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Traditional versus AI-Based Fraud Detection: Cost Efficiency in the Field of Automobile Insurance*

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Business practice and various industry reports all show that automobile insurance fraud is very common, which is why effective fraud detection is so important. In our study, we investigate whether today's widespread AI-based fraud detection methods are more effective from a financial (cost-effectiveness) point of view than methods based on traditional statistical-econometric tools. Based on our results, we came to the unexpected conclusion that the current AI-based automobile insurance fraud detection methods tested on a real database found in the literature are less cost-effective than traditional statistical-econometric methods.

Journal of Economic Literature (JEL) codes: G22, C14, C45

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1. Introduction

The consequences of insurance fraud have a serious impact on the insurance sector. Fraud creates distrust of the industry, causes economic damage and affects the overall cost of living. The Insurance Information Institute (III) in the USA (*III 2021*) reports that the total cost of insurance fraud in the USA between 2015 and 2019 amounted to between USD 38 billion and USD 83 billion per year. This means that the average American family has an additional expenditure on insurance fraud between USD 800 and USD 1,400 a year. The Association of British Insurers (ABI) highlights that in 2020 the value of fraudulent claims in the UK was GBP 1.1 billion (*ABI 2021*). Looking specifically at automobile insurance fraud, 7–10 per cent of insurance policies in the USA and Western Europe, 10–20 per cent in the Central

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and Eastern European regions, and 18–20 per cent in China are affected (*ABI 2021; III 2019*).

There is therefore no doubt that the identification of insurance fraud is an economically very important area of investigation. In our study, 24 academic journal articles and 3 conference proceedings on the detection of automobile insurance fraud indexed by the Web of Science database between 1990 and 2022 were analysed. This suggests that this area of research is still very much underdeveloped. There is an extensive literature on classical statistical-econometric fraud identification methods as well as on models based on artificial intelligence (AI) and machine learning, but there is a lack of systematic comparison and a lack of research on the cost-effectiveness of fraud identification. The literature in the Hungarian language is also incomplete in this area, and there is no generally accepted definition of insurance fraud, nor of fraudulent automobile insurance claims.

Therefore, this study aims to contribute to the development of our knowledge on automobile insurance fraud identification in three areas:

- After a comprehensive analysis of the international and Hungarian literature, we argue that the performance of any fraud detection system should be judged in terms of its cost-effectiveness. In other disciplines where the use of artificial intelligence (AI) has become widespread, such as healthcare, these cost-effective approaches have already become dominant (*Lee et al. 2017*; *Hill et al. 2020*).
- Considering the spread of numerous AI models available in the literature, we believe that there is a pressing need for a systematic meta-analysis that can present a ranking of these models and compare them in terms of their financial performance. Not least, we could not find any study that examined whether today's widespread AI-based methods are more financially (regarding their cost-effectiveness) efficient than the methods based on traditional statistical-econometric tools.
- Finally, we would like to contribute to the (quasi non-existent) literature in Hungarian on the subject, at least with generally acceptable definitions that will make it clear to the reader what insurance fraud or a fraudulent automobile insurance claim is.

After a review of the relevant literature (*Section 2*), our theoretical framework is presented (*Section 3*) in detail, together with the calculation method for cost savings proposed by *Benedek et al.* (*forthcoming*). In *Section 4*, we focus on the selected fraud detection methods and their cost-effectiveness, comparing traditional statistical and machine-learning-based fraud detection methods, and present the results of our detailed sensitivity analysis prepared using heatmaps. In the final section, the conclusions are drawn.

2. Overview of the literature

We begin our literature review by defining what is meant by insurance fraud and fraudulent automobile insurance claim. As defined by the Legal Information Institute (*LII 2023*) and under Massachusetts Regulation (MR) (which are the most widely accepted sources in the English-language literature), insurance fraud is any act done with the intent to obtain a fraudulent payment from an insurer. Police and prosecutors generally distinguish between two forms of insurance fraud: (1) intentional damage to the insured property (hard fraud) and (2) forgery of documents (soft fraud). Hard fraud is the less common of the two forms, when the perpetrator intentionally causes the destruction of property with the aim of obtaining the amount of damages later. A soft fraud occurs when the contracting party exaggerates an otherwise legitimate claim, or when he or she makes untrue statements and/or conceals certain conditions and circumstances. If we look specifically at the automobile insurance market, a fraudulent claim is one where the insured (1) makes a claim for an accident that did not happen; (2) makes multiple claims for a single accident; (3) submits a claim other than those resulting from the car automobile accident; (4) falsely reports lost wages/medical treatment costs for injuries; or (5) reports higher car repair costs than the repair actually cost (*LII 2023; MR 1993*).

2.1. International literature

In one of the earliest studies, *Weisberg and Derrig* (*1991*) listed potential fraud indicators (red flags) according to their relative frequency. In this study, 18 objective characteristics (out of 65 possible characteristics) of claims for bodily injury insurance were used to identify fraudulent claims. Despite this, the simplicity of the method used has led to only limited success. *Derrig and Ostaszewski*'s (*1995*) study of red flags and the problem of classifying fraudulent claims also shows that there is no consensus among experts regarding fraudulent claims. They therefore propose a fuzzy classification technique for the insurers. *Weisberg and Derrig* (*1998*) tested the usefulness of potential red flags, quantified the effectiveness of standard investigative techniques and mapped the ability of firms to further detect fraud.

Belhadji et al. (*2000*) presented an “expert system” that assists insurance company employees in decision-making. The tool is not directly applicable to a specific insurer because the parameters used are derived from calculations based on industry data, but it was an important step towards the data mining and artificial-intelligence-based fraud detection models that are prevalent today.

The novel approach (discrete choice model) presented by *Artís et al.* (*1999*; *2002*) tested the effect of the characteristics of the insured and the circumstances of the accident on the probability of committing fraud. In addition, these studies also focused on the problem of misclassification. Due to the nature of the model used and the characteristics of the real automobile insurance data series, fraudulent claims had to be overweighted in the estimation. This paved the way for the examination of asymmetric data series (such as automobile insurance fraud) using various overweighting or underweighting techniques. In parallel, *Viaene et al.* (*2002*) compared the performance of different fraud detection methods. The authors of the study used only indicators for property damage, as these are the only ones available at an early stage of the assessment process.

After *Artís et al.* (*1999*; *2002*) opened the door to oversampling or undersampling techniques and *Viaene et al.* (*2002*) introduced the use of early stage indicators, several authors presented some form of classification method based on oversampling or undersampling (especially for property damage). For example, *Pérez et al.* (*2005*) compared the performance of their consolidated tree algorithm with that of the well-known C4.5 algorithms on an oversampled real automobile insurance database. *Bermúdez et al.* (*2008*) proposed an asymmetric logit model that was able to handle unbalanced data sets. A few years later, the researchers proposed two new approaches for the undersampling of the majority class to improve the performance of classifiers in unbalanced datasets. In the first approach, *Sundarkumar et al.* (*2015*) proposed the one-class support vector machine (OCSVM)-based undersampling, while in the second approach *Sundarkumar – Ravi* (*2015*) proposed the combined use of k-nearest neighbour (KNN) and OCSVM.

Šubelj et al. (*2011*) presented a novel expert system using social network analysis to identify groups of fraudsters, rather than a few isolated cases of automobile insurance fraud. *Farquad et al.* (*2012*) used a modified active-learning-based approach in order to construct "if..., then" type rules from a support vector machine "black box" for customer relationship management. *Gepp et al.* (*2012*) compared the decision tree, survival analysis and discriminant analysis methodology with the logistic regression used by *Wilson* (*2009*). The novelty of the approach proposed by *Tao et al.* (*2012*) was that each insurance claim could be classified into two categories (lawful and fraudulent) with two different probabilities at the same time.

Yan – Li (*2015*) approached the detection of automobile insurance fraud as a problem of detecting outliers. Therefore, an improved outlier identification method based on a version of the nearest neighbour algorithm completed with pruning rules was proposed. *Nian et al.* (*2016*) suggested an unsupervised spectral ranking algorithm (SRA) method to detect anomalies. *Shaeiri and Kazemitabar* (*2020*) further developed the SRA approach and presented an implementation methodology that allowed real-time application of SRA on large datasets. *Li et al.* (*2018*) combined individual classifiers into multiple classifier systems to increase classification accuracy. *Wang and Xu* (*2018*) proposed a text analysis based on deep neural network and latent Dirichlet allocation (LDA).

Finally, some authors have approached the problem of detecting automobile insurance fraud from a strictly financial perspective, with a strong emphasis on cost-sensitive classification of damage. For example, *Phua et al.* (*2004*) compared the performance of their proposed approach with various widely used techniques and demonstrated the superior performance of the proposed method in terms of cost savings. *Viaene et al.* (*2007*) focused on the cost of the examination process rather than on minimising the error rate (misclassification) and showed that cost-sensitive fraud screening can be a profitable approach for property and casualty insurance companies. Finally, *Zelenkov* (*2019*) also proposed a cost-sensitivity-based approach, but with an example-dependent cost-sensitive meta-algorithm, AdaBoost (adaptive boosting), which assigned different costs not only to different classification errors (as in previous studies) but also to different compensation cases.

For a more comprehensive review of the related international literature, including the most important indicators used to identify fraud, the most commonly used databases and the most current challenges in fraud identification, see *Benedek et al.* (*2022*).

2.2. Literature in Hungarian

The use of fraud detection methods, or even insurance fraud as a scientific research topic, is completely absent from the Hungarian literature. In this respect, this study is certainly of premier value.

As there is a complete lack of scientific research on insurance fraud in Hungarian, we briefly review some literature in Hungarian where artificial intelligence and machine learning methods are applied to economic-financial problems.

The first economic and financial AI applications appeared in the field of corporate bankruptcy prediction models: a combination of logistic regressions and factor analysis was used by *Hámori* (*2001*), whose model had a classification accuracy of 95.3 per cent. *Virág – Kristóf* (*2005*) applied a neural-network-based model for bankruptcy prediction, using the advantage offered by multiple neural layers (4) and the backpropagation algorithm. The accuracy of the results obtained with neural networks exceeded the results obtained with linear discriminant analysis and logistic regression by a few percentage points. *Virág and Nyitrai* (*2013*) were the first to apply the support vector machine (SVM) method to data from Hungarian companies. Using different kernel functions, they achieved 5-per cent better performance with SVM than with neural networks. *Virág and Nyitrai* (*2014*) compared the performance of ensemble methods, AdaBoost and bootstrap aggregating, using C4.5 decision trees with data from nearly a thousand Hungarian companies between 2001 and 2012. Their results showed that bootstrap aggregating performed better, but very slightly ahead of AdaBoost. Among the more recent applications, we mention the study by *Ágoston* (*2022*), which applies SVM, bootstrap aggregating and random forest algorithms to bankruptcy prediction using a sample of firms in the Budapest and Pécs urban regions. Based on the accuracy of the out-of-sample classification indicators, the random forest seems to be the winner.

Among the AI studies outside the bankruptcy forecast but within the economy, the following are also worth mentioning: *Muraközy* (*2018*) argues that machine learning, which focuses on prediction, and econometrics, which studies causal relations, are not substitutes but rather complementary empirical disciplines. *Farkas et al.* (*2020*) discusses the potential applications of machine learning in agriculture. The application of AI can also be seen in the fields of business economics (management, marketing): *Benedek* (*1999*) analyses the efficiency of marketing actions using statistical and data mining methods, while *Danyi* (*2019*) looks at the likely effects of artificial intelligence in pricing policies and strategies. *Bánkúty-Balog* (*2020*) assesses the geo-economic impacts of the spread of AI in Hungary in the context of international competitiveness. Finally, *Csillag et al.* (*2022*) used machine-learning-based structural topic modelling (STM) to evaluate the prevalence of environmental topics in the media.

3. Conceptual and theoretical background

The identification of automobile insurance fraud is a binary classification problem, so the performance of any classification algorithm can be described by the confusion matrix in *Table 1.*[1]

Table 1
Binary classifier confusion matrix and performance indicators used in the evaluation

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Predicted value</td><td rowspan="2">Performance indicators</td></tr>
<tr><td>Fraudulent claim</td><td>Lawful claim</td></tr>
<tr><td rowspan="2">Actual value</td><td>Fraudulent claim</td><td>True positive (TP)</td><td>False negative (FN)</td><td>Sensitivity (TPR): $\frac{TP}{TP+FN}$</td></tr>
<tr><td>Lawful claim</td><td>False positive (FP)</td><td>True negative (TN)</td><td>Specificity (TNR): $\frac{TN}{FP+TN}$</td></tr>
<tr><td colspan="2" rowspan="2">Performance indicators</td><td>Precision (PPV): $\frac{TP}{TP+FP}$</td><td>Negative predictive value (NPV): $\frac{TN}{TN+FN}$</td><td>Estimation accuracy (ACC): $\frac{TP+TN}{TP+FP+TN+FN}$</td></tr>
<tr><td colspan="3">F-score $\frac{(1+\beta^2)*TPR*PPV}{\beta^2*TPR+PPV}$</td></tr>
</table>

Note: In the case of F-score, β is a coefficient to adjust the relative importance of precision and sensitivity.

[1] The methodology and theory of confusion matrices can be traced back to the work of *Green – Swets* (*1966*).

Various performance indicators can be derived from the confusion matrix. The most widely used measures of classifier performance are accuracy (ACC), sensitivity (TPR), specificity (TNR) and F-score. However, these measures also have their limitations, especially on asymmetric data sets such as automobile insurance fraud. A detailed description of each performance indicator and a discussion of possible limitations can be found in the work of *Benedek et al.* (*forthcoming*).

However, from a business perspective, one possible way to overcome all the problems with performance indicators is to quantify the operating costs of individual classifiers rather than looking at the performance of different classifiers. This approach allows for easy comparability and can take into account the costs of various misrepresentations. In addition, most insurers consider it more important to minimise the costs of the detection process than to minimise the error rate of the classifier.

To quantify the cost savings of a (semi-)automated fraud detection system, two key factors need to be considered: (1) the cost of continued use of the systems; and (2) the cost of operating the alternative system. Part of the cost of the ongoing use of the systems is the cost of the manpower needed to carry out the new tasks of the fraud analysis department. However, the most important item here is the cost arising from false signalling by the system. If a lawful claim is deemed fraudulent by the system, the insurer pays for the unnecessary investigation (because the system only flags a potential fraudulent claim, but this has to be verified and proven by an expert). Likewise, if a fraudulent claim is deemed lawful by the system, the insurer pays the fraudster. Considering the large number of claims processed by insurers, the costs of false signalling by the system can be very significant. In determining the operational costs of an alternative system, *Phua et al.* (*2004*) suggest that the alternative where the insurer takes no action to verify the legitimacy of claims and simply pays out all claims should be considered. Thus, the approach to quantifying the cost savings of any system (CSDM – cost saving of the decision method) given by equation (1) proposed by *Phua et al.* (*2004*) is as follows:

$$CSDM = NA - (MC + FAC + NC + HC) \qquad (1)$$

where *NA* is the "no action cost", i.e. the cost of the alternative where the insurer takes no action to verify the legitimacy of the claims. Furthermore, the misses cost (MC), false alarms cost (FAC), normals cost (NC) and hits cost (HC) are as follows:

$$MC = NFN * ACA;$$

$$FAC = NFP * (ACI + ACA);$$

$$NC = NTN * ACA;$$

$$HC = NTP * ACI,$$

where NFN is the number of false negative cases, NFP is the number of false positive cases, NTN is the number of true negative cases, NTP is the number of true positive cases, ACA is the average claim amount and ACI is the average cost per investigation.

Viaene et al. (*2007*) did not define the cost savings of a system, but its operating costs (OC) given by equation (2); however, the way of defining the inputs is the same as presented by *Phua et al.* (*2004*).

$$OC = MC + FAC + NC + HC \tag{2}$$

What is important from a business perspective is that in both cases the authors work under the assumption that true negative (TN) cases do not impose an additional cost (i.e. the additional cost of a true negative case is 0) for insurers, since in these cases it is about the normal claims process. However, during our interviews,[2] industry experts highlighted that in practice these true negative cases also have an additional cost. There is a similar discrepancy between business practice and the literature when it comes to calculating the costs of true positive cases. According to the literature, in true positive cases, the insurer does not pay the insured, i.e. the only costs incurred are those related to the investigation. In business practice, however, the situation is different. As several previous studies showed (e.g. *Derrig – Ostaszewski 1995*; *Weisberg – Derrig 1998*), the vast majority of automobile insurance fraud consists of so-called build-up[3] claims. Our interviewees pointed out that, contrary to the literature, in practice it is rare for an insurer to completely refuse to pay. They usually offer less than the amount requested for identified build-up claims. There are many reasons for this, such as the lengthy and costly court process or negative marketing.

In view of the differences between the literature and the business practice described above, we recommend the calculation method proposed by *Benedek et al.* (*forthcoming*), given by equation (3), to determine the real costs of detecting automobile insurance fraud:

$$CSDM = NA - (MC + FAC + NC + HC) \tag{3}$$

where *NA* is “no action cost”.[4] Furthermore:

$$MC = NFN * (ACA + AAC);$$

$$FAC = NFP * (ACI + ACA);$$

[2] We conducted three in-depth interviews with Romanian insurance company executives and experts from multinational insurance companies on automobile insurance fraud. A 22-question questionnaire was then prepared and sent to all partner institutions of UNSAR (the National Association of Insurance and Reinsurance Companies in Romania).

[3] Cases where the insured or the professional repairer claims more than the actual cost of the repair.

[4] In this paper, we use the approach presented by *Phua et al.* (*2004*), but the costing method we propose would also work perfectly well if we used the operating costs of an alternative system instead of the “no action cost”.

$$NC = NTN * (ACA + AAC);$$

$$HC = NTP * (ACA - ASCIFC + ACI);$$

where average administrative cost (AAC) and average savings in the case of identified fraudulent claims (ASCIFC) are denoted.

Finally, we should mention the preventive effect of fraud prevention programmes, because without effective prevention, over time premiums will have to be increased to a level that will "cope" with fraudulent payments, so that sooner or later the premium will reach a level that will no longer be competitive in the market. In this study, the prevention effect, which is much harder to quantify, is not explicitly included, but it would not even affect the results significantly, since the cost of prevention reduces the profitability of both classical statistical methods and AI-based methods in the short run.

4. Results

4.1. Cost-effectiveness meta-analysis of the selected methods

After reviewing the literature and identifying the research gaps, we conducted a meta-analysis of the selected methods, which enables us to rank and compare the methods of automobile insurance fraud identification. First, the cost saving potential of these methods was calculated using the proposed cost saving calculation method.

The logic behind the initially selected 24 journal articles and 3 conference papers was twofold. On the one hand, only the studies indexed by the Web of Science were considered, and on the other hand, we also kept in mind that we wanted to compare the performance of models using a traditional statistical-econometric approach from 1999–2012 with the performance of AI-based models from 2012–2022 tested on real data sets. However, some of the 27 studies identified were purely theoretical and offered no concrete fraud identification method. The authors of other studies (e.g. *Pathak et al. 2005*; *Padmaja et al. 2007*; *Bhowmik 2011*; *Xu et al. 2011*; *Karamizadeh – Zolfagharifar 2016*; *Badriyah et al. 2018*) conducted their research without using real company datasets. Finally, there were several studies in which the authors did not present the confusion matrix, so for these studies we were not able to determine the inputs necessary for our costing method.

Taking into account the above limitations, there are only 12 studies left in our sample with all the data needed to determine the cost-saving potential of each model. In the 12 articles, the authors propose and compare a total of 35 different methods, the full list of which can be found in *Table 4* in the *Appendix*.

As the percentages of fraudulent claims in the analysed studies are different, the sizes of the databases are very different, and, moreover, 2 of the 7 databases used are from the United States, 1 from Canada, 2 from Spain, 1 from Russia and 1 from Slovenia, we first built a general framework where we assume that an insurer processes 10,000 claims, of which 10 per cent are fraudulent. Metavariables such as the average cost per investigation or the average claim amount were determined on the basis of the questionnaire survey mentioned earlier. The questionnaire was fully completed by five Romanian insurance companies with a combined market share of nearly 70 per cent. In this study, we used a market-share-weighted average of the values provided by the five insurers. They showed an average cost per investigation of USD 145, an average claim amount of USD 2,420, an average saving of USD 485 for identified fraudulent claims, and an average administrative cost of USD 12.

Table 2 summarises the cost-saving potential of the 35 methods for three different scenarios. Rows 2 to 7 of the table show the input parameters of the given scenario. These are the input meta-parameters whose values come from industry experts and which are always constant for each classical statistical or AI-based method. Row 8 is the most important row, the output, since it is obtained by interacting and processing the meta-parameters with specific algorithm parameters. That is, the final operating cost of an algorithm is equal to the number of claims in the different categories (false positive, false negative) defined by the confusion matrix multiplied by the constant value of the meta-parameter (average cost per investigation, average claim amount) associated with that category. In economic language, row 8 shows how many of the 35 methods had a higher operating cost than that of the alternative, i.e. if the insurer did not investigate the validity of the claims and simply paid out the claims received. Counter-intuitively, the best-case scenario here is the one with the highest rate of fraudulent claims, since in this case even a less efficient method can achieve higher cost savings.

Table 2
Cost-effectiveness of methods used to identify fraudulent claims

	Most likely scenario	Worst case scenario	Best scenario
	35 models	35 models	35 models
Proportion of fraudulent claims (%)	10	5	20
Average claim amount (USD)	2,420	2,420	2,420
Average cost per investigation (USD)	145	193	97
Average administrative cost (USD)	12	12	12
Average savings for identified fraudulent claims (USD)	485	315	1,213
Number of methods with an operating cost higher than the “no action cost”	27	31	0

Note: For the worst and best case scenarios, we used the extreme values provided by the insurance companies.

We emphasise that the data summarised in *Table 2* well illustrate the importance of the proposed cost savings calculation method from a business perspective. While the cost-saving calculation method proposed by *Phua et al.* (*2004*) classifies almost all models as cost-effective, our proposed method (which takes into account the costs incurred in the real fraud detection process) classifies only 22.85 per cent of the models as cost-effective even in the most likely scenario, while only 11.42 per cent of the methods can be classified as cost-effective in the worst-case scenario, compared to the 94.28 (and 68.57) per cent of the methods proposed by *Phua et al.* (*2004*).

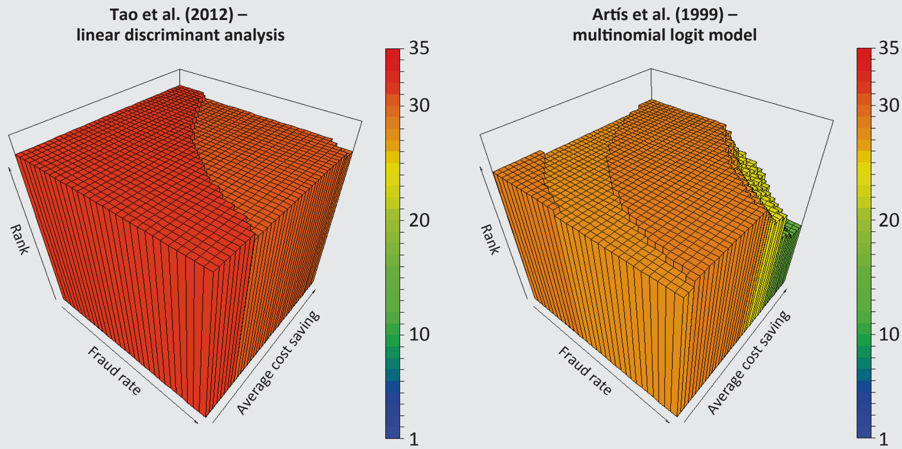
4.2. Heat maps of the cost-saving potential of fraud identification methods

In view of the rather surprising results revealed by the meta-analysis, we considered it an important step to further analyse each fraud detection method in depth and to investigate the circumstances under which the individual methods may be more beneficial than their counterparts. One reason for this approach is that, depending on the input parameters used in the meta-analysis (e.g. percentage of fraudulent claims, average cost per investigation), the cost-effectiveness of fraud detection methods varies significantly. The other reason is that some detection methods are unusable for some insurers, as these fraud detection methods use inputs (accident characteristics, police/medical reports, accident photographs) that are not (or not yet) available to the insurer.

In order to take into account as much as possible the specific characteristics of the fraud detection methods and to perform the meta-analysis with a wide range of input parameters, we ran 3 different simulations to investigate the performance of the methods and created heat maps to visualize the results.

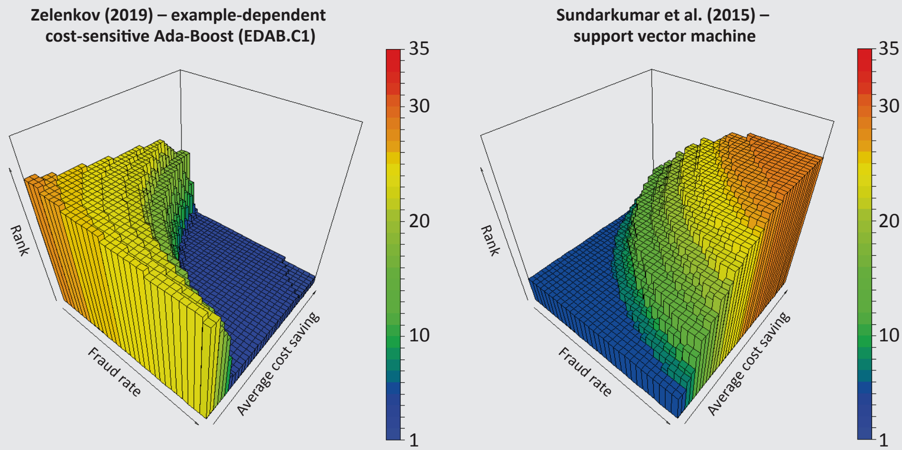
In the first simulation, a fixed investigation cost of USD 145 was assumed, while the percentage of fraudulent claims and the average savings in the case of identified fraudulent claims were varied. This approach can be very useful for insurance companies that work with a fixed cost per investigation (for example, by hiring a specialised external company to carry out the investigation and paying a pre-determined price for each claim), as they can easily decide which method is the most efficient for them in the given market circumstances. For example, if an insurance company is unable to use the fraud detection methods proposed by *Tao et al.* (*2012*) or *Bermúdez et al.* (*2008*) because it does not have the input parameters necessary to apply the model, but operates in a market with a high percentage of fraudulent claims and low average savings in the case of identified fraudulent claims, the multinomial logit model proposed by *Artís et al.* (*1999*) may be an optimal choice (*Figure 1*), as it performs almost as well as the method proposed by *Tao et al.* (*2012*). Likewise, any insurance company can easily choose the most appropriate method based on the percentage of fraudulent claims and the average savings in the case of fraudulent claims. For companies operating in a market with a low percentage of fraudulent claims and low average savings, the method proposed by *Zelenkov* (*2019*) seems to be better than the one proposed by *Sundarkumar et al.* (*2015*), see *Figure 2*.

Figure 1
Cost-saving ability of the models proposed by Tao et al. (2012) and Artís et al. (1999) on a heat map



Note: The cost-saving ability of the linear discriminant analysis model proposed by Tao et al. (2012) and the multinomial logit model proposed by Artís et al. (1999) compared to the cost-saving ability of the 35 models analysed under different scenarios.

Figure 2
Cost-saving ability of the models proposed by Zelenkov (2019) and Sundarkumar et al. (2015) on a heat map



Note: The cost-saving ability of the example-dependent cost-sensitive AdaBoost (EDAB.C1) model proposed by Zelenkov (2019) and the support vector machine model proposed by Sundarkumar et al. (2015) compared to the cost-saving ability of the 35 models analysed under different scenarios.

For the second simulation, the savings from identified fraudulent claims were held constant (USD 485) and the cost of investigation and the percentage of fraudulent claims were varied. In the third simulation, the percentage of fraudulent claims was held constant (10%) and the cost of investigation and the average savings in the case of identified fraudulent claims were varied.

4.3. Comparison of traditional statistical and machine-learning-based methods in terms of average cost savings

After the meta-analysis and heatmaps, a detailed non-parametric rank correlation analysis of the different fraud detection methods was performed. For a detailed discussion of Spearman's rank correlations, see *Benedek et al.* (*forthcoming*). The magnitude and significance of the correlations clearly show that the performance measures used in this study result in a consistent ranking of the fraud detection methods analysed (details in *Table 3* in the *Appendix*).

Perhaps the most interesting question in the study is whether AI-based detection methods are significantly more cost-effective than traditional statistical-econometric tools.

Obviously, AI and traditional statistical econometric methods are all parts of the same discipline generically called data science, and as such, the boundary between them is rather subjective and fluid, especially given the dynamic evolution of AI that is taking place before our eyes. For example, most machine learning courses start with the methodology of linear and logistic regression, which is also part of any standard econometrics curriculum. However, in our study, the following distinction was made: Any method developed after the emergence of the AI terminology in the literature was considered an AI or machine learning method. Therefore, e.g. linear and logistic regression as well as linear discriminant analysis were classified in the traditional category (since they do not require big data or neural nets) while genetic algorithms, neural nets, etc. were classified in the AI category.

As a first step, the differences in average cost savings between these two groups of methods were calculated, and the statistical significance of the differences was tested using the Mann–Whitney non-parametric test. These comparisons were performed on a wide range of combinations of input parameters (10,780 in total), resulting in a synthetic cross-tabulation between the average cost per test and the average savings of the identified fraudulent claims.

Table 5 in the *Appendix* clearly shows that the average cost savings for the vast majority of combinations are higher for traditional statistical methods[5] (the

[5] Although it is not the purpose of this study to examine the implementation costs of traditional statistical and AI methods, it is highly likely that the cost implications of traditional methods in this area are also lower, which further supports the conclusions observed in *Table 5* in the *Appendix*.

differences are positive and significant) than for AI-based methods, and we concluded that, surprisingly, there is no justification for insurance companies to invest heavily in AI-based fraud detection algorithms at this stage. This does not mean, of course, that these companies do not need software support in their operations, only that in most cases the traditional statistical software is sufficient.

5. Conclusions

In our research, we pointed out that there is a lack of literature examining the cost-effectiveness of methods for detecting automobile insurance fraud. Moreover, in the case of emerging markets, there is a complete lack of literature on the detection of automobile insurance fraud. Therefore, in this study, we applied the method proposed by *Benedek et al.* (*forthcoming*) to correctly calculate the cost-saving potential of automobile insurance fraud identification. The proposed method takes into account all costs incurred in a real fraud detection process (with particular emphasis on the fact that in the case of a fraudulent or partially fraudulent claim, the insurer will usually not deny payment completely but offer partial compensation).

In this cost-effectiveness study, we conducted a meta-analysis of 35 fraud detection methods from 12 different sources and concluded that most of the current methods of automobile insurance fraud detection in the literature are not profitable. In addition, we also pointed out that the approaches based on traditional statistical methods perform better than AI-based methods for the time being. In other words, there is no justification for insurance companies to make significant additional investments in AI-based fraud detection algorithms at this stage, and in most cases the use of traditional statistical software is sufficient. This result is consistent with that presented by *Benedek et al.* (*forthcoming*). This means that the use of traditional statistical methods is also more economical for the sample examined in this study (pre-2012 traditional statistical methods versus post-2012 AI-based approaches). With this result, the present study acts as a test of robustness and confirms previous research findings.

The most important limitation of the research, which is also an opportunity for further development, is that the input parameters in the meta-analysis are based on previous algorithms trained and tested on different datasets. The really convincing proof would be to run the same algorithms one by one on the same sample.

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Appendix

Table 3
Spearman's rank correlation coefficients between rankings based on different parameters

	Total savings	Sensitivity	Specificity	Precision	Negative predictive value	Estimation accuracy	F-score
Total savings	**1.000**						
Sensitivity	0.069 (0.731)	**1.000**					
Specificity	0.831 (49.41)***	–0.346 (–2.57)**	**1.000**				
Precision	0.924 (24.56)***	0.047 (0.48)	0.871 (19.15)***	**1.000**			
Negative predictive value	0.254 (2.47)	0.951 (33.51)***	–0.028 (–0.41)	0.252 (2.78)**	**1.000**		
Estimation accuracy	0.947 (98.34)***	–0.081 (–0.62)	0.957 (38.93)***	0.942 (25.87)***	0.135 (1.57)	**1.000**	
F-score	0.828 (19.11)***	0.278 (4.01)***	0.599 (6.85)***	0.792 (15.68)***	0.616 (6.29)***	0.732 (11.03)***	**1.000**

*Note: The formula used to determine the negative predictive value is: TN/(FN+TN). Student t-statistics in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.*

Table 4
The 35 fraud detection methods tested and their sensitivity and specificity

Author	Method	Sensitivity	Specificity
Artís et al. (1999)	multinomial logit model	0.6614	0.9065
	nested multinomial logit model	0.3209	0.8132
Belhadji et al. (2000)	probit regression – threshold 10%	0.6940	0.9145
	probit regression – threshold 20%	0.5373	0.9596
Artís et al. (2002)	logit regression with omission error	0.7793	0.6994
	logit regression without omission error	0.7703	0.7094
Bermúdez et al. (2008)	Bayesian skewed logit model	0.8515	0.9968
	standard logit and Bayesian logit models	0.8515	0.6043
Wilson (2009)	logit regression	0.5918	0.8163
Šubelj et al. (2011)	social network analysis	0.8913	0.8667
Tao et al. (2012)	linear discriminant analysis	0.7392	0.9738
	quadratic discriminant analysis	0.7933	0.9767
	naive Bayesian	0.8351	0.9815
Farquad et al. (2012)	MALBA (logistic) – 1,000 extra instances	0.8838	0.5534
	MALBA (normal) – 1,000 extra instances	0.8811	0.5588
	ALBA – 1,000 extra instances	0.8784	0.5656
	MALBA – 1,000 extra instances	0.8848	0.5560
Sundarkumar et al. (2015)	decision tree	0.9552	0.5658
	multi-layer perceptron	0.4859	0.7889
	support vector machine	0.9400	0.5639
	probabilistic neural network	0.9173	0.5533
	group method of data handling	0.7362	0.7148
Sundarkumar – Ravi (2015)	probabilistic neural network	0.8750	0.5894
	multi-layer perceptron	0.6458	0.7189
	decision tree	0.9074	0.5869
	group method of data handling	0.5686	0.8020
	support vector machine	0.9189	0.5839
Subudhi – Panigrahi (2017)	GAFCM – DT	0.6625	0.8765
	GAFCM – SVM	0.6970	0.8471
	GAFCM – MLP	0.6107	0.8400
	GAFCM – GMDH	0.5727	0.7976
Zelenkov (2019)	example-dependent cost-sensitive Ada-Boost (EDAB.C1)	0.2510	0.9301
	example-dependent cost-sensitive Ada-Boost (EDAB.C2)	0.5900	0.7327
	example-dependent cost-sensitive Ada-Boost (EDAB. C2-ROC)	0.4477	0.8050
	example-dependent cost-sensitive Ada-Boost (EDAB.C3)	0.2510	0.9301

Note: indicated in bold for traditional statistical econometric models

Table 5

Average cost savings differences between traditional statistical and AI-based identification methods

ASCIFC	ACI										
	100	110	120	130	140	150	160	170	180	190	200
160	73,100 (46)***	87,426 (45)***	101,753 (47)***	116,079 (48)***	130,405 (50)***	144,732 (51)***	159,058 (51)***	173,384 (51)***	187,711 (53)***	202,037 (53)***	216,363 (53)***
180	73,283 (45)***	87,610 (45)***	101,936 (46)***	116,262 (47)***	130,589 (48)***	144,915 (50)***	159,241 (51)***	173,568 (51)***	187,894 (51)***	202,221 (53)***	216,547 (53)***
200	73,467 (46)***	87,793 (46)***	102,120 (45)***	116,446 (46)***	130,772 (47)***	145,099 (48)***	159,425 (50)***	173,751 (51)***	188,078 (49)***	202,404 (51)***	216,730 (51)***
220	73,650 (44)***	87,977 (46)***	102,303 (46)***	116,629 (45)***	130,956 (46)***	145,282 (47)***	159,608 (48)***	173,935 (50)***	188,261 (51)***	202,588 (50)***	216,914 (51)***
240	73,834 (49)***	88,160 (46)***	102,487 (46)***	116,813 (45)***	131,139 (45)***	145,466 (47)***	159,792 (47)***	174,118 (48)***	188,445 (50)***	202,771 (50)***	217,097 (51)***
260	74,017 (49)***	88,344 (43)***	102,670 (47)***	116,996 (46)***	131,323 (45)***	145,649 (45)***	159,975 (47)***	174,302 (47,5)***	188,628 (48)***	202,955 (50)***	217,281 (50)***
280	74,201 (44)***	88,527 (49)***	102,853 (46)***	117,180 (46)***	131,506 (45)***	145,833 (45)***	160,159 (46)***	174,485 (47)***	188,812 (48)***	203,138 (48)***	217,464 (50)***
300	74,384 (42)***	88,711 (46,5)***	103,037 (43)***	117,363 (47)***	131,690 (46)***	146,016 (45)***	160,342 (45)***	174,669 (46)***	188,995 (47)***	203,322 (48)***	217,648 (48)***
320	74,568 (41)***	88,894 (48)***	103,220 (47)***	117,547 (46)***	131,873 (45)***	146,200 (46)***	160,526 (45)***	174,852 (45)***	189,179 (46)***	203,505 (47)***	217,831 (48)***
340	74,751 (42)***	89,078 (44)***	103,404 (47)***	117,730 (43)***	132,057 (46)***	146,383 (46)***	160,709 (45)***	175,036 (45)***	189,362 (45)***	203,689 (47)***	218,015 (47)***
360	74,935 (43)***	89,261 (42)***	103,587 (49)***	117,914 (46)***	132,240 (46)***	146,567 (45)***	160,893 (46)***	175,219 (45)***	189,546 (45)***	203,872 (46)***	218,198 (47)***
380	75,118 (47)***	89,445 (41)***	103,771 (46)***	118,097 (49)***	132,424 (44)***	146,750 (46)***	161,076 (46)***	175,403 (46)***	189,729 (45)***	204,056 (45)***	218,382 (46)***
400	75,302 (50)***	89,628 (42)***	103,954 (44)***	118,281 (46,5)***	132,607 (44)***	146,934 (46)***	161,260 (46)***	175,586 (46)***	189,913 (45)***	204,239 (45)***	218,565 (45)***
420	75,485 (51)***	89,812 (43)***	104,138 (42)***	118,464 (49)***	132,791 (49)***	147,117 (44)***	161,443 (47)***	175,770 (46)***	190,096 (46)***	204,423 (45)***	218,749 (45)***
440	75,669 (54)***	89,995 (43)***	104,321 (41)***	118,648 (45)***	132,974 (47)***	147,301 (44)***	161,627 (46)***	175,953 (46)***	190,280 (46)***	204,606 (46)***	218,932 (45)***
460	75,852 (60)***	90,179 (47)***	104,505 (41)***	118,831 (44)***	133,158 (49)***	147,484 (47)***	161,810 (44)***	176,137 (47)***	190,463 (45)***	204,790 (46)***	219,116 (45)***
480	76,036 (61)***	90,362 (50)***	104,688 (42)***	119,015 (42)***	133,341 (48)***	147,668 (49)***	161,994 (44)***	176,320 (46)***	190,647 (45)***	204,973 (46)***	219,299 (46)***
500	76,219 (61)***	90,546 (52)***	104,872 (43)***	119,198 (41)***	133,525 (44)***	147,851 (46,5)***	162,177 (47)***	176,504 (44)***	190,830 (47)***	205,157 (45)***	219,483 (46)***
520	76,403 (62)***	90,729 (53)***	105,055 (45)***	119,382 (41)***	133,708 (44)***	148,035 (49)***	162,361 (49)***	176,687 (43)***	191,014 (46)***	205,340 (47)***	219,666 (46)***
540	76,586 (65)***	90,913 (57)***	105,239 (47)***	119,565 (42)***	133,892 (42)***	148,218 (47,5)***	162,544 (47)***	176,871 (46)***	191,197 (44)***	205,523 (47)***	219,850 (45)***
560	76,770 (66)***	91,096 (60)***	105,422 (50)***	119,749 (43)***	134,075 (41)***	148,402 (44)***	162,728 (48)***	177,054 (49)***	191,381 (43)***	205,707 (46)***	220,033 (47)***
580	76,953 (73)***	91,280 (60)***	105,606 (51)***	119,932 (44)***	134,259 (41)***	148,585 (44)***	162,911 (49)***	177,238 (47)***	1915,64 (45)***	205,890 (44)***	220,217 (47)***
600	77,137 (73)***	91,463 (61)***	105,789 (51,5)***	120,116 (45)***	134,442 (42)***	148,769 (42)***	163,095 (46)***	177,421 (46,5)***	191,748 (47)***	206,074 (43)***	220,400 (46)***
620	77,320 (76)**	91,647 (62)***	105,973 (54)***	120,299 (47)***	134,626 (42)***	148,952 (41)***	163,278 (44)***	177,605 (49)***	191,931 (49)***	206,257 (44)***	220,584 (44)***
640	77,504 (77)**	91,830 (65)***	106,156 (60)***	120,483 (50)***	134,809 (43)***	149,136 (41)***	163,462 (44)***	177,788 (48)***	192,115 (47)***	206,441 (47)***	220,767 (43)***
660	77,687 (82)**	92,014 (66)***	106,340 (60)***	120,666 (51)***	134,993 (43)***	149,319 (41)***	163,645 (42)***	177,972 (45)***	192,298 (46)***	206,624 (49)***	220,951 (44)***
680	77,871 (87)**	92,197 (68)***	106,523 (60)***	120,850 (52)***	135,176 (46,5)***	149,503 (42)***	163,829 (41)***	178,155 (44)***	192,482 (49)***	206,808 (47)***	221,134 (47)***
700	78,054 (90)**	92,381 (73)***	106,707 (61)***	121,033 (54)***	135,360 (47)***	149,686 (43)***	164,012 (41)***	178,339 (44)***	192,665 (48)***	206,991 (46,5)***	221,318 (49)***

*Note: ASCIFC: average savings for identified fraudulent claims; ACI: average cost per investigation. Mann-Whitney U-statistics in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.*