Development of an Expert System for the Automatic Detection of Automobile Insurance Fraud

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Abstract

The goal of this study is to develop a tool to aid insurance company adjusters in their decision making and to ensure that they are better equipped to fight fraud. This tool is based on the systematic use of fraud indicators. We first propose a procedure to isolate those indicators which are most significant in predicting the probability that a claim may be fraudulent. We applied the procedure to data collected in the Dionne-Belhadji study (1996). The model allowed us to observe that 18 of the 50 indicators used were significant in predicting the probability of fraud. Our study also discusses the model's accuracy and detection capability. The detection rates obtained by the adjusters who participated in the study constitute the reference point of this discussion. As shown in Caron-Dionne (1997), there is the possibility that these rates underestimate the level of fraud.

Our second step was to develop software allowing us to use the results of the statistical model to estimate the probability of fraud in files and to decide whether or not an in-depth investigation should be conducted. This software contains the mathematical equation and the parameters calculated by the Probit model. As indicated in the report, these parameters reflect the data from all the firms having participated in the study and not from any one company in particular. It is not obvious that the same indicators would be significant or even that the coefficients would be the same for any one insurer in particular. Any insurer wishing to use the software is advised to carry out a systematic study of the company's own files.

Once adapted to the insurer's use, the software can easily be used by claims adjusters. It would then be a matter of entering the indicators present in the files. The software will calculate the probability of fraud in a file and help the adjuster to decide whether an in-depth investigation is warranted.

A floppy disk containing the software proposed is available from the authors. It can be used on a PC with a Windows 95/NT system and a Web navigator. Procedures for installing the software are given in the appendix.

Résumé

Le but de cette étude était de développer un outil d'aide à la décision permettant aux enquêteurs des compagnies d'assurance d'être mieux équipés pour combattre la fraude à l'assurance. Cet outil est basé sur l'utilisation de façon systématique des indicateurs de fraude. Dans une première étape, nous proposons une procédure afin d'isoler les indicateurs les plus significatifs pour prédire la probabilité qu'un dossier soit frauduleux. Nous avons appliqué la procédure aux données recueillies de l'enquête Dionne-Belhadji (1996). Le modèle nous a permis de constater que 18 des 50 indicateurs utilisés étaient significatifs pour prédire la probabilité de fraude. Nous avons également discuté de la précision et de la capacité de détection du modèle. Cette discussion avait comme point de référence les taux de détection obtenus des enquêteurs ayant participé à l'enquête. Or, comme démontré dans Caron-Dionne (1997), il est possible que ces taux représentent une sous-estimation de la fraude.

Dans une seconde étape, nous avons préparé un logiciel qui permet d'utiliser les résultats du modèle statistique afin de calculer les probabilités de fraude des dossiers, et de décider de l'opportunité d'effectuer ou non une enquête approfondie. Ce logiciel contient l'équation mathématique et les valeurs des paramètres calculés par le modèle Probit. Comme indiqué dans le rapport, ces paramètres reflètent les données des entreprises qui ont participé à l'enquête et non nécessairement celles d'une compagnie en particulier. Il n'est pas évident que les mêmes indicateurs soient significatifs, ni même que les valeurs des coefficients soient les mêmes pour un assureur en particulier. Il est recommandé de refaire une enquête systématique à partir des dossiers de l'assureur qui veut utiliser le logiciel.

Une fois le logiciel adapté à un assureur, celui-ci peut être utilisé facilement par les enquêteurs; il s'agira d'entrer les indicateurs présents dans les dossiers. Ce logiciel calculera la probabilité de fraude du dossier et aidera l'enquêteur à décider de la pertinence d'effectuer une enquête approfondie.

Une disquette contenant le logiciel proposé est disponible auprès des auteurs. Elle peut être utilisée sur un «pc» doté du système d'exploitation Windows95/NT et d'un navigateur Web. Une procédure d'installation est en annexe.

Introduction

The purpose of this research was to develop a tool to help professional insurance company adjusters detect fraud automatically. (In this report, the software's application is limited to the automobile sector.)

The work consists in setting up a simple computer system allowing the adjuster to calculate the probability of fraud in each file studied. After having determined the most significant fraud indicators and their respective weights, we formulated a function linking these indicators to a probability of fraud.

To make the system more user-friendly, we developed an interface linking the function described above to the fraud indicators that the adjuster must enter into the system.

We propose the development of user-friendly software with a graphic interface similar to the formulas traditionally used in opinion polls. The user will enter the information required for the different indicators. The fraud (probability) score will appear at the bottom of the "questionnaire sheet". Based on this probability score, supervisors can decide whether or not to investigate certain files in depth. A complementary feature was conceived to measure the profitability of pursuing an investigation in each particular case. However, for lack of certain data, this second part is still in the exploratory stage.

It is important to stress that the model cannot be directly applied to a specific firm, since the parameters used are derived from calculations made with data from the industry as a whole (see Dionne and Belhadji, 1996). The potential user will have to conduct his own study—based either on all his files for a specific time period or on a random sample—and then compute the corresponding parameters.

This report is divided into five sections. In the first section, we describe the procedure for sampling the files. In Section II, we review the literature on fraud indicators and we justify our choice of the indicators selected. We then calculate the parameters allowing us to pick out which indicators are significant in predicting the probability that a file contains fraud. Section III uses the statistically significant parameters to calculate the probabilities of fraud in different files. This section also explains the procedures to follow in constructing a sample of files to be reviewed, while keeping within the budget allotted to fraud by the company. Finally, this section looks at the prevalence of fraud, relying exclusively on the evidence provided by our model. Section IV briefly discusses the costs of investigations, and Section V presents avenues of research which might be of interest to insurers.

A floppy disk is available from the authors. It contains the FRAUD 1.0 software and can be used on PCs equipped with Windows 95/NT and a Web navigator.

I. Sampling Procedure

In this section, we will study, successively, the representativeness of our sample, the different stages of the study, the notions of suspected and established fraud, as well as the methods used to select the actual sample.

I.1 Representativeness of the Sample

After having studied the market shares of insurers in collaboration with the Insurance Bureau of Canada, we selected twenty insurance companies among the biggest in Quebec's automobile insurance sector. According to the data in the "*Rapport annuel sur les assurances*" (1994) from the Inspector General of Financial Institutions, the twenty companies selected held 78.5% of the automobile insurance market in Quebec. Eighteen (18) of the twenty (20) firms selected accepted to participate in the study: a 90% participation rate. Taking into account the relative market shares of these eighteen firms, we thus obtained the participation of firms representing 70% of the market—which is very satisfactory. So, we can conclude that our study is representative of the market studied.

The participating firms accepted to make a detailed analysis of their closed claims files, in order to provide us with the different kinds of information needed to understand the fraud phenomenon. Their collaboration also allowed us to evaluate the level of fraud and to study the main indicators of automobile insurance fraud.

I.2 Stages of the Study

The files were selected at random from among all the files closed during the period from 1 April 1994 to 31 march 1995. The number of questionnaires assigned to each company was proportional to its share of the market. We suggested a method of random sampling (described in Dionne and Belhadji, 1996) to the firms.

The study took place in the spring of 1995. The insurers chose which adjusters would answer the questionnaire. We had asked them to designate the adjusters who had already handled the files in the sample. Strict procedures were implemented to protect the identity of the adjusters and the companies.

The eighteen companies returned 2 509 completed questionnaires to us, corresponding to a response rate of 98% for the 18 participating companies. Table 1 gives the breakdown of the files received from the participating companies.

Table 1
Number of Questionnaires Received from Participating Companies

Company	Number of Questionnaires Completed	% of Sample
1	100	4
2	89	4
3	166	7
4	108	4
5	274	11
6	48	2
7	370	15
9	45	2
10	39	2
11	60	2
12	275	11
13	346	14
15	69	3
16	39	2
17	100	4
18	40	2
19	161	6
20	180	7
Total	**2 509**	**100**

I.3 Established and Suspected Fraud in the Data of the Sample

Table 2 gives the number of established and suspected cases of fraud. These numbers reflect the opinion of the adjusters who answered the questionnaires. By established fraud, we mean that there was effectively fraud in a particular file, whether or not the case was brought to court. Fraud is suspected if the adjuster had suspicions of fraud while handling a file which was never investigated further.

I.4 Sample Selected for Analysis of Indicators

One of the questions to be answered (question 17) required the enumeration of certain characteristics of files which we called “fraud indicators”. A list of 50 indicators was proposed to the adjusters, who had to select those corresponding to each file by recording their respective numbers. While processing the data, we noted that certain adjusters never entered indicators, no matter what file they were studying. There were two reasons which might explain this: either none of the 50 indicators applied to any of these adjusters' files or they (the adjusters) did not see the relevance of the question and never used indicators. Note that the list of 50 indicators may perhaps have been off-putting for some adjusters who just preferred to skip question 17. To solve this problem, we decided to limit our sample to all the files where adjusters had recorded at least one indicator for all the files they filled out. The files of a particular adjuster were all chosen if at least one of his or her files contained at least one indicator. This procedure allowed us to get around a possible bias in responses associated with the fact that some adjusters did not answer the question. It had the advantage of removing the files of those who neglected to answer the question, but it was radical in the sense that it may have eliminated files without indicators when the adjuster was willing to answer the question. For the moment, we have settled for this method, but other avenues of adjustment are under study. Finally, this process of elimination produced a smaller sample than the one originally planned: we went from 2, 509 to 2,068 cases, for which the breakdown is presented in table 2. We thus lost 441 observations.

Table 2
Classification of Files

Classification	N No Fraud	S Suspected Fraud	E Established Fraud	$\frac{S+E}{N+S+E}$	$\frac{E}{N+S+E}$	N + S + E
Total	1 937	113	18	6.33 %	0.87 %	2 068

II. Fraud Indicators

The survey made in the spring of 1995 had a dual purpose: it was aimed, on the one hand, at evaluating the extent of automobile insurance fraud[1] and, on the other hand, at developing an expert system for the automatic detection of such fraud. This second part of the study consists in determining a set of indicators sensitive to the detection of fraud and the suspicion of fraud. In this section we shall justify the choice of the indicators selected as well as the criteria forcing us to eliminate certain others.

II.1 Choice of Indicators

As indicated above, we presented a list of 50 fraud indicators to participating adjusters. We asked them to include one or more indicators in any file containing one or more correspondent characteristics.

The 50 indicators are enumerated and categorised in the appendix. The indicators recorded in bold type are the ones which are significant in predicting the probability that the file is fraudulent.

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[1] This part of the study has been completed and a copy of the report can be obtained from the Insurance Bureau of Canada (Dionne and Belhadji, 1996). It has also been published in broad outline in the October 1996 issue of the review *Assurances*.

In the literature on indicators, there is very little empirical evidence which could scientifically demonstrate why some fraud indicators should be more relevant than others. It is for this very reason that we were attracted to the subject.

The list we drew up (see appendix) and which was included in the questionnaire sent to the claims adjusters was based on the literature in print at the time when we made up our questionnaire.

Our list was compiled based on two types of literature: applied literature concerned with the attempt to pick out relevant indicators and writings based on the experience of insurance professionals. In the category of applied literature, we note the work done by the University of Florida's Institute Research Center. Their study dealt with automobile insurance fraud in Florida. Its authors calculated conditional probabilities of fraud for each of the 90 indicators proposed in their list. Some of them applied to very few files (less than 10) and we had to eliminate them. We selected all the indicators relevant to the coverage (chapters) offered in Canada and whose conditional probability of fraud was higher than 10%. One should, however, note that this American study has at no time studied all the indicators simultaneously: it only calculated probabilities of fraud based on the presence of one particular indicator in the file (one indicator at a time).

Another study (Weisberg and Derrig, 1993) was used to complete our list of significant indicators. This study, which uses multiple regression, has the defect of using a non-random sample of files.

To ensure that our list would contain a professional component, we drew on descriptive studies conducted for the Insurance Bureau of Canada and SACA and on internal information on indicators published in the March 1993 issue of *Property and Casualty Claims Services.* The idea behind the selection process was to retrieve indicators common to several different studies.

Finally, in order to add a component closely connected with the Quebec automobile insurance market, we consulted company executives to find out which indicators were most used.

The list of 50 indicators found in the appendix was thus drawn up based on these studies and these consultations.

II.2 <u>Criteria for Limiting the Number of Indicators to Be Included in the Regression</u>

Since our list contained a very large number of indicators, we wanted to find a way of reducing them to a reasonable number for inclusion in our regressions. It seemed that the most effective means of doing this (while also eliminating non-relevant indicators) would be to calculate the conditional probabilities of fraud for each of the indicators. Table 3 indicates these conditional probabilities. Column 1 reports the indicator's number as it appears in the appendix. Each indicator has been given a name, which is shown in the second column. The third column displays the total number of files where the indicator (number “1” for example) is recorded. The fourth column is similar to the third except that the number recorded is that of files marked “E” (established fraud) or “S” (suspected fraud). Finally, the last column reports on the probability of fraud in a file given the presence of a specific indicator (example: police): this figure is obtained by dividing the number from the fourth column by that of the third column.

Note that the confidence intervals can be calculated based on the data in the table below. For all the estimates of the table, the standard deviation can be calculated as follows:

$$\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

where p is the value of the estimate and “n” is the frequency of that particular indicator (3rd column). The confidence interval will thus be:

$$\left[\ \hat{P} - Z_{\frac{\alpha}{2}} \sqrt{\frac{\hat{P}\,(1-\hat{P})}{n}}\ ;\ \hat{P} + Z_{\frac{\alpha}{2}} \sqrt{\frac{\hat{P}\,(1-\hat{P})}{n}}\ \right]$$

where $Z_{a/2}$ is the 1-a/2 percentile of a normal distribution.

The standard deviation of the estimate for the number 3 indicator, for example, is calculated as follows:

$$\sqrt{\frac{(0.316)\ (0.684)}{57}} = 0.062$$

The confidence interval at 95% of the estimate for this indicator would thus be:

$$\{0.316 - 1.96\ (0.062)\ ;\ 0.316 + 1.96\ (0.062)\}$$

or expressed in other terms: {19.5%; 43.7%}

This table, which served only as a guideline in the choice of indicators, allowed us to eliminate all the indicators present in only 14 files or less. So, the indicators marked with an asterisk (5th column) should not be interpreted as being non significant, since the reason for their exclusion is merely insufficient data. Any future study dealing with a large number of files (many more than 2,500 files) should include and test these indicators.

Note that, because its different indicators are viewed in isolation, this table is not sufficient evidence of the possibility of fraud. A regression taking into account all the indicators present in a file would be preferable. This is what we will do in the Probit regressions below. These regressions will allow us to determine which are the most significant indicators: the latter are recorded in bold print in the appendix.

Table 3
Conditional Probability of Fraud (E or S)
Based on the Presence of Indicator "x"

Number	Indicator	Total number	Number (E + S)	Conditional Probability %
1	Police	363	34	9.40
2	Minor	74	6	8.10
3	Incon	57	18	31.60
4	Theft	32	12	37.50
5	Recent	80	7	8.75
6	Bill	30	3	10.00
7	Interest	71	13	18.31
8	Commer	24	3	12.50
9	Scope	41	5	12.20
10	Agent	148	9	6.08
11	Diffic	43	16	37.21
12	Occup	7	3	42.86*
13	Receives	71	12	16.90
14	Small	15	8	53.33
15	Rapid	56	15	26.79
16	Jargon	48	13	27.08
17	Travel	19	7	36.84
18	Eager	17	8	47.06
19	Proxim	87	13	14.94
20	Act68	3	0	0.00*
21	Taxi	17	7	41.18
22	Proof	19	12	63.16
23	Guilty	15	5	33.33
24	History	14	7	50.00
25	Third	22	2	9.09
26	Documen	21	5	23.81
27	Samegar	21	2	9.52
28	Represen	4	1	25.00*
29	Repair	20	3	15.00
30	Witness	97	19	19.59
31	Denial	13	4	30.77
32	Sole	142	19	13.38
33	Unident	69	7	10.14
34	Guarantee	9	3	33.33*
35	Rental	3	2	66.66*
36	Contact	8	3	37.50*
37	Sign	34	4	11.76
38	Settlem	6	3	50.00*
39	Cash	33	8	24.24
40	Unemploy	18	7	38.88
41	Found	6	3	50.00*
42	Overassur	8	0	0*
43	Prem	1	1	1*
44	Motel	1	0	0*
45	Agress	26	9	34.62
46	Refuse	15	1	6.66
47	Nervous	42	17	40.48
48	Numerous	129	12	9.30
49	Title	5	2	40.00*
50	Preced	7	2	28.57*

* Since they contain 10 cases and less, these results must be interpreted with caution.

II.3 Regression Model and Results

The Probit model that we use supposes a y_i* response variable as defined by the following relation:

$$y_i^* = b' x_i + u_i$$

where y_i* is not observable. The x_i vector represents the indicators present in the file, whereas the b' vector includes the values of their respective parameters.

We do, however, observe the binary variable y_i which is defined by:

$$y = 1 \quad \text{if } y_i^* > 0$$
$$y = 0 \text{ otherwise}$$

In our specific case:

y = 1 if the file has been judged fraudulent (suspected or established fraud)

y = 0 otherwise

It follows that:

$$\begin{aligned} \text{prob}(y_i = 1) &= \text{prob}(u_i > -b' x_i) \\ &= 1 - F(-b' x_i) \end{aligned}$$

where F is the cumulative distribution function of u. The likelihood function will thus be:

$$L = \prod_{y_i=0} F(-\beta' x_i) \prod_{y_i=1} [1 - F(-\beta' x_i)]$$

In the Probit model, u_i follows a normal distribution $N(0, s^2)$. In this case:

$$F(-\beta' x_i) = \int_{-\infty}^{-\beta' \frac{x_i}{\sigma}} \frac{1}{(2\pi)^{1/2}} \exp(-\frac{t^2}{2})\, dt$$

The results of the Probit regression are recorded in table 4 on the following page. In this table only the significant indicators are presented. These are the indicators which will be used to calculate the probabilities of fraud in files. The first and second columns give, respectively, the numbers and names of the indicators selected. The third column presents the estimated coefficients, whereas the last column indicates their degree of significance. It is to be noted that the indicators followed by the number 1 are those considered the most important for the investigator. In contrast, the indicators followed by a 2 represent those whose order of importance ranges between 2 and 12.

Table 4
Results of Probit Model Estimate

No	Indicateurs	Coefficients	t
	Constant	2.53842	23.87243
2	MINOR	0.65360	2.88309
*	W/OCOL	0.44192	3.14714
4	THEFT	1.26659	4.60894
11	DIFFIC2	0.83390	2.60732
14	SMALL	1.13099	2.78572
16	JARGON2	0.90678	3.19590
18	EAGER	1.58303	4.75648
19	PROXIM	0.63276	3.23234
21	TAXI	0.72584	1.89837
22	PROOF	1.64896	4.79668
26	DOCUM	1.24422	3.68028
30	WITNESS2	1.03962	3.69397
32	SOLE	0.69536	4.19627
39	CASH	0.81779	2.83649
45	AGGRESS	0.93629	3.10616
47	NERVOUS	1.04607	4.49000
**	W/OREP	0.57129	3.95309
3	INCON1	1.80978	7.86276
11	DIFFIC1	1.89913	2.34950
16	JARGON1	1.18581	3.03581
30	WITNESS1	0.95626	4.24095

* Accident without collision.

** Accident with collision and for which the claim was not accompanied by a police report, although one was required.

III. Model where Only Adjusters Predictions Are Relevant

We will first compare the predictions of our model with the results of the investigation; we will then propose examples of decisions as to whether or not further investigation should be conducted.

III.1 Comparison of Regression Results with Those of the Investigation

The predictions of our model are compared with the decisions of adjusters regarding their suspicions—these suspicions being considered as complete and that there is no other fraud (or suspicions) in the sample examined.

The model that we have used has generated probabilities of fraud for each file. These vary between 0.69% (no indicator) and 99.30%. We have not, for the moment, used a confidence interval.

In setting the probability threshold for a closer investigation of files, we implicitly determine the detection rate for fraud as well as the model's level of accuracy in spotting suspected cases of fraud.

We know that out of the 2 068 claims investigated, adjusters found 131 suspected or established fraudulent cases. This gives us a fraud rate of 6.33%[2].

Take for example the 10% threshold of probability. At the 10% level, the model will generate 336 cases of fraud. Among these 336 cases, the adjusters suspected (and/or established) 98 cases of fraud. The rate of accurate fraud detection is thus equal to 29.17% (or 98/336). The cases classified by the model as “non fraud” number 1 732 (or 2 068-336). Among these, 1 699 cases

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[2] Here it is supposed that the adjusters will detect all the cases of fraud contained in the files. This hypothesis has been questioned by Caron and Dionne (1997) who show that the adjusters observe only one third of the fraud.

are classified as “non fraudulent” by investigators: an accuracy rate of 98.09% (or 1 699/1 732). The fraud rate in the industry is the basis for the proportion of the sample to be selected[3]. The company will select “X” percentage of the files to be reviewed, as calculated by solving the following:

$$\alpha \,.\, X\,\% \;+\; (1 - \beta)\,(1 - X\,\%) = 6.33\,\%$$

where:

α: is the rate of accuracy (in %) for fraud cases captured by the model. If the threshold is 10%, this rate is equal to 29.17%.

β: is the rate of accuracy (in %) for non fraudulent cases generated by the model. If the probability threshold is 10%, this rate is equal to 98.09%.

Note that the equation above contains two parts: the first part, $\alpha \,.\, X\,\%$, expresses the percentage of fraud (as predicted by the model) to be found among the cases selected (cases where the probability of fraud exceeds the threshold). The second part, $(1 - \beta)\,(1 - X\,\%)$, expresses the proportion of fraud detected by the investigators, but a proportion lower than the threshold chosen (cases not selected for review).

For example, solving the equation above for a 10% threshold, we will obtain a proportion of the sample to be re-examined, “X”, equal to 16.21%.

To sum up:

For a 10% threshold of probability of fraud, we should select 336 cases (according to the regression model); among these cases, adjusters found that 98 cases were fraudulent and 238 non fraudulent, which means:

[3] This percentage can be replaced by another if the company feels its fraud rate differs from the average for the industry.

$$336 \rightarrow \begin{array}{l} \nearrow \text{NF} = 238 \\ \searrow \text{F} = 98 \end{array}$$

The proportion of the sample to be re-examined = X = 16.21%.

The accuracy rate for cases of fraud (F) : 98/336 = 29.17%.

The number of files below the 10% threshold is equal (according to the model) to 1,732. Among these, 1 699 cases are classified as non fraudulent by adjusters:

$$1\ 732 \rightarrow \begin{array}{l} \nearrow \text{NF} = 1\ 699 \\ \searrow \text{F} = 33 \end{array}$$

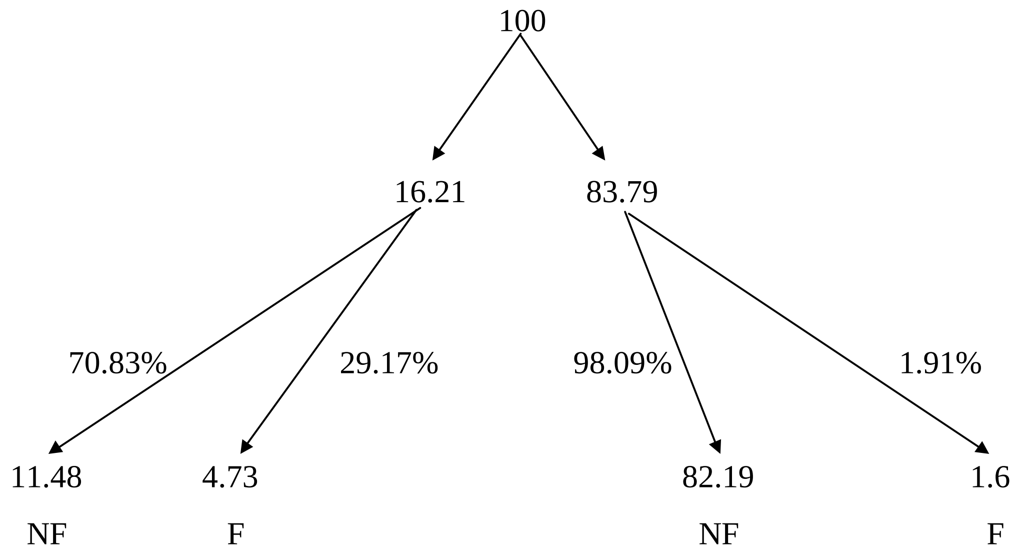
The rate of accuracy for “non fraud” (NF) = 1 699/1 732 = 98.09%.

III.2 Decision to Investigate

We now propose a model for the decision to investigate.

At a probability threshold of P=10%, the company should select 16.21% of its claims for re-examination, if it feels its fraud rate is equivalent to the industry's 6.33% level.

Thus, for 100 claims, we will get the following results:

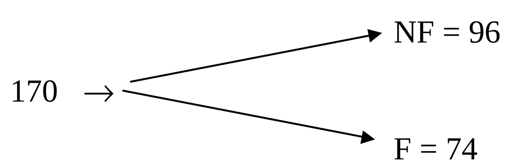


Total fraud rate = 4.73% + 1.6% = 6.33%[4]

Rate of accuracy for fraud cases (F) = 29.17% (see the calculation above)

Rate of detection = 4.73%/6.33% = 74.72%.

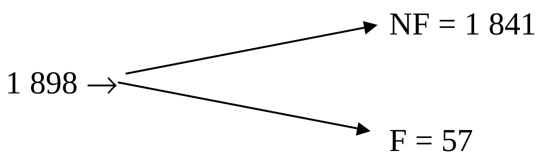
Similarly, for a P = 20% probability threshold, the model detects 170 cases of fraud. Of these, 74 were classified "fraudulent" by the investigators. The model's accuracy rate is thus 43.53% (or 74/170). When the threshold is dropped below 20%, the model generates 1 898 "non fraud" cases. Adjusters determined that 1 841 of these 1 898 cases, were not fraudulent. The "non fraud" accuracy rate is thus 97% (or 1 841/1 898). To sum up, a probability threshold of 20% will give us:



Proportion of sample to be re-examined = X = 8.22%.

Rate of accuracy for fraud cases (F): 74/170= 43.53%.

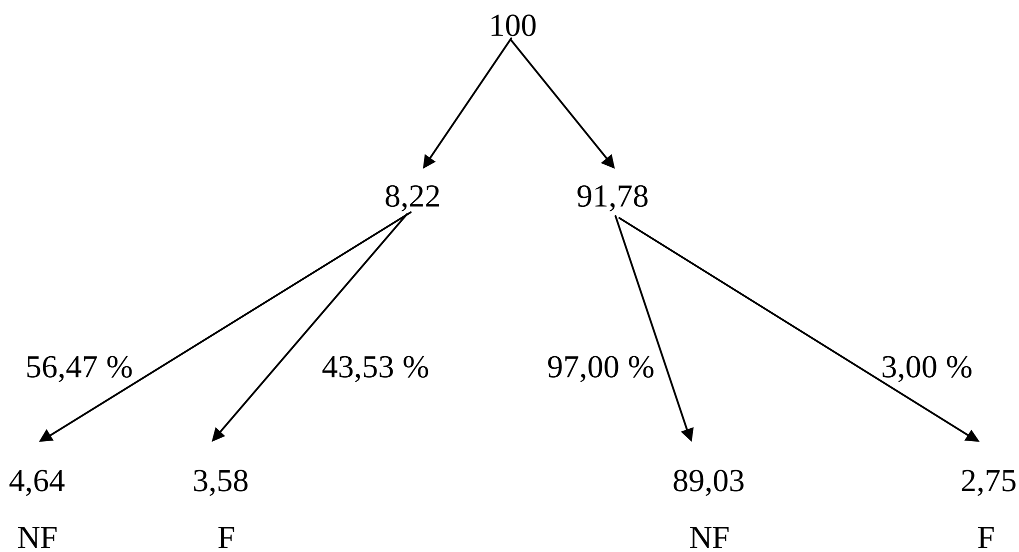
The number of files below the 20% threshold is (according to the model) 1 898. Among these, 1 841 cases are classified as non fraudulent by investigators:



The rate of accuracy for "non fraud" (NF) = 1 841/1 898 = 97%.

<u>At a P = 20% probability threshold</u>, the company should select 8.22% of its claims for re-examination, if it feels its fraud rate is equivalent to the industry's 6.33% level.

So, out of 100 claims, we will obtain the following results:



Total fraud rate = 3.58 + 2.75% = 6.33%[5]

Rate of accuracy for fraud cases (F) = 43.53% (see calculation above)

Rate of detection = 3.58%/6.33% = 56.56%.

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[4] Note that this figure may not be exactly equal to 6.33% due to the rounding off of percentages.

[5] Note that this figure may not be exactly equal to 6.33% due to the rounding off of percentages.

Similarly, calculating for a P = 90% probability threshold, we obtain the following results:

Proportion of sample = X = 0.38%

Rate of accuracy = 75%

Rate of detection of fraud = 4.58%

If these same calculations are repeated for different thresholds (P), we obtain the next summary table.

Table 5
Rates of Accuracy and Detection
for Different Thresholds of Probability of Fraud

Probability Threshold for Fraud	**Percentage of Sample (%)**	**Rate of Accuracy in %**	**Rate of Detection in %**
P > 10%	16.21	29.17	74.72
P > 15%	10.66	35.75	60.35
P > 20%	8.22	43.53	56.56
P > 25%	6.90	48.95	53.40
P > 30%	5.22	55.56	45.81
P > 35%	4.59	58.95	42.81
P > 50%	2.26	61.70	21.96
P > 65%	1.20	64.00	12.16
P > 85%	0.52	72.73	6.00
P > 90%	0.38	75.00	4.58
Average of the sample			
P > 25.5%	**6.85**	**49.30**	**53.40**
Column S	Column E	Column R	Column D

Table 5 dictates the following conclusions:

If the goal is detection, a large number of files must be sampled. Note that a sample where P > 10% contains more files than a sample where P > 20%. This methodology has the advantage of ferreting out a maximum number of suspect cases. It does, however, suffer from two shortcomings. The first is that reviewing a large sample of files is costly for the company. An average company which decides to re-examine every file with a fraud probability of over 10% will have to pay for the review of 2 468 files[6] (automobile accidents excluding broken windows). The second shortcoming is that re-examination of a broad range of files will entail some “unfairness” towards clients who are not cheaters but who will be closely investigated by their insurance company. For example, if the 10% threshold is chosen, we know that there will only be a 29.17% level of accuracy (see table 5) and, thus, over two thirds of the sample selected will not be cheaters (according to the adjusters in our study).

If, by contrast, the only concern is rate of accuracy, a very small number of files will be selected for re-examination. The advantage of applying such a method is the relatively low total costs of reviewing such a small sample. Indeed, an average company having decided to re-examine all files with a fraud probability of over 90% will have to pay for the review of only 58 files[7] (automobile accidents excluding broken windows). The other advantage is the level of accuracy: whereas the accuracy of the 10% threshold was 29.17%, the 90% threshold is 75% accurate. In this case, three out of four cheaters are detected. The shortcoming of this decision threshold (90%) is that only 4.58% of fraud is actually detected; most cheaters (95.42% of cases) will slip pass the company.

Having examined these extreme cases (P=10% and P=90%), we can see that there is a trade-off between detection and accuracy (see table 5): the higher the fraud probability threshold the greater the accuracy and the weaker the detection. A very conservative company with no wish to

[6] This figure is equivalent to 16.21% of the 15 224 claims files an average automobile insurance company handles annually. These figures are drawn from the Dionne and Belhadji study (1996).

[7] This figure is equivalent to 0.38% of the 15 224 claims files an average automobile insurance company handles annually.

get too involved in fighting fraud will probably opt for very high thresholds. An aggressive company with a strong wish to fight fraud and reduce its costs will opt for rather low thresholds. Finally, note that a threshold of about 25% (average threshold for the industry) will allow us to detect roughly half the fraud while achieving about 50% in accuracy.

This table can also be used by companies wishing to know their rates for accuracy and for detection of fraud. If a company knows its budget constraints and decides to allot a certain sum (Z) to in-depth investigations, it will thus know the number of files to select in conducting its investigations. To each sample size will correspond a rate of detection and accuracy (if the fraud rate is the same as that in the industry).

III.3 Cases where Our Model Predicts Correctly

According to this approach, our model for predicting fraud is used to estimate the overall incidence of fraud. We consider all the cases with a probability above a given threshold as fraudulent. However, for the proportion of cases below the chosen probability threshold, the opinions of adjusters do come into play. This thinking is in some sort motivated by the fact that our model (with its indicators) fails to explain all aspects of fraud. We are here thinking in particular of the essentially subjective aspects of a routine investigation.

Investigators may also fail to observe all the elements that point to fraud. The total number of estimated fraudulent cases may consequently be greater than the number evaluated as fraudulent by adjusters[8]**.** All the fraud detected by the model but not detected by investigators is added in. We should remember that in the preceding case, fraud amounted to 6.33% (equivalent to a threshold of P=25.5%). In this case, where all the files whose probability of fraud exceeds this threshold are considered fraudulent, fraud would climb to 9.82%. The rate differential

[8] See Caron and Dionne (1997) for further details. Their model's best estimator generates a 10% fraud rate or $113.5 million in the industry.

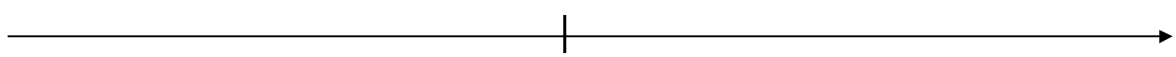
(i.e. 3.49%) could be due to hidden fraud which went undetected by adjusters. We are in fact faced with three scenarios:

1. A portion of fraud is detected simultaneously by our model and the investigators. These are the files with a probability of fraud higher than the threshold and which were spotted by the adjusters.

2. Another portion is detected by the model but not by investigators. These are the files whose probability of fraud is higher than the threshold but which were not detected by adjusters. This is what we have called hidden fraud.

3. Finally, a third portion is made up of files detected by adjusters but not detected by the model. We mentioned above the subjective aspects at play in spotting these fraudulent files. Their probability of fraud fell below the threshold. These three cases (1, 2, and 3) are reproduced in the following figure:

Threshold



Cases of non fraud (model)	Cases of fraud (model): (1 + 2)
. Certain cases are considered fraudulent by investigators (3)	. Certain cases are considered non fraudulent by investigators

IV. Some Notions about the Costs of In-Depth Investigations

In deciding to pursue an in-depth investigation, the insurance company is faced with the following choice: if the cost of settlement without in-depth investigation is lower than the expected cost with investigation, there will be no investigation; otherwise, the investigation will be pursued[9].

Given the following costs:

C_1: Cost of settlement without in-depth investigation

C_2: Cost of settlement after in-depth investigation

C_c: Cost of conducting an in-depth investigation[10]

$C_1 = R$ (value of the claim net of deductible)

$C_2 = C_c + p \, . \, R_2 + (1-p) \, . \, R_1$

where:

R_2: amount of the claim paid if the investigation succeeds

p : probability investigation will succeed

Note that the probability of the investigation's success will generally depend on several factors such as the probability of fraud (calculated and noted as P), experience and training of investigators (noted respectively as EX and T), and the organisation of the firm (noted as SIU). For example, the firm's organisation may or may not include Special Investigation Units. This probability of success may thus be represented by the following function:

$p = f$ (P, EX, T, SIUY).

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9 This deduction is valid only in short-term static thinking. A company which bases its decisions on more long-term strategies may wish to pursue the investigation even if, on average, its costs with investigation exceed its costs without investigation. In so doing, this company will earn a reputation for being active in the fight against fraud and cheaters will switch to other companies more tolerant of fraud. In the end, this will mean lower total costs (discounted) for claims and investigations.

It should, however, be mentioned that the probability of fraud is a determining factor in the above function: a file with a very weak probability of fraud (P) should not generate a high probability of success (p) no matter what the values of the other factors (EX, T, SIUY).

Finally, the firm's decision will take the following form:

If $C_1 \geq C_2$ => The investigation is conducted.
If $C_1 < C_2$ => The investigation is not conducted.

By replacing the values C_1 and C_2 in the first inequality above, we find that the company will conduct the investigation in the case where:

$$p (R_1 - R_2) B C_c \geq 0.$$

In other terms, the investigation will be conducted if the expected claim differential will at least cover the cost of the investigation.

V. Avenues of Research

The product developed is based on claims files randomly selected from the population of files belonging to participating insurers. It thus treats all possible cases of fraud for any conceivable claim. The model generates a probability of fraud for an ordinary file (see figure 1).

Insurance company executives may not only be interested in the probability of fraud in an ordinary file, but also in the probability an in-depth investigation will be successful (see figure 2). Indeed, these two complementary steps should be executed simultaneously: figure 3 sums up the procedure for this.

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[10] This amount may be estimated by the average cost of conducting an in-depth investigation. It is however more

It is first a matter of deciding whether or not an ordinary file should be investigated: this is the goal of the present work where we have used a model to generate a probability of fraud. Our sample in this work was made up of 0.64% of all the industry's automobile claims files (excluding broken windows).

Next, the so-called serious cases which have received special investigation must be studied. In these cases, the files having undergone in-depth investigation would need to be sampled. The ideal would be to sample a portion of the files handled by the Special Investigation Units (or any other division charged with conducting special investigations). To the indicators in the first stage of the investigation could be added indicators specific to the second stage (in-depth investigation). This stage of investigation would take into consideration the indicators themselves as well as the training and experience of specialised adjusters. The goal of this stage would be to generate a probability of success for the in-depth investigation. After this, the investigation's profitability could be calculated in monetary terms.

In our view, it is this second stage which must be achieved in order to complete the process of automatic investigation.

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accurate to consider each cost as being specific to a particular file. Some files are more difficult to handle than others.

Figure 1
Determination of the Probability of Fraud
(Decision of Adjusters)

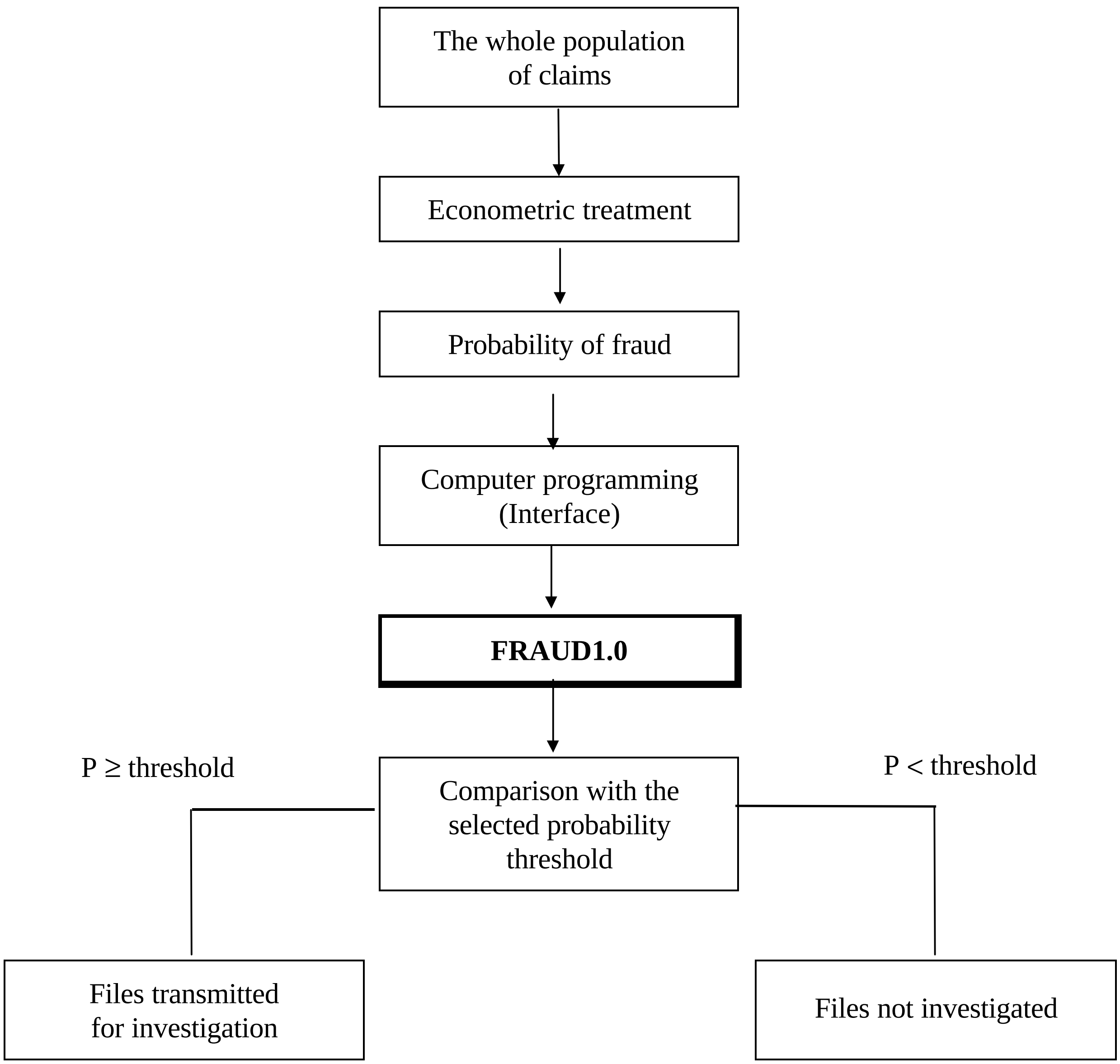


Figure 2
Determination of the Probability of Success of an Investigation
(Decision by Special Investigation Units)

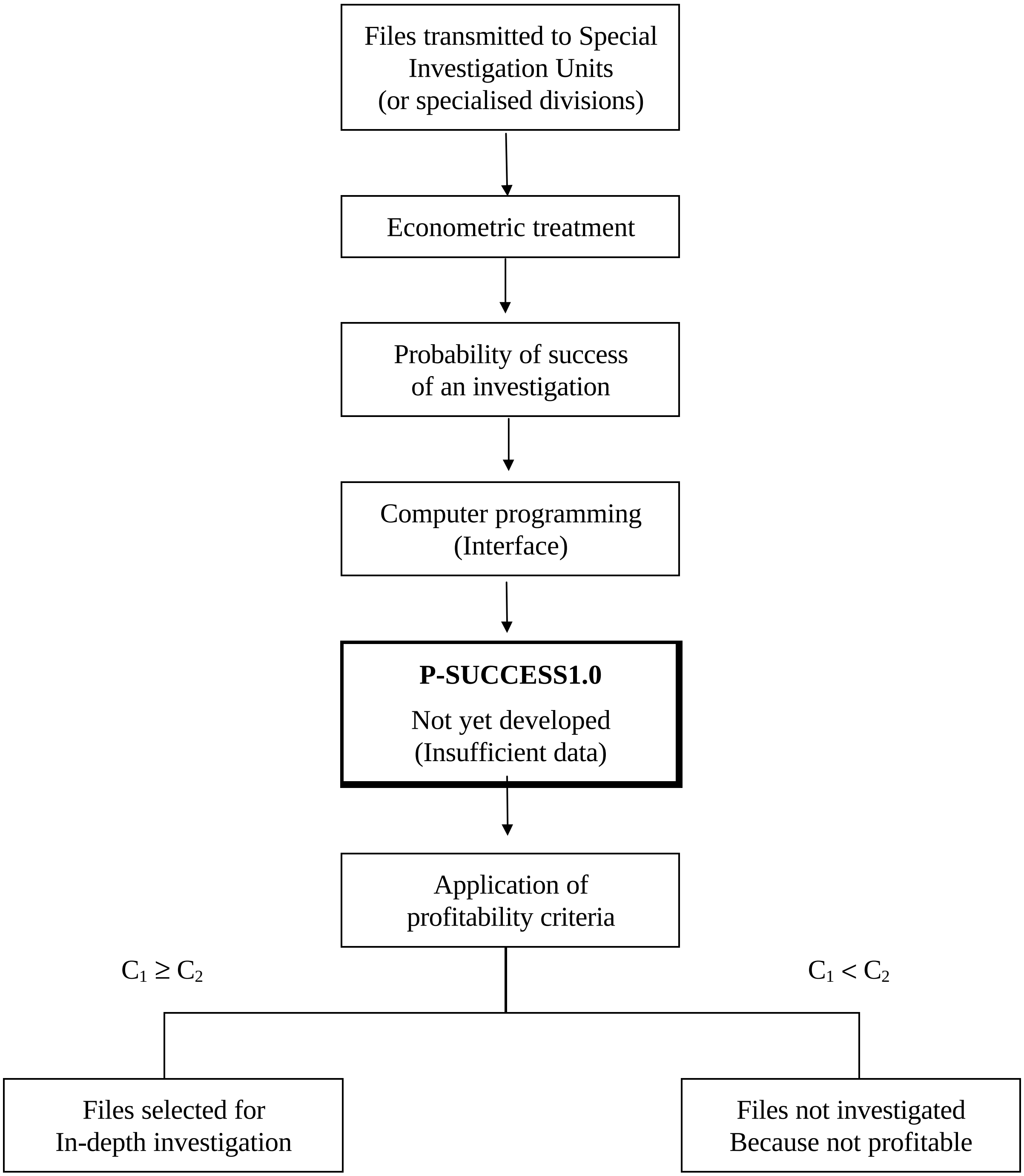
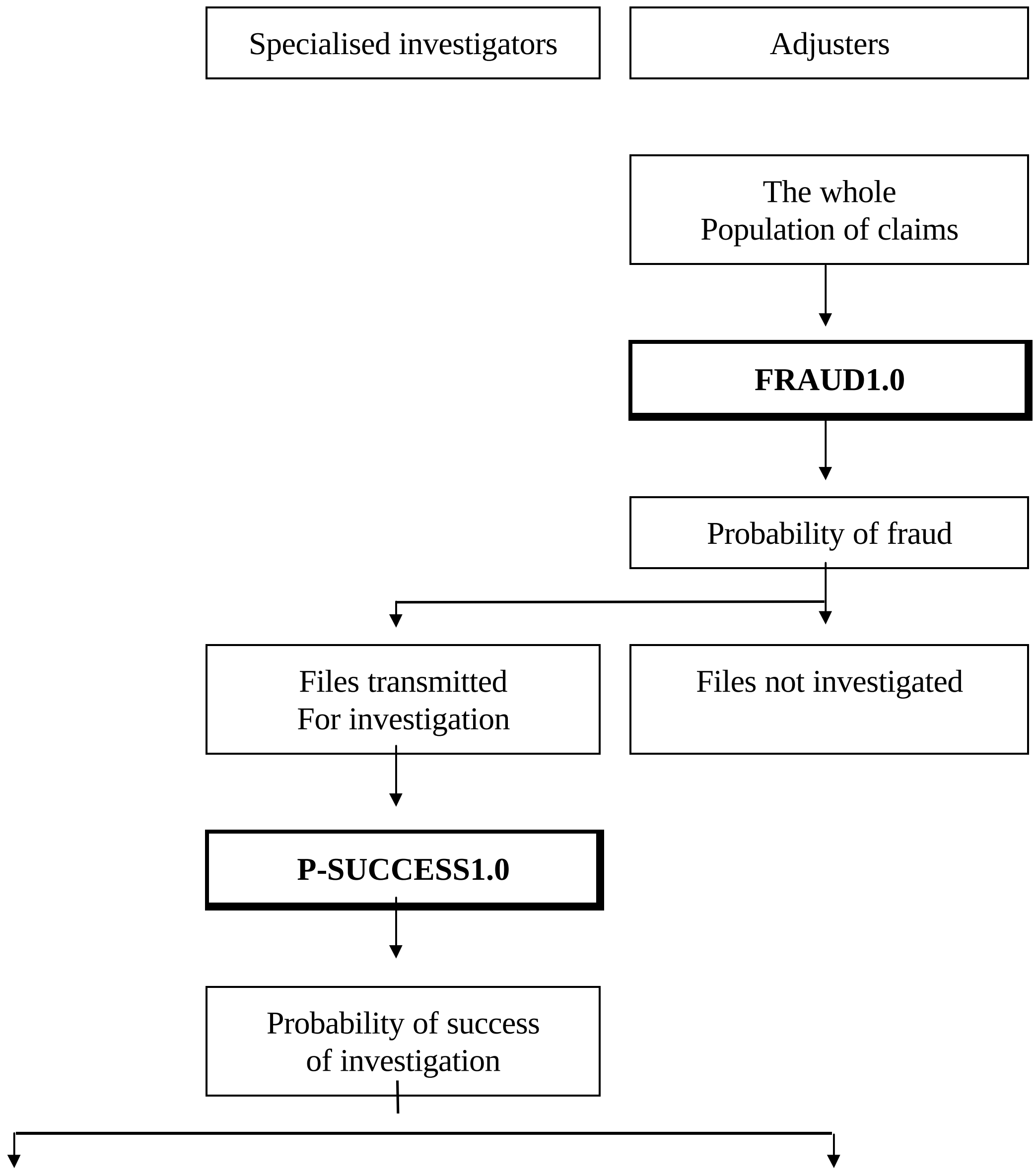


Figure 3
Probability of Fraud and Probability of Success of an Investigation
(Decision at two different levels)



Files selected for
in-depth investigation:
investigation profitable

Files set aside:
investigation not profitable

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APPENDIX

Appendix 1

Instruction Manual for FRAUD1.0 software

by

El Bachir Belhadji

Georges Dionne

Eric Le Saux

A1-1 Warning

This software was developed with industry-wide data and is thus not modeled on any one company in particular, but rather on all the firms having participated in the study. If an insurance company is interested in using the same product for its private needs, it would be preferable for that company to develop the same type of product based on its own specific reality. The company would thus use its own data, since it must not be assumed that the parameters calculated for the industry will apply directly to a particular firm.

A1-2 Purpose of the Software

The software is designed to serve as an aid in deciding whether or not to investigate supposedly fraudulent files. This product allows the company to accelerate the decision-making process and, thus, to save on time and resources. Using this product makes it possible to generate a probability of fraud for each file. Based on this probability and other information specific to the firm, this software will indicate whether or not it is profitable to pursue the investigation.

A1-3 Installation Procedure

1. <u>Operating System Required</u>

The fraud detection form was written in Java, a new computer language whose programs will operate on most existing operating systems (Windows 95 and NT, Unix, etc.). To use this program, a Web Browser is needed to navigate on the Internet. However, it is not necessary to be connected to the Internet for the program to work properly.

Several Web Browsers are now available via the Internet, and some are free. We advise you to procure **Netscape Navigator 3.01** or **HotJava 1.0.** Unfortunately, Microsoft Internet

Explorer 3 still has a few bugs that prevent it from running Java programs, so it will not be of any use to you.

2. Starting Up the Program

The software is provided on a PC formatted floppy disk. You can operate directly from the floppy disk by commanding your Browser to access the following reference:

file:/a:/fraud.html

You can also copy all the files on the floppy disk onto your hard disk. If you install them in the “C:\insurance”, directory, they will then be accessible with the reference “file:/c:/insurance/fraud.html”.

If your corporation already has its **Intranet** (its own Web site for in-house use), you can ask your analysts to install the software. This will spare you the trouble of installing the software on all your adjusters' PCs. They will be able to start up the software by using an address such as: “http:/www.bac.ca/investigator/fraud.html”.

You can also make the software accessible to the whole world via the Internet, by placing it on a conventional Web site.

3. Where Can You Procure a Browser?

You can procure a completely operational demo version of Netscape through FTP anonymous at the following address: “ftp//:ftp6.netscape.com/navigator”.

HotJava is available through FTP anonymous at “ftp://java.sun.com/pub/hotjava”.

A1-4 Filling Out the Form

Interface

The interface is divided into three main sections:

Interface Identification :

At **File**, please enter the policy number of the claims file.
At **Investigator's serial number**, please record your employee number.
At **Place of accident**, please enter the municipality where the accident occurred.
At **Date of accident,** enter, in order, the day, the month, and the year of the accident.
At **Guarantees purchased**, record all the coverage that the insured has purchased.

Interface Indicators:

This section serves mainly to introduce all the indicators present in the file that you are studying. You have only to click on a particular indicator with the mouse when you know that indicator is present. After having selected all the relevant indicators, you can go on to the next section. Don't forget to indicate the number of the indicator you feel is the most important.

Please note that you have to complete this section before going on to the next one. Please note that as you enter the data, the probability of fraud will appear on the bottom of the screen. The order in which the indicators are entered is not important.

Decision Interface:

This section allows the supervisor to decide whether or not to pursue a more thorough investigation.

At **Amount of settlement estimated if there is no investigation**, please indicate the amount of the damage (estimated at that date) minus deductible, if it is applicable. If you don't yet have this amount, leave the space blank. You can fill it in later.

Estimated amount of settlement if proof of fraud is established after an investigation. For each file, it is possible to estimate how much will be paid out to the insured if the investigation succeeds. In some cases, this amount will be zero, whereas in other cases, the company will pay out a certain amount, even if its investigation is considered successful. According to our data on automobile insurance fraud, this amounted, on average, to $1 671 (in 1995).

Estimated cost of an in-depth investigation. There will be a different level of difficulty in investigation for each file. As a rule, the more difficult the investigation, the higher its cost. An experienced professional adjuster can more or less accurately predict this cost. In the insurance milieu, the cost is usually expected to be between 20% and 30% of the value of the claim. In other terms, for an average claim[11] of $2 514, the cost of an in-depth investigation would be between $500 and $750.

This cost is, of course, an average and can only be applied to cases considered "average" in terms of difficulty of investigation and value of claim.

[11] Average as indicated by the data in the Dionne-Belhadji study (1996).

Subjective probability that the investigation will be successful. The estimate appearing below the indicators represents the probability of fraud in the file analyzed. In general, the higher this probability, the greater your chances of conducting a successful investigation. Your “chances” of a successful investigation will depend on the probability (above) that the file is fraudulent, on your experience, on your training, and on whether or not your firm has Special Investigation Units. Knowledge of all these parameters is needed to form your subjective opinion of whether or not the investigation will succeed. In cases where you feel you cannot give your subjective probability, please record the probability reported above.

Result. After all the relevant information has been entered, the program makes a calculation of profitability and advises you whether or not the investigation should be pursued based solely on profitability.

Remark: Since the program is based solely on short-term profitability criteria, it may in certain cases (notably in cases where the claim is too small) tell you not to pursue the investigation even if there is a strong probability of fraud (and/or a successful investigation). In these cases, the supervisor can decide whether or not to pursue the investigation based on the value of the probability of fraud. For further information on the value of this probability, consult the section entitled threshold of probability in the following pages.

A1-5 Example of a Particular Case

We will go over an example from a particular file to show how the interface should be filled out.

Interface Identification:

File: Policy number is *a1397*

Investigator's serial number: The adjuster's employee number is *0074*.

Place of accident: The accident took place in *Ste-Thérèse.*

Date of accident: The accident occurred on *4 October 1997*

Estimated amount of damages net of deductible: In this case, the estimated amount of damage is $5 527. The applicable deductible in the case of this accident is $250. The amount net of the deductible to be reported is thus $5 277.

Guarantees purchased: The insured has purchased the following types of coverage—*A; B2; B3.*

Interface Indicators:

The adjuster will use the mouse to click on the following indicators whose presence has been observed:

- The insured is too eager to take responsibility for the accident.
- The accident (or loss) occurred shortly after the vehicle was registered and insured or within the month preceding the end of coverage.

For the adjuster, the most important indicator is the second one mentioned above. After having entered these indicators, the probability of fraud appearing on the bottom of the screen will indicate 40%.

Interface Decision:

This section allows the supervisor to decide whether or not to pursue a more in-depth investigation.

Amount of settlement estimated without an investigation. In this case, the amount of damage is estimated at $5 527. The applicable deductible is $250. The amount net of the deductible is thus $5 277.

Amount of claim if investigation is successful. Given the experience and training of the adjuster as well as the absence of SIUs in the company (see above), the estimated amount the company would have to pay if the investigation succeeded would be $2 400.

Estimated cost of conducting an in-depth investigation. As the adjuster does not know the exact cost of an in-depth investigation, he or she will rely on the data from the industry to estimate it at $600. This assumes that the file was of average difficulty and that its investigation cost was in line with those in the industry (between $500 and $750).

Subjective probability of the investigation's success. The probability appearing below the indicators represents the “objective” probability of fraud in the file analyzed. If the adjuster is short on training and experience and if the company does not have any Special Investigation Units, the “subjective probability” of the investigation's success can be entered as 40%.

We may, on the other hand, suppose that our adjuster has an A.I.A.C diploma with seven years of experience in insurance work and that his or her company does not have any SIUs. In this case, he or she could estimate the probability of the investigation's success at 45% (granted that the probability of fraud is 40%).

Result: The result generated by the program is that *YES* it is profitable to do an in-depth investigation.

A1-6 Notions on the probability threshold

In some cases, the last section of the interface may only generate results where the investigation would not be profitable: this, for example, is the case when the claims involved are very small. If a firm is highly committed to fighting fraud, it will then base its decision solely on the level of the probability of fraud. If this probability exceeds a certain threshold, the firm will conduct an in-depth investigation; otherwise it will pay the claim and close the file. In order to find out the threshold of this probability, the company can use the table on the following page.

Since we have at our disposal the average data from the industry, we can here present a typical case of an "average" company.

Let's take an insurer who closes 15 220 files annually. This firm has an anti-fraud budget of $630 108 to carry out in-depth investigations. Each in-depth investigation costs on average $600. With its $630 108, the firm can investigate 1 050 files in depth. This represents 6.9% of the total claims treated each year.

Based on the table below (showing industry averages), the company in question will know that its probability threshold is 25%: every file above this threshold will be thoroughly investigated. If this company's data are comparable to the averages for the industry, then it will have used up its anti-fraud resources by the end of the year (neither more nor less will be devoted to fraud).[12]

[12] We often recommend that each company construct its own table, even if it feels it is representative of the average. In cases where the company is very large or very small, the above table is not suitable.

Table 1
Sampling, Detection, and Precision according to Probability Thresholds for Fraud

Probability Threshold Of Fraud	Percentage of Sample	Rate of Precision in %	Rate of detection in %
P > 10%	16.21	29.17	74.72
P > 15%	10.66	35.75	60.35
P > 20%	8.22	43.53	56.56
P > 25%	6.90	48.95	53.40
P > 30%	5.22	55.56	45.81
P > 35%	4.59	58.95	42.81
P > 50%	2.26	61.70	21.96
P > 65%	1.20	64.00	12.16
P > 85%	0.52	72.73	6.00
P > 90%	0.38	75.00	4.58
Average of the sample			
P > 25.5 %	**6.85**	**49.30**	**53.40**
Column S	Column E	Column R	Column D

Thus, knowing the value of the budget allotted to fraud, it is possible to find the threshold for the probability of fraud.

Relations between Precision and Detection

Let us suppose that our firm has the industry's average rate of fraud: 6.33%. Therefore, out of the 15 220 files closed annually, there will be 963 which are probably fraudulent.

At a probability threshold of 25%, the rate of detection is 53.40%. Out of the 963 fraudulent files, 514 will be detected.

When an investigation is made, there is no guarantee that all the cases investigated will actually be fraudulent. According to the table above, the higher the probability threshold the smaller the margin of error. At a 25% probability threshold for fraud, we have deduced that 514 cases of fraud were detected. Out of these 514 cases, 48.95% will actually be fraudulent. At the end of the line, for at the 25% threshold , 252 cases of real fraud are detected.

For further information on the interpretation of detection and precision rates, consult section III of this document.

Fraud 1.0 C Form

A – Identification

File

Adjuster

Place of accident

Date of accident
4 October 1997

Guarantees purchased

B – Fraud Indicators

Click on the square to the left of the indicators corresponding to the characteristics of fraud in the file. Then select the indicator which you feel is the most important by clicking on the adjacent triangle.

A minor collision has led to excessive repair costs.

Accident without collision.

The vehicle is reported stolen and found with heavy damage shortly after.

No police report when there should have been one or report requested at police station whereas the accident took place where the police usually respond quickly.

Existence of damage not related to the loss or inconsistent with the facts reported about the accident.

The insured is having personal or business-related financial difficulties.

The insured is ready to accept a relatively small settlement rather than produce all the documents related to the loss.

The insured is extraordinarily familiar with insurance or vehicle repair jargon.

The insured (or the claimant) is too eager to accept blame for the accident.

The accident (or loss) took place shortly after the vehicle was registered and insured, or in the months preceding the end of coverage.

Numerous taxi receipts or bills for vehicle rentals from a body work shop.

The bills or the receipts seem false or forged.

The documentation and estimate for repairs are not available.

Contradictory witness reports concerning the circumstances of the loss.

Accident involving a single vehicle.

Vehicle was purchased with cash.

The claimant is very aggressive. He or she threatens to hire a lawyer, appeal to the government, etc.

During the investigation, the insured is nervous and seems confused.

Probability of fraud: 40%

C – Decisional Analysis

Amount of reimbursement estimated if there is no investigation

Amount of reimbursement estimated if proof of fraud is established after an investigation.

Estimated cost of an in-depth investigation.

Subjective probability that the investigation will succeed.

Is an in-depth investigation recommended? YES

Appendix 2

Fraud Indicators

INDICATORS

The indicators below are reproduced exactly as they were presented to adjusters. Note, however, that adjusters were given detailed explanations of these indicators along with the list. The indicators in bold have been flagged as significant in explaining the probability of fraud in a file.

ACCIDENT/DAMAGE

1) N° police report when there should have been one (or report requested at the police station whereas the accident took place in sectors where the police usually respond quickly).

2) A minor collision has led to excessive repair costs.

3) Existence of damage not related to the loss or inconsistent with the facts reported about the accident.

4) The vehicle is reported stolen and found shortly after with heavy damage.

VEHICLE

5) Recent and expensive model.

6) Insured cannot produce bills for maintenance of the vehicle.

7) The vehicle is not attractive to thieves (i.e. ordinary old car).

8) Vehicle stolen in a shopping centre.

AGENT/ INSURER

9) Shortly before the loss, the insured checked the extent of coverage with his or her agent.

10) The insurance agent has never seen the insured vehicle.

FINANCIAL

11) The insured is having personal and business-related financial difficulties.

12) The insured's occupation does not justify the high value of his or her vehicle (and its accessories).

SETTLEMENT

13) The insured (claimant) is too eager to receive monetary compensation in lieu of repairs on his or her vehicle.

14) The insured is ready to accept a relatively small settlement rather than produce all the documents linked to the loss.

CLAIMANT/INSURED

15) The insured is very insistent on a quick settlement.

16) The insured is extraordinarily familiar with the insurance and vehicle repair jargon.

17) The insured offers to come to the claims office for payment.

18) The insured (or claimant) is too eager or too frank to accept blame for the accident.

19) The accident (or loss) took place shortly after the vehicle was registered and insured or in the months preceding the end of the policy (or of coverage).

20) Appealing to Act 68, the insured refuses to give his or her consent (for an in-depth investigation).

21) Numerous taxi receipts or bills for rental of vehicles from a body shop.

22) Bills or proofs of payment which seem phony or forged.

23) Insured's record: he or she has already been convicted of fraud or has already committed misdemeanours suggesting a potential for fraud.

TITLE AND OWNERSHIP

24) The history of the ownership of the vehicle cannot be established.

OTHER INDICATORS

ACCIDENT/DAMAGE

25) The claim (and/or loss) is reported by a third party.
26) Documentation of the estimate and repairs is not available.
27) All the damaged vehicles are sent to the same garage owner.
28) The claims representative (adjuster) is not allowed to examine the vehicle.
29) The vehicle was repaired before being checked by the claims representative (adjuster).
30) Contradictory witness reports concerning the circumstances of the loss.
31) The insured denies the versions of witnesses concerning the accident.
32) Accident involving a single vehicle.
33) Accident involving an unidentified third party.

VEHICLE

34) Vehicle with a history of mechanical problems; the manufacturer's guarantee has expired.
35) Rented vehicle with high mileage.
36) Ignition block intact after vehicle has been recovered.
37) No signs of forced entry (door lock intact…)

FINANCIAL

38) Loan payment on vehicle late.
39) Vehicle purchased with cash.
40) Insured is unemployed; works in a depressed industry; lives in a poor region.

CLAIMANT/INSURED

41) Vehicle found by insured.
42) Several types of coverage; several policies; over-insured loss.
43) Premium paid in person and in cash.
44) Problems with address: post office box; motel; false address; insured absent; lives with friends, etc.
45) Claimant is very aggressive (threatens to call a lawyer, contact the government, etc.)
46) Claimant refuses to answer questions about the accident.
47) During the investigation, insured is nervous and seems confused.

48) Numerous claims filed in the past.

TITLE AND OWNERSHIP

49) Title recently transferred from another province (or another state).
50) Title of ownership is still in the name of the previous owner.