Explainable Risk Scoring for Auditor-Facing Fraud Alerts

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Abstract

Auditors face risk scores generated from models more frequently, and the field of explainable artificial intelligence contains a rich array of techniques that help to explain them. There is little empirical evidence on how explanations influence judgment. This paper sets forth a study protocol for a 6 × 2 mixed experiment in which auditors will evaluate 24 fraud alerts under one of six explanation conditions, with and without a stated base rate. The study protocol distinguishes five different types of explanations that are often confused: global feature importance, local additive attribution, counterfactual explanation, nearest-neighbour exemplar, and rule extraction. For each type of explanation, the study protocol formulates the decision question and possible failure modes. Hypotheses on discrimination, calibration, quality of justification, decision times, and weighing of red flags are specified. The paper fixes the outcome variables, statistical models, exclusion rules, and procedures for exploratory analysis prior to data collection. The paper proposes that explanation design for auditors should focus on the decision that the auditor makes, and identifies four requirements for the design that the study tests.

Keywords: Explainable AI; auditor judgment; fraud risk assessment; decision support; risk scoring; human-AI interaction; calibration

DOI: 10.18091/ijsts.v6i1.10

1. Introduction

1.1 The arrival of the score

Risk assessment is at the heart of audit practice, and the task has always involved judgment under uncertainty (Appelbaum, 2017; Moffitt, 2018). Automation of auditing and implementation of robotic process automation means that the auditor faces a fraud alert as the product of a pipeline and not a selection resulting from professional inquiry (Moffitt, 2018; Issa, 2016). Thus, a score becomes a new piece of information to integrate into judgment. We take a score as a given and focus on its role in judgment.

A score transforms the auditor's task. In order to integrate a score into audit judgment, an auditor first needs to decide if he or she accepts an automated selection, and such a decision is itself a judgment. If an auditor cannot evaluate an automated selection, he or she either defers to it or disregards it, and both decisions need to be justified in the audit file (Power, 2013; Appelbaum, 2017). That is the motivation of the study. We do not assume that the score is necessarily wrong, and we do not assume that an explanation of the score would be useful.

1.2 Why explanation became the answer, and why the answer is incomplete

The approach in response has been to explain the score. An extensive body of technical literature provides attribution, counterfactual, surrogate rule, and representative neighbour techniques, and Shapley-value additive explanations have become a reference point (Lundberg, 2017; Ribeiro, 2016). Technical literature is well developed, yet the behavioral literature lags behind. Studies on audit applications of explanations are very few, while audit research agenda repeatedly calls for more evaluation of analytical techniques in use and not another description of how they compute (Issa, 2016; Wang, 2015).

This gap is significant in that explanation is not assessed based on its technical qualities alone. Explanation could be faithful to the model but fall short of expectations if it answers a question that the auditor does not have in mind (Lundberg, 2017; Ribeiro, 2016). The question that this protocol seeks to address, therefore, is not whether a certain technique generates valid attribution but whether a given explanation alters the decisions made by the auditor, increases his confidence, and affects how these decisions are documented.

1.3 What an auditor actually needs

There are three questions that need to be answered in the case of alerting an auditor, and all three are different.

Is the selection defensible? Would a fair reviewer, given what the model saw, see it necessary to take interest in such an item? Attribution or rule extraction is an appropriate response to this question (Lundberg, 2017; Quinlan, 1993).

Is the item an anomaly? Is this pattern unusual, a result of a legitimate process, data quality issue, or a known feature of the population? Reference case and base rate comparison can help to decide (Bell, 2000; Batini, 2009).

What should I do? What are the pieces of evidence that will be useful in making a decision on the latter question and documenting the results? Explanations of a model do not provide this information.

Each of the questions is related to a specific explanation type. The first one is the typical problem addressed by the attribution literature, the second is less frequently asked there, and the third one has not been addressed directly (Dowling, 2007; Trotman, 2011). Keeping the three questions

separate allows each of the explanation types to be evaluated in relation to the question it answers.

1.4 Research question and contribution

The protocol asks which explanation types affect auditor's decisions on fraud alerts, for which decision, and what costs it takes. It also asks if a stated base rate affects calibration more than any of the explanation formats. Experiments with decision aids have already shown the necessity of taking into account interaction between aid design and expertise (Arnold, 2004). Therefore, the protocol explicitly analyzes this interaction rather than assuming it as an uncontrolled variable.

The contribution of the protocol is a design which allows for separation of the five explanation types, pairing them with the decisions they are supposed to support, and predefining criteria and procedures for measuring and analyzing the outcomes. The protocol does not claim that an explanation type is effective. Instead, it defines the conditions for testing such claims, which are described in the following sections in future or conditional tense.

2. Literature

2.1 Attribution methods and their properties

Two families of explanation methods attribute a model's prediction to the features of its input in comparison to some baseline. Shapley-value attribution is the most popular method of this family (Lundberg, 2017). Another family of methods approximates the model in the neighbourhood of a single prediction and attributes features that drive this approximation (Ribeiro, 2016). Both approaches assume that contribution of a feature is a meaningful quantity for an observer, and this is what the audit setting allows us to test.

Attribution has known shortcomings. Correlated features get attributed equally regardless of the choice of baseline, and a feature can be attributed highly because the model learned a spurious association between the output and the feature. Then the explanation correctly represents the reasoning of the model, while the reasoning is faulty (Lundberg, 2017; Ribeiro, 2016). The latter pathology is particularly problematic for audit alerts, since features that lead to spurious correlations in the data often cause false alarms (Batini, 2009).

2.2 Counterfactuals, rules, and surrogates

Counterfactual explanation finds the minimum change to the input that would change the prediction. For the purposes of an audit, the statement that the invoice would not have triggered an alert if the amount were smaller identifies the critical feature but not whether it was suspicious. Counterfactuals belong to the family of local explanation and therefore have the single-prediction scope of that family (Ribeiro, 2016). They address the first question in Section 1.3 but only partially the second.

Rule extraction provides a human-readable proxy for the model's predictions but its drawback is that of fidelity. The surrogate rules sometimes disagree with the complex model in some regions of the input space, and the protocol assumes that the fidelity of the proxy will be lower in the tails where alerts are produced (Quinlan, 1993; Ribeiro, 2016). The protocol then measures how well do the surrogate rules agree with the complex model in terms of producing alerts on the alert population before any participant sees the rule, and then reports the results with the materials.

2.3 Exemplars, behavioural evidence, and audit judgment

Exemplar explanations describe past events with the same outcome and features as the predicted event. Availability of examples for comparison is a determinant of audit risk assessment, and exemplar explanation addresses the second question but can encourage availability bias as auditors tend to over-value easy-to-recall cases over the base rates (Kranacher, 2011; Hunton, 2004). Experimental research shows that judgments depend on the format of the data presentation, and for this reason the format of the explanation becomes an experimental factor rather than just the presentation mode (Hunton, 2004; Hodge, 2004).

The behavioural effects of explanations have not yet been studied thoroughly in the audit setting. There is concern that explanations might increase confidence without increasing accuracy, which can be even more detrimental than no explanation due to overconfidence and poor judgment (Arnold, 2004; Power, 2013). The protocol examines three moderators of potential inconsistency in the effect, namely task complexity, explanation fidelity and user expertise, and the audit situation varies in all of them (Arnold, 2004; Albrecht, 2012).

Auditor propensity for over-valuing easily recallable information and under-valuing the base rates is at the core of the experimental design. The protocol assumes that the auditor will over-value the fraud red flag and will be too insensitive to the base rate, which is the largest factor influencing the posterior probability of a fraudulent item among the ones that triggered an alert (Dorminey, 2012; Bell, 2000; He, 2009). Red-flag theory in fraud examinations provides the relevant terminology and the measurement in Section 5.2 is designed specifically to test it (Dorminey, 2012; Wells, 2011).

2.4 Base rates and the calibration of fraud alerts

The likelihood of fraud in an item flagged as suspicious depends on the prevalence of fraud among the items that generate alarms as well as on the score. There is a good body of machine learning knowledge about working with imbalanced data, and it shows that rarity of the target class significantly influences the interpretation of a score (He, 2009). The same message is conveyed in reviews of statistical fraud detection models that consider the prevalence of fraud as an inherent component of the decision problem rather than a nuisance parameter (Bolton, 2002).

Calibration measures the gap between the stated confidence level and observed accuracy. Base-rate information is an inexpensive way of changing the meaning of confidence in an auditor's

work. The protocol takes the base rate as one of the potential sources of the largest possible calibration effect in the study and specifies that it will be generated based on the actual outcomes of the organization, so that no unwarranted precision of the model is introduced (Provost, 2013; He, 2009).

3. Taxonomy, Framework, and Hypotheses

3.1 The five types and the questions they answer

Table 1 provides the taxonomy. This is a specification of the design. In every row, the question answered by a type is specified, the failure mode induced by its improper use, and the stage of the audit workflow where it should be placed.

Table 1. Five types of explanations, the question they answer, the failure mode they induce, and the position in the audit workflow.

Explanation type	**Question answered**	**Expected failure mode**	**Intended workflow position**
Global feature importance	What does the model rely on in general?	Misapplied to individual cases	Model validation, not case work
Local additive attribution	Why this item, in this model?	Faithful description of a spurious association	Triage
Counterfactual	What would have changed the outcome?	Read as advice on where to look	Triage and documentation
Exemplar	What did similar cases look like?	Availability bias, base-rate neglect	Substantive testing
Rule extraction	What general rule captures this?	Low fidelity in the tails	Methodology and documentation

Despite being a characteristic of the whole model, global feature importance is often presented as an explanation at the case level. A statement about the feature being the most important one is true of the whole model and has nothing to do with the particular case before the auditor (Lundberg, 2017; Wang, 2015). Therefore, Table 1 positions this type of explanation in the documentation on the validation of the model, and the protocol tests it under conditions when it is presented on a case screen to assess its costs.

3.2 Fit between explanation and decision

The protocol defines the problem of explanation choice in terms of fit between the information that an explanation offers and the informational needs of the decision. As long as decision

support research has been concerned with the value of the system, which was defined in relation to the match between its output and task (Chen, 2012; Dowling, 2007).

Triage decision requires a proper selection basis and assessment of plausibility. The protocol assumes that attribution and base rate provide such selection basis and plausibility measure, and that human judgment within the loop becomes the target of evaluation rather than its constant element (Ladapo, 2022; Alles, 2010). Substantive decision requires the information about the world. The comparison of case with similar one and the use of a rule can provide it only partially, and the protocol assigns the latter two methods to substantive testing and not triage (Mensah, 2022; Debreceny, 2010).

Decision about documentation requires the justification of the conclusion in a form of a statement, which would be understandable by a reviewer. The counterfactual and rule-based statements are propositional in form, and their ability to satisfy this need is more likely than magnitude of attribution (Trotman, 2011). Single format, accordingly, is unlikely to cover all three decisions, and the protocol design will test this assumption rather than presume it.

3.3 Hypotheses

The protocol formulates six hypotheses. They are fixed in this document before data collection, and the protocol analysis will test them as formulated.

H1. Local additive attribution is expected to improve discrimination, i.e. increase the ability to distinguish fraudulent items from the other ones, compared to score-only control (Lundberg, 2017).

H2. Counterfactual explanation is predicted to increase documentation quality without increasing discrimination, and to increase decision time (Trotman, 2011).

H3. Exemplar presentation is predicted to increase confidence without increasing discrimination, and to increase the weight assigned to a red-flag feature (Dilla, 2010).

H4. Stated base rate information is predicted to decrease miscalibration more than any other explanation style (He, 2009).

H5. Local additive attribution is predicted to mitigate red-flag over-weighting, in that it shows how a feature contributes relative to a reference point rather than just as its presence (Dilla, 2010).

H6. Benefit from explanation is predicted to be greater for participants who are less experienced, since those with experience have stronger priors that might conflict with the explanation. H6 is the hypothesis for which there is the greatest disagreement in the literature (Arnold, 2004). The protocol considers its direction to be exploratory but will report the effect size regardless.

3.4 Mechanism

The mechanism is claimed to be attentional. Both the attribution process and the exemplar process raise the issue of the degree to which the particular feature mattered, and the attribution process raises the issue of resemblance of the item to the confirmed items (Dilla, 2010; Lundberg, 2017).

Since the mechanism is supposed to be attentional, then the mechanism will show itself in the allocation of attention between the features of interest, as described in Section 5.2. The eye tracking studies of the search process in audit support the notion that audit attention can be measured directly, and the red-flag selection measurement is based on this principle as well (Dilla, 2010; Hodge, 2004). The reverse pattern is also specified in the protocol: If the weight of the red flags is changing independently of discrimination, the attentional explanation will be undermined, and this fact is to be mentioned in the report (Dilla, 2010).

4. Materials

4.1 The alert population and scoring model

The protocol involves 24 items generated based on a synthetic disbursement anomaly population calibrated to a public-sector accounts payable ledger. There will be 480,000 payment records and 31 engineered anomaly families, for which the ground truth is known thanks to the generation procedure (Okoli, 2022; Phua, 2010).

The items will be created in four difficulty levels, which are set in terms of the discriminability of the underlying signal. There will be the same number of items at each difficulty level. Level 4 items are expected to be hard to distinguish even from the distribution perspective, so the difficulty manipulation has a known floor (Okoli, 2022; Phua, 2010). The preliminary experiment involving a small group of auditors will test the correct ordering of difficulties of the four levels of difficulty. If the ordering is not correct, the items in question will be replaced before the main experiment starts, and the replacement will be noted.

There will be 24 items involved in the experiment, half of them being adverse, and the other half being benign. This imbalance is not accidental, since it allows balancing the difficulty manipulation and base rate problem.

Each item will include a one-page case file that is identical across all conditions except for the explanation panel, thereby enabling the effect of the condition to be identified solely through the panel itself (Arnold, 2004).

Each item will be scored using a gradient-boosted classifier with 41 features. The discrimination capacity of the classifier will be deliberately moderate, since a model almost perfectly capable of making the distinction leaves nothing for the auditor to do and no room for an explanation to

come into play. The protocol will report the precision-recall performance of the model on a held-out data set prior to the experiment (Provost, 2013; Breiman, 2001).

Scores will be mapped into five risk bands, since a number provides the precision that a model cannot achieve. This is an issue of presentation and will be treated as such in this protocol, not as a neutral manipulation of the score (Provost, 2013).

4.2 The six explanation conditions

The six conditions will be the following and summarized in Table 2. Condition C0 is Score Only, i.e., risk band and one sentence with the description of the anomaly family. Condition C1 is Global Importance, including five features on which the model depends the most. The protocol assumes that they will be unhelpful for making a case-level judgment. Condition C2 is Local Additive Attribution, i.e., six largest contributions to the score for the particular case. Condition C3 is Counterfactual Explanation, including three simple statements of the type 'This item will be out of the alert threshold if feature has value'. Condition C4 is Exemplar Explanation, with one confirmed fraud, one confirmed non-fraud and one ambiguous historical case. Finally, C5 is a Combined Attribution and Base Rate panel, i.e., the C2 explanation panel with the base-rate statement for all cases (Lundberg, 2017; Ribeiro, 2016).

Base-rate factor will be crossed with the explanation factor as outlined in Section 5.1. In the case of C0 to C4 base-rate factor will be present on half of each participant's items. Condition C5 includes a base-rate statement on every case and is therefore analyzed as a combined condition against C2 rather than a cell of a full factorial design.

Table 2. Planned explanation conditions, panel contents, and the base rate information statement used in conjunction with each condition.

Condition	**Panel content**	**Base-rate statement**	**Intended role**
C0, score only	Risk band and one sentence naming the anomaly family	Half of items (within subjects)	Control
C1, global importance	Five features the model relies on most, across all alerts	Half of items (within subjects)	Model-level context
C2, local attribution	Six largest signed contributions for the item	Half of items (within subjects)	Case-level selection basis
C3, counterfactual	Three minimal, plausible, and diverse statements of the form 'this item would fall below the alert threshold if [feature] were [value]'	Half of items (within subjects)	Documentation

Condition	**Panel content**	**Base-rate statement**	**Intended role**
C4, exemplar	One confirmed fraud, one confirmed non-fraud, and one ambiguous historical case	Half of items (within subjects)	Comparison
C5, combined	Same panel as C2	All items	Combined attribution and base rate

Each panel will be generated by one implementation and checked for fidelity, with additive attributions being calculated accurately for the tree ensemble (Komi, 2021; Arnold, 2004). Explanation experiments without verification for faithfulness are studies on visual designs, rather than explanations. For this reason, manipulation check will include asking C2 participants to identify the feature with the largest contribution, with the percentage of correct responses compared with C0 (Komi, 2021; Arnold, 2004).

4.3 Ground truth

Ground truth will be established by the generative process. The labels will be adjudicated by two independent audit partners based on the case files without model outputs, and compared with the generative labels. The protocol will set an agreement threshold in advance, and the number of items reviewed under this threshold will be counted and reported (Batini, 2009; Okoli, 2022).

Adjudication agreement will also serve as the upper bound for measurable accuracy. In case the two labels do not agree, protocol will report accuracy according to both standards, in order for readers to understand what is the extent of dependence of measured accuracy on the standard choice (Batini, 2009). Items that received conflicting decisions will be marked as borderline.

5. Method

5.1 Participants and design

Participants will be experienced auditors, having at least three years of experience. Pre-experiment questionnaire will measure fraud risk experience, analytics knowledge, and numeracy skills, which will be included in the models as covariates (Atakpa, 2021; Braun, 2003).

Power analysis will aim for 80 per cent power to detect a difference of 0.35 in d′ between conditions. Sample size per condition will be determined by the power analysis and the protocol will state the calculations together with the attained sample size so that the power of each comparison can be calculated.

Design is a 6 × 2 mixed design. Explanation condition is between subjects with six conditions, C0 to C5. Base-rate disclosure is within subjects with two conditions, absent and present, for half

of each participant's items in conditions C0 to C4. Item difficulty is also within subjects with four conditions. Condition C5 displays the base-rate statement on all items and compares to condition C2 as discussed in Section 4.2 (Arnold, 2004).

Participants will be allocated to conditions at random, stratified on experience band and auditor type. Stratification will ensure that the experience profile is the same in each condition, and anyway the models control for experience (Arnold, 2004; Braun, 2003).

5.2 Task and measures

Each participant responds in three ways on each item. The first is a binary decision on whether to escalate the item for substantive fraud investigation using a six-point scale. The second response is red flag selection, which involves picking the most indicative characteristic from a fixed list of eight characteristics. This is the process tracing measure. Thirdly, participants will provide justifications of two to four sentences, which will be rated for quality by blind raters. Confidence in each decision will be measured on a seven-point scale (Dilla, 2010; Trotman, 2011).

Table 3. Outcome Measures, Operationalisation, and Hypotheses Tested by Each Measure.

Measure	**Operationalisation**	**Hypotheses**
Discrimination (d′)	Hit and false-alarm rates across the 24 items, with a log-linear correction; separates discrimination from response bias	H1, H2, H3, H6
Calibration	Absolute difference between mean confidence in correct judgments and observed accuracy, plus a Brier-type score	H3, H4
Justification quality	Two raters score whether the justification names the operative feature, references a comparison class, reaches a conclusion that follows from the evidence, and identifies a corroborating procedure	H2
Decision time	Per-item time, with the top and bottom 1 per cent trimmed	H2
Red-flag weight	Proportion of items on which the participant selects the surface-salient feature	H3, H5

Discrimination will be estimated as d', separating discrimination from response bias. Calibration is necessary since the auditor takes action based on the stated level of confidence and assumes it to be true. Selections in the red-flag task reflect attention without relying on self-reporting. If the mechanism described in Section 3.4 is valid, there will be differences between selections under different conditions, and it will mediate the influence on discrimination (Dilla, 2010; Hodge, 2004).

5.3 Procedure, exclusion rules, and models

This study will be conducted online in one experimental session of the planned duration of 55 minutes: two practice items, and then 24 study items. Participants will receive compensation on the professional level. There are no criteria to be defined after collecting the data. Those who finish the experimental session in less than eleven minutes, or fail both practice attention tests, will be excluded from the experiment and will be informed about the exclusion criterion (Bierstaker, 2001).

All hypotheses, the main dependent variable, and the analysis plan are already established in this protocol prior to data collection. Any deviation from them will be disclosed as a deviation and will not be presented as planned analyses. Exploratory analyses are marked in Section 6.4 (Provost, 2013).

Table 4. Planned statistical models by dependent variable, including fixed effects, random effects, and hypotheses tested with each model.

Outcome	**Model**	**Specification**	**Hypotheses**
Discrimination (d′)	Linear mixed model	Condition, experience, auditor type, and numeracy as fixed effects; random intercepts for participant and item	H1, H2, H3, H6
Calibration gap	Linear mixed model	Condition, base-rate disclosure, and their interaction as fixed effects; random intercepts for participant and item	H3, H4
Justification quality	Ordered logistic model	Fixed effects of condition and covariates in each of the four dimensions; Random effect of participant	H2
Decision time	Log-scale linear mixed model	Condition, difficulty level, and covariates as fixed effects; random intercept for participant	H2
Red-flag weight	Linear mixed model	Fixed effects of condition, experience, auditor type, and numeracy; Random effects of participant and item	H3, H5
Mediation via red-flag weight	Bootstrapped indirect effect	Condition as predictor, red-flag weight as mediator, discrimination as outcome; 5,000 resamples	H5

Table 4 presents the planned models. Discrimination and calibration will be analyzed with linear mixed models with the random intercepts for participants and items, along with condition and

covariates such as experience, auditor type, and numeracy. The justification quality will be analyzed with the ordered logistic regression model and decision time on the log scale, and mediation with a bootstrap-based indirect effect estimate using 5,000 replicates (Provost, 2013; Bierstaker, 2001).

6. Planned Analysis and Inferential Criteria

6.1 Discrimination and calibration

Discrimination will be tested against H1 and H3 with the help of the contrasts of conditions in Table 4. The contrast for H1 will be C2 vs. C0, and the contrast for H3 will be C4 vs. C0. The protocol will state the difference estimate of d' with 95 per cent confidence interval. The analysis should be deemed as supporting the hypothesis if the interval does not include zero in the predicted direction (Provost, 2013).

Calibration will be tested against H4 by comparing calibration gaps for the base rate present and base rate absent items in each condition. C5 will be compared to C2 with the same measure. As base rate is the largest effect candidate, the protocol will provide the calibration gap by difficulty levels in order to show if any effect is specific to certain items (He, 2009; Bolton, 2002).

The item difficulty will be treated as within-subjects variable and will serve as an ordered covariate in the model. In case of the difficulty interaction with explanation condition, the protocol will report the interaction but not the average over difficulty since the cost of an explanation depends on the difficulty of the queue it operates in (Bolton, 2002).

6.2 Justification quality and decision time

Justification quality will be measured with ordered logistic regression in Table 4 separately for each of the four dimensions. Dimensions of justification quality will be structural (naming of the operative feature and following the conclusion from the evidence) and contextual (referring to the comparison class and naming of the procedure). The total score will be reported only as a descriptive statistic. The protocol suggests that counterfactual and combined panels will have greater improvements on the structural dimensions than on the contextual ones thus showing that documentation effect is located in the structure of justification (Trotman, 2011).

Inter-rater reliability will be provided for justification quality assessment. If there is substantial disagreement between the two raters on some justifications, a blind third rater will be recruited to score the controversial justifications according to a protocol established before rating begins (Dowling, 2007).

Analysis of decision time will be carried out using a log scale with the top and bottom 1 per cent of data being dropped as recommended in Table 3. Decision time will be interpreted in relation to the justification only since time is one of the costs associated with the generation of explanation (Chen, 2012).

6.3 Red-flag weighting and mediation

Red flag will be tested against hypotheses H3 and H5 where the former states that attribution increases the selection of the salient feature while the latter states that attribution decreases the same compared to C0. The contrasts for testing will be C2 versus C0 and C4 versus C0 in the red-flag model of Table 4 (Dilla, 2010).

Testing for the mediation hypothesis will involve estimation of the indirect effect of the condition on discrimination mediated by red-flag weight, and bootstrapping of the confidence intervals based on 5,000 resamples. According to the protocol, mediation will be treated as the test of mechanism claim only when the confidence interval does not include zero. Even if the indirect effect is non-zero, it does not necessarily imply that the attentional account holds since there may be other alternative pathways (Dilla, 2010; Hodge, 2004).

6.4 Experience moderation and exploratory analyses

Hypothesis H6 will be tested through inclusion of the interaction between condition and experience in the models of Table 4. Due to the uncertainty regarding the direction of the effect in the literature, the protocol suggests treating the interaction term as exploratory in direction, that is reporting the estimate regardless of its sign and significance (Arnold, 2004).

There are two exploratory analysis planned and which will be identified as such in the final report. The first involves exploration of the hypothesis that discrimination decreases across the 24 items due to fatigue in terms of item position being a covariate. The second one involves analysis of condition by experience interaction on confidence which is the measure most likely to differ for experienced participants (Arnold, 2004; Power, 2013). Exploratory analysis will not be used in the revision of the confirmatory analysis conclusions (Provost, 2013).

7. Interpretation of the Planned Outcomes

7.1 What a discrimination gain would establish

If local additive attribution causes discrimination as suggested by H1, the protocol will read the result as evidence of the discounting process rather than of improved fraud recognition skills. This reading will be based on how attribution answers will be recorded throughout the experiment. If the participants are able to identify the feature that makes the greatest contribution to the case and recognize it as a well-known artefact, they will discount the alarm, and the protocol will verify this reading by analyzing the explanations provided by participants for their recognition of the artefact (Batini, 2009).

This result does not mean that participants have become better in recognizing fraud. It means that they have become better in recognizing the non-frauds that are flagged by the detection system. Such an implication has great importance in large-scale settings because only a small part of

alerts in the triage queue is expected to be true frauds, and, in general, detection systems produce plenty of false alarms (Chandola, 2009).

7.2 Documentation gains and time costs

If counterfactual explanations increase justification quality without raising discrimination, as H2 predicts, the protocol will treat the result as the documentation gain, but not the judgment gain. In that case, whether the gain in documentation is justified by the time costs spent will depend on the triage queue used for the explanation, because time is a capacity cost and not per-item abstraction (Chen, 2012).

Therefore, the protocol will commit to presenting the per-item time difference along with the expected queue volume in the adopting organization, to state the capacity cost in terms of work hours instead of per-item seconds. This is a planning procedure, which is not included into the results of the research (Chen, 2012; Dowling, 2007).

7.3 Exemplars and the similarity heuristic

If exemplar presentation causes an increase in confidence without raising discrimination, as H3 suggests, the protocol will classify exemplars as inappropriate for fast triage interfaces, but leave them open for training and testing purposes. A similarity-matching mechanism of exemplar influence will be supported if red-flag weight increases in C4 and mediates the confidence increase (Dilla, 2010). The protocol will include confidence and red-flag weight in its results for C4 and analyze the correlation between them to test the hypothesis of mediation of confidence increase by red-flag weight. The similarity-matching mechanism will be supported if both confidence and red-flag weight increase in the same direction. Otherwise, the mechanism will require reconsideration (Dilla, 2010; Arnold, 2004).

The focus here is on the triage interface. This is neither to argue against the use of case-based reasoning in training or substantive testing, wherein comparative cases play a different role, nor to extend the results to a domain not covered by the protocol in advance (Arnold, 2004).

7.4 The base-rate condition and the explanation literature

The result would indicate that the base-rate statement reduced miscalibration more than any other explanation format, thus implying, as the hypothesis H4 suggests, that the extent of base-rate neglect is greater than that of the explanation format in these conditions. This finding would be of importance to how the explanation literature invests its efforts. This implication is made in conditional form only, since a synthetic population can reveal nothing about the generalisation of the effect (He, 2009; Bell, 2000). Moreover, the protocol fixes in advance what could not follow from the result. First, the fact of a large base-rate effect would not mean that explanation formats are pointless, as they have been selected specifically for contrasting purposes and are not a sample of all conceivable designs. Second, it would not suggest replacing explanation formats

with base rates in the operational system, because the two can be combined in ways beyond the scope of the study (Provost, 2013).

8. Implications

8.1 Match the explanation to the decision

The main implication suggested by the hypothesis H4 is a fit rule. The triage panel will present local attribution and a base rate, substantive testing will present comparison cases and rules, and a documentation template will present a counterfactual structure that can be mapped on to the structure of an audit conclusion (Ladapo, 2022; Trotman, 2011).

If the same explanation format is presented across the board, then it serves best one specific decision-making task. Global feature importance on a case screen is a clear-cut example of this type. It is true of the model, it refers to the model rather than to the case, and it distracts the attention needed for the case (Lundberg, 2017; Wang, 2015).

8.2 Pair every explanation with its constraints

The very presence of explanations increases the confidence in the result, so a solution would consist in presenting, together with the explanations, the information that sets the upper bound for the confidence. The protocol suggests four pieces of information to provide. They are the frequency of confirmed impropriety in the alert band, the precision of the model in the alert band, the list of known data artefacts that will help the auditor decide on the attribution to discount, and what the score means not, for instance, a sentence such as 'a high score indicates that this item resembles items previously confirmed as improper; it does not indicate that this item is improper' (Provost, 2013; Batini, 2009).

The base rate needs to derive from the organisation's actual results and be accompanied by the associated uncertainty level. Prevalence range estimates are wider intervals provide a less significant discount than the point values imply, and the protocol considers the statement on the uncertainty as an independent disclosure (He, 2009; Bolton, 2002).

8.3 Requirements to be tested

There are four design considerations suggested. They are meant to be evaluated with the help of the study, and any of them can be altered should the planned analysis prove otherwise.

R1, Decision-fit. Each component of explanation should justify the decision it makes and be removed if no decision is made. Global importance of the features needs to be part of model validation documentation instead of case screens (Lundberg, 2017).

R2, Constraint Pairing. Every explanation should be supplied with base rate, band-level accuracy and the statement about the limitations of the score in one screen (Provost, 2013).

R3, Artefact Labeling. All attributions based on the features which have known quality or process artefacts need to be labelled to discount intelligently rather than from experience (Batini, 2009).

Rule 4, Separation of Documentation. Rule-Based Explanation and Counterfactual explanation must be provided to the documentation workspace rather than the triage workspace since the protocol expects that the benefit lies in justification while its cost lies in time (Quinlan, 1993; Trotman, 2011).

9. Conclusion

Explanation of the model-derived risk scores is not one thing, and the assumption that it is one has generated a literature able to calculate attributions but unable to determine which among these attributions are helpful to the auditor. The protocol distinguishes among five types of explanations according to the question each is supposed to answer, and the protocol also distinguishes how these distinctions could be tested.

The test would examine, using 24 fraud alerts and experienced auditors, whether local additive attribution increases discrimination because it allows auditors to discount artefact-driven alerts, whether counterfactual statements increase the quality of written justification at some time cost, whether exemplars increase confidence without increasing accuracy, and whether stating the base rate decreases miscalibration more than any other explanation format.

The design implication the study is intended to examine is a fit rule rather than a format preference. Triage would require both attribution and a base rate, substantive testing would require comparison cases removed from the rapid interface, and documentation would require a propositional structure. Lack of accuracy while maintaining confidence is a potential failing of auditors for which professional skepticism serves to guard.

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This paper refers to 200 sources: 100 taken from the client reference library provided for this project, and another 100 drawn from the author's own literature researches. Each of them is dated 2022 or older, the cutoff date stated in this paper's title.

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