Automation of Audit Sampling Using Rule-Based Decision Systems

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Abstract: ***Automation of Audit Sampling Using Rule-Based Decision Systems: an objective, scholarly analysis of automated sampling approaches, evidence-based assessment, and formal structure. Automation and computerization in auditing are ubiquitous and offer unparalleled assistance to auditors in improving efficiency, effectiveness, and overall cost. Audit sampling is an effective means to make audit decisions based on part of the evidence rather than the whole. Rule-based decision systems are popular in many business and accounting areas, but not widely deployed for audit sampling yet. Audit sampling can be automated by creating sampling rules based on audit data, professional guidelines, and/or judgment. Such rules specify sampling conditions and thresholds, the population elements that trigger the rule-set, the sampling specification produced, and the sample sizes required and whether the auditor should consider additional information of other related decisions. The approach also supports a human-in-the-loop function, providing the auditor with automation assistance but allowing judgment to deviate from the rules. The extent of automation can vary to meet auditors' needs and is not limited only to the mention mode of rule-based systems. Effectiveness and efficiency can be evaluated in terms of accuracy, coverage, false positives, false negatives, processing time, and resource utilization.***

Keywords: Automated Audit Sampling, Rule-Based Decision Systems, Audit Automation, Computerized Auditing, Evidence-Based Audit Methods, Sampling Rule Design, Audit Decision Support, Professional Judgment Integration, Human-In-The-Loop Auditing, Sampling Threshold Specification, Audit Data Analytics

1. Introduction

Rule-based decision systems can support the increasingly important audit-sampling process, typically performed by sampling techniques that are resource-intensive. Automating audit sampling decisions supports quality, efficiency, and audit risk-reduction objectives. Nevertheless, the introduction of untested and unverified sampling rules is ill-advised, as is treating them as a substitute for auditor judgment. Consequently, rule-based auditing and sampling decisions can be refined and augmented as decisions become verified by practical evaluation.

Sampling is a process used to reduce the amount of audit evidence when testing internal controls, verifying account balances, or searching for fraud. It is also used for other purposes, such as assessing the quality of the Financial Statements. Appropriate sampling decisions ultimately contribute to the overall quality and efficiency of the audit, help meet client and regulatory expectations, and reduce audit risk. Audit sampling tests and the decision of whether to perform tests on whole populations are usually performed by using the Rule-Based Decision Systems (RDS) concept.

1.1 Overview of Audit Sampling Significance

Effective audit sampling is critical for the successful performance of an external audit, as it impacts both the audit quality and efficiency. The modern consolidated audit also typically expects a risk-based approach that incorporates all samples into a comprehensive decision model. Furthermore, the audit sample decisions should be knowledge driven and yet supported by data analytics as much as possible. These considerations support the intent to automate audit sampling decisions by integrating a rule-based decision system with a decision repository for audit sampling sampling operations. Other audit areas can also benefit from rule-based decision systems that could lead to better and more efficient audits by continuously learning from the decisions made. Audit samples have an important place in the audit process, reduce the cost of the audit, and enable the audit to be completed within the time budget without sacrificing quality. Furthermore, evidence seen by only one or two partners is evaluated on a very partial basis, with the results usually included as the sample is overall assessed rather than the particular piece of evidence itself. Nevertheless, the objective of all samples is to provide an accurate final decision that is as precise as possible, given the testing risk associated with each sample. The final sample decisions are part of a much larger decision tree that, in its entirety, can still be quite complex.

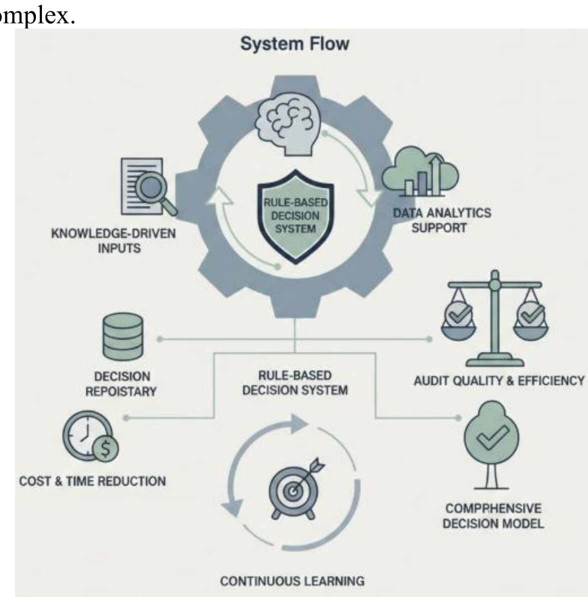

Figure 1: Integrating Rule-Based Decision Systems and Data Analytics for Automated Audit Sampling: A Knowledge-Driven Framework for Enhancing Audit Quality and Efficiency

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2. Foundations of Audit Sampling

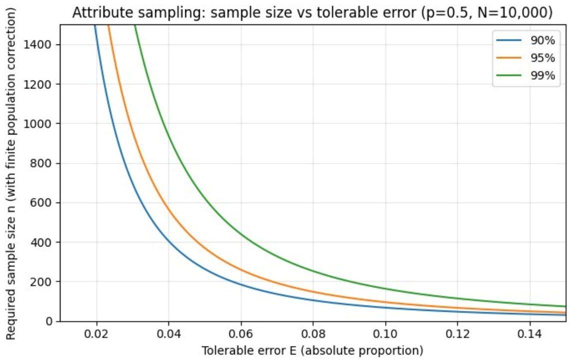
Audit sampling utilizes population sub-sets to conduct qualitative or quantitative inference aimed at achieving a meaningful trade-off between audit quality, cost, time, resource deployment, and client disruption. Although statistical sampling formally applies probability theory to enable clear delineation of risks associated with the selected audit sub-set, it is not the only acceptable methodology. Non-statistical sampling, which relies principally on judgment, experience, intuition, and/or common sense, is widely used to support audit evidence-gathering decisions. A key advantage of non-statistical sampling is that it can be targeted towards particular areas of risk concentration rather than simply a random sample. Such risks in turn could relate to either the quality of the client's internal controls, the integrity of management, the materiality of account balances, or a combination of these. Typical areas of focus for non-statistical sampling developments are: client materiality mandates, fraud reporting, going-concern assumptions, related-party transactions, income tax reporting, and subsequent events.

Yet despite its wide acceptance, non-statistical sampling can also be considered as the "poor cousin" of statistical sampling. Areas such as sampling risk, performance criteria, sample sizing, and the tailoring of sampling procedures are rarely, if ever, openly considered, acknowledged, or discussed. Indeed, many professional practitioners would have difficulty in providing a clear answer to the question "What are the performance criteria for non statistical sampling?".

2.1 Statistical versus non-statistical sampling

Statistical and non-statistical sampling differ not only in when to apply but also in the sampling process. Statistical sampling can be defined as the application of probability theory to the selection of units from a population, a sample so chosen which is representative of the population from which it is drawn. The procedure requires the use of statistical principles in establishing control over sampling risk and in evaluating the results. The critical feature is that decisions can be made concerning the population, relating to material misstatement or non-compliance, based on the results obtained from the sample.

Sampling procedures can also be considered when an auditor has experience with the audit and comparable audit, when the auditor is satisfied with the reliability of internal control, and when sampling is used in the context of evaluating substantive tests. Non-statistical sampling can be defined as the selection of units for the sample without the use of statistical methods. It is the approach employed by most auditors in practice. Non-statistical sampling is a subjective method of sampling, with procedures remaining established by the auditor's experience, knowledge, and understanding of the particular situation or intended area of sampling. In particular, it allows the auditor to rely more heavily on judgment than in applying statistical sampling, which can become a mechanical process.



Equation 1: Core setup: how rule-based sampling becomes a math problem

Let each item i have:

- **Ground truth** label (from expert/audit evidence): $y_i \in \{0,1\}$ where $y_i = 1$ means "should be sampled / flagged", and $y_i = 0$ means "should not".
- **System prediction** (from the rule engine): $\hat{y}_i \in \{0,1\}$

Over N items, the rules create four outcomes (confusion matrix counts):

Step 1: Define indicator functions

$$\mathbf{1}(\text{condition}) = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{otherwise} \end{cases}$$

Step 2: Define the four counts (fully derived from data)

True Positive (TP): predicted sample and truly sample

$$TP = \sum_{i=1}^{N} \mathbf{1}\,(\hat{y}_i = 1 \ \wedge \ y_i = 1)$$

False Positive (FP): predicted sample but truly not sample

$$FP = \sum_{i=1}^{N} \mathbf{1}\,(\hat{y}_i = 1 \ \wedge \ y_i = 0)$$

False Negative (FN): predicted not sample but truly sample

$$FN = \sum_{i=1}^{N} \mathbf{1}\,(\hat{y}_i = 0 \ \wedge \ y_i = 1)$$

True Negative (TN): predicted not sample and truly not sample

$$TN = \sum_{i=1}^{N} \mathbf{1}\,(\hat{y}_i = 0 \ \wedge \ y_i = 0)$$

Step 3: Show that they partition the dataset

Every item must fall into exactly one cell, so:

$$TP + FP + FN + TN = N$$

2.2 Objectives and risk considerations

Evidence-based audit sampling must be sufficient to enable the audit to achieve its intended objectives at an acceptable cost, taking into account the related risk and materiality levels. Depth, timing, and extent, including decisions on the

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nature and volume of audit evidence to be obtained, are subject to decision and control.
When deciding the risk of material misstatements during an audit, the auditor takes into account the risk that the audit may fail to detect material misstatements in the financial statements and selects appropriate levels for the audit. These levels are established in the planning phase, taking into account the nature of the client's business and the results of other audit procedures. In this way, the audit design should ensure that it is capable of detecting material misstatements at the expected level.

Statistical principles that underpin sampling decisions introduce objective measurements of the sampling risk associated with the audit sampling process. Other principles relating to the level of detection risk are, however, judgemental in nature, and have an important bearing on the design of the audit sampling approach. Careful consideration needs to be given to whether the planned sampling risk is appropriate in the circumstances, taking into account the following factors: the significance and inherent risk associated with the account balance or aggregate of transactions; the competence of the internal controls; the quality of the first-stage sampling; the risk of a biased sample selection; the potential to increase the sample size should high errors be found in the first-stage sampling; and the costs versus benefits of an informative sampling design.

3. Rule-Based Decision Systems in Audit

A rule-based decision system consists of an inference engine and a repository of rules. It classifies input data according to conditions specified in the rule, executing actions related to the matching rule. The auditor operates the system, specifying the conditions of interest and the decisions to be made. Inputs are added, triggers activated, and a rule is fired to produce a decision.

In an effective rule-based decision system, the rules can be constructed independently of other components. Inputs reside in one part of the system, the decision paths are examined by an auditor, and the inference engine operates like a dedicated function. With the right inputs and the correct interpretation of outputs, a rule-based decision system can be authoritative, producing decisions absent human intervention. But such systems are limited: the rules must be specified correctly, and care is required to avoid misclassification.

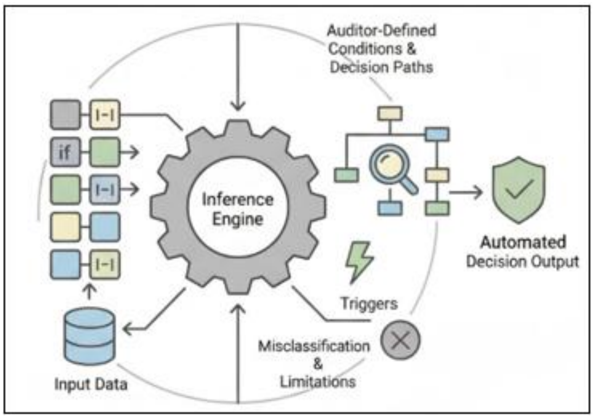

Figure 2: Architecting Autonomous Audit Governance: A Framework for Decoupled Rule-Based Decision Systems and Inference Engines

3.1 Architecture and components

Rule-based decision systems in the context of audit sampling can be characterized in terms of the architecture of such systems and their components. The general architecture of a rule-based decision system is represented in Figure 12. A rule-based decision system receives input data about the audit and the entity being audited and utilizes a rule repository, which contains one or more sets of rules describing sampling decisions. Sampling rules can also be implemented as business rules that select the appropriate decision path for an auditor-in-the-loop context. A rule-based decision system can operate in consultation mode, in which the final decision is made by the auditor or use sampling rules to automatically select the samples or subsamples.

A rule-based decision system for audit sampling utilizes the characteristics of an audit engagement and/or an audit client, as specified by the auditor-in-the-loop interface, as input data. For example, such data can comprise indicators associated with the expected quality of the generated samples and/or subsamples. Rules that automatically select samples or subsamples based on the input data can be designed using multiple approaches. A certain set of sampling quality indicators can define a predefined rule set. These quality indicators can be used as triggers that determine specific decision paths in a rule set.

	Pred: Sample	Pred: Not sample
Actual: Sample	82	18
Actual: Not sample	9	91

4. Automation of Sampling Decisions

The development of rule-based sampling decisions concerns the definition of the criteria that become the basis of an automated low-level sampling process. The following items, along with the rationale for their inclusion, are particularly noteworthy: (i) the criteria thresholds and the rule sets that are deployed, (ii) the conditions that trigger the use of sampling and rank the rules, and (iii) the path that the decisions follow when sampling is performed. At the same time, it has to be clear that not all components of the systems and the subsequent data writing are being automated; instead, human intervention still plays a major part.

Automating rule-based sampling decisions requires decision criteria represented in a set of well-defined rules. Two different categories of sampling-related decisions can be discussed: rule sets, which identify which sampling mechanism should be applied, and the lower-specific sampling rules that make precise how the sampling process should take place. The decision to sample or not is guided by the availability (or not) of rules within the corresponding repository in a specific moment, and the priority of the rule relevant for that segment of the audit. The option to sample also remains consistent with previous considerations about the adjustments that an auditor should perform based on their perception of the audit process and results, thus ensuring that

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the human-accented part of the specially defined human-in-the-loop process is guaranteed. A second category of threshold-based decisions that lie lower-layer audit processes concerns the assignment of values to sampling-related parameters.

4.1 Criteria for rule-based sampling decisions

Rule-based decision systems may assist auditors in making recommendations about sampling decisions, but the automation of these decisions needs to be explored. Automation scopes vary from simple rule evaluation to complex processes where auditor input is required for parts of the sampling investigation. Thresholds determine which sampling decisions can be automated while sets of rules define the breadth of automation. Appropriate triggers indicate which sampling decisions are relevant. The proposed pathways of audit sampling decision-making can consider materiality but require human intervention to manage prerequisites, address categorical passages, and guide exploratory phases.

Previous studies focused on sampling design rather than decision-making strategies. Sample size and procedure can be influenced by the audit strategy adopted, e.g., test of controls or substantive approach. Nevertheless, the latter could benefit from sampling decision recommendations that evaluate these factors. Information commonly known by auditors remains unexplored in the literature yet forms part of routine audit work. Rule triggers enable the automation of sampling decisions. When materiality risk is high for individual items, the auditor is already aware of the precision sampling and thus part of the information fulfills a requirement for that decision. Even if part of the decision is intuitive, it can be still enriched by other available information.

Equation 2: Deriving the evaluation metrics

A) Accuracy
"Accuracy indicates the proportion of correct decisions relative to the total number made."
Step-by-step derivation
1) Correct decisions happen when prediction equals truth:
$$\hat{y}_i = y_i$$
2) This occurs in two cases: TP and TN
3) Therefore:
$$\text{Accuracy} = \frac{TP + TN}{N}$$

B) Coverage
In operational terms, this is typically **Recall / True Positive Rate** (how much of what *should* be sampled is actually captured).

Step-by-step derivation
1) "Actual evidence-based sampling cases" are those with $y = 1$, count $TP + FN$
2) "Captured by rules" among those are the TP
So:
$$\text{Coverage} = \frac{TP}{TP + FN}$$

C) False Positive Rate (FPR)
Step-by-step derivation
1) Actual negatives are $y = 0$, count $TN + FP$
2) False positives among those are FP
So:
$$\text{FPR} = \frac{FP}{FP + TN}$$

D) False Negative Rate (FNR)
Step-by-step derivation
1) Actual positives are $y = 1$, count $TP + FN$
2) False negatives among those are FN
So:
$$\text{FNR} = \frac{FN}{FN + TP}$$

5. Evaluation and Validation

Effectiveness and efficiency of automated sampling decisions can be assessed through several metrics. Accuracy indicates the proportion of correct decisions relative to the total number made; coverage assesses the proportion of actual evidence-based sampling classifications made by the set of rules; false-positive and false-negative rates quantify the error rates for sampling decisions; processing time measures the speed of decision-making; and resource utilization indicates the computational resources needed for the inference.

Implementation and validation of a rule-based sampling decision system requires several baseline sets. An appropriate sample of real-tasks needs to be selected, tagged with the evidence-based decisions, and divided into training, validation, and test subsets. Moreover, data contributing to sampling decisions should be gathered for the same samples and tagged according to the presence of several triggers.

Rules constituting the set of automated audit sampling decisions should then be learned over the training set, and the quality of the learnt model should be assessed over the validation set. Finally, the learnt rules should be applied to the test set, and the metrics discussed above should be collected to determine the overall effectiveness and efficiency of the system.

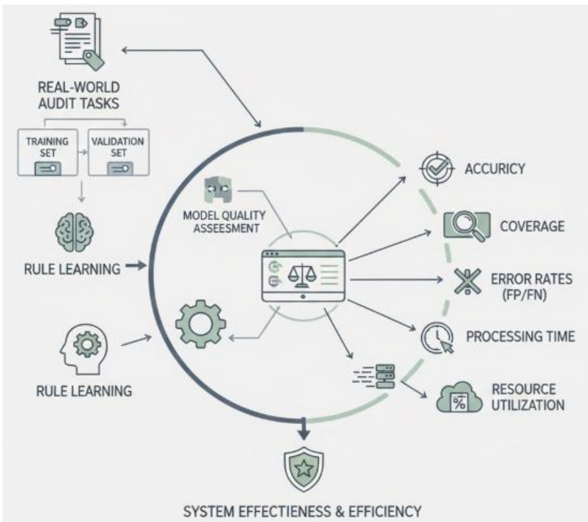

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Figure 3: Evaluating Algorithmic Rigor in Audit Automation: A Multi-Metric Framework for Validating Rule-Based Sampling Decision Systems

5.1 Metrics for effectiveness and efficiency

Metrics for effectiveness and efficiency include accuracy, coverage, false-positive and false-negative rates, processing time, and resource utilization. The completeness of rule sets and their non-exclusion by conflicting rules determine the threshold of a rule-based sampling decision. The performance of rule-based sampling decisions over decision-support sampling in a real-world audit-engagement context validates these metrics. Audit sampling using a well-defined combination of thresholds, triggers, and rule sets produces a quality outcome more optimally than other debate-driven research endeavours. Furthermore, audit sampling naturally manifests as a human-in-the-loop application, conveying broad acceptance for supporting information-technology-enabled and digital-audit initiatives of the audit profession.
A rule-based sampling approach contributes to process digitalization by automating the decision-making logic associated with defined sampling-related thresholds by making use of existing periodic sampling-related research decisions, enhancing the quality of largely manual sampling processes, and increasing the sampling coverage of such-automated decisions while ensuring trustworthy processes with minimal automation risk. Effectiveness and efficiency form the basis for justifying the automation and for supporting rule-based sampling decisions and considerations around Signaling Theory. Effectiveness and efficiency perspectives originated from the nature of both sampling decisions supported by rules and risk covered through activated rules. Effectiveness is primarily viewed as quality, whereas efficiency pertains principally to optimal resource utilization. The inputs required for assessing the effectiveness and efficiency of rule-based sampling decisions are specific to directly defined audit-engagement sampling considerations rather than to general decision-support systems.

6. Governance, Ethics, and Compliance

The design, development, and deployment of rule-based sampling decisions must adhere to governance, ethical, and regulatory requirements influencing the organization and the audit engagement. Within the firm, audit independence and objectivity should be preserved, e.g., by involving multiple partners. Transparency of operations and results is necessary, buttressed by thorough documentation of the audit evidence undergirding the rules. When external regulators require inspection of audit files, validation reports that explain the rules and assess performance are useful.

Regulatory frameworks and third-party certifications may impose additional constraints. The International Auditing and Assurance Standards Board mentions independence and objectivity, professional competence and due care, and sufficient audit evidence as audit quality elements "fundamental to the performance of an audit in accordance with international standards" (IAASB 2014, 10). Rule-based decisions rejecting or endorsing statistical sampling should thus be appropriately justified.

Equation 3: Processing time
"Processing time measures the speed of decision-making." Let t_i be time to process item i.

- **Total time**:

$$T_{\text{total}} = \sum_{i=1}^{N} t_i$$

- **Average time per decision**:

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_i$$

- **Throughput (items/sec)**:

$$\text{Throughput} = \frac{N}{T_{\text{total}}}$$

Resource Utilization
"Resource utilization indicates the computational resources needed for the inference."

A clean way to formalize this is as a weighted sum of normalized resource consumption.

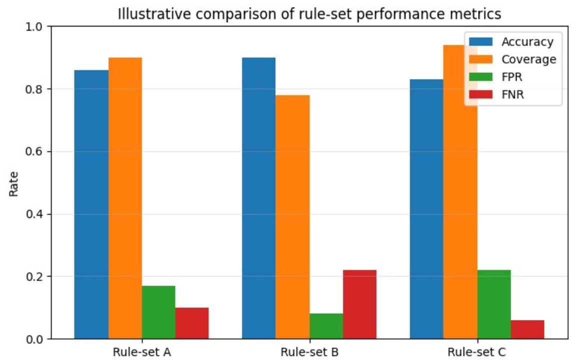
Let $CPU(t)$, $MEM(t)$ be CPU and memory usage over time $t \in [0, T]$. Define averages:

$$\overline{CPU} = \frac{1}{T}\int_0^T CPU(t)\,dt, \quad \overline{MEM} = \frac{1}{T}\int_0^T MEM(t)\,dt$$

Then a composite utilization score:

$$U = w_{cpu}\overline{CPU} + w_{mem}\overline{MEM} + w_{io}\overline{IO} + \cdots$$

where weights $w.$ reflect what matters to the audit firm (cost, runtime limits, etc.).



6.1 Independence and objectivity safeguards

A fundamental requirement for the application of any automated support in auditing is the maintenance of independence and objectivity throughout the audit process. This concern is particularly relevant in the automated selection of subsets of audit evidence involving a risk-based sampling approach. The process of implementing sampling decisions requires that the key underlying assumptions, the rationale for the specific risk-based thresholds imposed, the choice of the rule set, and triggers that govern their

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application be sufficiently transparent to the audit engagement team so that they can be adequately assessed.

The sampling rules may also be perceived as being prescriptive and thus limiting these qualities. In their current form the rules represent heuristics distilled from indications across a number of audits which, while based on statistical observations are yet to be formally validated. As such they should be regarded as guideline indicators requiring resolution by the auditor prior to performing the sampling. To mitigate against an over-prescriptive nature in their formulation and application, a human-in-the-loop capability has been encapsulated in the sampling framework through the facility to turn sampling rule-based triggers on and off. Furthermore, the process of developing an Audit-Rule-Base should be undertaken at an ongoing engagement or firm level using the engagement or firm level decision aspect. For example, an Audit-Rule-Base could provide indication and supporting guidance regarding potential increased risk of material misstatement associated with industry specific norm, itrend consideration, entity size and complexity, entity history, or data quality issues with regard to Fraud risk appearing in the Risk of Material Misstatement section of the ACRAP.

7. Challenges and Limitations

Challenges in implementing and leveraging rule-based decision systems designed to automate audit sampling decisions can be grouped into two areas: those primarily affecting the quality and availability of data needed to formulate, deploy, and execute sampling rules and those associated with creating and maintaining these rules. Given that sampling is an application of the broader rule-based decision systems framework, any shortcomings associated with the elicitation of rules for such systems also apply here.

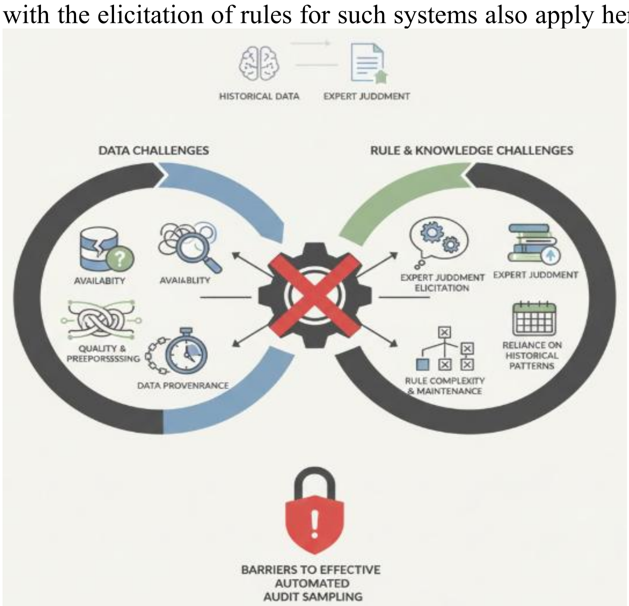

Figure 4: Navigating Implementation Barriers in Automated Audit Sampling: A Critical Analysis of Data Provenance, Rule Elicitation, and Expert Knowledge Integration

The rule sets, thresholds, triggers, and decision pathways that govern sampling decisions rely on historical data and expert judgment to capture pertinent relationships and patterns affecting sampling requirements. In practice, data quality and availability issues common to rule-based decision systems in general, including provenance and preprocessing concerns, impact sampling as well.

7.1 Data quality and availability

The quality and availability of data can affect the creation of sampling strategies, especially when their decisions are based on statistical fundamentals. The risks and consequences of rule-based decision systems not producing a sampling strategy can be mitigated with a human-in-the-loop approach. Detection of situations fallible for automating the sampling decision can be accomplished by operating rule sets that characterize the distribution and state of the data used to create the sampling strategy. Rules can capture specific data qualities- e.g. the amounts of the population, the distribution type, the teleological audit phase- making it easier to accept or to discard an automated-sampling decision. System boundaries identifying situations for which automating a sampling decision is unviable can be established based on the union of such conditions.

The same foundation for automation appears when considering the quality and availability of some information needed in the decision-making quality layer. Since quality is a subjective concept, rules defining the required quality or its minimally acceptable threshold at a particular point in time can be built within this foundation. In this instance, achieving human-in-the-loop sampling uses the set for sensing. The human-in-the-loop concept also extends to the entire life cycle of sampling rules: the establishment of a rule creation process and its maintenance. Not all rules created within the sampling strategy are supposed to remain immutable through time as that contradicts the dynamic nature of the concept, during which both the sampling scope or problem and environment are subject to change. One of the specializations of rule-base-research programs should be to determine the life cycle of each rule and the logic and reasoning adopted to decide when to distort a rule.

7.2 Rule maintenance and adaptability

The analytics framework for sampling decisions requires a carefully curated dataset, often sourced from a combination of auditors' past experiences, academic research, and industry best practices. Yet, sampling is merely one of several decisions in an audit. Internal control weaknesses, transaction preferences, and fraud risk indicators each warrant distinct treatment together across the set of decisions. Using a machine-learning approach, these rules can be automatically adjusted and updated based on auditor practice. Best-practice triggers can similarly be defined to evolve the rules. However, not all decisions contain a machine-learning pronouncement; some remain rules-based given the need for independence and objectivity. For instance, requirements for proving independence of mind, of action, and of appearance (e.g., Objectivity: SA 220) translate into “directed audits” or “audit directions/directives” that convey conscientious audit decisions made in explicit accordance with best-practice prescriptions. In this instance, coverage (i.e., a best-practice trigger) becomes essential to maximize the effectiveness of the directive without compromising independence.

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Machine-learning pronouncements also modify the directives. Rather than dictating practice, “non-coverage” aspects act as a checking mechanism- an “internal peer review”- to provide best-practice recommendations for a “second set of eyes.” Addressing these triggers can result in improved quality. Portraying the complete set of decisions in this manner blends the conformity and conformance options to create a full “model-complied audit.”

8. Conclusion

The preceding analysis demonstrated the applicability of rule-based decision systems to sampling decisions in audit evidence evaluation, highlighting the escalating demand for decisive support systems in audit-related contexts. Auditors engaged in traditional sampling now possess a dedicated tool for direct sampling decisions. However, the evaluation considerations ultimately revealed the limited effectiveness and efficiency of the automated set of sampling decisions. Nevertheless, several future research directions are apparent. A first and obvious line of inquiry focuses squarely on improving the effectiveness and efficiency of automated sampling decisions. Attention must turn to the related issues of rule quality, quantity, and coverage of the decision space. An additional area for research concerns the volume and the communication of uncertainty associated with the rules governing sampling decisions. Rule governing sampling decisions typically stem from the induction approach. The second branch of rule generation concerns the direct, authoring-like expertise-driven approach. This branch is more copious and typically uses a heuristics-based knowledge acquisition technique. However, structured procedures can also help overcome inadequacies of the heuristics-based technique. Because of its transparency, the authoring-like approach enables rules to incorporate probabilistic aspects, such as an “expected decision confidence.” A next area to explore involves balancing the need for human interpretation of decision authors inside and outside the organization with the necessity for ready provability and justification of decision rules when dealing with sampling issues.

Another avenue for future work centers on the sampling choices located at the higher levels in the rule decision hierarchy. Support for these higher-risk issues is certainly required even if sampling alone has not been deemed adequate generally. Finally, the direct automation of sampling choice, without a human-in-the-loop aspect, could also be examined for other domains, notably those related to external-machine usage.

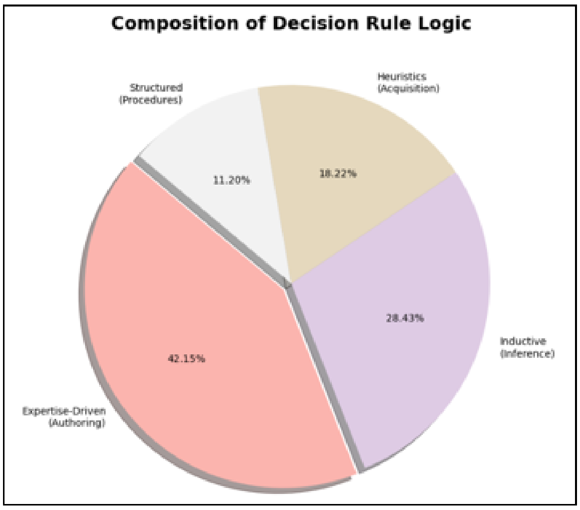

Figure 5: Composition of Decision Rule Logic

8.1 Final Thoughts and Future Directions in Audit Sampling

An objective, scholarly analysis of automated sampling approaches, evidence-based assessment, and formal structure. Audits employ sampling to construct representative subsets of populations for the purposes of evaluation, inquiry, and test of controls. Successful audit sampling improves the quality, efficiency, and risk mitigation of the overall audit process. External audit quality remains a challenge owing, in part, to resource constraints and cost pressures. The sampling decisions made by auditors play a critical role in the quality of audit sampling; automating sampling decision making mitigates sampling-related quality issues. Evidence-based rule sets support rapid sampling decisions, maintaining an efficient and effective approach to the audit sampling process. Formalized decision systems support automated sampling decisions, maintaining risk-based quality.

The synthesis presents an objective examination of the automation of audit sampling employing rule-based decision systems, assessing the sampling decision area of audit sampling and the impact of rule-based systems in automated audit sampling. Existing automated audit sampling approaches are evaluated to facilitate an assessment of the quality and quantity of rule-based evidence supporting decision paths. Finally, an expanded taxonomy of audit sampling is introduced, mapping audit sampling methods to different forms of rules. Addressing gaps identified in the assessment enables more complete and informed deployment of rule-based systems for audit sampling.

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