance fraud. As a result, most consumers are not aware of the savings that could be made if claims fraud was minimised within insurance markets (ibid.).

3.2.4.2 The lack of consumer education by insurance providers is even more problematic when the number of claims being repudiated increases due to an aggressive fraud combating approach. This was discussed in section 2.6.2. It is thus advisable for insurance providers, especially in the field of microinsurance, to combine fraud combating methods with consumer awareness programmes so as not to instil a negative perception of insurance in the members of the target market.

3.2.4.3 It is suggested by Yusuf & Babalola (op. cit.) that claims fraud education programmes will do a great deal to deter fraud, especially in the field of microinsurance. If the benefits of minimising claims fraud are effectively communicated to consumers, then it is rational to believe that individuals will be less inclined to commit fraud (ibid.).

3.2.4.4 The problem with this suggestion is that the benefit of reduced fraud is for the group of policyholders as a whole and not individual policyholders committing the fraudulent actions. Those who commit fraud and get away with it will benefit more than what they would from reduced premiums, at the expense of other policyholders. Thus, consumer education on the benefits of reducing fraud may not be as effective as hoped.

3.3 Ex-post Approaches – Detect Fraudulent Claims

3.3.1 Ex-post approaches refer to any fraud combating approaches that are aimed at detecting fraud once it has taken place. Claims verification processes, data mining techniques and statistical methods will be discussed below.

3.3.2 Claims Verification Processes

3.3.2.1 Tennyson & Salsas-Forn (2002) suggest that in the presence of exaggerated loss amounts and fictitious claims, active verification through claims investigation and auditing is an important claims management tool to detect fraud. This management tool is however costly and often insurers are forced to devise methods of rationing limited investigative resources across different claims (ibid.). Usually claims for larger amounts and those that exhibit greater potential for opportunism are allocated a greater portion of a firm’s investigative resources (ibid.). In many cases, efficient
claims verification systems have proven to be highly successful in detecting fraudulent claims (Brockett et al., 2002).

3.3.2.2 In the context of microinsurance, adequate claims verification processes are often not possible because of the associated costs involved as mentioned in Section 2.6.1. In practice, claims verification processes in microinsurance are usually limited to questions surrounding the details of the claim (Cohen, Mccord & Sebstad, op. cit.). Even then, Tennyson & Salsas-Forn (op. cit.) suggest that any questions asked are actually for record-keeping purposes only and not to assess the validity of a claim.

3.3.2.3 Although we have classified claims verification processes under ex-post approaches, Tennyson & Salsas-Forn (op. cit.) argue that the presence of a claims verification process acts as a deterrent to fraud. This argument is based on the belief that if policyholders are aware of the existence of a claims verification process, then they are less likely to file fraudulent claims out of fear of being caught out (Tennyson & Salsas-Forn, op. cit.).

3.3.2.4 However, as a counter to this argument, if claims verification is ineffective, it is likely that fraudsters will realise this and the presence of a claims verification process will quickly lose its effect as a fraud deterrent.

3.3.3 Data Mining Techniques

3.3.3.1 Data mining is defined as the discovery of interesting, unexpected or useful patterns within large datasets (Hand, 2007). Marzen (op. cit.) states that many insurers make use of data mining techniques to identify useful patterns in insurance claims data. Marzen suggests that this is a useful technique to assist in the allocation of investigative resources (ibid.).

3.3.3.2 Hand (op. cit.) however is quick to point out that data mining is a specialised statistical field that requires expensive human and computing resources on an ongoing basis. This characteristic of data mining detracts from its usefulness in microinsurance because it is at odds with making microinsurance affordable as these expenses are ultimately borne by consumers (Brockett et al., op. cit.). However, the PRIDIT method which we present in the next section of this paper is a data mining technique that is simple to implement and requires relatively little expertise.

3.3.3.3 Marzen (op. cit.) documents the case of the Risk Management Agency (RMA) using data mining techniques in an innovative way to combat crop insurance claims fraud. If any single policyholder’s claims exhibited abnormal characteristics compared to all other claims over a given period and within a given location, then the policyholder’s farm was inspected. This approach is believed to have resulted in an estimated $838 million saving, between 2001 and 2010, due to fraudulent behaviour being deterred and detected (ibid.).

3.3.3.4 Simplified data mining techniques that are cost effective and not time consuming to undertake could be coupled with similar approaches taken by the RMA to combat fraud in various other types of microinsurance markets (ibid.). This is indeed what the PRIDIT method of fraud identification does as we will see in the next section.
3.3.4 **Statistical Methods**

3.3.4.1 Artis, Ayuso & Guillén (2002) testify to the success of discrete choice models with misclassification error in detecting fraudulent claims from automobile insurance claims data.

3.3.4.2 Essentially, discrete choice models are generalised linear regression models with a dichotomous response variable (ibid.). In this case, the response variable would be defined as the presence or absence of fraud for a given claim (ibid.). Misclassification error within this technique allows for claims that have not been identified as fraudulent, but in reality are in fact fraudulent (ibid.).

3.3.4.3 One crucial requirement for this statistical method is the existence of a training sample, which is a collection of past claims data for which the response variable is known i.e. for each claim in the sample it is known whether the claim was fraudulent or not (ibid.). These details are established through a claims verification process (ibid.).

3.3.4.4 In essence, the model works by comparing the characteristics of future incoming claims with the characteristics of past claims that have been identified as fraudulent. Any new claims exhibiting similar characteristics to past claims which were identified as fraudulent would be assigned a high probability of being fraudulent.

3.3.4.5 Investigative resources can then be used more efficiently by prioritising the investigation of claims with a high probability of being fraudulent (ibid.). Such methods are also known as supervised methods as they are informed by past data.

3.3.4.6 The crucial requirement of a training sample mentioned above is a major obstacle to the success of such models in detecting claims fraud in microinsurance. It has already been mentioned several times in this paper that claims verification processes in microinsurance are minimal and hence the existence of a training sample enabling the estimation of the parameters of discrete choice models is unlikely. This issue was in fact borne out in the claims data used in sections 5 and 6 of this paper. Less than 0.01 % of the claims had been identified as fraudulent in the past.

3.3.4.7 Brockett et al. (op. cit.) state that when a training sample is unavailable (i.e. when it is not possible to ascertain whether past claims are fraudulent or not) or when the cost associated with establishing a training sample is prohibitive, then traditional fraud identification techniques are not possible to implement. This is certainly the case in microinsurance.

3.4 **Summary**

We have shown that a number of approaches have been used to combat fraud in insurance. Some may prove useful in microinsurance, such as innovative contract design features and consumer education to prevent fraud. However, the challenge of identifying fraud remains a problem due to the prohibitive cost of the abovementioned identification methods including data mining and training sample based regression methods.
3.5 Centralisation of Fraud Investigations

3.5.1 Boyer (2000) makes the case for the centralisation of fraud investigations within countries. It is suggested that industry-wide fraud investigation units should be set up to allow for collaborative data collection and analysis efforts (ibid.). Boyer (op. cit.) suggests that such an approach will allow for economies of scale to reduce the costs of fraud detection across the insurance industry as a whole.

3.5.2 Yusuf & Babalola (op. cit.) support this suggestion and believe that it will be especially successful in the case of microinsurance as the establishment of a single insurance fraud combating institution within a country will allow smaller insurers, who currently have insufficient resources to directly address the issue of claims fraud, an opportunity to do so.

3.5.3 The South African Insurance Crime Bureau (SAICB) was established in 2008 with the primary objective of combating organised crime in the short-term insurance industry (SAICB, unpublished). Although the SAICB allows for the pooling of resources to combat organised crime committed by syndicates, it does not provide support against opportunistic fraud by policyholders (ibid.). The PRIDIT method presented in the next section does however address opportunistic fraud.

3.6 Churchill (op. cit.) suggests that insurers need to recognise that viewing microinsurance products as existing insurance products with smaller sums insured is not sufficient. Instead, microinsurance requires new approaches that are different from regular insurance (ibid.). It is now clear that this suggestion by Churchill (op. cit.) can be extended to include the approaches that have historically been used to identify fraudulent claims in traditional insurance. New approaches to identifying fraudulent claims in microinsurance need to be developed as very few of the existing methods are practical/affordable.

3.7 In the following section we introduce such a method of fraud identification. The method is known as Principle Component Analysis of RIDIT Scores for fraud classification, developed by Brockett et al. in 2002 in an attempt to identify fraudulent claims when no training sample is present.

3.8 This is ideal for microinsurers because, as we have noted, a training sample is costly to attain due to the costs of claims assessment, and not having a training sample renders many of the statistical methods of fraud identification impossible.

3.9 In the following section we will introduce the theoretical framework of the method, at the same time as presenting a simplified worked example. We will then present an application of the method to data obtained from a South African insurance company in the subsequent sections. It is our intention that these worked examples can be used by microinsurance companies to implement the PRIDIT fraud identification method themselves at low cost.
4. **THE PRIDIT METHOD FOR FRAUD CLASSIFICATION – THEORETICAL FRAMEWORK AND WORKED EXAMPLE**

4.1 Introduction to the PRIDIT Method

4.1.1 Brockett et al. first presented the PRIDIT method for fraud classification in 2002. An overview of this technique will be given in this paper. For full details of the theory underlying the method we refer the reader to Brockett et al. (2002) and Ai et al., (2009).

4.1.2 The PRIDIT method is based on a method known as RIDIT introduced by Bross in 1958 (although Bross used the method in his own work for several years prior to publishing it). The RIDIT method was developed by Bross to assist researchers in scientific studies in biological and behavioural sciences when dealing with what he referred to as “borderland” variables, which included categorical variables where the response was on a subjective scale such as “‘minor’, ‘moderate’, ‘severe’”. Brockett et al. (2002) slightly adjusted the calculation of the RIDIT score and then further applied an iterative weight refining method to place more importance on variables that better explain the variability in claims data. Ai et al. (op. cit.) then extended the method to allow for the inclusion of continuous fraud predictor variables in addition to categorical variables.

4.1.3 The PRIDIT method is intended to rank each claim in a claim file (say all claims in the last week) in decreasing order of fraud suspicion (Brockett et al., 2002). This enables insurers to allocate limited claims assessment resources to the claims which have the highest fraud suspicion, resulting in a more efficient use of limited investigation resources (ibid.). A further advantage of this method suggested by Brockett et al. (2002) is that insurers can pay claims with low fraud suspicion without delay. This may help microinsurance companies build trust, which is necessary to increase business volumes and reduce fraud (see Sections 2.2 and 2.6).

4.1.4 The biggest advantage of this method is that it does not require a training sample (ibid.). It is for this reason that we suggest that this method of claims fraud detection is suitable for use in microinsurance because microinsurance companies are unlikely to have the resources to build up a training sample. That being said, this method may improve the ability of microinsurance companies to develop a training sample.

4.1.5 Brockett et al. (op. cit.) and Ai et al. (op. cit.) conducted a number of tests on past claim data sets where it was known whether claims were fraudulent or not. The performance of the PRIDIT method was very satisfactory in identifying fraudulent claims in absolute terms and when compared to the fraud identification ability of other statistical methods parameterised using past data. For details of these tests we refer the reader to these papers. We also explain the tests briefly in section 4.8.

4.1.6 We argue that the practicability of the method in the microinsurance context and its demonstrated usefulness on at least one insurance claims dataset give enough motivation to suggest that the method be implemented by microinsurers as a step in identifying fraudulent claims; particularly by microinsurance companies
who currently do not have any fraud identification strategy in place. In the remainder of Section 4 we explain the method by using hypothetical examples and imaginary variables. In the Sections 5 and 6, we then present an application of the method to a real life dataset.

4.2 Calculation of RIDIT Scores

4.2.1 Let us assume that we have a “borderland” variable with the categories “low”, “medium” and “high” in increasing order of intensity i.e. not just a random ordering of categories. While the categories are in increasing order of intensity, the exact interpretation of each of the categories is open to interpretation. In the context of claims fraud identification, this variable, which we will call Variable 1, might be a variable stating “how suspicious a policyholder sounded” when the claim was submitted for example – a value subjectively given by the claims capturer. Note that this variable is unrealistic and is for illustration purposes only. We will suggest a few more realistic potential fraud identification variables when we conduct the PRIDIT analysis on a real life dataset in Section 5, but for now we will use this example to demonstrate the calculation of a RIDIT score.

4.2.2 A RIDIT transformation provides a way to assign a numerical value to each of our subjective categories (Bross, 1958). Each categorical response, previously described by a name (low, medium, high) is transformed into a number between −1 and 1. This number is referred to as the RIDIT score. The transformation to a numerical value is useful because it allows for more rigorous analysis and manipulation of the responses (ibid.).

4.2.3 The formula for the RIDIT transformation used in the PRIDIT method for category \( i \) on a certain variable is:

\[
B_i = \sum_{j<i} p_j - \sum_{j>i} p_j,
\]

where \( p_j \) is the percentage of claims in our claim file exhibiting category \( j \) on that variable. The RIDIT score for category \( i \) is thus the percentage of claims in a lower category than category \( i \) on the variable minus the percentage of claims in a higher category than category \( i \) on the variable. The formula results in a value in the range \([-1,1]\). Bross’ (op. cit.) original RIDIT transformation method actually transformed variables into the range \([0,1]\), where a value close to 0 for category \( i \) indicated that category \( i \) was least extreme and a value close to 1 was most extreme, but Brockett et al. (op. cit.) adjusted the method slightly so that the transformation was to the range \([-1,1]\) which has the desirable characteristic of having a midpoint of zero.

4.2.4 Before we interpret this RIDIT formula, we will present a simple example to help the reader gain some insight into how exactly the transformation works. We will adjust the numbers in the example as we proceed to aid in our explanation of how to interpret the resulting RIDIT scores.
4.3 Example and Interpretation of RIDIT Scores

4.3.1 In this example we will use the same Variable 1 introduced in §4.2.1. Now imagine a claim file containing 100 claims is submitted for analysis. Closer inspection of the claims file reveals that the percentage of claims in each of the low, medium, and high categories on our variable is 60%, 30% and 10% respectively. If we assign integer value subscripts to identify the categories (“low” = 1, “medium” = 2, “high” = 3), then \( p_1 = 0.6, p_2 = 0.3 \) and \( p_3 = 0.1 \).

4.3.2 We now calculate a RIDIT score for each category using the percentages of claims falling into each category (the \( p \)'s) as follows: \( B_1 = 0 - 0.4 = -0.4 \), \( B_2 = 0.6 - 0.1 = 0.5 \) and \( B_3 = 0.9 - 0 = 0.9 \). This is a direct application of the formula given in §4.2.3.

4.3.3 It is important to note that the RIDIT score for category \( j \) will never be greater than the RIDIT score for category \( i \) if \( j > i \). In other words, the ordering of categories is maintained through the transformation. This is desirable because it allows the user to use subjectivity in deciding on the ordering of the categories i.e. to specify which categories are more severe.

4.3.4 Before we interpret the above RIDIT scores, it will be helpful to consider the scenarios in which we will obtain scores of 0, 1 and –1.

4.3.4.1 Score of 0 If the percentage of responses that fall into categories below category \( i \) is the same as the percentage of responses that fall into categories above category \( i \) then the RIDIT score for category \( i \) will be zero. In other words the category lies in the middle of all categories and since the categories are in order of severity, to be in the middle of all of the categories is the same as saying that the category lies exactly between the extreme values/categories of the variable in question.

4.3.4.2 Scores of 1 If the percentage of responses below category \( i \) is greater than the percentage of responses above category \( i \), then the RIDIT value will be closer to 1 indicating a more severe response on the variable. The extreme of 1 will occur when calculating the RIDIT score for the most severe category (“high” in our example) where all responses are in categories below the most severe category i.e. if no claims exhibit “high” for Variable 1.

4.3.4.3 Scores of –1 Similarly, if the percentage of responses above category \( i \) is greater than the percentage of responses below category \( i \), then the RIDIT value will be closer to –1, indicating a less severe response. The extreme of –1 will occur when calculating the RIDIT score for the least severe category (“low” in this case) where all responses are in categories above the least severe category. Let us now interpret the RIDIT scores in our example.

4.3.5 In our example, the RIDIT score on the “middle” category (which is “medium”) is higher than 0 and it is closer to the RIDIT score for category “high” than it is to the RIDIT score for category “low”. This indicates that it is closer to “high” than it is to “low” on the severity scale of Variable 1.

4.3.6 If the percentages in category “low” and “high” were similar, say 40% and 30% respectively, with the percentage in the “medium” category remaining unchanged, the RIDIT scores would become: \( B_1 = 0 - 0.6 = -0.6 \), \( B_2 = 0.4 - 0.3 = 0.1 \), \( B_3 = 0.7 - 0 = 0.7 \).
We can see how transferring some of the mass from the lowest category to the highest category resulted in a more even distribution of scores, with the score for the “medium” category being closer to 0, exactly between the two extremes of –1 and 1.

4.3.7 Now let’s consider what would happen if a lower percentage of claims exhibited the extreme characteristics on our variable i.e. “low” or “high”. If the percentage of claims in each of low, medium, and high categories on our variables were 5%, 60%, 35% respectively, instead of 60%, 30%, 10% as before, our RIDIT scores for each category would be: $B_1 = 0 - 0.95 = -0.95$, $B_2 = 0.05 - 0.35 = -0.3$, $B_3 = 0.65 - 0 = 0.65$. Here we can see that our “low” category has a score which is closer to the low extreme on our severity interval of $[–1, 1]$. Similarly, if the percentage of claims in the “high” category was 5%, then the RIDIT score for the “high” category would be 0.95, which is close to the high extreme on our severity interval of $[–1, 1]$.

4.3.8 **Influences on RIDIT Scores**

We can see from these simple alterations to our example that the RIDIT score for a given category is influenced by two things: 1) the user-defined ordering of the categories and 2) the percentage of claims falling into each category.

— **User-defined ordering of the categories** As mentioned previously, a category can never have a higher score than a category which is deemed to be less severe according to the user-input.

— **The percentage of claims falling into each category** A smaller percentage of claims in a particular category will result in the score for the category being similar to the scores in adjacent categories. Also, the smaller the percentage of claims in the extreme categories, the closer the RIDIT scores of the extreme categories (lowest and highest) will be to –1 and 1 respectively.

4.4 **Applying RIDIT Scores to more than One Variable**

4.4.1 This transformation resulting in RIDIT scores for each category can be applied to all variables with more than one category and the interpretation remains the same. For example, on a variable with 10 categories, categories with RIDIT scores close to zero are categories that have severity in the middle of the extremes (whatever the extremes may be for that variable), while categories that have severity closer to –1 and 1, have severity closer to the extreme low and high limits respectively for the variable in question (where the limits may be different for each variable depending on what the variable is measuring).

4.4.2 This comes in handy particularly when trying to compare variables with different numbers of categories. For example, it would be difficult, if not impossible, to compare a response of 5 on a variable with categories 1 to 5 (call this Variable 2), with a response of “medium” on Variable 1 with categories “low”, “medium”, “high”. But if we knew that the proportion of claims falling into categories 1 to 5 on Variable 2 were equal to say 5%, 15%, 15%, 25% and 40% respectively, we would calculate the RIDIT score for category 5 as $B_5 = 0.6 - 0 = 0.6$ and see that it is close to the RIDIT score of 0.5
for category “medium” on Variable 1, which means that they are actually quite similar in severity on each of their variables’ scales, even though 5 is the most severe category on Variable 2 and “medium” is not the most severe category on Variable 1. We might also compare the RIDIT score of 0.6 for category 5 of Variable 2 with the RIDIT score of 0.9 for the “high” category of Variable 1 and deduce that the extreme category on Variable 1 is more extreme on the Variable 1 severity scale than category 5 is extreme on the Variable 2 severity scale.

4.4.3 When computing RIDIT scores on each category for more than one variable, we need to adjust the formula to specify which variable \( t \) the score applies to. The formula becomes (Brockett et al., 2002):

\[
B_{t_i} = \sum_{j<i} p_{t_j} - \sum_{j>i} p_{t_j},
\]

where \( i \) is a particular category on variable \( t \) and the number of variables is greater than 1.

4.5 Combining RIDIT Scores to get a Total Score for Each Claim

4.5.1 Now that we have the RIDIT score for each category on each variable, we need some way of ranking claims in order of least extreme to most extreme, by taking into account how extreme each claim is with respect to each variable. A claim will be deemed to be more extreme if it exhibits characteristics which are extreme on a number of the variables in our model. We will clarify exactly what we mean by “extreme” in the next few paragraphs.

4.5.2 The simplest way to get an overall score of how extreme a particular claim is, is to sum across all variables the RIDIT score of the category which the claim falls into on each variable. For example, a claim that exhibited a “medium” for Variable 1 and category 4 for Variable 2 will have a combined “extremeness score” equal to 0.5 + (–0.5) = 0, suggesting that this particular claim is not very extreme in either direction, low or high.

4.5.3 One potential pitfall arises when summing RIDIT scores across variables in this manner. In our analysis, we are not just interested in whether claims are extreme in a low or high direction, but specifically in a fraudulent direction. If one variable was specified such that the highest category was most indicative of fraud, as with our Variable 1, while another variable was classified in the opposite order – say a 1 on Variable 2 was most indicative of fraud, while a 5 on Variable 2 was least indicative of fraud – then a claim exhibiting characteristics “high” and “1”, the two categories most indicative of fraud on variables one and two respectively would have a combined score of 0.9 + (–0.95) = –0.05; a score which does not suggest that the claim is extreme. This is an anomaly caused by the scores on the two variables cancelling each other out. We can see that a rule is needed to ensure that our combined “extremeness score” can be interpreted as a “fraud likelihood score”.

4.5.4 To overcome the problem of variables cancelling each other out when
ordered differently, Brockett et al. (op. cit.) suggest that the categories within each variable should always be ranked from most indicative of fraud (category 1) down to least indicative of fraud. Following this suggestion leads to the following interpretation of RIDIT scores: scores close to minus one are deemed to be more extreme in the fraud direction i.e. more likely to be fraudulent, while scores closer to positive one are deemed to be more extreme in the non-fraud direction. Thus, when claim scores are summed across categories, the lower the combined score, the more likely the claim is to be fraudulent.

4.5.5 In our example, we thus need to adjust our Variable 1 so that categories are ordered “high”, “medium”, and “low” since a “high” score for “how suspicious a policyholder sounded” is most indicative of fraud. If we recalculate the PRIDIT scores, they are now $B_1 = -0.9$, $B_2 = -0.5$, $B_3 = 0.4$. Our abovementioned claim exhibiting “high” for Variable 1 and 1 for Variable 2, will now have a combined score of $-0.9 + (-0.95) = -1.85$, a score more indicative of fraud than before since $-1.85$ is close to $-2$ which is the smallest possible combined RIDIT score over two variables.

4.5.6 This approach can be followed for each claim in the claim file and the claims can be ranked from lowest to highest combined score i.e. from most extreme in a fraudulent direction to least extreme. The microinsurer can then quickly pay claims which are not extreme in a fraudulent direction, say those claims with a combined score greater than 0 (Brockett et al., 2002), while investigating as many claims as their resources allow, starting with the claim most likely to be fraudulent (the lowest combined score) and working down the list.

4.6 Improvements to the Basic RIDIT Method

4.6.1 The method as described above is the foundation of the PRIDIT method presented by Brockett et al. in 2002. There are two significant improvements to this basic method, though. The first improvement, suggested in the same paper by Brockett et al. (op. cit.), is a method of assigning more weight to variables with greater discriminatory power.

4.6.2 The second improvement, presented in 2009 by Ai, Brockett and Golden, is the ability to calculate RIDIT scores on variables where measurement is on a continuous scale as opposed to categorical variables. We will first explain the second improvement because it is a relatively simple extension of what we have explained about RIDIT scores so far. We will then proceed to explain the method of weight refining which added the “P” to RIDIT.

4.6.3 Calculating RIDIT Scores on Continuous Variables

4.6.3.1 Ai et al. (op. cit.) demonstrated that categorising continuous variables can reduce the ability of the PRIDIT method to accurately identify fraudulent claims. This was demonstrated by using a dataset of individuals classified as either high-income or low-income with a number of predictor variables. The PRIDIT method was applied to the data to estimate which individuals were high- or low-income and then
the model output was checked against the actual income status of each individual in the dataset for accuracy of prediction.

4.6.3.2 Ai et al. (op. cit.) found that the PRIDIT method lost twenty percentage points of accuracy in its ability to identify high-income individuals when continuous predictor variables were categorised compared to modelling them as continuous variables.

4.6.3.3 While this is not the same problem as identifying fraud, there are similarities in the nature of the problem. Both problems involve using a number of predictor variables to classify each data point into one of two categories; high- or low-income in the example, or fraud or non-fraud in our case.

4.6.3.4 To conduct this test in the context of identifying fraud, we would require a set of past claims where we knew the fraud status of each claim. The PRIDIT model could then be applied to the data and the PRIDIT model output compared to the actual fraud status of each claim. Brockett et al. (op. cit.) used such a dataset to test the PRIDIT method. However, the dataset did not have continuous predictor variables and was thus inappropriate for testing the loss of accuracy when categorising continuous variables. Nevertheless, from the test conducted by Ai et al. (op. cit.), it is clear that being able to calculate RIDIT scores for continuous variables is desirable.

4.6.3.5 The method that Ai et al. (op. cit.) suggest to calculate RIDIT scores for continuous variables is intuitively quite similar to RIDIT scores for categories. However, instead of calculating a RIDIT score for each category of a variable, we now calculate a RIDIT score for each distinct observation on a variable in the claim file. The formula for the RIDIT score of a particular observed value $x$ of continuous variable $X$ is given by (this is a slightly different notation to that used by Ai et al. (op. cit.)):

$$B(x) = \Pr(X < x) - \Pr(X > x)$$

where $X$ is the continuous variable and $x$ is an observed value of $X$ on a particular claim in the claim file. Notice that the subscript $i$, indicating category $i$, is no longer present, but rather we calculate such a score for each observed $x$ in our claim file, where it is possible that $x$ is different for each claim.

4.6.3.6 If we introduce fraud predictor Variable 3 as claim amount, a continuous variable, then for the first part of the RIDIT formula, instead of asking, “what percentage of claims are in a category below category $i$?” we now ask, “what percentage of claims have claim amounts less than the claim amount on this claim?” Similar logic applies to the second part of the RIDIT formula.

4.6.3.7 For example, if we have the following ten claims in our claim file (Table 1), we would first sort the claims by claim amount in ascending order and then for each claim calculate the number of claims in the claim file with value less than the claim and subtract from this the number of claims in the claim file with value greater than the claim and express this difference as a percentage of the total number of claims in our claim file (as in Table 2).
Table 1 Unordered claim amounts

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Claim size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6 600</td>
</tr>
<tr>
<td>2</td>
<td>12 000</td>
</tr>
<tr>
<td>3</td>
<td>4 500</td>
</tr>
<tr>
<td>4</td>
<td>7 000</td>
</tr>
<tr>
<td>5</td>
<td>7 000</td>
</tr>
<tr>
<td>6</td>
<td>4 700</td>
</tr>
<tr>
<td>7</td>
<td>4 000</td>
</tr>
<tr>
<td>8</td>
<td>4 700</td>
</tr>
<tr>
<td>9</td>
<td>6 300</td>
</tr>
<tr>
<td>10</td>
<td>3 000</td>
</tr>
</tbody>
</table>

Table 2 Ordered claim amounts and RIDIT scores

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Claim size (x)</th>
<th>Count &lt; claim</th>
<th>Count &gt; claim</th>
<th>B(x)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>3 000</td>
<td>0</td>
<td>9</td>
<td>-0.90</td>
</tr>
<tr>
<td>7</td>
<td>4 000</td>
<td>1</td>
<td>8</td>
<td>-0.70</td>
</tr>
<tr>
<td>3</td>
<td>4 500</td>
<td>2</td>
<td>7</td>
<td>-0.50</td>
</tr>
<tr>
<td>6</td>
<td>4 700</td>
<td>3</td>
<td>5</td>
<td>-0.20</td>
</tr>
<tr>
<td>8</td>
<td>4 700</td>
<td>3</td>
<td>5</td>
<td>-0.20</td>
</tr>
<tr>
<td>9</td>
<td>6 300</td>
<td>5</td>
<td>4</td>
<td>0.10</td>
</tr>
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</tr>
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<td>7 000</td>
<td>7</td>
<td>1</td>
<td>0.60</td>
</tr>
<tr>
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<td>12 000</td>
<td>9</td>
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<td>0.90</td>
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</tbody>
</table>

4.6.3.8 For each claim \(i\) we calculate the percentage of claims with claim amounts strictly less than the claim amount on claim \(i\). We then subtract the percentage of claims with claim amounts strictly greater than the claim amount on claim \(i\). In Table 2, claims have been ordered from smallest to largest, making calculations easier. For example, claim 10 has the lowest claim amount, thus nine out of ten claims are greater than claim 10 and no claims are less than claim 10, resulting in a RIDIT score of \(0 - 0.9 = -0.9\). This reordering is not necessary in practice as simple Excel functions can be used to calculate the number of claims greater than and less than each claim.

4.6.3.9 Calculations are similar for the remaining claims. However, we will work through the calculation for claim 6 due to a subtlety that arises because claims 6 and 8 are of the same amount. For claim 6, three claims are less than claim 6, but only five claims are greater than claim 6 and not six as might be expected with claim 6 being the
fourth largest claim out of ten claims. This is because the amount of claim 6 is equal
to the amount of claim 8. The RIDIT score is thus equal to 0.3–0.5=−0.2. A similar
principle applies when calculating the RIDIT score for claims 8, 4 and 5.

4.6.3.10 One thing that Ai et al. (op. cit.) fail to take into account is the situation
when the highest value on the predictor variable is most indicative of fraud. If, in our
example of Variable 3, claim amount, we assume that high claims are more likely to be
fraudulent, then we want the highest claims in our sample to have a RIDIT score close
to −1 and not close to 1. A simple amendment to the existing formula will solve this
problem. In the event that the highest value of a continuous variable is most indicative
of fraud, simply reverse the two components of the RIDIT score formula as follows:

\[ B(x) = \Pr(X > x) - \Pr(X < x) \]

The calculations will then be made easier by ordering claims from largest to smallest
as in Table 3 below.

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Claim size</th>
<th>Count &gt; claim</th>
<th>Count &lt; claim</th>
<th>Bi</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>12 000</td>
<td>0</td>
<td>9</td>
<td>−0.90</td>
</tr>
<tr>
<td>4</td>
<td>7 000</td>
<td>1</td>
<td>7</td>
<td>−0.60</td>
</tr>
<tr>
<td>5</td>
<td>7 000</td>
<td>1</td>
<td>7</td>
<td>−0.60</td>
</tr>
<tr>
<td>1</td>
<td>6 600</td>
<td>3</td>
<td>6</td>
<td>−0.30</td>
</tr>
<tr>
<td>9</td>
<td>6 300</td>
<td>4</td>
<td>5</td>
<td>−0.10</td>
</tr>
<tr>
<td>6</td>
<td>4 700</td>
<td>5</td>
<td>3</td>
<td>0.20</td>
</tr>
<tr>
<td>8</td>
<td>4 700</td>
<td>5</td>
<td>3</td>
<td>0.20</td>
</tr>
<tr>
<td>3</td>
<td>4 500</td>
<td>7</td>
<td>2</td>
<td>0.50</td>
</tr>
<tr>
<td>7</td>
<td>4 000</td>
<td>8</td>
<td>1</td>
<td>0.70</td>
</tr>
<tr>
<td>10</td>
<td>3 000</td>
<td>9</td>
<td>0</td>
<td>0.90</td>
</tr>
</tbody>
</table>

4.6.4 **Summary of RIDIT Scores on Three Variables in Example**

4.6.4.1 Table 4 below presents a summary of the RIDIT scores on each of our
three variables. Note that the RIDIT scores for Variable 3 cannot be presented in this
form due to each observation having its own RIDIT score because Variable 3 is a
continuous variable. The RIDIT score would need to be calculated for each and every
claim in the dataset. The RIDIT scores for Variable 3 are thus only shown in Table 5,
which shows the RIDIT scores for each claim depending on the characteristics for
each variable.

4.6.4.2 In Table 5 we now assume that we have 10 claims in our claim file with
the following characteristics (these are the same claims as in Tables 2 and 3 but with
additional information for Variables 1 and 2).
Table 4 RIDIT scores on Variables 1 and 2

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable 1</th>
<th>Variable 2</th>
<th>Variable 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.90</td>
<td>-0.95</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.50</td>
<td>-0.75</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.40</td>
<td>-0.45</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>0.60</td>
<td></td>
</tr>
</tbody>
</table>

RIDIT scores for continuous variables calculated separately for each claim, not per category

Table 5 Claim file with information on each predictor variable

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Variable 1 (suspicion)</th>
<th>Variable 2</th>
<th>Variable 3 (claim amount)</th>
<th>Bi</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Med</td>
<td>4</td>
<td>6 600</td>
<td>-0.30</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>2</td>
<td>12 000</td>
<td>-0.90</td>
</tr>
<tr>
<td>3</td>
<td>Low</td>
<td>4</td>
<td>4 500</td>
<td>0.50</td>
</tr>
<tr>
<td>4</td>
<td>High</td>
<td>2</td>
<td>7 000</td>
<td>-0.60</td>
</tr>
<tr>
<td>5</td>
<td>Low</td>
<td>4</td>
<td>7 000</td>
<td>-0.60</td>
</tr>
<tr>
<td>6</td>
<td>Med</td>
<td>5</td>
<td>4 700</td>
<td>0.20</td>
</tr>
<tr>
<td>7</td>
<td>Med</td>
<td>2</td>
<td>4 000</td>
<td>0.70</td>
</tr>
<tr>
<td>8</td>
<td>Med</td>
<td>4</td>
<td>4 700</td>
<td>0.20</td>
</tr>
<tr>
<td>9</td>
<td>High</td>
<td>5</td>
<td>6 300</td>
<td>-0.10</td>
</tr>
<tr>
<td>10</td>
<td>Low</td>
<td>5</td>
<td>3 000</td>
<td>0.90</td>
</tr>
</tbody>
</table>

4.6.4.3 The RIDIT scores for each claim can be looked up from Table 4 for the categorical variables 1 and 2 and calculated for Variable 3 (this calculation was done in the last column of Table 5 above).

Table 6 Claim file with RIDIT scores for each claim on each predictor variable

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Variable 1 (suspicion)</th>
<th>Variable 2</th>
<th>Variable 3 (claim amount)</th>
<th>Total score (equal weighting)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.50</td>
<td>-0.05</td>
<td>-0.30</td>
<td>-0.85</td>
</tr>
<tr>
<td>2</td>
<td>0.40</td>
<td>-0.75</td>
<td>-0.90</td>
<td>-1.25</td>
</tr>
<tr>
<td>3</td>
<td>0.40</td>
<td>-0.05</td>
<td>0.50</td>
<td>0.85</td>
</tr>
<tr>
<td>4</td>
<td>-0.90</td>
<td>-0.75</td>
<td>-0.60</td>
<td>-2.25</td>
</tr>
<tr>
<td>5</td>
<td>0.40</td>
<td>-0.05</td>
<td>-0.60</td>
<td>-0.25</td>
</tr>
<tr>
<td>6</td>
<td>-0.50</td>
<td>0.60</td>
<td>0.20</td>
<td>0.30</td>
</tr>
<tr>
<td>7</td>
<td>-0.50</td>
<td>-0.75</td>
<td>0.70</td>
<td>0.55</td>
</tr>
<tr>
<td>8</td>
<td>-0.50</td>
<td>-0.05</td>
<td>0.20</td>
<td>0.35</td>
</tr>
<tr>
<td>9</td>
<td>-0.90</td>
<td>0.60</td>
<td>-0.10</td>
<td>-0.40</td>
</tr>
<tr>
<td>10</td>
<td>0.40</td>
<td>0.60</td>
<td>0.90</td>
<td>1.90</td>
</tr>
</tbody>
</table>
4.6.4 To avoid confusion, we must make it clear that the \( p_j \)'s used to calculate RIDIT scores for Variables 1 and 2 (the categorical variables) are estimated using the proportions in the entire claim file i.e. not just the 10 claims listed in Table 6 for illustration purposes. This explains why the proportions (calculated from the entire claim file) do not equal the proportions observed in each category in the above 10 claims.

4.6.4.5 The final step is to rank claims from lowest total score to highest total score, so that claims are in order from most likely to be fraudulent to least likely to be fraudulent.

### Table 7 Ranked claim file

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Total score</th>
<th>Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>–2.25</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>–1.25</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>–0.85</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>–0.55</td>
<td>4</td>
</tr>
<tr>
<td>9</td>
<td>–0.40</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>–0.35</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>–0.25</td>
<td>7</td>
</tr>
<tr>
<td>6</td>
<td>0.30</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>0.85</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>1.90</td>
<td>10</td>
</tr>
</tbody>
</table>

4.6.5 **Placing Greater Weight on Variables with More Discriminatory Power**

4.6.5.1 We’ve seen how transforming the responses on each variable to the interval \([-1,1]\) allow us to more accurately assess the extremity of each category within each variable. This essentially puts all variables on the same scale so that certain variables do not get weighted more heavily in the final fraud likelihood score by virtue of the number of categories or the scale of measurement of the variable.

4.6.5.2 However, it may not be desirable for all variables to have equal weighting in the final sum of RIDIT scores, because certain variables may prove to be better indicators of extreme behaviour in a fraudulent direction than other variables.

4.6.5.3 Brockett et al. (op. cit.) proposed a method by which the weights assigned to each variable when summing RIDIT scores across variables can be refined so that variables with higher discriminatory power will be assigned higher weight.

4.6.5.4 This is done by initially giving equal weight to each variable (simply summing RIDIT scores across categories as we did in the example above) and then assessing the correlations between the RIDIT scores on each of the variables with the total score to see which variables give scores that are most consistent with the total combined score on each claim. The variables that are more closely correlated to the
final score are assigned more weight when summing RIDIT scores across variables. The new weights give rise to a new set of total scores against which the correlation between each of the variables can be calculated. This process is repeated until the weights assigned to each variable converge.

4.6.5.5 Brockett et al. (op. cit.) use matrix algebra to show that the converged vector of weights assigned to each variable is the eigenvector corresponding to the largest eigenvalue of the matrix $F'F$, where matrix $F$ is the matrix of RIDIT scores for each claim and variable, which is columns 2 to 4 of Table 6 above in our example. The matrix $F$ has dimensions $n \times m$, where $n$ is the number of claims and $m$ is the number of predictor variables. $F'F$ is thus an $m \times m$ matrix i.e. a square matrix with number of rows and columns equal to the number of predictor variables. To understand this result better it will be helpful to understand what the matrix $F'F$ represents and how to interpret the eigenvector corresponding to the largest eigenvalue of a matrix.

4.6.5.6 Before moving on to interpret this result, we will work through the calculations in our example to explain the iterative method of weight refining. Our 10×3 matrix $F$ is shown in Table 8 below (shaded in gray):

**Table 8** Matrix of RIDIT scores on each claim and variable

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Variable 1 (suspicion)</th>
<th>Variable 2</th>
<th>Variable 3 (claim amount)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.50</td>
<td>-0.05</td>
<td>-0.30</td>
</tr>
<tr>
<td>2</td>
<td>0.40</td>
<td>-0.75</td>
<td>-0.90</td>
</tr>
<tr>
<td>3</td>
<td>0.40</td>
<td>-0.05</td>
<td>0.50</td>
</tr>
<tr>
<td>4</td>
<td>-0.90</td>
<td>-0.75</td>
<td>-0.60</td>
</tr>
<tr>
<td>5</td>
<td>0.40</td>
<td>-0.05</td>
<td>-0.60</td>
</tr>
<tr>
<td>6</td>
<td>-0.50</td>
<td>0.60</td>
<td>0.20</td>
</tr>
<tr>
<td>7</td>
<td>-0.50</td>
<td>-0.75</td>
<td>0.70</td>
</tr>
<tr>
<td>8</td>
<td>-0.50</td>
<td>-0.05</td>
<td>0.20</td>
</tr>
<tr>
<td>9</td>
<td>-0.90</td>
<td>0.60</td>
<td>-0.10</td>
</tr>
<tr>
<td>10</td>
<td>0.40</td>
<td>0.60</td>
<td>0.90</td>
</tr>
</tbody>
</table>

In our first iteration of calculating the total score for each claim we assign a weight of 1 to each variable. This is equivalent to multiplying the matrix $F$ by a $3 \times 1$ vector of 1’s. We will call this vector $W^{(0)}$ (sticking to the notation used by Brockett et al. (op. cit.)), where the “$W$” stands for weights and the superscript is the number of the iteration. The result is an $n \times 1$ vector of total scores, which we refer to as $S^{(0)}$. Note that we have already calculated $S^{(0)}$ in the last column of Table 6 above.

4.6.5.7 Once we have our overall score, it will be useful to see which variables correlate highly with the overall score. These variables can then be assigned higher weight (Brockett et al., op. cit.). Ai et al. (op. cit.) explain that if a particular variable has a small score at the same time that the overall score is small or a large score at the same
time that the overall score is large, and this occurs consistently over all claims in the claim file, then the variable is better at predicting the overall score. A measure of this correlation is the Pearson correlation, which is closely related to the normalised inner product. For a particular variable, the inner (or dot) product will be the transpose of the vector of the RIDIT scores on the variable for each claim multiplied by the vector of overall scores, S(0). For example on Variable 1, the inner product will be $(-0.50)(-0.85)+(0.40)(-1.25)+\ldots+(0.4)(1.9) = 3.46$. Thus the matrix multiplication of $\mathbf{F}'\mathbf{S}(0)$ will give us a $3 \times 1$ vector of inner dot products between each of our 3 variables and the overall scores vector $\mathbf{S}(0)$. Normalising this $3 \times 1$ vector by dividing each value in the vector by the length (or norm) of the vector gives us a $3 \times 1$ vector of unit length that measures the correlation between each variable and the overall fraud score. This vector is the next iteration of $\mathbf{W}$ i.e. $\mathbf{W}^{(1)}$.

4.6.5.8 By multiplying $\mathbf{F}$ by $\mathbf{W}^{(1)}$ instead of $\mathbf{W}^{(0)}$ as we did in our first step, we assign higher weight to variables that are more closely correlated with the overall score when calculating the revised overall score. The process is repeated until the value of $\mathbf{W}$ converges to $\mathbf{W}^{(\infty)}$. In our example, the weights converge as shown in Table 9.

4.6.5.9 Claims can then be ordered by the final scores, $\mathbf{S}^{(\infty)}$, in ascending order to help focus claims investigation resources as before.

4.6.5.10 Interestingly, something not mentioned by Brockett et al. (op. cit.), is that the steps involved in the method of weight refining are exactly the steps carried out in an iterative method of solving for the eigenvector corresponding to the largest eigenvalue of a matrix known as the Power Method (Jolliffe, 2004). So it is not surprising then that the result of the iterative weight refining method is the dominant eigenvector of the matrix.

Table 9 Iterative process of refining the weights assigned to each variable (W)

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\mathbf{W}^{(0)}$</th>
<th>$\mathbf{W}^{(1)}$</th>
<th>$\mathbf{W}^{(\infty)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0.50086</td>
<td>0.22998</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0.57543</td>
<td>0.61745</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>0.64654</td>
<td>0.75224</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Claim number</th>
<th>$\mathbf{S}^{(0)}$</th>
<th>$\mathbf{S}^{(1)}$</th>
<th>$\mathbf{S}^{(\infty)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.85</td>
<td>-0.473</td>
<td>-0.372</td>
</tr>
<tr>
<td>2</td>
<td>-1.25</td>
<td>-0.813</td>
<td>-1.048</td>
</tr>
<tr>
<td>3</td>
<td>0.85</td>
<td>0.495</td>
<td>0.437</td>
</tr>
<tr>
<td>4</td>
<td>-2.25</td>
<td>-1.270</td>
<td>-1.121</td>
</tr>
<tr>
<td>5</td>
<td>-0.25</td>
<td>-0.216</td>
<td>-0.390</td>
</tr>
<tr>
<td>6</td>
<td>0.30</td>
<td>0.224</td>
<td>0.406</td>
</tr>
<tr>
<td>7</td>
<td>-0.55</td>
<td>-0.229</td>
<td>-0.052</td>
</tr>
<tr>
<td>8</td>
<td>-0.35</td>
<td>-0.150</td>
<td>0.005</td>
</tr>
<tr>
<td>9</td>
<td>-0.40</td>
<td>-0.170</td>
<td>0.088</td>
</tr>
<tr>
<td>10</td>
<td>1.90</td>
<td>1.127</td>
<td>1.139</td>
</tr>
</tbody>
</table>
4.6.5.11 However, interpreting the significance of the limiting weight being the eigenvalue corresponding to the largest eigenvalue is of more importance than merely knowing it to be the case. The fact that the most explanatory weights are derived as the dominant eigenvector of the matrix $F'F$ has an interesting interpretation. Recall that the formula for the covariance between two variables $X$ and $Y$ is:

$$\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})$$

When the means of the variables are equal to zero, this formula simplifies to:

$$\sum_{i=1}^{n}X_iY_i$$

Now combining the fact that the $ij$th element of the matrix $F'F$ is:

$$\sum_{k=1}^{n}F_{ki}F_{kj}$$

and that the variable scores are “centred with mean zero”, we can see that the matrix $F'F$ is the matrix containing sample covariances between variables (Ai et al., op. cit.). Friedman (1981) explains that the $R^2$ statistic is useful in the context of regression where a dependent variable is modelled on a number of independent variables. But in the context where a researcher is trying to establish how several variables may influence the same underlying variable (likelihood of fraud in our case), the largest eigenvalue of the correlation matrix (which is the same as the largest eigenvalue of the covariance matrix) is the test statistic that indicates the “maximum amount of variance of the variables which can be accounted for with a linear model by a single underlying factor” (Friedman, op. cit.). The largest eigenvector is also known as the principal component of the data. It is a new variable created by a linear combination of the existing variables in the data. For an eigenvector to be the principal component it needs to account for the maximum amount of variability in the data i.e. the variance on this new variable needs to be a maximum (Abdi & Williams, 2010).

4.6.5.12 If we use the principal component only and no other eigenvectors to arrive at our final fraud scores, we are essentially assuming that there is only one dimension of interest. In our case that would be the fraud dimension, which is a straight line in an $m$-dimensional space (the number of variables we have) from least likelihood of fraud to highest likelihood of fraud.

4.6.5.13 Brockett et al. (op. cit.) and Ai et al. (op. cit.) demonstrate that the weights obtained by this method are closely related to each variable’s ability to discriminate between fraud and non-fraud claims, with lower weighted variables having lower discriminatory power. This may be useful if it is costly for the company to collect
certain data fields. Data on variables with PRIDIT weights close to zero may not be worth collecting. For the reader wishing to work through the derivations in Brockett et al. (op. cit.) that deal with variable discriminatory power, the textbook written by Graybill (1983) will be extremely helpful; in particular Theorems 8.4.3 and 8.5.2.

4.7 Key Advantages of the PRIDIT Method

As we have worked through the above example, some of the advantages of the PRIDIT method may have been evident. However, it is worth explicitly stating the advantages of the method in the context of microinsurance:

— No training sample required. The method used only the claim file. There is no need to parameterise the model using past data.

— Ability to rank claims from highest fraud likelihood to lowest fraud likelihood. This output is particularly useful for reasons discussed previously.

— Easy to implement with little expertise required. The methods can easily be implemented in spreadsheet software such as Microsoft Excel, or in a more advanced program. Please email the authors if you wish to view the Excel spreadsheet which was used to conduct the calculations in the example presented above.

— Does not need to be updated regularly unless it is suspected that the underlying nature of fraud has changed. Ai et al. (op. cit.) suggest that the PRIDIT weights calculated for categorical variables need not be calculated every time a new claim file comes in. They argue that it is only necessary to update the RIDIT scores if there is reason to believe that the underlying nature of claims has changed which will result in different RIDIT scores for categories on certain variables; and

— Ability to adapt to a change in the nature of fraud. Related to the previous point is that if the underlying nature of fraud does change then a recalibration of the PRIDIT model is a simple, inexpensive process. For a supervised learning method, however, a change in the underlying nature of fraud may result in the model parameters being inaccurate as all the data on which the model is based exhibit outdated fraud patterns. Ai et al. (op. cit.) suggest that fraudsters developing new methods of committing fraud may result in supervised fraud identification methods becoming less effective, while PRIDIT is unaffected.

4.8 Testing the Method

4.8.1 With all these advantages mentioned above, there is one critical bit of information that we have not discussed – the accuracy of the PRIDIT method in identifying fraudulent claims. If the method is practical, simple and robust, but is not accurate, then it is not a suitable method for identifying fraudulent claims.

4.8.2 Ai et al. (op. cit.) explain why it is challenging to test the PRIDIT method. It is challenging to test unsupervised methods for the same reason that unsupervised methods are useful; there is no training sample. If a past dataset of claims information was available where, for each claim it was known whether the claims were fraudulent
or not, then it would be possible to test how accurate the unsupervised method is in identifying fraudulent claims by applying the method to this dataset. However, as has been explained before, in microinsurance one is unlikely to have access to a sample of claims where it is known whether each claim is fraudulent or not.

4.8.3 But while it may be some time before we can scientifically test the accuracy of the PRIDIT method in the context of microinsurance, it will be helpful to see the results of tests done in an insurance context where a training sample was available. In both Brockett et al. (op. cit.) and Ai et al. (op. cit.), the PRIDIT method was tested using a past claims dataset of 1399 personal injury protection claims provided by the Automobile Insurance Bureau (AIB) in Massachusetts that had information on a number of variables (which could be used as predictor variables) and, importantly, whether each claim was fraudulent or not (the fraud status). The fraud status of each claim was obtained by expert claims assessors.

4.8.4 Tests were done to compare the performance of the PRIDIT method against supervised fraud identification methods, including logistic regression, Support Vector Machines and Bayesian Additive Regression Trees (BART). The tests were conducted by assessing the correlation between the PRIDIT scores and fraud likelihood measures generated by the supervised fraud identification methods. The correlations were high (ranging from 0.55 to 0.91) and significant at a very extreme level of significance (0.0001). Ai et al. (op. cit.) interpreted this as follows:

This suggests that while the PRIDIT method uses only the consistency of the internal structure of the predictor variables, its predictions of the suspicion levels are similar to those of the more information intensive supervised methods.

4.8.5 A particularly interesting finding by Ai et al. (op. cit.) when comparing the PRIDIT method to supervised fraud detection techniques was that, while supervised fraud identification techniques were more accurate overall in identifying both fraudulent and non-fraudulent claims, when focusing on fraudulent claims only the PRIDIT method more accurately identified fraudulent claims. This was measured using the F1-measure which is “the number of correctly classified fraudulent claims divided by the total number of claims classified as fraudulent”. This is desirable because according to Ai et al. (op. cit.), the risk of inaccurately classifying truly fraudulent claims as non-fraudulent (false negative) is greater than the risk of classifying non-fraudulent claims as fraudulent (false positive). The reason for this suggestion is that the cost of failing to identify the fraudulent claim (the cost of paying the claim) will likely be higher than the costs of assessing a claim to determine if it is fraudulent. This may be less applicable in microinsurance due to the low average claim size, but the greater accuracy in identifying fraudulent claims is still a desirable feature of the PRIDIT method.

4.8.6 Ai et al. (op. cit.) aptly note that supervised learning methods are not competitors with unsupervised learning methods in situations where a training sample is not available. However, it is still remarkable that a seemingly less sophisticated
method of fraud identification can give similar results to more sophisticated methods that require high levels of expertise to parameterise and come at great expense to build up training samples over time. We are quick to warn, though, that the results of these tests are specific to the dataset concerned and there is no evidence that the PRIDIT method will always identify fraudulent claims more accurately than supervised fraud detection methods.

4.8.7 A question remains of how the PRIDIT method compares to other unsupervised fraud identification methods, which are indeed competitors of the PRIDIT method. Ai et al. (op. cit.) conducted a number of tests to compare the accuracy of the PRIDIT method compared to two other unsupervised methods: Kohonen’s feature map and Cluster analysis. The results of the tests were that the three supervised methods gave the same classifications (fraud or non-fraud) on most claims (Ai et al., op. cit.). However, the two non-PRIDIT methods suffered from certain disadvantages. According to Ai et al. (op. cit.), Kohonen’s feature map produces graph results which are difficult to interpret and the “method is computationally intensive”, while the main drawback of cluster analysis is its lack of ability to rank claims from highest fraud likelihood to least, which is a key feature of a fraud detection model.

4.8.8 Because of these disadvantages of the two competitor unsupervised methods, the similar performance of all three methods and the ease of implementation of the PRIDIT method (and other advantages listed in the previous section), we believe that the PRIDIT method is the best option of the unsupervised methods for a microinsurance company aiming to introduce a fraud identification method into their operations.

4.8.9 While these tests were not conducted in a microinsurance context, they do at least provide us with evidence of the success of the method in another insurance context. It should be explicitly noted that, as with all statistical methods, the PRIDIT method does not purport to identify fraudulent claims with complete accuracy. However, we believe that there is enough evidence of success to give microinsurers confidence that if they implement the method it will prove to be beneficial to their companies; particularly if they currently have no existing fraud identification strategy in place.

4.8.10 In the next section we apply the PRIDIT method to a claims dataset for two microinsurance products offered by a South African microinsurer.

5. DATA USED FOR APPLICATION OF PRIDIT TO MICROINSURANCE

5.1 The data that we use to demonstrate the workings of the PRIDIT method for fraud classification was obtained from a South African insurance company. For competitive reasons, the company will not be named. The data is from two types of insurance products that the company offers to the low-income market. In the remainder of this section, the first product will be referred to as product A and the second product will be referred to as product B. The details of products A and B will be explained in §5.2 and §5.3 respectively. Both insurance products are distributed
through an institution that sells consumer goods on credit. The institution requires that an individual purchasing goods on credit, purchase at least insurance product A, while product B is an extension of product A that offers more comprehensive cover. The purpose of this requirement is to limit financial loss, to both the insured and the institution, in the event that one of the insured perils occurs. The way in which this is achieved by each of the two insurance products differs and will also be explained in §5.2 and §5.3 respectively.

5.2 When an individual purchases a good from the institution on credit, they are required to pay monthly instalments that include both interest and capital for an agreed term until the loan is repaid. Product A is required to be taken out at the same time as the purchase of the good and is paid for by monthly premiums that are added to the monthly loan instalments. During the repayment term, if the good is damaged or stolen, product A will pay the outstanding balance on the loan at the date that the insured peril occurred subject to the terms and conditions set out in the policy document. Product A eliminates the financial loss sustained by the insured because they do not have to pay any further monthly instalments for goods that they no longer have the use of. At the same time, it limits the financial loss to the institution because if the insurance was not in place, the purchaser would be less willing to continue paying the monthly instalment and hence default would be more likely.

5.3 At the point of purchase, the individual can opt to purchase product B instead of product A. Product B operates similarly to product A but instead of settling the outstanding balance on the loan at the date that the insured peril occurs, product B either provides for the repair of the good in the case of reparable damage or provides for the replacement of the good on a new-for-old basis in the case of theft or irreparable damage. This limits the financial loss to both the insured and the insurer because the insured has an incentive to continue paying the monthly instalment, while from the insured's perspective, the good is repaired or replaced.

5.4 The data that were used for the application of the PRIDIT method included both details of policies in force and details surrounding claims that arose from these polices during the investigation period. The investigation period extended from 1 January 2009 to 31 December 2010. This investigation period was chosen because it was believed that all claims that occurred during the period were fully run-off by the time that the analysis was performed. The data was extensively analysed for errors and omissions. Any errors and omissions that were identified were excluded from the dataset in order to reduce the chances of any distortions in the final results.

5.5 The dataset contained variables for each policy record and claim record during the investigation period. The variables relating to the policy details and the claims details that were used in the application of the statistical method are shown in Tables 10
and 11 respectively. The reasons why these variables were used in the application of the statistical method will become clearer in Section 6.

**Table 10** Policy data variables

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>STARTDATE</td>
<td>Date of policy inception</td>
</tr>
<tr>
<td>ENDDATE</td>
<td>Date of policy termination</td>
</tr>
<tr>
<td>LOCATION</td>
<td>Geographical location of the insured</td>
</tr>
<tr>
<td>PRODUCTTYE</td>
<td>Product A or product B</td>
</tr>
</tbody>
</table>

**Table 11** Claim data variables

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>INCIDENTDATE</td>
<td>Date that the claim event took place</td>
</tr>
<tr>
<td>REPORTINGDATE</td>
<td>Date that the claim event was reported to the insurer</td>
</tr>
<tr>
<td>CLAIMTYPE</td>
<td>Cause of claim</td>
</tr>
<tr>
<td>CLAIMAMOUNT</td>
<td>Amount of claim</td>
</tr>
</tbody>
</table>

5.6 The institution offering the insurance products had a total of 161 physical branches distributed throughout South Africa during the investigation period. The variable LOCATION refers to the branch at which the insurance policy was taken out. For the reason of non-disclosure, the names of these locations will not be revealed in this paper. The variable CLAIMTYPE refers to the cause of a claim. The cause of a claim was either damage or theft.

5.7 Descriptive Statistical Analysis of the Data

5.7.1 **Product Type**

The proportion of type A policies in force during the investigation period was 11.7%, while the proportion of type B policies in force was 88.3%. The proportion of the claims arising from type A policies during the investigation period was 12.3%, while the proportion of the claims arising from type B policies was 87.7%.

5.7.2 **Reporting Delay**

The average reporting delay for the claims during the investigation period was approximately 35 days. This was obtained by taking the number of days between the INCIDENTDATE variable and the REPORTINGDATE variable for each claim, summing these values up and then dividing the result by the number of claims that occurred during the investigation period. The significance of the average reporting delay will be explained in Section 6.
5.7.3 **Cause of Claim**

Approximately 19.2% of claims were as a result of damage and 80.8% as a result of theft. During the investigation period, a total of 2 141 claims occurred.

5.7.4 **Claim Amounts**

The average claim amount was R4 083–76. Since this is a relatively small amount, it is clear that these two insurance products can be classified as microinsurance products.

6. **Applying PRIDIT to the Data**

We will work through four steps covered in section 4:

— Step 1: selection of predictor variables;
— Step 2: assigning categories for predictor variables and determining ordering;
— Step 3: calculating RIDIT scores;
— Step 4: optimising weights between variables by calculating the largest eigenvector of the matrix $F'F$; and
— Step 5: ranking claims from ‘most likely’ to be fraudulent to ‘least likely’ to allow channelling of limited resources.

6.1 **Step 1: Selection of Predictor Variables**

6.1.1 Recall from section 4 that the first step in applying the PRIDIT method is to identify claim characteristics that can be used as predictor variables that may be indicative of fraud.

6.1.2 The selection of variables may be based on past evidence of variables being associated with fraud – for example, Artis, Ayuso & Guillén (op. cit.) found that the longer it takes for a policyholder to report a claim to the insurer, the greater chance there is of that claim being fraudulent. The reason suggested by Artis, Ayuso & Guillén (op. cit.) for this finding is that once an individual has staged a claim event, they may be hesitant in contacting the insurer because they are fearful of being caught out. This fear results in a delayed notification as the policyholder eventually finds the courage to notify the insurer of the claim event (ibid.). This suggests that reporting delay can be used as a predictor variable with longer reporting delays being more indicative of fraud.

6.1.3 However, an insurer may have a number of variables for which there is no such evidence of fraud. In this case, the decision of which variables to choose may seem daunting, particularly for someone without a background in detecting fraudulent behaviour, but there are two things that reduce the risk of error:

6.1.3.1 If the user inputs a variable that is not closely related to fraud occurrence, then the measure of variable discriminatory ability developed by Brockett et al. (op. cit.) will be close to zero for that variable and the corresponding weight assigned to the variable will be small (Ai et al, op. cit.). There is thus virtually no consequence of the user adding additional variables to the model that are poor indicators of fraudulent
claims. So while it is required that as many variables as possible that give some clue of fraud likelihood are included in the model, it is not required that variables that don’t give some clue of fraud likelihood are manually excluded from the model. The model will automatically “exclude” them by assigning lower weight if they turn out to add little to the model’s classification ability.

6.1.3.2 Ai et al. (op. cit.) also explain that if user-input is incorrect, in that the relationship is opposite to what is expected (for example, it is suspected that a long reporting delay is indicative of fraud when in fact a short delay is more indicative of fraud) then the abovementioned measure of variable discriminatory power will be negative and the negative relationship will correct the ordering error made by the user. Thus, even though the user has got the ordering incorrect, the method will still highlight claims that are more likely to be fraudulent.

6.1.3.3 To summarise the above points, the user should rather include too many variables in the model to increase the chances of including significant indicators of fraud likelihood. Even if the wrong relationships are described for certain variables it will not detract from the ability of the model to identify fraudulent claims. This makes it clear that a high level of expertise is not required to calibrate the model, making it even more suitable to microinsurance companies striving to keep expenses down to a minimum.

6.1.4 In this exercise, besides the help from literature on the reporting delay variable, the selection of the predictor variables was essentially an exercise of judgement that was guided by the results of the descriptive statistical analysis performed on the data. In other words, with the data that was available there was no scientific way of selecting the predictor variables and someone else applying this method to the same products and data may select different predictor variables. Careful consideration was also given to the features of the two products that present opportunities for fraud in order to inform the selection of the predictor variables. A total of five predictor variables were selected for the application of this method.

6.1.5 Product Type

It was explained in section 2.5.4 that when individuals are compelled to take out insurance, they are more likely to be accepting of fraudulent behaviour (Tennyson, op. cit.). ‘Product type’ was thus chosen as a predictable variable because the institution required the individual to take out product A when purchasing goods on credit, whereas the individual had the option to select product B in place of product A. A claim on product A would thus have a higher suspicion of fraud than a claim on product B.

6.1.6 Cause of Claim

The cause of claim, either theft or damage, was not used directly as a predictor variable in the model. It was however important to distinguish between the two
causes in order for a method of assigning a value to the ‘duration of policy at claim date’ predictor variable to be established. The following section explains the reason for this.

6.1.7 Duration of Policy at Claim Date

6.1.7.1 The selection of ‘duration of policy at claim date’ as a predictor variable was based on the consideration of the features of each product. For product A, a theft or damage claim that occurred soon after the policy commenced would have a higher suspicion of fraud than a theft or damage claim that occurred towards the end of the term of the policy. This is because soon after the policy commenced the amount outstanding on the loan would be greater than what it would be towards the end of the term of the policy. In other words, the potential financial gain from submitting a fraudulent claim on product A is much greater at earlier durations of the policy.

6.1.7.2 For product B, a damage claim that occurred soon after the policy commenced would have a lower suspicion of fraud than a damage claim that occurred towards the end of the term of the policy. This is because the financial gain from submitting a fraudulent damage claim soon after the policy was taken out is much smaller than what it would be from submitting a fraudulent damage claim towards the end of the term of the policy. At an earlier duration, the damaged good would either be repaired or replaced, if the damage was irreparable, but the policyholder would still have to continue paying the monthly instalments. At later durations, when the good is much older, the damaged good may be replaced with an updated version, since the policy operates on a new-for-old basis, or restored to its original condition in the case of repairable damage. The policyholder would in this case have only a few loan instalments remaining. The same however is not necessarily true for theft claims. A fraudulent theft claim at earlier durations would still have a significant financial gain because even though the policyholder would be required to continue paying the monthly instalments, a replacement good would be provided and in addition, the policyholder would still have the use of the original ‘stolen’ good.

6.1.8 Reporting Delay

As described in section 6.1.2, reporting delay may be a useful indicator of fraudulent behaviour and is thus included in our model.

6.1.9 Geographical Location

6.1.9.1 Recall that the institution had a total of 161 physical branches distributed throughout South Africa. This data allowed for a claim incidence rate to be calculated for each of the branches. This was done by taking the number of claims and dividing it by the total exposed to risk for each branch, during the investigation period. This calculation was performed in the standard actuarial way.

6.1.9.2 The purpose of calculating a claim incidence rate for each of the branches was to identify branches that had an ‘unusually high’ claim incidence rate.
The definition of ‘ unusually high’ was relative to the average incidence rate across all the branches.

6.1.9.3 The link between geographical region and suspicion of fraud is that claims from a region with an unusually high claim incidence rate have a higher suspicion of fraud than claims from a region where the incidence rate is deemed to be ‘normal’ or ‘ unusually low’ (Artis, Ayuso & Guillén, op. cit.). The rationale behind this suggestion is that members within a community often exhibit similar attitudes towards insurance fraud, which may have a significant effect on the incidence of claims within that area (Tennyson, op. cit.). In addition, fraud is sometimes committed by organised syndicates that operate in specific geographical locations (ibid.).

6.1.10 **Claim Amount**

The claim amount was selected as a predictor variable because it has been suggested by Brockett et al. (op. cit.) that the prevalence of fraud varies with the amount of a claim. Brockett et al. (op. cit.) hypothesise that the prevalence of fraud increases as the average claim amount increases. Tennyson (op. cit.) suggests that the potential financial gain from committing fraud has to be large enough to outweigh the potential consequences of being caught out. This is perhaps the reason for the hypothesis proposed by Brockett et al. (op. cit.).

6.1.11 It is important to note that consideration of any of the above predictor variables in isolation is inappropriate and does not make sense (Brockett et al., op. cit.). For example, it does not make sense to suggest that a claim arising from product A is more likely to be fraudulent than a claim arising from product B when considering the ‘product type’ predictor variable in isolation. Instead, the predictor variables should be jointly considered. It is the overall fraud score that is produced from the PRIDIT method that should be considered before any conclusions are drawn (ibid.).

6.2 **Step 2: Establishing a Method for assigning Values to the Predictor Variables**

6.2.1 Establishing a method for assigning values to the predictor variables is also an exercise of judgement, hence many different methods are possible (Brockett et al., op. cit.). The only requirement is that the predictor variables are treated consistently (ibid.).

6.2.2 For each of the predictor variables, categories need to be created (ibid.), unless the variable is a continuous variable (Ai et al., op. cit.). These categories are then ranked in order of decreasing fraud suspicion (Brockett, op. cit.). Once the categories have been arranged in order of decreasing fraud suspicion, an integer value in increasing order is assigned to each category (ibid.). In other words, the category with the highest fraud suspicion is assigned a value of one, the category with the second highest fraud suspicion is assigned a value of two and continuing in this fashion until the last category as we saw in section 4 (ibid.).

6.2.3 For example, on the ‘product type’ variable, a claim from Product A will be
assigned a value of one, while a claim from Product B will be assigned a value of two.
The value of one, which corresponds to a claim from Product A is more indicative of
fraud than a claim from Product B since Product A is compulsory, while product B is
not.

6.2.4 The list of variables that have been used to define these limits is shown in
Table 12. The chosen categories for the predictor variables in this exercise are shown
in Table 13. It is important to note that the limits defining each of the categories have
been subjectively chosen (ibid.). ‘Subjectively’ in this context is intended to mean that
they are based on judgement and what is believed to be appropriate (ibid.). Another
individual conducting this research might well have chosen different limits.

6.2.5 Up until this point, the dataset has simply been used to inform the selection
of predictor variables and the setting of appropriate limits for each of the categories.
Although, this method does not require that historical data be used for this purpose is
has been used here in order to help inform the subjectivity that has been exercised.

### Table 12 Variables used to define the category limits

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PT_k$</td>
<td>Product type for claim $k$</td>
</tr>
<tr>
<td>$CDA_k$</td>
<td>Duration of policy A at claim date for claim $k$</td>
</tr>
<tr>
<td>$CDB_k$</td>
<td>Duration of policy B at claim date for claim $k$</td>
</tr>
<tr>
<td>$CD_k$</td>
<td>Duration of policy at claim date for claim $k$</td>
</tr>
<tr>
<td>$T_k$</td>
<td>Term of policy for claim $k$</td>
</tr>
<tr>
<td>$RD_k$</td>
<td>Reporting delay for claim $k$</td>
</tr>
<tr>
<td>$L_k$</td>
<td>Geographical location of claim $k$</td>
</tr>
<tr>
<td>$CA_k$</td>
<td>Claim amount for claim $k$</td>
</tr>
<tr>
<td>$CIR_i$</td>
<td>Claim incidence rate for branch $i$</td>
</tr>
<tr>
<td>$CIR_{ik}$</td>
<td>Claim incidence rate for claim $k$ from branch $i$, where $i = 1, 2, \ldots, 161$</td>
</tr>
<tr>
<td>$ACIR$</td>
<td>Average claim incidence rate $= \frac{1}{161} \sum_{i=1}^{161} CIR_i$</td>
</tr>
<tr>
<td>$SDCIR$</td>
<td>Standard deviation of claim incidence rates</td>
</tr>
</tbody>
</table>
Table 13 Categories for the predictor variables

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Coding</th>
</tr>
</thead>
</table>
| $PT_k$        | 1 if product A  
                2 if product B |
| $CD_k$        | Product A: 1 if $CDA_k < \frac{1}{2}T_k$ for both theft and damage  
                2 if $CDA_k > \frac{1}{2}T_k$ for both theft and damage  
                Product B: 1 if $CDB_k > \frac{1}{2}T_k$ for both theft and damage  
                1 if $CDB_k < \frac{1}{2}T_k$ for theft  
                2 if $CDB_k < \frac{1}{2}T_k$ for damage |
| $L_k$         | 1 if $CIR_{ik} > ACIR + 2SDCIR$  
                2 if $ACIR + SDCIR < CIR_{ik} < ACIR + 2SDCIR$  
                3 if $CIR_{ik} < ACIR + SDCIR$ |
| $RD_k$        | Modelled continuously |
| $CA_k$        | Modelled continuously |

6.3 Steps 3 and 4: Calculating RIDIT Scores and refining Weights

6.3.1 As in section 4, we calculate RIDIT scores for each category on each categorical variable. For each claim, the observed values of the predictor variables were calculated according to the method shown in Table 13. The percentage of claims in each category on each variable was then calculated, allowing us to calculate RIDIT scores for each category on each variable. For each claim, the corresponding RIDIT scores were looked up depending on the characteristics of the claims. These values were then arranged in matrix form, with each row representing a single claim record and the column entries for that row representing the corresponding RIDIT values of the predictor variables in the same order as presented in Table 13.

6.3.2 The iterative method of weight refining was then carried out on the abovementioned matrix of RIDIT scores.

6.4 Step 5: Ranking Claims and taking Action

6.4.1 For the random sample of ten claims under investigation, the resultant fraud suspicion scores are shown in Table 14. These scores are ordered from smallest to largest.
6.4.2 From the scores in Table 14, claims one and eight have the highest suspicion of fraud, while claims four and ten have the lowest suspicion of fraud. Brockett et al. (op. cit.) suggest that a suitable method of deciding which claims to investigate further, would be to investigate all claims that have a negative fraud suspicion score. In the above scenario, claims one and eight would be investigated further.

<table>
<thead>
<tr>
<th>Claim number</th>
<th>Fraud suspicion score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.836</td>
</tr>
<tr>
<td>8</td>
<td>-1.786</td>
</tr>
<tr>
<td>6</td>
<td>0.059</td>
</tr>
<tr>
<td>7</td>
<td>0.192</td>
</tr>
<tr>
<td>2</td>
<td>1.314</td>
</tr>
<tr>
<td>9</td>
<td>1.584</td>
</tr>
<tr>
<td>5</td>
<td>2.620</td>
</tr>
<tr>
<td>3</td>
<td>2.626</td>
</tr>
<tr>
<td>4</td>
<td>3.732</td>
</tr>
<tr>
<td>10</td>
<td>3.738</td>
</tr>
</tbody>
</table>

6.4.3 Although the results of this method seem trivial, Brockett et al. (op. cit.) propose that the decision to investigate specific claims based on the results of this method is a better alternative to randomly selecting claims from the set to investigate, given that all claims cannot be investigated due to limited resources.

7. DISCUSSION AND CONCLUSION

7.1 Microinsurance has the potential to make a big difference in the world economy, in local economies and in individuals’ lives by helping individuals recover from losses caused by uncertain events. However, fraud poses a serious threat to the viability of the microinsurance market and hence the availability of insurance products for low-income earners.

7.2 There is no question that something needs to be done to combat fraud, but the traditional methods of combating fraud are often unaffordable in the context of microinsurance as premiums need to be kept to a minimum to make policies affordable to low-income earners.

7.3 A key part of the fraud mitigation process is identifying fraudulent claims. The principle component analysis of RIDIT method for fraud classification is a method that appears to be well suited to identifying fraud in microinsurance initiatives where it is critical to keep costs low. The method is easy to implement, is statistically sound and
tests on conventional insurance claims data show that the method has been reasonably accurate in detecting fraud with at least one dataset.

7.4 The one challenge with the method is the subjectivity that is used to select the predictor variables and the criteria for assigning values to them. However, as discussed in ¶6.1.3, there are certain safety nets that result in the method auto-correcting when variables are incorrectly categorised and assigning low weight to variables with low indicativeness of fraud.

7.5 Apart from this one challenge, there are a number of advantages that make the method very appealing, not least the combination of low-cost and satisfactory accuracy when compared to supposedly more sophisticated methods.

7.6 We are of the view that microinsurance companies who currently have no fraud identification strategy in place have nothing to lose by implementing this method. It can be implemented by staff who are not expert claims assessors and the output is in an extremely useful form, allowing limited claim follow-up resources to be used optimally and non-suspicious claims to be paid immediately so as to improve the insurer's reputation in the fragile microinsurance market.

7.7 Because the method has not been adequately tested in a microinsurance context, there is a possibility that the PRIDIT method will prove to be less accurate in identifying fraudulent claims than other supervised identification methods. However, even if this is the case, it is important to remember that developing an effective fraud detection system is not achievable overnight. In contrast, an effective fraud detection system requires an ongoing and dynamic process that incorporates emerging information and trends with time. The PRIDIT method for fraud classification may be viewed as a step in this process. We expect that using the PRIDIT method will allow a microinsurance company to build-up a training sample in less time than if it were to follow up on claims at random. The training sample could then be used in the future to apply advanced and mathematically rigorous statistical techniques.

7.8 That being said, there are certain advantages of the PRIDIT method over supervised methods, such as the failure of supervised methods to adapt as fraudsters adopt new methods of committing fraud. Only time will tell just how successful the PRIDIT will be for microinsurance companies.

8. RECOMMENDATIONS FOR FURTHER RESEARCH
8.1 It is clear that the PRIDIT needs to be tested more adequately to establish just how successful it is at identifying fraudulent claims. This is certainly an area for further research.
8.2 An industry body that collects data on fraudulent claims from a number of insurers (possibly each applying the PRIDIT method to channel their limited claim checking resources and speed up the process of developing a training sample) will allow this research to be done for the benefit of all microinsurers. If such an initiative were to begin we would encourage microinsurers to participate for the benefit of the entire industry, just as we hope this paper will benefit all microinsurers.

ACKNOWLEDGEMENTS
Special thanks to the South African insurance company that provided the data on which the application in Sections 5 and 6 was based.

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