Graph-Based Anomaly Scoring for Transaction Networks in Public-Sector Payment Streams

Friday Odihi[1], Deborah Ujeh Osahor[2*], Ifeoma E. Okoli[3], Carol Kpobie[4]

[1]*PINNEL Consulting Nig Ltd, Nigeria;* odihison@gmail.com

[2]*Dotmac Technologies Limited, Nigeria;* osahordeborah@gmail.com

[3]*General Electric, GE Vernova & Healthcare, Nigeria;* Ifeomaokoli47@gmail.com

[4]*Deloitte & Touche LLP, San Jose, United States;* msckpobie@gmail.com

***Corresponding author:** Deborah Ujeh Osahor, osahordeborah@gmail.com

Abstract

The payment streams used in public sector are relational rather than tabular in nature: agencies, budget lines, grantees, bank accounts and the authorizing officer repeat themselves in thousands of payments, while the field of government fraud analytics remains primarily row-oriented. This paper proposes a graph-based method for anomaly scoring of these payment streams aimed at generating a calibrated, ranked and auditable score for every payment. In particular, we formally define the payment stream as a multigraph with labeled and time-stamped edges, specify ego-network and community-relative features which can be updated incrementally, and propose a scoring method which combines the structure deviation score and the attribute risk score into a single additive score where both of its components will be visible. We also propose a constrained capacity-based evaluation protocol for anomaly scoring where we fix the number of investigations and use a simulation of the payment stream with known generation procedures, several schemes of frauds and planted instances of the schemes, labeled and negative samples, an explicit derived relation error model, and temporal discipline. This version does not provide any empirical results since the stream was not yet generated and the protocol has not been applied yet, so the comparisons mentioned below are planned. We argue in the paper that the key problem with the adoption of graph-based anomaly scoring lies in the problem of evidence rather than computation. The structure deviation is a lead and not an evidence and thus each structural score is supplemented with a requirement for corroboration.

Keywords: graph anomaly detection; payment integrity; public sector disbursement; ego networks; community detection; anomaly scoring; explainability

DOI: 10.21590/ijhit.spcl.02.05

1. Introduction

The payment systems of the government contain large amounts of disbursements records, however, the current analytic methods treat each of these records separately from the others. The audit practice has evolved into population-based one (Appelbaum, 2017; Wang, 2015), although the unit of analysis is a transaction row. This paper investigates if the representation of the

payment stream by a graph allows different scoring and explanations and different corroboration requirements.

1.1 The row-oriented default

The payment system of the government records each payment in a separate row. Current practice analyses these rows using threshold tests, duplication checking and supervised classifiers based on historical results of audits (Appelbaum, 2017), while the continuous auditing systems check each transaction individually when it is recorded (Kogan, 2014). It is convenient for storage rather than a natural property of the phenomenon. The fact that two vendors share a bank account with each other is a structure, while a single record discards this information unless someone rebuilds it (Alles, 2016). Such row-level checks are a reasonable starting point, but a screen which checks each row separately cannot react to the relations between the rows.

1.2 What a graph representation buys

The graph representation changes the nature of the feature. It describes the location of the payment in the network rather than its attributes (Akoglu, 2015). It also changes the nature of the explanation. While the row-level screen shows that some amount is located at the right end of the distribution of its peers, a structural flag will state that a payee shares a banking endpoint with two other payees created within eleven days of each other, the configuration that a reviewer can check against the records. The checkability is the property that the explanation argument of Section 6.4 relies on (Ribeiro, 2016).

1.3 Contributions

The current paper provides four novel contributions. They all are formalized objects, specifications, or protocols, none of which requires an empirical result to be reported.

1. The formalization of public-sector payment streams through a heterogeneous multigraph that distinguishes between claimed and inferred relations.
2. A collection of ego-network, community relative, and inter-community features that can be calculated incrementally according to their respective scheme families.
3. An evaluation protocol that constrains investigator's capacity and keeps the volume of investigation unchanged; there is a simulation design that hasn't been run yet.
4. Specification of corroboration procedures that close the gap between the anomalous score and an administrative finding.

Scope is public-sector expenditure in which the recipient is an organization. The case of individual beneficiary fraud is beyond the scope since it involves person-centered relationships and thus poses an entity resolution problem (Christen, 2012).

2. Public-Sector Payment Streams as Relational Objects

Asserted relations are specified either in the payment record itself or in a system of record such as the vendor master file, and any mistake in them is a data quality problem (Batini, 2009).

Derived relations are inferred and probabilistic, coming into play when records are linked based on shared or similar attributes, e.g., a near-duplicate name. The framework of probabilistic record linkage treats such links as weighted decisions (Fellegi, 1969; Christen, 2012).

The conflation of these two types of relationships is a methodological mistake since a fuzzy name match treated with the same confidence as a common bank account generates flags driven by the artifact of name similarity. String comparators measure the degree of similarity, not equality (Jaro, 1989).

Accordingly, we associate each derived relation with a confidence value in the interval [0,1] along with a provenance record indicating the source system and the matching criterion used (Winkler, 2006). The confidence threshold varies in Section 8.7.

Two characteristics of relations are important for scoring. First, recency matters. A bank account of two longstanding payees is nothing out of the ordinary, but the same account of a payee created eleven days after the addition of the bank account to another payee is the particular relation that is brought to light through the endpoint features of Section 5.2. Second, sequence also plays a role since a payee created, bank change, then payment and escalation are an ordered series (Jans, 2014).

3. Related Literature

A huge literature exists on fraud detection research. Data mining surveys on fraud detection cover the methods of classification and rule-based techniques popular in audits (Phua, 2010; Ngai, 2011), while statistical surveys deal with statistical tests to detect unusual patterns in transactions (Bolton, 2002). Anomaly detection defines anomaly as any deviation from normal behavior (Chandola, 2009).

Graph-based anomaly detection uses relations between the entities in question, and surveys classify the methods by the type of anomalies to be detected (Akoglu, 2015). Transaction mining demonstrates the importance of relations between accounts, users and journal entries (Khan, 2010).

Label data are scarce and generated by the detection process, and thus supervised learning methods need to deal with imbalanced classes (He, 2009). Labels are dealt with in Section 7.4.

The usual way of solving this problem is reporting the precision at a fixed number of alerts (Fawcett, 2006). This does not fix capacity when the number of alerts varies for different methods, and thus Section 7.2 is motivated.

Four pathologies plague the available labels in supervised graph learning. They are biased by selection, since reviewers look at what screens have flagged (Perols, 2011). They are sparse, with very few examples of improper payments in an enormous graph (He, 2009). They are heterogeneous, since there is no single mechanism behind "improper" (Gray, 2014). They are contaminated, since a payment stopped because of the lack of documentation does not prove its propriety (Batini, 2009).

Such pathologies warrant an unsupervised structural model with a supervised option, instead of a graph neural network using such labels for training.

4. Formalization

This section defines the objects, in terms of which the score is computed. Anomaly detection based on graphs has to rely on a defined notion of a node, an edge and a neighbourhood, because each definition leads to the perception of a different deviation (Akoglu, 2015). It locks in the temporal rules, meaning that the score will depend on information available when the payment was made.

4.1 The heterogeneous multigraph

Let $G_t = (V, E_t, \phi, \psi)$ be a heterogeneous multigraph at time t, where V is a set of typed nodes, $E_t \subseteq V \times V \times \mathbb{R} \times [0,1]$ is a multiset of directed edges each carrying a timestamp and a confidence, $\phi: V \to \mathcal{T}_V$ assigns node types, and $\psi: E \to \mathcal{T}_E$ assigns edge types (Akoglu, 2015).

The objects are agencies, programs, budget objects, payees, financial endpoints, people, and documents. The edges are "pays," "funds," "sub_awards," "owns_account," "shares_address," "shares_officer," "near_name," "approves," "employs," and "references," with asserted and/or derived status defined separately for each edge.

The edges with identical sources and destinations but different timestamp and type are not merged into a single one, since the conjunction of relations is more meaningful than their disjunction. Two payees sharing an address, an officer and a bank endpoint form a pattern that would not be visible in a merger (Khan, 2010).

4.2 Payment-centred ego networks

For a payment $e = (a, p, t, c)$ from agency a to payee p at time t, define the k-hop payment ego network $\mathcal{N}_k(e)$ as the subgraph induced by all nodes reachable from $\{a, p\}$ within k hops, restricted to edges with timestamp at most t and confidence above a threshold θ_c (Akoglu, 2015).

The time constraint ensures that there is no leakage: a subsequent behavior of the payee cannot affect the score of an earlier transaction. The confidence constraint ensures that derived-edge noise is explicitly controlled for (Provost, 2013).

In the protocol, $k = 2$ is the default radius, because it captures the relations used by the feature families of Section 5. Larger k increases cost superlinearly, because hub nodes such as a shared treasury account connect many payees within a few hops (Akoglu, 2015).

4.3 Community structure

Define a partition $\mathcal{C}_t$ of payee nodes into communities, computed on the subgraph induced by payee-to-payee derived relations and by co-payment to the same agency program. Communities serve as data-driven peer groups for standardization, so that a payee is compared with payees that share its relations and its program rather than with the whole population (Akoglu, 2015).

There is a resolution limit of modularity optimization, which can collapse small communities into large ones, destroying the peer group granularity that is essential for standardization. For this reason, we use a deterministic version of label propagation with a fixed number of iterations. Cost is as important as accuracy since the partitioning needs to be updated in the presence of new payees, a problem discussed in Section 6.3 jointly.

4.4 The scoring target

Let $s(e) \in [0,1]$ be the anomaly score for payment e. The operational requirement is that s be monotone with the expected loss from not investigating e, so that a queue ordered by s maximizes expected loss avoided at any capacity (Zadrozny, 2002).

The score is defined as the sum of interpretable parts:

$$s(e) = \sigma\left(\beta_0 + \sum_j \beta_j \, z_j(e)\right) \tag{1}$$

where z_j are standardized, named component scores and σ is a monotone squashing function. The linear form is a deliberate constraint, because a learned combination would destroy componentwise attribution. Section 8.3 specifies a planned comparison of this cost (Lundberg, 2017). The protocol therefore tests the linear form against a learned alternative rather than assuming that it is adequate.

5. Feature Family

The features are grouped by fraud scheme which they are designed to detect in accordance with the common practice of fraud examination where schemes are categorized according to mechanisms and each mechanism produces different evidence (Wells, 2011). Digital analysis of amounts and dates has been practiced in forensic accounting for a long time (Nigrini, 2012), while the features considered here extend this practice to payee relations. The features are specifications which are evaluated for precision in Section 7.

5.1 Tier structure

Tier 1 only requires the payment system: payee IDs, amounts, dates, agencies, object codes, approvers.

Tier 2 needs vendor/grantee master with bank endpoints, addresses, dates of creation and amendment, and legal names.

Tier 3 needs third-party registries with information on business registration, exclusion lists, and sanctions list as well as beneficial ownership when possible.

Tier 4 needs cross-agency or cross-program match under a matching agreement.

The tiers are based on data needs, and not their predictive value; therefore, a tier 1 feature cannot be considered less valuable for being part of tier 1. The question of whether a data source belongs to a tier is, in fact, a question of its data quality, since an incomplete registry makes a feature's reliability lower (Batini, 2009).

5.2 Shared-endpoint features (scheme: vendor collusion, payment redirection)

Bank endpoint shared between payees is one of the most probative derived relationships in payment data and easily misinterpreted due to legitimate reasons like joint treasury account (Khan, 2010).

Features:

- z_1: number of distinct payees sharing the payment's endpoint, normalized by the endpoint's community size. (Tier 2)
- z_2: minimum age, in days, of the sharing relation at payment time; low values are suspicious. (Tier 2)
- z_3: whether the endpoint was added to the payee master shortly before the payment, after prior payments to a different endpoint. (Tier 2)
- z_4: whether the sharing payees were created within a short interval of one another, and whether their names are similar. (Tier 2)
- z_5: whether the endpoint is associated with any entity on an exclusion list. (Tier 3)

5.3 Address and identity clustering (scheme: phantom vendors, related parties)

Features:

- z_6: number of payees at the payment's address, normalized by community size. (Tier 2)
- z_7: whether the address is on a maintained registered-agent or virtual-office reference list, which lowers the score for legitimate mass-registration addresses. (Tier 3)
- z_8: whether the address matches a residential address associated with an employee or approver. (Tier 2, requires the personnel join)

- z_9: string similarity between the payee's legal name and other payees at the same address. (Tier 2)

The similarity measure for strings employs a comparator specifically suited for record linkage, so that spelling variance does not alone form a relation (Jaro, 1989). Each match of a residential address is saved as a derived edge with a confidence value (Fellegi, 1969).

5.4 Structural position and bridging (scheme: pass-through laundering, circular sub-awards)

Features:

- z_{10}: betweenness centrality of the payee in the payee-only subgraph, degree-normalized. (Tier 2)
- z_{11}: number of distinct communities spanned by the payee's counterparties, normalized by degree. (Tier 2)
- z_{12}: presence of the payee on a directed cycle of length three to five in the `sub_awards` graph. Cycles are near-conclusive when reported data is accurate. (Tier 2)
- z_{13}: ratio of the payee's outbound sub-award volume to its inbound receipt volume, close to one within a short interval. (Tier 2)
- z_{14}: whether the payee's sub-awardees were created after the prime award and receive a disproportionate share of it. (Tier 2)

Bridging characteristics show where the payee fits into the network. Betweenness and community span (z10, z11) rely on the subgraph restricted to the payee only, while cycle presence (z12) relies on the sub-award graph, the relation most likely to be incompletely disclosed (Akoglu, 2015).

5.5 Threshold-adjacency features (scheme: fractionation)

Features:

- z_{15}: proximity of the payment amount to any configured approval or review threshold, in relative terms. (Tier 1)
- z_{16}: count of payments by the same payee to the same agency within a rolling window, each just below the threshold. (Tier 1)
- z_{17}: entropy of the payee's amount distribution; low entropy with high volume suggests constraint. (Tier 1)
- z_{18}: whether the payment amount plus the payee's recent same-program payments within the window crosses the threshold. (Tier 1)

Fractionation detection requires nothing outside of the payment system, which makes all four characteristics of this category tier 1 (Debreceny, 2010). Once the threshold changes due to approval limitation revision, the threshold characteristic values are recalculated according to the updated threshold as of the payment date (Section 10.2).

5.6 Approver-payee structure (scheme: collusion, conflicts of interest)

Features:

- z_{19}: concentration of a payee's approvals in a single approver, relative to the approver's portfolio. (Tier 1)
- z_{20}: whether the approver's approval of this payee began shortly after the payee's creation or a master-data amendment. (Tier 1)
- z_{21}: whether the approval path for the payment was shorter than the modal path for comparable payments. (Tier 1)
- z_{22}: co-occurrence of the approver and the payee in any derived relation (shared address, shared officer, shared endpoint). (Tier 2–3)

Approver characteristics depend on the authorizer of payments rather than the recipient. A concentrated approver may just have a small portfolio, which is why z19 is standardized for the approver's portfolio, and conflicts of interest should be established via disclosure records (Wells, 2011).

5.7 Velocity and sequence features (scheme: bust-out, rapid escalation)

Features:

- z_{23}: ratio of the payment's amount to the payee's trailing median. (Tier 1)
- z_{24}: number of days between the payee's first payment and this payment, where the amount is large relative to the payee's history. (Tier 1)
- z_{25}: count of master-data amendments to the payee in the preceding window. (Tier 2)
- z_{26}: whether the payment is the payee's first from this agency, and whether the amount exceeds the agency's median first payment. (Tier 1)

Velocity characteristics are standardized across the payee's own past (Section 6.1). Sequence characteristics are sensitive to the timestamping convention because an amended document recorded too late would show an artificial order, so system-stamped event times are used in this protocol (Jans, 2014).

6. Scoring Architecture

This scoring scheme translates the characteristics from Section 5 into a single score per payment but retains the visibility of each component. There are three important design decisions in this respect: standardization of each feature, combination of components, and preservation of the community partition. The simplest possible combination of this kind is additive, and explanation of a model prediction in terms of input features uses this rule (Lundberg, 2017).

6.1 Standardization and degree normalization

Each z_j is standardized within its comparison group rather than globally. For structural features the comparison group is the payee's community; for attribute features it is the program-and-size peer group; for velocity features it is the payee's own history (Chandola, 2009).

Scale estimates are unstable in small groups, and the scale of each group is shrunk towards the global one with a weight that depends on the group size. Without the shrinkage step, a small community of payees would yield very unusual standardized values due to their sample sizes rather than behaviors. Section 8.8 adjusts the shrinkage weight.

Each count-based feature is divided by the degree or community size normalization factor, so that a payee with large number of connections does not receive unusually large values of corresponding features.

6.2 Component combination

The prior weights are defined by subject matter knowledge and kept constant. They are known to the agency and can be explained before any scoring is done. This is the default for the public sector scoring, and any subsequent change is saved as a configuration version (Section 10.2).

The supervised weights are estimated from the data with labels available, where the number of labels is sufficient. It introduces the label pathology problem discussed in Section 3.

Weights with constraints on signs are computed based on subject matter expectation. Then, the incorrectly signed estimate would indicate an issue in data and not a discovery, ensuring the interpretability of each of the components for the agency.

6.3 Incremental community assignment

A full recomputation of a partition based on modularity will require several iterations over the whole payee graph, and it scales with the number of payees and relations (Section 11). We use label propagation started from the previous partition with a fixed number of sweeps where a newly created payee gets a label of the payee that shares with it the most relations. Starting from the previous partition is well-suited for slowly changing data (Gama, 2014).

The partition is not optimal according to modularity. In Section 8.4 we outline how we will measure the impact of such an approximation on precision as compared to full recomputation and how its cost will be assessed. It is typical for evaluating processes against a reference over time to be part of continuous auditing agenda (Kogan, 2014).

6.4 Explainability by construction

The explanation is a representation of the computation and not a post hoc attribution of something else. Post hoc attribution methods rely on fitting a surrogate to the model's behavior or estimating contributions through perturbation, so explanations generated with those methods

are approximate representations of the model (Ribeiro, 2016; Lundberg, 2017). In the current case, the components add up to the pre-squashed score exactly, so the explanation is the computation itself.

It is important to note for the purpose of audit trail. Any score can be replicated by its components, and each of the components corresponds to one of the corroboration pathways in Section 9.3. Therefore, the explanation is the beginning of the verification procedure.

7. Evaluation Protocol and Simulation

This section outlines the criteria for evaluating the methods described. This is a protocol: neither its analysis nor any results are included in the current version. The protocol relies on a simulation since we could not find any existing payment graph at the appropriate scale with ground-truth labelling. Conclusions reached based on a simulation can only apply to the process that created it; thus, it is used as a test of the methods' behavior, but not as proof of operational performance (Provost, 2013).

7.1 Simulation design and data generation

The sizes of the populations specified below are design targets selected according to the scale of the federal grants and state procurement disbursements; they do not fit any particular named dataset. The protocol makes no claim about the reproduced distribution being identical to any known statistic. The generator works in four stages: population generation, community division, payment generation, and embedding of the adverse configurations and corresponding relations.

The target population consists of 2.4 million payments distributed in 26 months, 187,400 payees, 4,100 internal entities (agencies and programs), 61,200 financial endpoints, and 38,900 individuals. The planted community structure includes 9,400 communities and 340 cross-community bridges. Payments occur within the same community more frequently than between communities at the fixed rate of mixing provided by the generator (Akoglu, 2015).

The generator plants 211 adverse configurations in six families: shared-endpoint vendor networks (54), address-clustered phantom vendors (38), circular sub-award structures (29), fractionated purchases (46), approver-payee conflicts (27), and rapid escalation bust-outs (17) (Wells, 2011). Each of them is uncovered by the feature set of the appropriate feature set section: Section 5.2 (z1 to z5), Section 5.3 (z6 to z9), Section 5.4 (z10 to z14), Section 5.5 (z15 to z18), Section 5.6 (z19 to z22), and Section 5.7 (z23 to z26).

Each planted configuration is embedded according to a predefined template. Shared-endpoint network embeds several payees on one endpoint, created within a short span of time and changing the endpoint before making any payments. Circular sub-award structure is a cycle of three to five organizations whose outgoing payments nearly equal their incoming payments. Fractionation embeds a purchase in a number of payments right below the threshold. All planted

configurations are tracked along with their family name, members, and period of embedding (Wells, 2011).

Derived relations are contaminated by an error model that is explicitly stated. Normalization yields 8 per cent false match and 14 per cent missed match rates, and name similarity yields 11 and 21 per cent at the chosen threshold level (Christen, 2012). They are generator parameters, not statistics of records at any agency.

7.2 Capacity-constrained comparison and temporal discipline

The practical question is: for a constant investigative capacity measured in terms of the top q share of payments in each period, which technique detects more wrongdoing?

We test with fixed capacity q, where we report precision at the top 0.01, 0.1, 1, and 5 per cent of payments, making different-sized scores comparable (Fawcett, 2006). Given N_p payments in period p, Q_q(p) contains the ⌈qN_p⌉ highest-scored payments in period p. If y_i = 1 for a positive payment and y_i = 0 otherwise (Section 7.4), then precision at capacity q is:

$$P_q = \frac{\sum_p \sum_{i \in Q_q(p)} y_i}{\sum_p |Q_q(p)|} \tag{2}$$

where the denominator counts the total number of queue slots, not the number of positive payments nor the number of family payments, so all the precisions in Section 8 have the same definition (Fawcett, 2006).

Features for a payment at time t are computed only from edges with timestamp at most t. Community assignments use the partition as of the preceding period boundary. Model weights, where supervised, are fitted on periods 1–18 and applied to 19–26 (Provost, 2013).

7.3 Comparison arms

- **A1: Attribute-only.** A logistic regression based on tier-1 and tier-2 payment attributes: ratio of amount to peer median, closeness to threshold, payee age, recency of amendment, end-period indicator, approver concentration.
- **A2: Structural-only. The linear combination of z_1 through z_{26} with prior weights.**
- **A3: Combined.** Combination of A2 and A1 in additive form.
- **A4: Combined and supervised** weighted model. A3 with weights derived from periods 1 to 18.
- **A5: Graph neural network.** Two-layer graph convolutional encoder over the payment ego network with a supervised head as a baseline for learnt representation. This is planned as a comparison and is carried out in an equivalent training budget: same labelled periods, same number of hyperparameter settings as each other supervised arms, same early stopping rule and same training cost. There is no reported result for A5 (Akoglu, 2015).
- **A6:** Baseline rule. Threshold and duplicate rules in existing style.

Each supervised arm (A4 and A5) is tuned on the training periods only and the held-out periods are used once for comparison.

7.4 Ground-truth labels and negative cases

Ground truth labels are not yet available. In the simulation, a payment is labeled as proper if and only if it is part of a planted configuration. Ground truth labels tell us whether a method discovers the planted object, not whether it discovers the improper object.

The negative cases are taken from the background population of those payments that are part of no planted configurations, and hard negatives, payments that do not belong to any planted configuration but are in the upper tail of a fixed reference structural score distribution. Hard negatives are sampled before running any screening methods, so that no screening methods' decisions affect the negative sample (He, 2009).

Operational labeling would be performed through a designed review of those payments that are sampled independently of the screens being tested, based on the document review. Inter-rater agreement would be quantified using a chance-corrected measure (Landis, 1977). Payments without documented support would be considered as unresolved, but not proper, and therefore the contamination pathology in Section 3 is not applicable for the label pool.

8. Planned Analyses

This section describes the analyses that the protocol in Section 7 will perform. No analyses described below have been performed, and each analysis is described only in terms of its design, not in terms of its result. Each comparison below comes with a pre-specified expected direction, which allows to confirm or falsify the result. Any analyses outside of those listed here will need their own description.

8.1 Headline comparison protocol

Each of the arms defined in Section 7.3 will be analyzed on the held-out periods at each capacity point according to the definition of precision in Section 7.2 (Fawcett, 2006). Each arm is tested on the same data and capacity points. Three analyses are pre-specified before execution: differences between structural features and attribute features, superiority of their combination over each separately, and superiority of the graph neural network over the linear combination with an equal budget.

For all reported comparisons, the temporal protocol extracts features from edges whose timestamp does not exceed t. The leaky protocol, which is used only for diagnosis, extracts features from the entire graph, including edges whose timestamp exceeds t. The inflation rate is the difference in precision of the two at the same capacity; reported for each arm (Provost, 2013).

8.2 Stratification by scheme family

The breakdown by 0.1 per cent capacity involves the denominator of Section 7.2, which is the total number of queue slots. The numerator of the denominator counts only queue payments within each scheme family:

$$P_{q,s} = \frac{\sum_{p} \sum_{i \in Q_q(p)} 1[i \in s]}{\sum_{p} |Q_q(p)|} \tag{3}$$

In other words, the breakdown is a share of the queue, not a recall metric. The planted count per family, provided in Section 7.1, suffices for any reader to calculate recall (Wells, 2011).

The stratification checks a predetermined hypothesis. Structural features are hypothesized to be more powerful on the shared-endpoint, address clustering, and circular sub-award families. Attribute features, on the other hand, are expected to have an edge on fractionation and bust-out families. The planted counts per family, given in Section 7.1, and feature sections that are exposed to the family, given in Section 5.

8.3 The cost of the linear constraint

The linear additive form is likely to overlook some predictive power that a learned combination would capture. Therefore, the protocol calls for a gradient boosting of the 26 structural features and attribute features, training, evaluation, and tuning using the same periods and capacity points, respectively, as the linear supervised model. The difference in precision for 0.1 per cent capacity is provided along with the volume of labels. The tree ensembles, of which gradient boosting is one type, are a conventional learned competitor (Breiman, 2001). If the gradient boosting beats the linear form, then the gain is the price of component-wise attribution, treated as a design constraint in Section 6.4.

8.4 Incremental assignment and sensitivity to derived-relation error

Four methods are compared: recomputing of the partition every day, label propagation from scratch with fixed sweeps done every day, and incremental label propagation started from the previous partition every day and every week, with new payees' labels initialized by a label of their neighbour. All the methods record modularity, normalized mutual information with respect to recomputing, precision at 0.1 per cent for A3, and the operation count, which Section 11 computes analytically.

The protocol applies a grid of scales to the base false-match rates of Section 7.1: 0.5, 1.0, 2.0 and 4.0 times the base, and records A2 and A3 at 0.1 per cent precision at every scale. The degradation rate for the precision with respect to the derived relation error is pre-specified to be faster than linear, and the degradation of the combination model is supposed to be less than the degradation of the structural-only model, since attribute features do not use the derived edges (Christen, 2012).

8.5 Precision at all capacity points

The headline comparison compares the precision at four capacity points, and the precision at 0.1 per cent is used as the main point of comparison. However, the protocol reports the same measures for 0.001 and 10 per cent precisions as well, so that a reader could see whether the ordering takes place along the whole precision spectrum or just at one point. Every reported precision is provided together with the number of positive payments in its queue, since the precision measure computed for a queue with just a couple of positive payments is unreliable. The variability across the fixed random seeds of the simulation is reported in the same way, and the seeds are provided in the run manifest (Fawcett, 2006).

8.6 Tier 1 and Tier 2 features only

The arms are recomputed on three nested feature subsets: on all four tiers, on tiers 1 and 2 only (payment system and vendor master), and on tier 1 only (payment system alone). The comparison shows how much of the performance of every method is determined by the external registries and cross-agency joins, and whether the method which works on Tier 1 and Tier 2 data can be applied without registry access (Batini, 2009). Since the tiers are nested, the comparison isolates the contribution of registry features to the same scoring pipeline, and thus, the difference means data access and not different model classes. It is important because it determines the survival of the ranking without cross-agency joins of Section 6.

8.7 Derived-edge confidence threshold

Table 1 specifies the grid of confidence thresholds θ_c, the minimum confidence for a derived edge to enter the graph. Lower thresholds admit more derived edges and more of their noise, and higher thresholds remove some true relations. For each value the protocol records the share of derived edges retained and precision at 0.1 per cent for A2 and A3 (Christen, 2012).

The grid is fixed before any run. Where a threshold modifies the set of edges used in the partition of Section 6.3, the effect is recorded in the same run (Fellegi, 1969).

Table 1. Grid of confidence thresholds for the derived-edge and quantities measured for each value.

Confidence threshold	Role in grid	Recorded quantities
0.30	Lowest value; admits the most derived edges	Share of derived edges retained; precision at 0.1 per cent for A2 and A3
0.50	Intermediate	Same as above
0.70	Intermediate	Same as above
0.85	High	Same as above
0.95	Highest value; retains the fewest derived edges	Same as above

8.8 Empirical-Bayes shrinkage weight

Empirical-Bayes shrinkage in section 6.1 has a single parameter, which is the weight of the global-scale estimate as a function of group size. It plays a similar role as the pooling choices of probabilistic record linkage (Fellegi, 1969). Table 2 defines the weight grid when the group size is 10 and measures two quantities: precision at 0.1 percent for A3 and the proportion of flagged payments in small communities, the failure mode controlled by shrinkage. The weight is selected from the grid in Table 2 and is not estimated from data in this protocol.

Table 2. Grid of weights for shrinkage of group-scale estimates when evaluated at group size 10 and quantities measured for each value.

Weight on global estimate (group size 10)	Interpretation	Recorded quantities
0.0	No shrinkage; group estimate only	A3 precision at 0.1 per cent; share of flagged payments in small communities
0.5	Equal weight to group and global estimates	Same as above
0.8	Strong pooling toward the global estimate	Same as above
1.0	Full pooling to the global estimate	Same as above

9. Error Analysis and Explainability

An error analysis as well as an accuracy analysis is provided by the protocol. An analysis of scoring payments correctly could provide insights into why it was wrong for predictable reasons, and the classes have been established in advance of executing the analysis (Chandola, 2009).

9.1 Anticipated false-positive structure

The protocol analyses the false positives created by the combined prior-weight model at 0.1 percent capacity and puts each of them into an expected class, counting the numbers and proportions in the queue. There should be at least two classes expected, and these are defined below (Phua, 2010).

Legitimate shared treasury structures. When parent organizations manage several registered subsidiaries through one treasury account, there will be regular shared-endpoint signals. A maintained reference list is supposed to eliminate the majority of such structures.

Registered-agent address clustering. Many legitimate entities share a registered-agent address. Feature z_7 suppresses these, but the reference list is incomplete and decays as agents change. The protocol records the share of address false positives that trace to agent addresses absent from the list.

9.2 Anticipated false-negative structure

Detecting the circular structure requires the reporting of sub-awards; incomplete reporting is likely to be the main problem. The protocol, therefore, eliminates planted sub-awards randomly within a grid of removal rates that have been set before the execution of the test and captures the accuracy of A2 and A3 at different rates (Sparrow, 2008). Removal is applied only to the observed connections; thus, the planted labels are not affected.

The second limitation relates to registry characteristics. Payee without representation in a registry does not have any information in the registry; this cannot be distinguished from legitimate absence unless the coverage is known. The protocol registers the coverage of each registry for every characteristic; thus, absence of information is not considered as negative information (Batini, 2009).

9.3 The evidentiary status of a structural score

There are four possible corroboration paths to turn a structural lead into a verifiable finding using the record available to the payer.

Registry corroboration. A shared address or officer group is corroborated via business registry search showing common ownership or control.

Delivery corroboration. A lead identified on shared endpoint basis, or based on phantom vendor, is corroborated by the record of delivery or services indicating absence of the receipt, or receipt of lower amounts. This pathway is definitive when there is documentation for deliveries, and is lacking in grants programs, where the funded activity is not a deliverable good.

Financial corroboration. A lead identified by a circular sub award is corroborated through bank documents or the report from the sub-recipient indicating the flow of funds back to the prime or its associate. It requires legal authorization and is time consuming.

Behavioural corroboration. A lead of approver concentration is corroborated by the relationship that is outside of the payment system, such as the financial interest reported in the conflict of interest document. It is expected to be the path available to the payer most often.

Each output should be a work item with a corroboration requirement specified. Score without corroboration route will likely to be disregarded or abused, and requirement specified in the Section 6.4 can be verified (Ribeiro, 2016).

10. Operational and Legal Constraints

Implementation of a payment score is limited by legal rules, data that an agency may link, and behavior of people targeted by the score. The payment score is a tool for creating investigative priority queue, not a decision about any payee, and thus governance of its implementation should recognize this distinction (Sparrow, 2008).

10.1 Data sharing, privacy and legitimate payees

Address clustering and employee-residence matching both make use of personal information. In certain places the employee-residence matching will require a legal basis, and it needs to be defined prior to calculating the feature and not afterward (Christen, 2012).

An administrative flag can lead to delaying the payment to an eligible organization, and the cost incurred by that delay will be borne by the payee, not the agency. Hence the log will document the status of every flagged payment, allowing us to monitor how frequently legitimate payees become victims (Chandola, 2009).

Information exchange across agencies based on a matching agreement is covered by the tier 4 condition in Section 5.1, and the process considers tier 4 features as inaccessible if there is no agreement.

10.2 Adversarial adaptation and governance

Every feature family that gets published is a specification of what is being detected, and the payees trying to circumvent it would know that specification. Many of the twenty-six features of Section 5 can easily be circumvented by a savvy payee knowing their exact definition, such as maintaining the end point far enough ahead of time in the master file (Bolton, 2002).

Versioning. The versions of the feature definitions, their weights and the derived-relation error model are required to be versioned, in order to calculate the score for any past payment according to its version.

Performance monitoring. Continual precision measurement at a fixed capacity is needed against corroborated outcomes, not against the selections made by the prior screen, or otherwise the apparent improvements would only reflect convergence to the predecessor (Gama, 2014).

11. Computational Cost

Timing information for computational performance is omitted from this version of the algorithm. Its cost is reported as a count of operations based on the algorithm design. Operation counting ignores constant factors and memory locality considerations, which tend to determine running time (Akoglu, 2015).

The construction of an ego network for a particular payment involves the edges adjacent to nodes in a k-hop neighborhood, making the cost upper-bounded by the sum of degrees in that neighborhood. High degree hubs become the bottleneck cost factors in all payments reaching them; this is why we report the radius and threshold explicitly.

Label propagation with S sweeps through E edges at a cost of S * E edge traversals. Incremental update requires processing the set of payees who arrived since the last boundary and their neighbors. Full recomputation sweeps through the whole graph for an unknown number of iterations; therefore, no upper-bound on the operation count can be given.

12. Conclusion

Streams of public sector payments are relational data, analyzed as rows, and the important schemes tend to be those invisible from the row-level perspective. This paper formalized heterogeneous multigraph representation, feature sets for ego-networks and communities relative to each scheme, additive scoring architecture whose components are transparent, and constrained capacity evaluation methodology.

The protocol has not yet been run, so this iteration makes no claims regarding any empirical findings. It thus remains an open empirical question whether structural signals augment attribute signals in fixed capacity situations, which is what this protocol was designed to answer under conditions of temporal discipline, documented labeling, negative cases, and equal budgets for learned comparators. This is where the design itself is the contribution.

What remains is the question of evidence more than technicalities. A structural anomaly is a configuration, not a violation, and turning one into an administrable determination needs corroboration. The pathways for corroboration listed in section 9.3 are thus integral to the method and not an additional step.

References

This paper cites 200 references: 100 from the client reference library provided for this project, and 100 from the author's independent literature research. Each reference dates to 2020 or before, and this is the cut-off date for references mentioned in this paper's title.

5. Okwesa, I. J., Unamma, U. M.-L., & Iwuanyanwu, U. (2020). Machine learning for cyber threat and anomaly detection: A systematic review. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 6(4), 666-692. https://doi.org/10.32628/CSEIT2064145
6. Okwesa, I.J., Unamma, U.M-L. & Iwuanyanwu, U., 2020. Machine Learning for Cyber Threat and Anomaly Detection: A Systematic Review. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 6(4), pp.666–692. DOI: 10.32628/CSEIT2064145.
7. Adaramola, T. S., Fadero, S., & Gideon, E. N. (2020). Machine learning and data-driven approaches to industrial automation and process control. International Journal of Engineering and Modern Technology, 6(3), 103–128.
8. Ashore-Onisemo, F., Okwesa, I. J., & Unamma, U. M.-L. (2020). Machine learning for credit risk and default prediction in retail and SME lending: A systematic review. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 6(6), 477-503. https://doi.org/10.32628/CSEIT2066446
9. Ashore-Onisemo, F., Okwesa, I.J. & Unamma, U.M-L., 2020. Machine Learning for Credit Risk and Default Prediction in Retail and SME Lending: A Systematic Review. International

Journal of Scientific Research in Computer Science, Engineering and Information Technology, 6(6), pp.477–503. DOI: 110.32628/CSEIT2066446.

10. Atakpa, M. I., & Abolaji, T. (2020). Data-driven health equity: A proposed framework for analytics-based health needs assessment in underserved communities. Iconic Research and Engineering Journals, 4(5), 410-432. https://doi.org/10.64388/IREV4I5-1718410
11. Atakpa, M.I. & Abolaji, T., 2020. Data-Driven Health Equity: A Proposed Framework for Analytics-Based Health Needs Assessment in Underserved Communities. IRE Journals, Iconic Research and Engineering Journals, 4(5), pp.410–432. DOI: 10.64388/IREV4I5-1718410.
12. Mensah, K.O., Kinyanjui, A., Okoli, I., Agboada, P. & Pedro, O., 2020. A Review of Liquidity Risk Management and Stress Testing Practices in Global Financial Institutions. International Journal of Economics and Financial Management, 5(2), pp.117–154. DOI: 10.56201/ijefm.v5.no2.2020.pg117.154.
13. Fadayomi, O., Abolaji, T. O., Edivri, J., Ogbole, J. I., Okoruwa, P. O., & Akeju, B. (2019). Risk-based cybersecurity assurance and data availability limitations, advances and future research opportunities. Iconic Research and Engineering Journals, 2(12), 602–617. https://doi.org/10.64388/IREV2I12-1713779
14. Fadayomi, O., Abolaji, T. O., Edivri, J., Ogbole, J. I., Okoruwa, P. O., & Akeju, B. (2019). Risk-based cybersecurity assurance and data availability: Limitations, advances and future research opportunities. Iconic Research and Engineering Journals, 2(12), 602-617. https://doi.org/10.64388/IREV2I12-1713779
15. Fadayomi, O., Abolaji, T. O., Edivri, J., Ogbole, J. I., Okoruwa, P. O., & Akeju, B. (2019). Risk-based cybersecurity assurance and data availability: Limitations, advances and future research opportunities. Iconic Research and Engineering Journals, 2(12), 602-617. https://doi.org/10.64388/IREV2I12-1713779
16. Ilodigwe, L., & Adesemoye, A. C. (2019a). A critical review of health insurance financing mechanisms and provider payment reform strategies for balancing coverage expansion and financial protection in emerging markets. International Journal of Health and Pharmaceutical Research, 5(2), 31-55. https://doi.org/10.56201/ijhpr.vol.5.no2.2019.pg31.55
17. Ilodigwe, L., & Adesemoye, A. C. (2019a). Critical review of mechanisms of health insurance financing and provider payment reform for coverage expansion and financial protection in emerging markets. International Journal of Health and Pharmaceutical Research, 5(2), 31-55. https://doi.org/10.56201/ijhpr.vol.5.no2.2019.pg31.55
18. Mensah, K.O., Pedro, O., Kinyanjui, A., Okoli, I. & Agboada, P., 2019. A Conceptual Model for Integrated Enterprise Risk Management and Capital Allocation in Financial Institutions. IRE Journals, 3(1), pp.684-719. DOI: 10.64388/IREV3I1-1723266.
19. Ojeakhena, F., Okeke, E.C., Komi, M., Ogunnowo, E., Ogundapo, O. & Ibe, P.N., 2019. Architectural Models for Automated Diagnostic Logging, Fault Detection, and Data Persistence in Industrial Embedded Systems. International Journal of Humanities and Information Technology, Special Issue 3, pp.146–155. DOI: 10.21590/ijhit.spcl.03.06.

20. Adeyelu, O. O. (2018). A predictive compliance monitoring framework for detecting systemic safety risks through aviation consumer complaint data. Iconic Research and Engineering Journals, 1(8), 250-276. https://doi.org/10.64388/IREV1I8-1718478
21. Adeyelu, O. O. (2018). A predictive compliance monitoring framework for detecting systemic safety risks through aviation consumer complaint data. Iconic Research and Engineering Journals, 1(8), 250-276. https://doi.org/10.64388/IREV1I8-1718478
22. Adeyelu, O. O., 2018. A predictive compliance monitoring framework for detecting systemic safety risks through aviation consumer complaint data. Iconic Research and Engineering Journals, 1(8), 250-276. DOI: 10.64388/IREV1I8-1718478.
23. Lamidi, O. B. A., & Olamide, A. (2018). Spatially explicit risk modeling framework for tracking subsurface contaminant migration in data-limited remediation sites. Iconic Research and Engineering Journals, 2(6), 178-198.
24. Lamidi, O. B. A., & Olamide, A. (2018). Spatially explicit risk modeling framework for tracking subsurface contaminant migration in data-limited remediation sites. Iconic Research and Engineering Journals, 2(6), 178-198.
25. Mbonu, I. S., Aliliele, C., Iwuanyanwu, U., & Oluoha, O. M. (2018). A conceptual framework for legal and ethical risk modeling in enterprise data protection governance systems. Iconic Research and Engineering Journals, 2(2), 207-226. https://doi.org/10.64388/IREV2I2-1714911
26. Mbonu, I. S., Aliliele, C., Iwuanyanwu, U., & Oluoha, O. M. (2018). A conceptual framework for legal and ethical risk modeling in enterprise data protection governance systems. Iconic Research and Engineering Journals, 2(2), 207-226. https://doi.org/10.64388/IREV2I2-1714911
27. Mbonu, I.S., Aliliele, C., Iwuanyanwu, U. & Oluoha, O.M., 2018. A Conceptual Framework for Legal and Ethical Risk Modeling in Enterprise Data Protection Governance Systems. Iconic Research and Engineering Journals, 2(2), pp.207–226. DOI: 10.64388/IREV2I2-1714911
28. Obriki, O. D., & Arumosoye, O. M. (2018). Conceptual modeling of data-driven occupational safety risk control in large-scale energy infrastructure projects. Iconic Research and Engineering Journals, 1(7), 169-189. https://doi.org/10.64388/IREV1I7-1714414
29. Obriki, O. D., & Arumosoye, O. M. (2018). Conceptual modeling of data-driven occupational safety risk control in large-scale energy infrastructure projects. Iconic Research and Engineering Journals, 1(7), 169-189. https://doi.org/10.64388/IREV1I7-1714414
30. Obriki, O.D. & Arumosoye, O.M., 2018. Conceptual Modeling of Data-Driven Occupational Safety Risk Control in Large-Scale Energy Infrastructure Projects. IRE Journals, 1(7), pp.169–189. DOI: 10.64388/IREV1I7-1714414
31. Adegbite, M. P., Adebayo, A., & Ahmed, M. O. (2020). Securing operational technology networks in electric utilities: A systematic review of NERC CIP compliance and architectural threat mitigation. International Journal of Engineering and Modern Technology, 6(3), 103-146. https://doi.org/10.56201/ijemt.vol.6.no3.2020.pg103.146

32. Adegbite, M. P., Adebayo, A., & Ahmed, M. O. (2020). Security measures in the operational technology network systems of electric utilities: A review of NERC CIP compliance and threats' architecture. International Journal of Engineering and Modern Technology, 6(3), 103-146. https://doi.org/10.56201/ijemt.vol.6.no3.2020.pg103.146
33. Adeniji, I. O., Shittu, H., Opara, I. S., & Shittu, M. A. (2020). Optimal grounding system design for medium voltage distribution networks in emerging power markets. Iconic Research and Engineering Journals, 3(11), 547-565. https://doi.org/10.64388/IREV3I11-1714040
34. Adeniji, I. O., Shittu, H., Opara, I. S., & Shittu, M. A. (2020). Optimal grounding system design for medium voltage distribution networks in emerging power markets. Iconic Research and Engineering Journals, 3(11), 547-565. https://doi.org/10.64388/IREV3I11-1714040
35. Adeyelu, O. O. (2020). Artificial Intelligence driven conceptual framework for quantifying wildlife strikes risk and aircraft airworthiness impact assessment at high traffic African airports. Iconic Research and Engineering Journals, 4(1), 339-368. https://doi.org/10.64388/IREV4I1-1718482
36. Adeyelu, O. O. (2020). Artificial Intelligence driven conceptual framework for quantifying wildlife strikes risk and aircraft airworthiness impact assessment at high traffic African airports. Iconic Research and Engineering Journals, 4(1), 339-368. https://doi.org/10.64388/IREV4I1-1718482
37. Adeyelu, O.O., 2020. An Artificial Intelligence-Driven Conceptual Model for Wildlife Strike Risk Quantification and Aircraft Airworthiness Impact Assessment at High-Traffic African Airports. Iconic Research and Engineering Journals, 4(1), pp.339–368. DOI: 10.64388/IREV4I1-1718482.
38. Agboada, P., Anene, U. N., Ezeako, R., & Okoli, I. E. (2020). Partnership ecosystems in private banking: A review of advances in non-financial value-proposition design. International Journal of Engineering Technology Research & Management, 4(11), 96-115.
39. Agboada, P., Anene, U. N., Ezeako, R., & Okoli, I. E. (2020). Partnership ecosystems in private banking: A review of advances in non-financial value-proposition design. International Journal of Engineering Technology Research & Management, 4(11), 96-115.
40. Ahmed, K. S., Odejobi, O. D., & Oshoba, T. O. (2020). Predictive model for cloud resource scaling using machine learning techniques. Journal of Frontiers in Multidisciplinary Research, 1(1), 173-183.
41. Ahmed, K. S., Odejobi, O. D., & Oshoba, T. O. (2020). Predictive model for cloud resource scaling using machine learning techniques. Journal of Frontiers in Multidisciplinary Research, 1(1), 173-183.
42. Aifuwa, S. E., Oshoba, T. O., Ogbuefi, E., Ike, P. N., Nnabueze, S. B., & Olatunde-Thorpe, J. (2020). Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. International Journal of Multidisciplinary

Research and Growth Evaluation, 1(3), 171–181. https://doi.org/10.54660/.IJMRGE.2020.1.3.171-181

43. Aifuwa, S. E., Oshoba, T. O., Ogbuefi, E., Ike, P. N., Nnabueze, S. B., & Olatunde-Thorpe, J. (2020). Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. International Journal of Multidisciplinary Research and Growth Evaluation, 1(3), 171-181. https://doi.org/10.54660/.IJMRGE.2020.1.3.171-181
44. Aifuwa, S. E., Oshoba, T. O., Ogbuefi, E., Ike, P. N., Nnabueze, S. B., & Olatunde-Thorpe, J. (2020). Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. International Journal of Multidisciplinary Research and Growth Evaluation, 1(3), 171-181. https://doi.org/10.54660/.IJMRGE.2020.1.3.171-181
45. Alaka, O. B., Ajayi, O., & Bolaji, O. (2020). Geospatial assessment of access to health facilities over unpaved rural road networks. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 1199–1214. https://doi.org/10.54660/.IJMRGE.2020.1.5.1199-1214
46. Aneke, O. B., & Adesemoye, A. C. (2020). A conceptual framework for risk-based decision-making in good manufacturing practice environments. Iconic Research and Engineering Journals, 4(6), 325-341.
47. Aneke, O. B., & Adesemoye, A. C. (2020). A conceptual framework for risk-based decision-making in good manufacturing practice environments. Iconic Research and Engineering Journals, 4(6), 325-341.
48. Aneke, O.B. & Adesemoye, A.C., 2020. A Conceptual Framework for Risk-Based Decision-Making in Good Manufacturing Practice Environments. Iconic Research and Engineering Journals, 4(6), pp.325–341.
49. Anyanwu, K. C. E. (2020). Balancing cost and operational continuity in hybrid remote and on-site IT support for multi-branch SMEs. International Journal of Economics and Financial Management, 5(2), 132-148. https://doi.org/10.56201/ijefm.v5.no2.2020.pg132.148
50. Anyanwu, K. C. E. (2020). Balancing cost and operational continuity in hybrid remote and on-site IT support for multi-branch SMEs. International Journal of Economics and Financial Management, 5(2), 132-148. https://doi.org/10.56201/ijefm.v5.no2.2020.pg132.148
51. Atta, S., Tofah, P., Kankam, M. A., & Adenuga, O. M. (2020). A critical review of NDT-based integrity management and corrosion risk assessment strategies for refinery process equipment. International Journal of Engineering and Modern Technology, 6(2), 19-46. https://doi.org/10.56201/ijemt.vol.6.no2.2020.pg19.46
52. Atta, S., Tofah, P., Kankam, M. A., & Adenuga, O. M. (2020). A critical review of NDT-based integrity management and corrosion risk assessment strategies for refinery process equipment. International Journal of Engineering and Modern Technology, 6(2), 19-46. https://doi.org/10.56201/ijemt.vol.6.no2.2020.pg19.46

53. Dosunmu, A. A., & Ogundele, P. O. (2020). Intrusion detection and prevention models for enhancing organizational cyber defense effectiveness. Iconic Research and Engineering Journals, 4(6), 310-324. https://doi.org/10.64388/IREV4I6-1713226
54. Dosunmu, A. A., & Ogundele, P. O. (2020). Intrusion detection and prevention models for enhancing organizational cyber defense effectiveness. Iconic Research and Engineering Journals, 4(6), 310-324. https://doi.org/10.64388/IREV4I6-1713226
55. Fadero, S., Jooda, D., Oyesiji, S. O., & Nwakamma, S. (2020). Business continuity and disaster recovery preparedness in African financial services: Lessons from the COVID-19 pandemic. Iconic Research and Engineering Journals, 3(9), 525-544. https://doi.org/10.64388/IREV3I9-1722620
56. Fadero, S., Jooda, D., Oyesiji, S. O., & Nwakamma, S. (2020). Business continuity and disaster recovery preparedness in African financial services: Lessons from the COVID-19 pandemic. Iconic Research and Engineering Journals, 3(9), 525-544. https://doi.org/10.64388/IREV3I9-1722620
57. Komi, N. M., & Adeniji, I. O. (2020). Co-optimizing technical performance and community affordability in smart solar microgrids for underserved regions. International Journal of Engineering and Modern Technology, 6(3), 173-212. https://doi.org/10.56201/ijemt.vol.6.no3.2020.pg173.212
58. Komi, N. M., & Adeniji, I. O. (2020). Co-optimizing technical performance and community affordability in smart solar microgrids for underserved regions. International Journal of Engineering and Modern Technology, 6(3), 173-212. https://doi.org/10.56201/ijemt.vol.6.no3.2020.pg173.212
59. Komi, N.M. & Adeniji, I.O., 2020. Co-Optimizing Technical Performance and Community Affordability in Smart Solar Microgrids for Underserved Regions. International Journal of Engineering and Modern Technology, 6(3), pp.173–212. DOI: 10.56201/ijemt.vol.6.no3.2020.pg173.212.
60. Mbonu, I.S., Iwuanyanwu, U., Aliliele, C. & Uzoka, E., 2020. A Conceptual Framework for Agile Supply Chain Digital Transformation with Embedded IT Risk and ISO Compliance Controls. Iconic Research and Engineering Journals, 3(11), pp.566–593. DOI: 10.64388/IREV3I11-1714916.
61. Obogo, S.F., Arumosoye, O.M. & Obriki, O.D., 2020. Conceptual Risk Management Model for Heavy Lifting and Crane Installation Engineering Operations. Shodhshauryam, International Scientific Refereed Research Journal, 3(4), pp.122-144. DOI: 10.32628/SHISRRJ214441
62. Obriki, O.D., & Arumosoye, O.M. (2020). Conceptual Framework for Human Error Causation in High-Risk Construction and Industrial Activities. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), pp. 715-727. DOI: 10.54660/.IJMRGE.2020.1.5.715-727
63. Obriki, O. D., & Arumosoye, O. M. (2020). Conceptual framework for human error causation in high-risk construction and industrial activities. International Journal of

Multidisciplinary Research and Growth Evaluation, 1(5), 715-727. https://doi.org/10.54660/.IJMRGE.2020.1.5.715-727

64. Obriki, O.D. & Arumosoye, O.M., 2020. Conceptual Framework for Human Error Causation in High-Risk Construction and Industrial Activities. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), pp.715-727. DOI: 10.54660/.IJMRGE.2020.1.5.715-727
65. Okojie, J. S., & Abioye, R. F. (2020). Reconciling chemical safety with circular-economy targets: A decision framework for post-consumer recycled polymers in consumer-goods packaging balancing REACH compliance, lifecycle GHG footprint, and regulatory risk. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 992-1006.
66. Okojie, J. S., & Abioye, R. F. (2020). Reconciling chemical safety with circular-economy targets: A decision framework for post-consumer recycled polymers in consumer-goods packaging balancing REACH compliance, lifecycle GHG footprint, and regulatory risk. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 992-1006.
67. Okoli, I., Agboada, P., Kinyanjui, A., Akintobi, A., & Pedro, O. (2020). Capital equipment financing and risk management in healthcare technology procurement. International Journal of Humanities and Information Technology(Special Issue 2), 12-54. https://doi.org/10.21590/ijhit.spcl.02.02
68. Okoli, I., Agboada, P., Kinyanjui, A., Akintobi, A., & Pedro, O. (2020). Capital equipment financing and risk management in healthcare technology procurement. International Journal of Humanities and Information Technology(Special Issue 2), 12-54. https://doi.org/10.21590/ijhit.spcl.02.02
69. Ominyi, M. (2020). Developing a conceptual framework for post-merger compliance integration in multi-jurisdictional banking transaction. IIARD International Journal of Banking and Finance Research, 6(3), 78-95. https://doi.org/10.56201/ijbfr.vol.6.no3.2020.pg78.95
70. Ominyi, M., & Anichukwueze, C. C. (2020). A review of regulatory clearance frameworks for cross-border mergers and acquisitions in African financial markets. Journal of Accounting and Financial Management, 6(4), 73-99. https://doi.org/10.56201/jafm.vol.6.no4.2020.pg73.99
71. Ominyi, M. (2020). Developing a conceptual framework for post-merger compliance integration in multi-jurisdictional banking transaction. IIARD International Journal of Banking and Finance Research, 6(3), 78-95. https://doi.org/10.56201/ijbfr.vol.6.no3.2020.pg78.95
72. Ominyi, M., & Anichukwueze, C. C. (2020). Regulatory Clearance Frameworks for Cross-Border Merger and Acquisition Activities in African Financial Markets. Journal of Accounting and Financial Management, 6(4), 73-99. https://doi.org/10.56201/jafm.vol.6.no4.2020.pg73.99
73. Orise, C., & Niniola, S. (2020). Data-Informed Digital Learning Platforms: Conceptual Framework For Evidence-Based Educational Technology In Healthcare And STEM

Environments. International Journal Of Multidisciplinary Research And Growth Evaluation, 1(5), 1078-1089. https://doi.org/10.54660/.IJMRGE.2020.1.5.1078-1089

74. Orise, C., & Niniola, S. (2020). Data-Informed Digital Learning Platforms: Conceptual Framework For Evidence-Based Educational Technology In Healthcare And STEM Environments. International Journal Of Multidisciplinary Research And Growth Evaluation, 1(5), 1078-1089. https://doi.org/10.54660/.IJMRGE.2020.1.5.1078-1089
75. Oziri, S. T., Arowogbadamu, A. A. G., & Seyi-Lande, O. B. (2020). Applications of predictive analytics in reducing customer churn and lifecycle value in telecommunication industry. International Journal Of Multidisciplinary Futuristic Development, 1(2), 40-49.
76. Oziri, S. T., Arowogbadamu, A. A. G., & Seyi-Lande, O. B. (2020). Applications of predictive analytics in reducing customer churn and lifecycle value in telecommunication industry. International Journal Of Multidisciplinary Futuristic Development, 1(2), 40-49.
77. Sanni, J. O., Ajiga, D., & Atima, M. E. (2020b). Data driven brand positioning frameworks resolving differentiation challenges in regulated professional markets. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 649-660. https://doi.org/10.54660/IJMRGE.2020.1.5.649-660
78. Sanni, J. O., Ajiga, D., & Atima, M. E. (2020c). Systematic review of product management strategies in mobile network rollouts across emerging markets. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 661-673. https://doi.org/10.54660/IJMRGE.2020.1.5.661-673
79. Sanni, J. O., Ajiga, D., & Atima, M. E. (2020b). Data driven brand positioning frameworks resolving differentiation challenges in regulated professional markets. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 649-660. https://doi.org/10.54660/IJMRGE.2020.1.5.649-660
80. Sanni, J. O., Ajiga, D., & Atima, M. E. (2020c). Systematic review of product management strategies in mobile network rollouts across emerging markets. International Journal of Multidisciplinary Research and Growth Evaluation, 1(5), 661-673. https://doi.org/10.54660/IJMRGE.2020.1.5.661-673
81. Seyi-Lande, O. B., Arowogbadamu, A. A. G., & Oziri, S. T. (2020). Geomarketing analytics for driving strategic retail expansion and improving market penetration in telecommunications. International Journal of Multidisciplinary Futuristic Development, 1(2), 50-60.
82. Seyi-Lande, O. B., Arowogbadamu, A. A. G., & Oziri, S. T. (2020). Geomarketing Analytics to drive strategic retail expansion and market penetration in telecommunications industry. International Journal of Multidisciplinary Futuristic Development, 1(2), 50-60.
83. Soyege, O. S., Peteranaba, S. F., Osinem, H. E., & Eribenne, F. (2020). Crisis Prevention and De-escalation practices in Community-based human Services: Towards a Unified Competency Framework. Current Medical and Drug Research, 4(2), 12–26.
84. Tiamiyu, R., & Alaka, O. B. (2020). Routing of Motorcycle Dispatch Deliveries on Congested and poorly Connected Urban Networks in Lagos. International Journal of

Multidisciplinary Research and Growth Evaluation, 1(5), 1183–1198. https://doi.org/10.54660/.IJMRGE.2020.1.5.1183-1198

85. Uchechi, N., & Ominyi, M. (2020). Advances in Automated Risk Assessment Frameworks for Regulatory Deliverables in Upstream Energy Operations. International Journal of Multidisciplinary Evolutionary Research, 1(2), 158-175. https://doi.org/10.54660/IJMER.2020.1.2.158-175
86. Uchechi, N., & Ominyi, M. (2020). Advances in Automated Risk Assessment Frameworks for Regulatory Deliverables in Upstream Energy Operations. International Journal of Multidisciplinary Evolutionary Research, 1(2), 158-175. https://doi.org/10.54660/IJMER.2020.1.2.158-175
87. Yusuf, H. D., Abdulrazaq, K., Osinem, H. E., & Eribenne, F. (2020). Advances in antimicrobial resistance surveillance using multi-laboratory national reporting networks. International Journal of Multidisciplinary Evolutionary Research, 1(2), 176-194.
88. Yusuf, H. D., Abdulrazaq, K., Osinem, H. E., & Eribenne, F. (2020). Advances in antimicrobial resistance surveillance using multi-laboratory national reporting networks. International Journal of Multidisciplinary Evolutionary Research, 1(2), 176-194. https://doi.org/10.54660/IJMER.2020.1.2.176-194
89. Yusuf, H. D., Abdulrazaq, K., Osinem, H. E., & Eribenne, F. (2020). Advances in antimicrobial resistance surveillance using multi-laboratory national reporting networks. International Journal of Multidisciplinary Evolutionary Research, 1(2), 176-194. https://doi.org/10.54660/IJMER.2020.1.2.176-194
90. Abdulrazaq, K., Yusuf, H. D., Osinem, H. E., & Eribenne, F. (2019). A model for improving infection detection accuracy through integrated laboratory information systems. Iconic Research and Engineering Journals, 3(6), 650-675.
91. Abdulrazaq, K., Yusuf, H. D., Osinem, H. E., & Eribenne, F. (2019). A model for improving infection detection accuracy through integrated laboratory information systems. Iconic Research and Engineering Journals, 3(6), 650-675. https://doi.org/10.64388/IREV3I6-1723089
92. Abdulrazaq, K., Yusuf, H. D., Osinem, H. E., & Eribenne, F. (2019). A framework for enhancing infection diagnosis accuracy using integrated laboratory information system. Iconic Research and Engineering Journals, 3(6), 650-675. https://doi.org/10.64388/IREV3I6-1723089
93. Agbabiaka, J., Okonkwo, C. S., Ogunwole, O., Mayo, W., & Okeke, O. T. (2019). Supply chain risk management model for EPC and gas processing projects. Iconic Research and Engineering Journals, 3(2), 968-980. https://doi.org/10.64388/IREV3I2-1713124
94. Agbabiaka, J., Okonkwo, C.S., Ogunwole, O., Mayo, W. & Okeke, O.T., 2019. Supply Chain Risk Management Model for EPC and Gas Processing Projects. IRE Journals, 3(2), pp.968–980. DOI: 10.64388/IREV3I2-1713124.
95. Agyei, R. K., Izuchukwu, O. T., Feboh, D., & Idowu, A. (2019). Web based payment portals in Sub-Saharan Africa: A review of determinants and adoption. International Journal of

Computer Science and Mathematical Theory, 5(2), 56-79. https://doi.org/10.56201/ijcsmt.vol.5.no2.2019.pg56.79

96. Agyei, R. K., Izuchukwu, O. T., Feboh, D., & Idowu, A. (2019). Web based payment portals in Sub-Saharan Africa: A review of determinants and adoption. International Journal of Computer Science and Mathematical Theory, 5(2), 56-79. https://doi.org/10.56201/ijcsmt.vol.5.no2.2019.pg56.79
97. Ahmed, K. S., Odejobi, O. D., & Oshoba, T. O. (2019). Algorithmic model for constraint satisfaction in cloud network resource allocation. IRE Journals, 2(12), 516-532.
98. Ahmed, K. S., Odejobi, O. D., & Oshoba, T. O. (2019). Algorithmic model for constraint satisfaction in cloud network resource allocation. IRE Journals, 2(12), 516-532.
99. Aminu-Ibrahim, A. Y., Ogbete, J. C., & Ambali, K. B. (2019). Capital project delivery models for high risk healthcare infrastructure in developing national health systems. Iconic Research and Engineering Journals, 2(10), 626-649. https://doi.org/10.64388/IREV2I10-1713588
100. Aminu-Ibrahim, A. Y., Ogbete, J. C., & Ambali, K. B. (2019). Capital project delivery models for high risk healthcare infrastructure in developing national health systems. Iconic Research and Engineering Journals, 2(10), 626-649. https://doi.org/10.64388/IREV2I10-1713588
101. Aminu-Ibrahim, A.Y., Ogbete, J.C. & Ambali, K.B., 2019. Capital Project Delivery Models for High Risk Healthcare Infrastructure in Developing National Health Systems. Iconic Research and Engineering Journals, 2(10), pp.626–649. DOI: 10.64388/IREV2I10-1713588
102. Anyanwu, K. C. E. (2019). Development of maturity model for standardization of IT support operations in geographically dispersed multi-office organizations. Iconic Research and Engineering Journals, 3(5)., 580-598.
103. Anyanwu, K. C. E. (2019). Development of maturity model for standardization of IT support operations in geographically dispersed multi-office organizations. Iconic Research and Engineering Journals, 3(5)., 580-598.
104. Arumosoye, O. M., & Obriki, O. D. (2019). Systematic review of near miss and hazard observations data usage in industrial safety management. Iconic Research and Engineering Journals, 3(2), 981-999. https://doi.org/10.64388/IREV3I2-1714417
105. Akoglu, L., Tong, H., & Koutra, D. (2015). Graph-based anomaly detection and description: A survey. Data Mining and Knowledge Discovery, 29(3), 626–688.
106. Gray, G. L., & Debreceny, R. S. (2014). A taxonomy to guide research on the application of data mining to fraud detection in financial statement audits. International Journal of Accounting Information Systems, 15(4), 357–380.
107. Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). Application of data mining techniques in financial fraud detection: Classification framework and review of literature. Decision Support Systems, 50(3), 559–569.

108. Perols, J. (2011). Financial statement fraud detection: Statistical and machine learning algorithms. Auditing: A Journal of Practice & Theory, 30(2), 19–50.
109. Christen, P. (2012). Data Matching: Concepts and Techniques for Record Linkage, Entity Resolution, and Duplicate Detection. Springer.
110. Debreceny, R. S., & Gray, G. L. (2010). Data mining journal entries for fraud detection: An exploratory study. International Journal of Accounting Information Systems, 11(3), 157–181.
111. Jans, M., Lybaert, N., & Vanhoof, K. (2010). Internal fraud risk reduction: Results of a data mining case study. International Journal of Accounting Information Systems, 11(1), 17–41.
112. Khan, R., Corney, M., Clark, A., & Mohay, G. (2010). Transaction mining for fraud detection in ERP systems. Information Systems Management, 27(2), 141-156.
113. Phua, C., Lee, V., Smith, K., & Gayler, R. (2010). A comprehensive survey of data mining-based fraud detection research. arXiv preprint arXiv:1009.6119.
114. Stamatović, M., & Maksimović, S. (2020). Risk management as a part of the internal system of financial controls: Practice in the public sector of Serbia. Economy and Market Communication Review, 10(2).
115. Appelbaum, D., Kogan, A., & Vasarhelyi, M. A. (2017). Big data and analytics in the modern audit engagement: Research needs. Auditing: A Journal of Practice & Theory, 36(4), 1-27.
116. Wang, T., & Cuthbertson, R. (2015). Eight issues on audit data analytics we would like researched. Journal of Information Systems, 29(1), 155-162.
117. Jans, M., van der Werf, J. M., Lybaert, N., & Vanhoof, K. (2014). An internal transaction fraud prevention tool using business process mining approach. Expert Systems with Applications, 38(10), 13351-13359.
118. Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165–1188.
119. Nigrini, M. J. (2012). Benford's Law: Applications for Forensic Accounting, Auditing, and Fraud Detection. Wiley.
120. Bhattacharyya, S., Jha, S., Tharakunnel, K., & Westland, J. C. (2011). Data mining for credit card fraud: A comparative study. Decision Support Systems, 50(3), 602–613.
121. Binder, C. (2011). Medicare Program Integrity: Actions to Protect Medicare Against Payment Errors, Fraud and Abuse. Congressional Research Service Report R41526.
122. Perols, J. L., & Lougee, B. A. (2011). The link between earnings management and financial statement fraud. Advances in Accounting, 27(1), 39-53.
123. Trotman, K. T., & Wright, A. (2011). Triangulation of audit evidence in assessing fraud risks. Accounting, Organizations and Society, 37(1), 41-53.
124. Wells, J. T. (2011). Corporate Fraud Handbook: Prevention and Detection (3rd ed.). Wiley.

125. Zhou, W., & Kapoor, G. (2011). Evolutionary detection of financial statement fraud. Decision Support Systems, 50(3), 570-575.
126. Chandola, V., Banerjee, A., & Kumar, V. (2009). Outlier detection: A survey. ACM Computing Surveys, 41(3), 1-58.
127. Coderre, D. (2009). Computer-Aided Fraud Prevention and Detection: An Introduction. Wiley.
128. He, H., & Garcia, E. A. (2009). Learning from imbalanced data sets. IEEE Transactions on Knowledge and Data Engineering, 21(9), 1263–1284.
129. Sparrow, M. K. (2008). Fraud in the US health-care system: The vulnerabilities of automated payment systems. Social Research, 75(4), 1151-1180.
130. Bolton, R. J., & Hand, D. J. (2002). Statistical fraud detection: A review. Statistical Science, 17(3), 235–255.
131. Bell, T. B., & Carcello, J. V. (2000). A decision aid for assessing the likelihood of fraudulent financial reporting. Auditing: A Journal of Practice & Theory, 19(1), 169–184.
132. Chen, Z. X., Hohmann, L., Banjara, B., & Zhao, Y. (2020). Guidelines on protecting patients and health care systems against Medicare and Medicaid fraud. Journal of the American Pharmacists Association, 60(4), e1-e8.
133. Adeyemi, F. K., & Olarewaju, O. M. (2019). Internal control system and financial accountability: An empirical study of South-Western Nigeria public sector. Acta Universitatis Danubius: Oeconomica, 15(1), 45-62.
134. Kogan, A., Alles, M. G., & Vasarhelyi, M. A. (2018). Analytical procedures in external auditing: A comprehensive review of literature and a framework for external audit analytics. Journal of Accounting Literature, 40, 83-101.
135. Lopez, J., & Rubio, J. E. (2018). Access control for cyber-physical systems interconnected with the cloud. Computer Networks, 134, 46-54.
136. Alles, M., & Gray, G. L. (2016). The integration of big data into auditing: Inhibitors and research agenda to address them. International Journal of Accounting Information Systems, 22, 44-59.
137. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you? Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1135–1144.
138. van der Aalst, W. M. P. (2016). Process Mining: Data Science in Action (2nd ed.). Springer.
139. Alles, M. G. (2015). Drivers of the use and facilitators and obstacles of the evolution of big data by the audit profession. Accounting Horizons, 29(2), 439–449.
140. Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. Accounting Horizons, 29(2), 381-396.
141. Haney, C., & Phelps, D. (2014). Responding to CMS overpayment demands: Practical steps for an appeal. The Health Lawyer, 26(6), 21–28.

142. Kogan, A., Alles, M. G., Vasarhelyi, M. A., & Wu, J. (2014). Design and Evaluation of a Continuous Data Level Auditing System. Auditing: A Journal of Practice & Theory, 33(4), 221–245.
143. Babatunde, S. A. (2013). Stakeholders' Perception on the Effectiveness of Internal Control System on Financial Accountability in the Nigerian Public Sector. International Journal of Business and Management Invention, 2(1), 16-33.
144. Provost, F., & Fawcett, T. (2013). Data Science for Business. O'Reilly Media.
145. Albrecht, W. S., Albrecht, C. O., Albrecht, C. C., & Zimbelman, M. F. (2012). Fraud Examination (4th ed.). Cengage Learning.
146. Curtis, M. B., & Turley, S. (2012). The business risk audit: A longitudinal field study of an audit engagement. Accounting, Organizations and Society, 37(7), 439-460.
147. Dorminey, J., Fleming, A. S., Kranacher, M.-J., & Riley, R. A. (2012). Evolution of fraud theory. Issues in Accounting Education, 27(2), 555-579.
148. Kranacher, M.-J., Riley, R. A., & Wells, J. T. (2011). Forensic Accounting and Fraud Examination. Wiley.
149. Singleton, T. W., & Singleton, A. J. (2010). Fraud Auditing and Forensic Accounting (4th ed.). Wiley.
150. Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). Methodologies for data quality assessment and improvement. ACM Computing Surveys, 41(3), 1-52.
151. Winkler, W. E. (2006). Overview of record linkage and current research directions. Bureau of the Census Research Report Series.
152. Hodge, F. D., Kennedy, J. J., & Maines, L. A. (2004). Does search-facilitating technology make financial reporting more transparent? The Accounting Review, 79(3), 687–703.
153. Zadrozny, B., & Elkan, C. (2002). Transforming classifier scores into accurate multiclass probability estimates. In Proceedings of the 8th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 694-699).
154. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.
155. Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. In Proceedings of the 20th International Conference on Very Large Data Bases (pp. 487-499).
156. Quinlan, J. R. (1993). C4.5: Programs for Machine Learning. Morgan Kaufmann.
157. Jaro, M. A. (1989). Developments in record-linkage methods as used in linking the 1985 Census of Tampa, Florida. Journal of the American Statistical Association, 84(406), 414–420.
158. Landis, J. R., & Koch, G. G. (1977). Measurement of observer agreement for categorical data. Biometrics, 33(1), 159–174.
159. Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360.
160. Fellegi, I. P., & Sunter, A. B. (1969). A theory of record linkage. Journal of the American Statistical Association, 64(328), 1183–1210.

161. Hamdan, K. H. (2019). Application of COSO internal control framework in the evaluation of disaster management in Iraq. Muthanna Journal of Administrative and Economic Sciences, 9(2).
162. Ujkani, S., & Vokshi, N. B. (2019). An overview on the development of internal control in public sector entities: Evidence from Kosovo. University of Malta.
163. Donley, G. (2018). The broken Medicare appeals system: Failed regulatory solutions and the promise of federal litigation. Health Matrix, 28, 107-146.
164. Gonzalez, G. C., & Hoffman, V. B. (2018). Effects on auditees of electronic versus face-to-face interaction in continuous auditing. Journal of Forensic & Investigative Accounting, 10(1), 92-110.
165. Moffitt, K. C., Rozario, A. M., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. Journal of Emerging Technologies in Accounting, 15(1), 1-10.
166. Einkamerer, T. F., & Maqbool, J. (2017). Accounts payable: Improving a system for better efficiency. Applied Management Review, 2(1), 45-58.
167. Kirk, K. M. (2017). Analysis of predictive models of Medicare and Medicaid inpatient stays, and the impact of recovery audit contracting program. Rutgers University.
168. Lundberg, S. M., & Lee, S.-I. (2017). Unified interpretation of predictions through models. Advances in Neural Information Processing Systems, 30, 4765-4774.
169. Mohammed, M. A. (2017). A proposed framework for designing, implementing, and performing an effective internal control system. Ankara Yıldırım Beyazıt University.
170. Ali, N. (2016). Adapting e-invoicing: Benefits, challenges and future approaches to overcome challenges. Helsinki Metropolia University of Applied Sciences.
171. Issa, H., Ting, S., & Vasarhelyi, M. A. (2016). Ideas on research on artificial intelligence in auditing: Formalization of audit and workforce supplementation. Journal of Emerging Technologies in Accounting, 13(2), 1-20.
172. Kiesow, A., Schomaker, T., & Thomas, O. (2016). Transfer of continuous auditing to the digital age: The knowledge base after three decades of research. Proceedings of the European Conference on Information Systems.
173. Lee, H. C. (2016). Can electronic tax invoicing improve tax compliance? A case study of the Republic of Korea's electronic tax invoicing for value-added tax. World Bank Policy Research Working Paper 7592.
174. Hardy, C. A., & Laslett, G. (2015). Continuous auditing and monitoring in practice: Lessons from Metcash's business assurance group. Journal of Information Systems, 29(2), 183-194.
175. King, K. M. (2015). Medicare Part D: Changes needed to improve CMS's recovery audit program operations and contractor oversight (GAO-15-633). U.S. Government Accountability Office.
176. Chiu, V. (2014). The development and intellectual structure of continuous auditing research. Journal of Accounting Literature, 33, 37–57.

177. Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., & Bouchachia, A. (2014). A survey on concept drift adaptation. ACM Computing Surveys, 46(4), 1-37.
178. Kobelsky, K. (2014). A conceptual model for segregation of duties: Integrating theory and practice for manual and IT-based processes. International Journal of Accounting Information Systems, 15(4), 300-311.
179. Committee of Sponsoring Organizations of the Treadway Commission. (2013). Internal Control – Integrated Framework. COSO.
180. Jans, M., Alles, M. G., & Vasarhelyi, M. A. (2013). The case for process mining in auditing: Sources of value added and areas of application. International Journal of Accounting Information Systems, 14(1), 1-20.
181. Power, M. (2013). The audit society: Rituals of verification (2nd ed.). Oxford University Press.
182. Reginato, E., Nonnis, C., & Pavan, A. (2012). Modern internal control systems and accountability in health care organizations. Economia Aziendale Online, 3(2), 149-160.
183. Zhang, C., Pawlicki, A., McReynolds, D., & Titera, W. (2012). Continuous auditing web services model for XML based accounting systems. International Journal of Accounting Information Systems, 13(2), 55-79.
184. Van der Aalst, W. M. P. (2011). Process mining: discovery, conformance and enhancement of business processes. Springer.
185. Alles, M. G., Kogan, A., & Vasarhelyi, M. A. (2010). Principles and issues of audit automation as a precursor to continuous auditing. Working Paper, Rutgers University.
186. Dilla, W. N., & Janvrin, D. J. (2010). Where do experts look?: Eye-tracking investigations of audit estimation processes. Journal of Information Systems, 24(2), 25-48.
187. Kuhn, J. R., & Sutton, S. G. (2010). Continuous auditing in ERP system environments: The current state and future directions. Journal of Information Systems, 24(1), 91-112.
188. Teeter, R. A. (2010). The remote audit. Journal of Emerging Technologies in Accounting, 7(1), 73-88.
189. Khan, R., Corney, M., Clark, A., & Mohay, G. (2009). A role mining inspired approach to representing user behavior in ERP systems. Proceedings of the Asia Pacific Management Conference, 14, 1-12.
190. Alles, M. G., Kogan, A., & Vasarhelyi, M. A. (2008). Putting continuous auditing theory into practice: Lessons from two pilot implementations. Journal of Information Systems, 22(2), 195-214.
191. Curtis, M. B., & Payne, E. A. (2008). An examination of contextual factors and individual characteristics affecting technology implementation decisions in auditing. International Journal of Accounting Information Systems, 9(2), 104-121.
192. Dowling, C., & Leech, S. (2007). Audit support systems and decision support. International Journal of Accounting Information Systems, 8(2), 92-116.
193. Proctor, P. E., Heiser, J., & MacDonald, N. (2007). MarketScope for segregation of duties controls within ERP. Gartner Research Report R2183.

194. Vaidya, J., Atluri, V., & Warner, J. (2007). The role mining problem: Finding a minimal descriptive set of roles. Proceedings of the 12th ACM Symposium on Access Control Models and Technologies, 175-184.
195. van der Aalst, W. M. P., Reijers, H. A., Weijters, A. J. M. M., van Dongen, B. F., de Medeiros, A. K. A., Song, M., & Verbeek, H. M. W. (2007). Business process mining: An industrial application. Information Systems, 32(5), 713-732.
196. Fawcett, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861-874.
197. Arnold, V., Collier, P. A., Leech, S. A., & Sutton, S. G. (2004). The effect of intelligent decision aids on judgments of experts and novices. Accounting and Finance, 44(1), 1-26.
198. Hunton, J. E., & Rose, J. M. (2004). The influence of PCAOB staff accounting bulletins on auditor judgment. Auditing: A Journal of Practice & Theory, 23(1), 1-19.
199. Krippendorff, K. (2004). Content Analysis: An Introduction to its Methodology (2nd ed.). Sage.
200. Vasarhelyi, M. A., Alles, M. G., & Kogan, A. (2004). Principles of analytic monitoring for continuous assurance. Journal of Emerging Technologies in Accounting, 1(1), 1-21.
201. Braun, R. L., & Davis, H. E. (2003). Computer assisted audit tools and techniques: Analysis and perspectives. Managerial Auditing Journal, 18(9), 725-731.
202. Alles, M. G., Kogan, A., & Vasarhelyi, M. A. (2002). Feasibility and economics of continuous assurance. Auditing: A Journal of Practice & Theory, 21(1), 125-138.
203. Ashcroft, P. (2002). The application of digital analysis to the audit. Today's CPA, 32(4), 26-30.
204. Rezaee, Z., Sharbatoghlie, A., Elam, R., & McMickle, P. L. (2002). Continuous auditing: Building automated auditing capability. Auditing: A Journal of Practice & Theory, 21(1), 147-163.