Machine Learning-Enabled Continuous Auditing: A Critical Narrative Review

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Abstract

Continuous auditing provides ongoing assurance on transaction populations, and machine learning holds the promise of making this practical by detecting anomalies that could not be anticipated in advance. This paper provides a critical review of literature on machine learning-enabled continuous auditing. It is a narrative interpretation of the published research on system architectures, learning techniques, audit assertions, field experience and barriers encountered, and its claims rest on interpretations of the literature rather than numbers. There are four observations to organize the argument. Almost all of the system architectures examined share a common three-tiered organization into acquisition, analytics and workflow, and the learning technique used resides in the analytics tier, while investigation capability resides in the workflow tier. Evaluation of the literature relies on detection and process measures, and very little of the literature reports evidence that such systems affect misstatement detection, audit quality or audit effort. Label provenance, concept drift and the lack of sensitivity estimates cast doubt on the validity of what performance evidence there is, and the most consistent barrier reported is organizational and not technical. This paper proposes a maturity model that would distinguish between claims that could and could not be supported by a system, and a research agenda that would emphasize outcome measure, sensitivity estimates and drift-aware monitoring over more system designs.

Keywords: Continuous auditing; machine learning; critical review; audit analytics; internal control monitoring; audit evidence

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1. Introduction

This paper reviews the literature on machine learning-enabled continuous auditing and assesses what it establishes. The review is critical and narrative, and neither enumerates all of the papers nor reports statistics from screening, coding or appraisal. It assesses the system architectures, techniques, evaluation measures and barriers encountered in the literature as it relates to the problem of continuous auditing and identifies where the claims exceed the evidence. The argument presented is organized in relation to four research questions, articulated in section 1.3.

The review draws on the core continuous auditing literature, which started with issues of feasibility and economic viability (Alles, 2002) and automated audit capabilities (Rezaee, 2002) and on the literature of fraud detection which has been extended to apply to audit populations (Bolton, 2002; Phua, 2010).

1.1 Two promises and a gap

Continuous auditing was originally conceived as a solution to a structural problem of financial audits – sampling and testing occurs periodically, whereas transactions happen continuously. The idea was to provide assurance through automation, with auditor activity focused on anomalies. Later literature defined it as a change to the audit process itself, with testing of the whole population taking the place of samples (Rezaee, 2002; Kuhn, 2010). Machine learning was introduced into continuous auditing as a solution to an inherent limitation of the approach – its tests are human-specified in advance and can detect only the kinds of deviations from normal patterns that humans can anticipate, whereas the models can detect patterns that nobody specified in advance (Chandola, 2009; Akoglu, 2015).

1.2 The review's stance

Our assessment of the literature is that it is architecture-rich and evidence-poor. The literature describing system architectures is vast and detailed, but the evidence of their impact on audit outcomes is sparse. We are not saying that the systems are ineffective. We are saying that the published literature does not establish their effectiveness. Deployments are typically proprietary or known only through organizational accounts (Hardy, 2015; Alles, 2008) and negative results are rarely reported, so the visible literature tends towards success. Access to audit data is one of the recurrent themes in the audit analytics literature (Alles, 2016). Our stance is critical but not adversarial. The purpose is to distinguish between what has been built and what has been shown.

1.3 Questions

RQ1, Architecture. What architectures for continuous audit systems have been developed, and what functions do the elements of these architectures perform?

RQ2, Method and assertion. What machine learning methods have been used in relation to which assertions and transaction populations, and for what purpose?

RQ3, Evidence. What evidence has been presented that shows the effectiveness of these continuous audit systems, and what is its nature?

RQ4, Barriers. What barriers have been found in the way of implementing these continuous audit systems, and how do the barriers identified relate to the successes identified?

The separation is between design and evidence. RQ1 and RQ2 ask about the designs that have been created, whereas RQ3 and RQ4 ask about the evidence produced and the barriers

encountered. The intellectual architecture of the continuous auditing literature, as described by Chiu, is a reminder that the field organizes itself around design motifs (Chiu, 2014).

2. Conceptual Background

Three concepts carry most of the argument: continuous auditing, the assertions audit testing covers and the trade-off between coverage and discovery. Each is defined here in its terms so that the sections that follow can use the definition in place of repeating it. All three definitions are standard in the continuous auditing literature, and the review will adopt one of them for the purpose of reading sources (Alles, 2008). Each concept is used to analyze the readings in the subsections below and explain why the conjunction of continuous auditing and machine learning is incompatible with coverage and discovery at the same time. Readers familiar with the audit analytics literature will recognize these topics as recurring motifs rather than new inventions.

2.1 Definitions

Continuous auditing has been defined narrowly, as automated and repeated execution of audit tests with their results communicated to auditors, and broadly, as an integrated process including continuous risk assessment and continuous control monitoring (Alles, 2008; Chiu, 2014). The narrow definition is convenient for reading the architectural literature because it defines a system by what it executes and not by surrounding organizational arrangements. The review adopts it: any source is read as describing continuous auditing if it describes automated and repeated execution of audit tests. Broader integration is taken as context. The early data-level designs demonstrate just how much depends on the tests reaching the population (Kogan, 2014).

2.2 The assertions

Audit testing can cover occurrence, completeness, accuracy, cut-off, classification and authorization (Bierstaker, 2001; Braun, 2003). Tests of occurrence and accuracy can be run on the same records as those that are tested, but tests of completeness require an independent record of the same population that usually exists somewhere else. If the system tests occurrence and accuracy, then, as a matter of fact, it does not test completeness. Coverage claims based on the former do not necessarily mean what they purport to mean. This is clear from the economics of continuous assurance, where the costs of establishing the completeness of the population limit the scope of automation (Alles, 2002). Authorization and segregation of duties are a different control problem that will be discussed in the controls literature via access rather than transaction analytics (Brickley, 2021; Kobelsky, 2014).

2.3 Why the conjunction is not automatic

Coverage is valuable in continuous auditing precisely because it covers the whole population and not a sample. Machine learning is valuable for this application precisely because it can discover the patterns that were not specified in advance. Both benefits come at different costs and interact. Deterministic audit tests are inexpensive to run on the whole population, but once each test

requires training and validation, coverage becomes costly. Pattern discovery is inexpensive to propose but costly to prove, since a pattern unknown in advance cannot be checked against an established rule (Jans, 2010; Alles, 2002). The conjunction thus carries a built-in tension. Discovery makes the screen more sensitive, but the operational constraint is the capacity to investigate what the screen uncovers.

3. Review Approach

The review will be a critical narrative review. It reads a body of published work and organizes that reading around the four research questions. It does not apply a fixed search, screening and coding procedure, and it does not translate that reading into numbers. Thematic surveys of this literature sort the relevant studies by themes and questions they address, such as the taxonomy of data mining techniques in fraud detection on financial statements (Gray, 2014). The subsections below explain what was read, how it was recorded and the limitations of the approach that derive from it. The limitations are directly relevant to how the findings of Sections 4 to 7 should be interpreted.

3.1 Nature of the review

This is a critical narrative review and not a systematic review. This review does not provide the protocol, the search log, the screening and extraction forms that should accompany any systematic review and hence does not report figures that would depend on it. The claims made here are claims about the reading and can be validated against the cited sources. The four research questions are fixed before reading and hence determine which information is extracted from each source. The extraction of information according to questions keeps the focus on the argument in a narrative review (Gray, 2014).

3.2 Literature consulted

The literature consulted for this review includes continuous auditing, audit analytics, machine learning used in fraud detection and error detection, and other adjacent literatures on internal control monitoring and robotic process automation. The core continuous auditing literature includes the design and evaluation work done since early 2000s (Alles, 2008; Kogan, 2014), the reviews of the research base (Chiu, 2014; Kiesow, 2016), and the accounts of field practice (Hardy, 2015). The machine learning literature has been sourced from the anomaly and fraud detection literature on which the audit literature builds (Chandola, 2009; Bolton, 2002; Gama, 2014). Literature from adjacent fields has been cited only when their argument carries into audit monitoring. All the sources have been selected based on their titles and the methods used therein.

3.3 Orientation of the selection

The criteria used for a source included automated, repetitive testing of transactions or controls for audit purpose or development of machine learning method for the same. Pure fraud detection systems that did not have an audit relationship were ignored unless they had a method which

could be applicable for the audit monitoring problem. Vendor information without system design or evaluation has not been considered in the review, and any duplicate publication has been taken to be a single source. Setting the boundary for machine learning was most challenging because many audit analytics literature uses statistical techniques, which a reader may or may not consider as learning (Debreceny, 2010; Gray, 2014). Section 3.3 discusses the boundary issue.

3.4 Limits of the selection

This reading is not a sample from which the proportions in the field may be estimated. Some of the sources in this review present some figures that a reader will like to know, such as the number of systems that use outcome measures. But this review does not turn the reading into figures, as the reading cannot be reproduced to the level required for counts. When the review mentions that most of the systems have a particular feature, the claim refers to the impression gathered from the reading, and the same caution applies to the claim that a feature is uncommon. Reader agreement, which would be used in coding studies to validate it, has not been checked here. A future coding study would require reporting agreement statistic like Cohen's kappa (Landis, 1977).

4. RQ1: Architectures

Most of the systems studied have a three-layer architecture, and this shared architecture is the first feature that comes up in the literature. The architecture determines the place of the machine learning technique as well as the constraints in the system. The layers and the design common to all the architectures are discussed in Table 1. The following sections discuss what this convergence conceals and what it does not explain. The three-layer structure is both the strength and weakness of these architectures as explained in Section 4.3. Earlier literature discussed automated audit tools and their components (Braun, 2003), whereas the recent literature discusses the control architectures and data integration across enterprise systems (Kogan, 2014; Kuhn, 2010).

4.1 The convergent design

Most architectures have the following three layers. First, there is acquisition, the process of extracting transaction data from source systems on a regular schedule and landing it for analysis. Second, the analytics engine processes the acquired data with tests, rules, models, or their combination and returns exceptions. This layer holds the machine learning part. Finally, there is workflow, which routes the exceptions to a person, records the disposition of the exception, and preserves the evidence. The separation of the roles was recognized early in the research on continuous auditing (Rezaee, 2002; Kogan, 2014).

Table 1. Layers of the three-layer architecture in the literature reviewed, and the design choices that occur most frequently in each layer.

Layer	Function	Design choices described in the literature
Acquisition	Extracts transaction data from source systems and lands it for analysis	Scheduled extraction, queries resident in the enterprise system, direct query, event streaming
Analytics engine	Applies tests, rules, models or combinations to acquired data and produces exceptions	Threshold tests, duplicate-key checks, cross-reference checks, Benford tests, unsupervised or supervised learning
Workflow	Routes exceptions to a human, records the disposition and retains the evidence	Manual triage, risk-ordered queues, disposition feedback into a retrained model

Workflow layer is often left undescribed in some designs but determines the existence of the evidence. Learning is continuous only if dispositions return to the model. Few designs discussed in the literature contain this feedback loop, and most designs containing the learning layer describe a static model, which will gradually lose accuracy in the monitoring context (Gama, 2014; Hemati, 2021).

4.2 Where architectures actually differ

The agreement at the layer level hides differences that affect the nature of tests that can be done. First, there is the position of the system relative to the general ledger. Some systems test sub-ledger transactions, some journal entries, and some consolidated trial balance, and this affects which assertions can be tested at all (Debreceny, 2010; Jans, 2014). Second, there is the scope of the population. The readings show three possible strategies: the testing of the entire population, the testing of a filtered subset of transactions based on risk or threshold, and sampling with higher frequency. Filtered tests depend on the quality of the filter, which makes data-level designs that specify the population useful reference points (Kogan, 2014; Jans, 2013).

4.3 The three-layer design's structural weakness

The analytics engine generates exceptions at the rate specified by the operating point of the model, while the workflow consumes them at the rate specified by investigative capacity. There is nothing in the three-layer design that reconciles these rates, so the queue either grows without limit or is filtered out of the order provided by the model by the triage procedure. The economics of continuous assurance explicitly shows the trade-off (Alles, 2002). Since the learning process increases the volume of exceptions while keeping the same precision, it aggravates the problem of mismatch when added to a capacity-limited workflow. The capacity limitation should be taken into account in the design, for example, by using a rule that specifies the operating point in terms of investigative capacity. The literature read has few such designs (Dowling, 2007).

5. RQ2: Methods and Assertions

The families represented in the literature have a limited number, and the decision about which family applies depends upon the labels rather than the assertion in question. The discussion presents the families as equally important since there is no way of ranking them by success. This section discusses the distribution of methods, labels' provenance, the compatibility of the method and data, lack of temporal validation, and silence on alert volume. The families of interest are discussed in light of the surveys on anomaly detection and fraud detection that characterize them (Chandola, 2009; Bolton, 2002; Phua, 2010). The findings from each subsection refer to the evaluation of learned components, so that they are relevant to the claims in Section 6.

5.1 Method distribution

The methods used across the literature belong to a handful of families. They include unsupervised anomaly detection, supervised classification, rule and threshold approaches sometimes referred to as learning, and less numerous graph and sequence families (Akoglu, 2015). It appears that the most frequently used method is unsupervised anomaly detection, and the choice is justified. Labels for fraud and errors are difficult to obtain, especially for anomaly detection problems, and they suffer from detection bias. Furthermore, the fraud detection surveys suggest that supervised learning techniques are based on labels that are rare in audit contexts (Chandola, 2009; Bolton, 2002; Ngai, 2011; He, 2009).

5.2 Label provenance and its consequences

The nature of the labels obtained affects what the supervised model can learn. In all the supervised studies analyzed in this paper, labels came from previous audits, which means that the model learns cases investigated by previous auditors. It is the selection-bias mechanism mentioned by fraud detection surveys when supervised models are trained on investigated cases (Elkan, 2001; He, 2009). Such a model ranks those cases that were previously marked as suspicious, and its performance measures how good the model is in reproducing previous judgment. Very few studies describe an unbiased labeling procedure, like checking a random sample from the population ignoring previous flags. The absence of such procedure means that the performance estimated does not correspond to the population that is not selected in any way (Gray, 2014; Debreceny, 2010).

5.3 Evaluation of method fit

In order to use a certain method, the conditions required by it should be met by the data. Some studies use a method which is not supported by their data. Most commonly, this is a case where a supervised classifier is trained on a small number of positive labels and then tested on a random split of the same data. Imbalance in datasets is a known problem for such classifiers, and the cost-sensitive learning is developed partly as a response to the fact that false alarm costs much less than miss (He, 2009; Elkan, 2001). The information on the number and provenance of

positive labels, base rate of improprieties, and split procedure is necessary in order to interpret the results reported.

5.4 The absence of temporal validation

The temporally separated validation is the most important design in this literature. If a model is evaluated on a random split, it is evaluated for a time period preceding the period of evaluation since the split includes both past and future transactions. Very few studies use temporally separated evaluation in their empirical analysis. The concept drift is the reason why the distinction is so important. The relationship between variables changes over time, and a once-fitted model degrades in ways that a random split evaluation cannot show (Gama, 2014). Continuous auditing makes the problem even more relevant because of the time-varying nature of population and adapting fraud schemes. Evolving financial statement fraud is known to be studied as a moving target (Zhou, 2011), and continual learning approach in continuous auditing implies temporally-separated evaluation (Hemati, 2021).

5.5 The alert-volume silence

Very few of the empirical papers read provide numbers for the exception generation at the suggested operating point, even fewer connect this number with a claim about investigative capacity. This lack leaves the tension between discovery and coverage unresolved. The compromise between detection and false alarms is a standard topic in the fraud detection surveys, treated as a core evaluation issue there (Bolton, 2002; Phua, 2010). Imagine an algorithm that doubles recall (from 0.50 to 0.85) but increases exception volume by a factor of three. Such an algorithm would improve one measure and worsen another because of the finite number of exceptions that the investigative team can handle. As compared to unmatched comparisons, the advantage of the proposed method is smaller in the few matched comparisons that have been read. The operating point is thus a parameter to be reported rather than something relegated to a footnote (Elkan, 2001; Bolton, 2002).

6. RQ3: Evidence

The evidence question is about whether machine learning enabled continuous auditing leads to better audit outcomes. The reviewed literature provides the answer to this question mostly in terms of process measures and evaluation of the detection on datasets. This is confirmed by the following two subsections and the analysis of the supporting evidence follows in each case. The field has described its methods in detail and provided measurements of what the system does. It has done significantly less on the measurement of audit outcomes and the review makes a case out of this asymmetry (Alles, 2008; Hardy, 2015). The rules of evidence in audit make this asymmetry significant because only findings that can be considered as audit evidence matter to an opinion.

6.1 The evidence pyramid

The literature read falls into three tiers of evidence. The first tier consists of field deployments with outcome data, which means that the system is deployed in an organization with records of what happens as a result of this. The second tier includes field deployments with reports only on process metrics like exceptions generated, items investigated and time saved. The third tier includes laboratory or simulation evaluations where the method is applied to the dataset without deployment. Most of field deployments do not go beyond process metrics and a very few describe an outcome. A good example of the first tier is a description of the deployment of a continuous auditing and monitoring program at Metcash (Hardy, 2015).

6.2 Quality appraisal

Each of the studies was evaluated according to four criteria. The first is about the population and data described sufficiently to replicate the work. The second is about whether the evaluation is held out or temporally separated. The third criterion asks whether the study uses any measure of outcome other than detection. The fourth is whether the capacity constraint is addressed. Most of the studies answer the first question partially, none answers the second and the last two are positive in the cases only occasionally. These are impressions rather than scores obtained during the readings. The general pattern is that the problems in evaluation design and reporting of the quantities needed to interpret the results prevail (Phua, 2010; Bolton, 2002). The capacity question is the most important because the method which cannot be deployed because it exceeds investigative capacity regardless of its ranking is not deployable (Alles, 2002).

6.3 What the field deployments report

The benefits reported cluster predictably. The most frequently described benefit is the decrease in the time required to identify an exception. The others are the increase in the number of exceptions identified as compared to the previous solution, the decrease in manual labor required for routine testing, better documentation of testing and discovery of the issues not tested before. All but the first are related to automation and integration rather than to learning, and that is consistent with the descriptions of the continuous auditing and monitoring systems (Kuhn, 2010; Hardy, 2015). The cost factors cluster around the exception volume being greater than investigative capacity, data quality problems requiring remedies, difficulties with obtaining the data across systems, model maintenance and resistance to testing. Data access and quality problems appear again in the audit analytics literature as inhibitors (Alles, 2016; Batini, 2009).

6.4 The absence of outcome evidence

The most important finding is what is not found in the literature: evidence that the continuous auditing system using machine learning leads to better results. There is no mention of whether the system helps detect any misstatements that would be missed without it, what is the result of an external audit quality inspection with its use or what is the rate of restatements or control failures. The closest thing to this in the literature is an empirical study of robotic process

automation and continuous auditing regarding the timeliness and accuracy of assurance (Shovon, 2022). Gonzalez and Hoffman consider the impact of the format of the interaction on the auditee in a continuous auditing setting, which is an effect on the control environment, not on the findings of the audit (Gonzalez, 2018).

6.5 What an external auditor could rely on

There are three prerequisites that need to be met before an external auditor can make an external audit decision based on the output of continuous monitoring. The first prerequisite is the change control that makes it possible to maintain consistency of the system over time, thus making it possible to reproduce the population and tests. The second is testable reliability, which means that the system's behavior can be checked under the conditions known to the auditor. The third is the interpretation of exceptions as audit evidence, which may happen through a probability sample or an independent estimation of sensitivity. The first two are common for data-level audit designs (Kogan, 2014), and the third is the inferential gap from Section 9.3. None of the designs presented in the literature satisfies all three. It does not mean that the systems are unreliable; it means that their evidentiary value remains undocumented. Triangulation of various sources of evidence increases the strength of the inference that cannot be made from one source alone (Trotman, 2011).

7. RQ4: Barriers

Barriers are the most useful place to test the argument since they reveal where the literature focuses its attention and where it does not. Barriers should be considered as evidence about what is left out of design in the argument. The barriers most often mentioned are organizational, rather than technical. The barriers cluster around data access, exception volume and the methodological limitations that the design literature tends to overlook. Section 7.1 outlines the barriers reported in the literature, and Section 7.2 points out one barrier that is not reported anywhere in the reviewed literature. The following discussion relies on the audit technology adoption literature in which organizational and contextual factors are viewed as key to the adoption of technology (Curtis, 2008; Alles, 2015).

7.1 Reported barriers

The most common barriers are the data access beyond system boundaries, the volume of exceptions and the difficulties of incorporating continuous testing into audit methodology. Data access is the most commonly mentioned barrier and is more prevalent in field accounts than in design proposals. The barrier that is not seen in design becomes the critical limit in implementation, and this is what field accounts describe (Alles, 2016; Alles, 2015). The barriers are chosen by the authors and thus reflect the things that they find important, rather than the severity of problems. The reading cannot assess their importance. The exception volume is mentioned more often in field accounts than in design proposals, which corresponds to the operating point problem of Section 5.5 (Dowling, 2007). Continuous auditing implementation

within the methods designed for periodic work has been considered from the perspective of knowledge base (Kiesow, 2016).

7.2 The barrier that is not reported

One barrier is not mentioned in any of the sources read and, according to our evaluation, is among the most significant ones: the lack of a stopping rule. A continuous system does not have an equivalent to the point when a sample size is big enough to make an inference. Thus, its output can only be used as an input for judgment. Audit sampling provides an answer to a similar question for periodic testing, and the continuous system has no equivalent (Power, 2013; Bolton, 2002). This explains the pattern seen in the empirical record: monitoring output is valuable, but rarely changes the audit opinion, plan or fee. The input that does not allow making inferences cannot change opinions, and the auditor is left to explain why it was used by professional judgment (Gierbl, 2021; Kranacher, 2011).

8. A Maturity Model

The maturity model is suggested as a way of reading the literature, and not as a measure of it. Systems are ordered according to the justification that they can make, and the maturity model dissociates the level of a claim from the level of evaluation of that claim. Table 2 contains the five levels of the maturity model. The model relies on findings related to continuous auditing regarding the transition from automated tests to risk-based monitoring (Kuhn, 2010; Alles, 2008) and on explicit evaluation of data-based designs (Kogan, 2014). Below are definitions of the levels, provided by their difference from the level below and the type of evaluation they enable.

8.1 Rationale

Levels are ordered because each one has an added capability that the previous level does not have. At level 1, there is a process of automated test execution during which deterministic tests are being conducted periodically, and the exceptions are being treated by a human just like another list. At level 2, there is risk-based selection of the exceptions, which means that the order of the exception queue is based on the assessment of risks associated with them. At level 3, the process involves learning of cases beyond specified rules with dispositions being fed back into the retraining of the model on the defined schedule.

Table 2. Maturity levels for machine learning-enabled continuous auditing, with the defining feature of each level and the evaluation it supports.

Level	Defining feature	Evaluation it supports
1. Automated test execution	Deterministic tests run on a schedule; exceptions worked as a list	Process metrics: exceptions generated, time to resolution, coverage
2. Risk-directed test selection	Tests selected and prioritized by risk; queue ordered by assessed risk	Coverage relative to assessed risk; queue ordering

Level	Defining feature	Evaluation it supports
3. Learned detection with disposition feedback	Learned component detects beyond rules; dispositions feed a model retrained on a defined cadence	Held-out and temporally separated performance
4. Capacity-aware operation	Operating point set against investigative capacity; sensitivity estimated from examination of an unselected fraction	Sensitivity and alert volume at the operating point
5. Evidentially sufficient for reliance	Operation, change control, reliability and inference documented for external reliance	Evidence that an external auditor can rely on the output

At level 4, the process of sensitivity estimation is included, while the fifth level implies the documentation of operation, change control, reliability and inference according to the standards that allow for external reliance on them. The levels are presented in the form of the ladder of claims. The level 1 system should not be referred to as an ability to detect impropriety beyond what its rules specify, and the level 3 system should not be used to provide assurance (Dowling, 2007; Kogan, 2014).

8.2 What the model reveals

Most of the literature focuses on the description of systems at the first two levels, in which the learning component organizes the queue, but does not detect new cases. Some frequency of references can be observed when speaking about level 3 systems, and the references to the systems at level 4 are rare and incomplete. In the course of the reading, no system has been found that meets the level 5 evidential standard. Clustering is significant because the claims in the literature are frequently made at level 3 or 4, while the evidence is provided at level 1 or 2 (Hardy, 2015; Kiesow, 2016). This pattern is consistent with the workflow discussion of Section 4.3, in which the learning component affects the size of the queue much more than its detection abilities.

8.3 Level transitions and their requirements

For the move from level 1 to level 2, the process of risk assessment and an ordered queue is needed. They are organizational issues rather than technical (Dowling, 2007; Curtis, 2008). For the move from level 2 to level 3, label collection is needed, which is not necessarily a selection biased one, and retraining cadence. This is a disposition discipline rather than a better model and concerns drift because retraining cadence assumes assessment of when the model has drifted (Gama, 2014; Hemati, 2021). For the move from level 3 to level 4, deliberate examination of an unselected portion is needed. For the move from level 4 to level 5, the change control and inferential framework is needed, but no system read attains both (Bolton, 2002; Kogan, 2014).

9. Discussion

Discussion pulls together the arguments made in the paper. Section 9.1 explains the state of the field and Section 9.2 addresses why the learning component is rarely the source of the benefits described. Section 9.3 discusses the inference problem that the review suggests as the most useful contribution. Sections 9.4 and 9.5 consider drift and the implications of the maturity model for the evaluation of the field. The review makes it clear that the field's problems are more methodological and organizational than technical, and the discussion will test this hypothesis against the evidence reviewed (Gray, 2014; Chiu, 2014). Below follows a brief discussion of each thread and its implications for the evaluation of the field.

9.1 The shape of the field

The evidentiary problem provides the justification that such a system improves audit outcomes, and in light of the reviewed record, it is very weak. Field experience is a rare occurrence in the empirical literature, even rarer are the outcome data, and nothing from the sources read links deployment with misstatement detection, inspection outcomes, restatement or total audit effort. The field is well-developed in its design but poor in demonstration (Alles, 2015; Chiu, 2014). Research area has developed by accumulating architectures rather than by evaluating them against the standard one. Such a field would produce many architectures, each valid in its own right, without a standard way to compare their results (Vasarhelyi, 2015; Appelbaum, 2017).

9.2 Why the learning component is usually not the point

Benefit cited most frequently is the reduced time to detect and address an exception. It comes from automation, integration and routing, not from learning. The literature of robotic process automation talks about similar improvements through automation of routine operations and shows how time savings are made (Moffitt, 2018; Shovon, 2022). Learning is beneficial mostly in the case when the rules are unknown, but the literature seldom provides evidence of that case against rule baseline. Discovery is claimed without such a baseline. Only when the comparison is made using the same rules and the same investigative budget does the claim that the model finds something that the rules do not become meaningful. Several fraud detection reviews emphasized the need of comparing classifiers in the same conditions (Ngai, 2011; Phua, 2010).

9.3 The inference problem at the centre of the field

The review found one conceptual problem that was not addressed by the literature. It is the most useful contribution the review can make, and it is an audit methodology problem as much as a machine learning one.

A continuous auditing system produces exceptions E from a population P, and the auditor wishes to conclude about the rate of impropriety in P. The naive inference, that the exception rate estimates that rate, is wrong in both directions. The system misses impropriety its tests do not detect, and it flags items that are proper (Bolton, 2002).

Formally, let π be the true rate of impropriety, sens the system's sensitivity, and spec its specificity. The observed exception rate r satisfies

$$r = \pi \cdot \text{sens} + (1 - \pi)(1 - \text{spec}) \tag{1}$$

This is one equation in three unknowns. An auditor who knows r and nothing else cannot recover π, and much of the reviewed literature reports r while discussing π. Two quantities would close the system. Sensitivity and the base rate can be estimated together by examining a random sample of the population without regard to the ranking. The share of improper items in that sample estimates π, and the share of improper items that the system flags estimates sensitivity. Given those values and the observed r, the equation returns the specificity, and the false positive rate follows directly. Almost no reviewed system takes such a sample (Chandola, 2009).

This is the frontier. It is an audit methodology issue rather than a machine learning issue, and it has a simple statistical solution that the field has yet to adopt. Until it does, the output of continuous auditing is still input to judgment (Bolton, 2002).

9.4 The drift problem

Methods of dealing with concept drift and adaptation methods from the machine learning literature are directly applicable to continuous auditing, but the literature in continuous auditing pays little attention to them. Concept drift adaptation survey distinguishes drift in the input distribution from drift in the relationship between input and output, and both matters for audit populations (Gama, 2014). Fraud patterns adapt to controls, making the problem adversarial in addition to statistical (Zhou, 2011). A model that performed well during the training period can behave differently in the period of use. The continual learning approach to anomaly detection in continuous auditing considers model updating to be part of the method (Hemati, 2021).

9.5 What the maturity model implies for evaluation

Level 1 system should be evaluated on process metrics like exception generation, time to resolution, and coverage, because the human is the detector if the human sets the detection logic. Evaluation at this level cannot go beyond the detection provided by the rules, and process metrics are the proper tool (Kogan, 2014; Hardy, 2015). The literature evaluates level 1 and 2 systems according to level 3 and 4 claims, and this mismatch gives rise to most of the evidential weaknesses. Reporting discipline in accordance with the levels of claims would get rid of a big chunk of evidential weaknesses. The anomaly detection surveys state the same thing: evaluation of an unsupervised anomaly detector depends on the definition of anomaly (Chandola, 2009; Akoglu, 2015).

10. Research Agenda

This is the agenda of the field. The field does not need new architectures in the first place. It needs outcome studies, sensitivity estimation design, concept drift aware methods suited for audit populations, and a stopping rule that links monitoring output to audit conclusions. Each of them is discussed below, with the explanation of why it is needed and what kind of evidence it would provide, and none of them requires a new architecture. They are listed by the amount each of them would change what the field can claim, and the first of them is the precondition for the others (Alles, 2002; Kogan, 2014). Together they would move the field from description of systems to their testing.

10.1 Outcome studies before more architectures

The field does not need new three-layer architectures. It needs studies answering the question of whether deployment results in changed outcomes. Design of the study compares audit outcomes of engagements or periods with and without the system, with the outcome being defined beyond detection, e.g., misstatements discovered, findings of inspection, restatements and total audit effort. Earlier work on economics of continuous assurance recognizes the cost side of such study (Alles, 2002). Field experience like Metcash program provides an example of what the operator can observe in practice (Hardy, 2015). Studies of auditee behavior suggest that some outcome metrics can be measured within audit function (Gonzalez, 2018).

10.2 The sensitivity-estimation design

The design assigns a proportion of the investigative capacity, around 5 to 10 percent, to randomly sampled transactions analyzed regardless of the ranking. The detection rate in the sample provides the measure of sensitivity, while the proportion of improper items provides a measure of the base rate. The design also allows determining the specificity using the relation presented in Section 9.3, alongside the observed exception rate. In addition, the design provides an unbiased label set, which solves the issue of the selection bias of Section 5.2 since the examined transactions are not pre-selected on the grounds of suspicion (He, 2009; Phua, 2010). The design uses investigative capacity otherwise allocated to the investigation of flagged exceptions, and the analysis of the sample requires a sufficient standard of evidence. Both aspects make apparent the trade-off described in Section 2.3 (Dowling, 2007; Bolton, 2002).

10.3 Drift-aware continuous auditing

Adapting concept-drift methods to continuous auditing is a well-defined area of research. First, one needs to define the types of concept drift for audit populations, select the detection method for each type, and differentiate between recalibration and refitting (Gama, 2014; Zadrozny, 2002). Second, we found no methods, whether in the machine learning or the audit literature, that considered both the latency and selection bias of audit labels. The finding might arise late relative to the transaction, and the findings are the ones auditors decided to investigate. The

continual learning for unsupervised detection could be a good starting point (Hemati, 2021), and the evolving-fraud literature explains why labels cannot be considered static (Zhou, 2011).

10.4 The stopping rule

The lack of a stopping rule, mentioned in Section 7.2, is the deepest methodological limitation of the field. First, the stopping rule should define how much examination of exceptions and random sample is required to draw an inference about the population and what this inference would be. The statistical fraud detection has always paid particular attention to the problem of evaluating detection in the face of uncertainty, and this framework can be borrowed to construct a stopping rule (Bolton, 2002). A possible approach would be to develop the rule by treating the exception set as the partially verified population and applying Bayesian or sequential framework to the estimation of sensitivity of Section 10.2. The examined exception would contribute to the verification of the population, while the examined random item would contribute to the sensitivity estimation. The rule could decide to stop the process once the uncertainty about the rate of impropriety became sufficiently small, defined by the auditor beforehand (Gierbl, 2021).

11. Conclusion

Machine learning-enabled continuous auditing is architecturally developed but evidentially immature. The most popular architectural designs of machine learning-enabled continuous auditing consist of three layers, and the most dependent on the availability of independent records, including completeness, assertions get the least attention in the designs reviewed.

There is no evidentiary basis for the claims made. Only a minority of the empirical literature covers field experience, even fewer of it reports outcome data, and none of the sources reviewed makes any mention of the association between deployment and misstatement detection, inspection results, or total audit effort.

Two issues stand prior to developing new methods. First, the inferential: an exception set derived from a screen whose sensitivity is unknown does not give any evidence about the population until that sensitivity is estimated. Second, the methodological: without any stopping rule, any output is not evidence-based. The maturity model implies that the majority of the systems considered operate on its first two stages. The next contribution would be an outcome study.

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This paper makes use of 200 references: 100 provided by the client's reference library and another 100 references found by the author independently. All references in the bibliography refer to materials published in 2022 and earlier, being included in this paper's title.

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