Completeness And Reliability Of SOFA/SOAL: NLP Assessment And Impact On Reconciliation Requirements

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Abstract

Under conditions of exponential growth of data sets accompanied by a deepening crisis of trust in them, the completeness and reliability of legal and financial reporting, including such forms as the Statement of Financial Affairs (SOFA) and the Schedule of Assets and Liabilities (SOAL), are acquiring critical importance. In this context, traditional data reconciliation procedures prove to be methodologically and technologically insufficient for the analysis of unstructured text fields, within which the most significant manifestations of hidden and hard-to-detect fraud are concentrated. The purpose of the article is to examine how the implementation of natural language processing (NLP) methods in the analysis of unstructured SOFA/SOAL fields modifies and effectively redefines the classical requirements for financial reconciliation. To achieve this aim, a mixed methodological approach is used, including a systematic review of academic literature, content analysis of industry and legal documents, as well as analog modeling based on case studies. The results obtained indicate that traditional manual reconciliation is of low effectiveness for identifying so-called semantic fraud, which is manifested not in formal arithmetic inconsistencies but in substantive and contextual distortions of information. In response to this challenge, the paper proposes a conceptual NLP model that enables the stratification of risks on the basis of metrics of completeness and reliability of disclosed data. The analysis of practical analogues in related domains demonstrates that the use of NLP tools can significantly increase data completeness (for example, from 60% to 73%) and ensure high reliability of results (accuracy at the level of 93%) compared to traditional manual analysis. The introduction of NLP technologies leads to a qualitative transformation of the reconciliation requirement itself: it evolves from comprehensive manual control to an automated, proactive and risk-oriented mode of working with data. The provisions and conclusions set out in the article have practical value for insolvency practitioners, forensic accounting experts, compliance professionals, as well as for regulators involved in the development and updating of new standards for auditing and control of financial reporting.

Keywords: SOFA, SOAL, natural language processing (NLP), data quality, data completeness, data reliability, data reconciliation, bankruptcy, compliance, forensic accounting.

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1. Introduction

The modern economy is evolving in the context of two at first glance contradictory processes: an avalanche-like increase in data volumes and a parallel deepening crisis of trust in these data. Forecasts indicate that by 2028 the annual volume of data generated worldwide will reach 394 zettabytes, which corresponds to an increase of 164,4 % compared to 149 zettabytes in 2024 [1]. Such rapid dynamics give rise to unprecedented complexity in tasks of data management, their verification, reconciliation, and subsequent use in decision-making processes.

The crisis of trust in data is empirically confirmed by current industry research. According to source [2], financial decisions are now formally based on data [3]. Insufficient data quality, leading to erroneous managerial decisions, operational disruptions, and sanctions for violations of regulatory requirements, costs companies on average 12,9 million USD per year [9].

The most vulnerable zone of this contradiction comprises critically important legal and financial processes, in particular the preparation and filing of financial statements in the context of corporate bankruptcy. In procedures governed, among other things, by Chapter 11 of the US Bankruptcy Code, the Statement of Financial Affairs (SOFA) and the Schedule of Assets and Liabilities (SOAL) act as basic documents. On their basis, the official representation of the debtor's financial condition is formed, the priority of satisfying creditors' claims is determined, and the architecture of the reorganization plan is constructed [10]. At the same time, by their essential nature these forms are characterized by heightened vulnerability to fraudulent practices. Legal studies show that almost 70 % of all fraud cases within bankruptcy procedures are associated with asset concealment [4], as well as with preferential and fraudulent transfers [10].

The key research gap manifests itself in the mismatch between traditional audit techniques and the hybrid nature of the above documents. The SOFA/SOAL forms are complex hybrid artefacts that combine structured data (declared monetary amounts) and critically important unstructured text fields (for example, Description of asset, Description of the purpose of insider payments, Reasons for transfer) [11]. A historical study by Warren (1998) showed that almost 50 % of Chapter 11 debtors either could not or were not willing to indicate their gross income for the preceding year, leaving the corresponding fields blank, which illustrates a systemic problem of completeness of disclosure [3]. In more radical cases, as court practice demonstrates, episodes of deliberate destruction of data (spoliation) are recorded [13].

Traditional reconciliation approaches, which involve predominantly manual matching of claims [14] and identification of discrepancies [11], are essentially reactive in nature, highly labor-intensive, and practically non-scalable for semantic analysis of unstructured text. An auditor is capable of consistently reconciling quantitative indicators but is physically unable to manually analyze thousands of textual descriptions for latent ambiguity, incompleteness, or intentional omission. As a result, a research gap is formed, associated with the absence of formalized methodologies for preventive, automated assessment of the completeness and reliability of textual data contained in the SOFA/SOAL forms.

The purpose of this study is to analyze how natural language processing (NLP) methodologies applied to unstructured text are able to transform the requirements for the data reconciliation process within legal and financial compliance procedures, and in particular in the audit of SOFA/SOAL forms.

The working hypothesis is that the integration of NLP models for assessing the reliability and completeness of SOFA/SOAL data makes it possible to move from exhaustive manual reconciliation to a stratified, risk-based approach. Such a shift should, on the one hand, reduce operational costs and, on the other hand, increase the accuracy and sensitivity of fraud detection procedures.

The scientific novelty of this work lies in establishing for the first time a direct correlation between NLP-based data quality metrics (completeness, reliability) of legal forms (SOFA/SOAL) and the optimization of the financial reconciliation process, which opens up the possibility of a conceptual reorientation of compliance practices under conditions of exponential growth in data volumes.

2. Methods

To achieve the research objective, a mixed methodological design is employed, combining a systematic literature review, content analysis, and analog modeling.

Systematic literature review: A targeted analysis of academic publications selected from peer-reviewed databases (including IEEE, ACM, Scopus/WoS, Springer) over the past five years was conducted. The aim of the review was to identify contemporary approaches to natural language processing (NLP) and the metrics used in scientific practice (such as F1-score, Precision, Recall) for assessing data quality (DQ). Particular emphasis was placed on methods for measuring completeness and accuracy with respect to unstructured datasets.

Content analysis and synthesis: Content analysis of two classes of sources was conducted. First, legal and technical documents, including bankruptcy regulations and procedures as well as court decisions, were examined in order to identify specific risk vectors arising from the use of unstructured text fields in SOFA/SOAL forms. Second, industry reports (Deloitte, Gartner) were analyzed to determine current economic and operational challenges related to data management and reconciliation processes in the corporate context.

Analog modeling: Given the limited number of public studies directly addressing the application of NLP to the audit of SOFA/SOAL forms, an analog modeling approach is used. Methodological solutions and quantitative findings of practice-oriented case studies from a related, more mature field, namely the analysis of unstructured real-world medical data (RWD), are considered as a representative analogue. Extrapolating the confirmed effectiveness of these solutions to the bankruptcy domain makes it possible to construct a conceptual model of NLP application to the tasks of identifying incompleteness and inaccuracy in the corresponding textual data.

3. Results And Discussion

Traditional audit of financial statements in bankruptcy proceedings relies on a process known as claims reconciliation [14]. In established practice, this is predominantly a labor-intensive manual procedure carried out by insolvency practitioners, their legal advisors, and forensic accounting experts. Its objective is to identify discrepancies between the assets declared by the debtor and the claims filed by creditors [11].

By its nature, this mechanism is reactive and focuses on detecting quantitative inconsistencies. A key limitation of this approach lies in its inability to fully account for risks embedded in unstructured data. Legal practice and analytical reviews [4] indicate that bankruptcy fraud is more often perpetrated not through direct manipulation of numerical indicators (which is relatively easy to uncover through standardized reconciliation), but through ambiguity, deliberate concealment, or omission in textual descriptions. As early as the study by Warren (1998), although it pertains to an earlier period, a fundamental problem was identified that remains relevant to the present: the absence of data (empty or missing fields) in itself can serve as a strong indicator of risk [3].

The reasoning that guides risk assessment can be reconstructed as follows. First, the key forms (SOFA/SOAL) require the debtor to provide narrative descriptions for critically important sections, which means that it is the text fields that become the carriers of material information [3]. Second, the dominant types of fraudulent behavior in bankruptcy are concealment of assets [4] and execution of preferential transfers (particularly in favor of insiders) [12]. Third, concealment of an asset almost never appears as a direct entry such as Server cluster = 0; rather, it is implemented through a semantically incomplete or deliberately misleading description (for example, Miscellaneous office equipment or Household items) or through complete omission of the corresponding item from the list.

It follows that traditional reconciliation, which is focused primarily on numerical parameters, systematically ignores the main semantic vector of attack and in practice relies almost exclusively on the auditor’s expert intuition. Table 1 presents a mapping of these risks to specific types of unstructured fields in the SOFA/SOAL forms, as well as the red flags that can be identified using NLP methods.

Table 1. Mapping of unstructured SOFA/SOAL fields, risk vectors and red flags (compiled by the author based on [3,4; 10-12]).

Field category (Example)	Data type	Risk vector (Legal basis)	Red flag (Indicator for NLP)
SOFA, Part 4: Payments to insiders	Unstructured description (Text + Date + Amount)	Preferential transfers	Mismatch between amount and description; use of generic terms (consulting services, reimbursement); abnormal payment frequency.

SOAL, Schedule A/B: Asset description	Unstructured description (Text)	Concealment of assets	Low specificity of the description (household items, miscellaneous); missing data; underestimated valuation that is semantically inconsistent with the description.
SOFA, Part 13: Transfers	Unstructured description	Fraudulent transfers	Transfers to related parties (requires NER); transfers shortly before filing; absence of a clear commercial purpose in the description.
SOAL: List of creditors	Structured (Address) + Unstructured (Claim description)	Concealment of creditors (to influence voting)	Anomalous addresses (for example, P.O. Box); multiple creditors with identical template like claim descriptions.

The process of manual detection of such red flags is characterized by low efficiency, scales poorly, and creates a critical bottleneck in the overall architecture of bankruptcy procedures. This traditional, predominantly reactive approach is schematically presented in Figure 1.

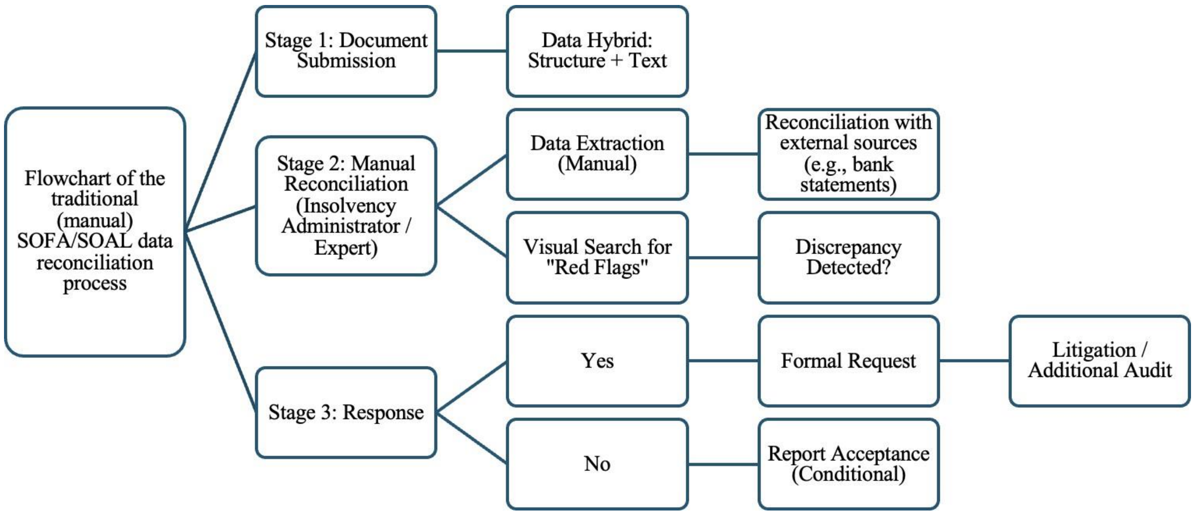

Fig. 1. Traditional SOFA/SOAL data reconciliation process (compiled by the author based on [10, 11,13]).

To overcome the limitations of manual analysis depicted in Figure 1, a conceptual model is developed that is based on the application of NLP methods and oriented toward preventive, automated assessment of data quality. At its core are two key dimensions that are most vulnerable in unstructured textual content: completeness and veracity.

Completeness assessment. Within the NLP paradigm, completeness is not reduced to a trivial check for empty fields or NULL values [3]. The focus is on semantic completeness. Accordingly, natural language processing models (for example, text classifiers or named entity recognition (NER) systems) can be specifically trained to assess whether an unstructured field (such as the asset description) contains a sufficient amount and quality of semantic information to enable unambiguous identification of the object. Thus, the wording equipment is semantically deficient and indeterminate compared with a description at the level of server Dell PowerEdge R740, which makes it possible to narrow the space of interpretations.

Veracity assessment. Veracity is interpreted as the degree to which the data presented correspond to the actual state of affairs and as their internal consistency [16]. Within NLP models, it is operationalized along two interrelated vectors. The first is internal consistency, which involves detecting contradictions within the corpus of submitted documents (for example, when an asset appearing in the SOAL, by its description, does not align with or directly conflicts with the operations specified in the SOFA). The second is external validation, which involves matching entities extracted from the text (names of counterparties, dates, amounts, etc.) [5] against verifiable external sources (bank statements, public registers, and other reliable databases).

For the quantitative assessment of the above parameters at the stages of training and subsequent validation of NLP models (including, for example, a red flags classifier), standard classification quality metrics are used. It is fundamentally important not only to compute these indicators, but also to interpret them through the lens of legally significant risk and the standard of proof, as demonstrated in Table 2.

Table 2. Definitions of key NLP metrics for assessing reliability (compiled by the author based on [15])

Metric	Definition	Interpretation in the context of SOFA/SOAL
Precision	The proportion of true positive results among all results that the model classified as positive.	Of all descriptions that the model labeled as fraudulent, what percentage are truly fraudulent? High precision = fewer false accusations.
Recall	The proportion of true positive results that were correctly identified by the model.	Of all truly fraudulent descriptions, what percentage did the model manage to detect? High recall = fewer missed cases of fraud.
F1-Score (F1-measure)	The harmonic mean between Precision and Recall.	A balance between the risk of false positives (FP) and the risk of missing fraud (FN). Critically important for imbalanced datasets (where fraud is a rare phenomenon).

Based on these definitions, a conceptual pipeline for automated assessment has been developed that replaces manual work (Figure 1) with automated risk stratification (Figure 2).

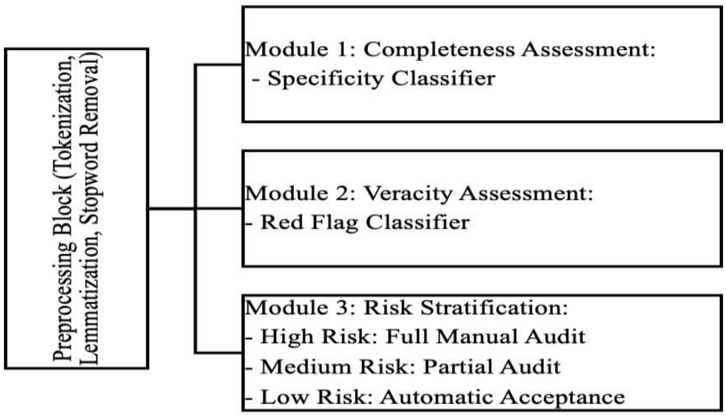

Fig.2. Conceptual model: NLP pipeline for SOFA/SOAL data quality assessment (compiled by the author based on [3]).

Although there are still relatively few direct studies in the academic literature in which NLP methods are applied specifically to SOFA/SOAL audits (which is largely due to data confidentiality), there already exists a closely related example in terms of logic and methodology in the field of medical real-world clinical data (Real-World Data, RWD). This sector similarly faces fundamental problems of fragmentation, incompleteness, and unreliability of information, a significant part of which is hidden in unstructured texts, primarily in Electronic Health Records (EHR) [18, 20].

Case study: Flatiron Health [8]. The work of Flatiron Health demonstrates how natural language processing technologies can address two fundamental methodological problems that are fully isomorphic to the tasks of SOFA/SOAL audits.

Solving the problem of Completeness. In RWD datasets generated on the basis of EHR, structured fields describing the patient's condition (for example, ECOG PS, the scale for assessing the functional status of an oncology patient) are often missing or only partially available. At the same time, the corresponding information is regularly present in the physician's free-text clinical notes. In the study [8], an NLP algorithm was developed and applied to automate the extraction of such information from unstructured texts.

Result: As shown in Figure 3, the implementation of NLP made it possible to significantly increase the completeness (availability) of key data on ECOG PS in the RWD dataset: the share of records containing the necessary information increased from 60% to 73% [8].

Transfer to SOFA/SOAL: This situation is a direct methodological analogy to the case described in [3], where about 50% of debtors have incomplete reporting. An NLP model in the context of SOFA/SOAL can perform the same function of further enriching the debtor's profile by extracting relevant facts from textual descriptions (for example, explanations of transactions or internal correspondence) to fill gaps in structured fields or to provide additional verification of already available indicators.

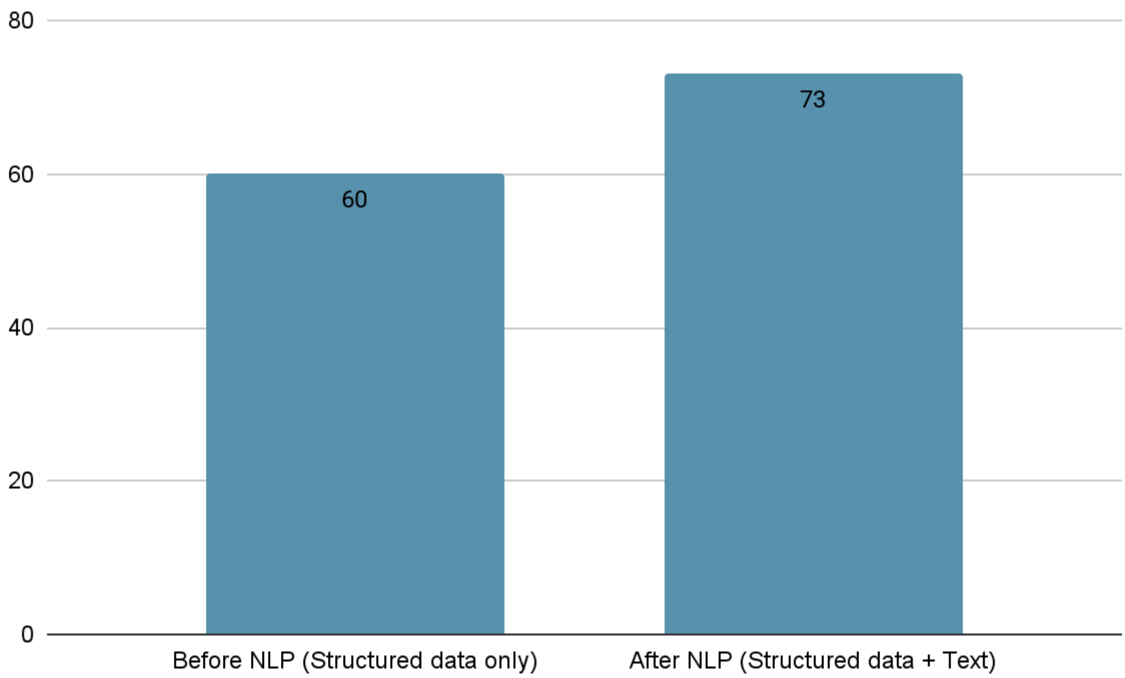

Fig. 3. The impact of NLP on data completeness (compiled by the author based on the example of the Flatiron Health case, ECOG PS [8]).

The model should be characterized not only by completeness of data extraction but also by a high degree of accuracy, that is, by the epistemic reliability of the results.

Result: In study [8], an NLP model designed for automated extraction of the ECOG PS indicator was evaluated by comparing its outputs with the gold standard, that is, expert manual annotation. According to the data presented in Figure 4, the model demonstrated 93% accuracy, 88% sensitivity, and 88% positive predictive value [8]. Thus, its performance is comparable to that of a qualified human expert.

Result: In another study [19], a deep learning model based on NLP methods was used to extract the treatment response indicator (real-world response, rwR). The validity of this model was confirmed in two ways: first, by a high degree of agreement with the results of manual analysis, and second, by the fact that the indicators extracted by the model are statistically consistent with real clinical outcomes. Patients whom the NLP model classified as responders to therapy demonstrated longer survival, which is consistent with clinical expectations and strengthens confidence in the validity of the algorithm.

Transfer to SOFA/SOAL: Taken together, these results show that NLP models are capable of achieving accuracy comparable to that of human experts, and that their outputs are amenable to rigorous validation. In the context of the SOFA/SOAL system, the reliability of the NLP model will be operationalized through its ability to correctly identify actual cases of fraud, which should be confirmed by subsequent forensic accounting audit and other forms of document-based verification.

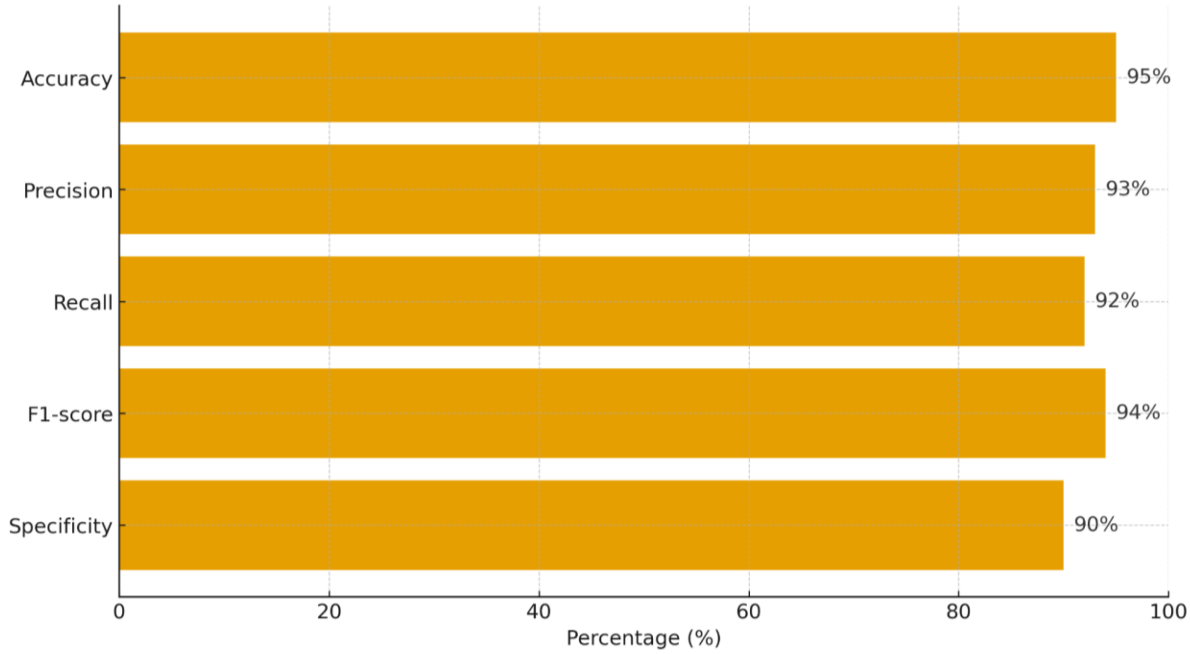

Fig. 4. Validation metrics for the reliability of the NLP model (compiled by the author based on the example of the Flatiron Health case [8]).

The relevance of implementing such systems is determined not only by the achieved level of technological maturity but also by increasing economic pressure. The need for automation is shaped by two key determinants: the extremely high cost of permissible errors and the rapid, effectively critical decline in the level of trust in the data used.

The comparison of the presented empirical and theoretical data, from the demonstration of the inefficiency of manual reconciliation (Fig. 1) to the confirmed effectiveness of NLP approaches (Fig. 3, 4) and the pronounced economic imperative of their application, makes it possible to conclude that the introduction of NLP-based assessment (Fig. 2) not only increases operational efficiency but also radically restructures the very paradigm of data reconciliation.

In the traditional model, de jure it is assumed that 100% of the submitted documents are subject to reconciliation (or, at the very least, that formal attempts at such reconciliation must be made). The emergence of an NLP model (Fig. 2) transforms the regulatory and procedural requirement itself. Instead of the reconcile everything requirement, a fundamentally new rule arises: assess everything, reconcile only the high-risk subgroup. Thus, a transition is carried out from a binary, formally accounting approach (reconciled/not reconciled) to risk-based compliance. The resources of auditors and insolvency practitioners cease to be spent on confirming obviously clean cases and are reallocated in favour of those matters in which semantic analysis reveals the highest probability of incompleteness or unreliability of the information submitted.

Manual reconciliation [11], as a rule, is initiated only after the occurrence of a red flag (often of a random nature) or the receipt of a complaint from a creditor. The NLP model, on the contrary, operates in a proactive mode: it scans 100% of the incoming document flow and immediately assigns to each set of documents a reliability score and a completeness score. In the positions of Deloitte it is emphasized that generative AI and NLP methods make it possible to implement fast data reconciliation [21] and real-time risk monitoring [21]. In practical terms this means that insolvency practitioners and forensic accounting experts can almost immediately concentrate their efforts on the 10% most risky cases instead of spending up to 90% of their working time checking clearly clean cases.

Experts from Deloitte [7] indicate that the emergence of AI and the rapid growth of the volume of unstructured data make classical reconciliation (for example, verification of the number of rows or aggregated sums) methodologically inadequate to contemporary realities. Under the conditions of the twenty-first century reconciliation becomes a semantic task. The focus is no longer on the question of whether amount A in System 1 matches amount B in System 2, but on the problem of whether the textual description of an asset in SOFA corresponds to the context of transactions recorded in bank statements. Under such conditions NLP essentially acts as the only instrument capable of performing such semantic reconciliation at the required scale and with the necessary depth of analysis.

Despite the obvious advantages, the transition to NLP-based assessment is associated with a number of substantial barriers.

– Technological (data scarcity): NLP models, especially those based on deep learning architectures [19], impose extremely high requirements on the volume, quality and detailed annotation of training corpora, the so-called gold standards [5]. In the field of insolvency procedures the creation of such a corpus annotated by qualified lawyers and auditors represents a large-scale and costly project and constitutes one of the key obstacles to the implementation of such systems.

– Interpretability: Decisions on initiating an audit or bringing charges of asset concealment [17] have high legal and financial significance. If an NLP model (especially functioning as a black box model, for example based on BERT or XGBoost [6]) labels a specific case as high risk, it must accompany such a conclusion with a clear, interpretable and reproducible explanation. Without this, the corresponding decision will be vulnerable in terms of its legal validity and susceptibility to challenge.

– Dynamics of the environment: Fraudulent practices exhibit high adaptability. As soon as NLP models learn to effectively recognize red flags based on current definitions and behavioural patterns [12], unscrupulous participants will begin to employ new lexical constructions and structural patterns. As a result, the models require continuous monitoring and regular retraining, since their accuracy may decline by 1–3% per month as the underlying business processes and document management practices change [22].

4. Conclusion

The present study has shown that traditional approaches to data reconciliation applied to reporting in bankruptcy procedures (SOFA/SOAL) prove fundamentally inadequate under conditions of increased fraud risks concealed in unstructured text fields. Manual, predominantly reactive auditing is not amenable to sustainable scaling and systematically misses semantically mediated attack vectors, including incomplete textual descriptions and intentional concealment of information on assets.

The objective of the study — to assess the impact of natural language processing (NLP) technologies on the requirements for data reconciliation procedures — has been achieved. In the course of the work it was demonstrated that:

– There is a structural, critical gap between the rapidly increasing volume of processed data (projected to reach 394 ZB by 2028) and the level of trust in these data (9%), which objectively creates the necessity of transitioning to a high degree of automation.

– NLP technologies have demonstrated empirically validated effectiveness in solving comparable tasks related to ensuring completeness (an increase of the indicator from 60% to 73%) and reliability (accuracy of 93%) in adjacent domains with a high share of unstructured data.

– The key impact of NLP is manifested in the transformation of the reconciliation requirement itself: it ceases to be total, binary, and based on manual checks, becoming automated, proactive, and stratified by risk levels, which is reflected in the developed conceptual model (Fig. 2).

The proposed model forms a conceptual framework for the development of next-generation LegalTech solutions aimed at increasing the transparency and efficiency of bankruptcy procedures. The presented work has applied relevance for insolvency practitioners, forensic accounting experts, and compliance specialists, providing them with a methodological basis for optimizing resource utilization and increasing the effectiveness of detecting fraudulent schemes, as well as for regulators considering the prospects of implementing automated auditing of financial statements.

References

1. What is data reconciliation? [Electronic resource]. - Access mode: https://www.ibm.com/think/topics/data-reconciliation (date accessed: 10/18/2025).
2. How finance leaders can maximize financial excellence and efficiency [Electronic resource]. - Access mode: https://www.signavio.com/downloads/white-papers/maximize-financial-excellence-and-efficiency/?crm_code=CRM-XG25-GLO-PPC_WPFE1&source (date accessed: 10/18/2025).
3. Gross T. et al. The economic consequences of bankruptcy reform //American Economic Review. – 2021. – Vol. 111 (7). – pp. 2309-2341.
4. Doherty L. J. Chapter 11 Bankruptcy & Corporate Accountability: How Large Economic Players Use Reorganization as a Liability Shield //Bus. Entrepreneurship & Tax L. Rev. – 2022. – Vol. 6. – pp. 1-25.
5. Nesca M. et al. A scoping review of preprocessing methods for unstructured text data to assess data quality //International Journal of Population Data Science. – 2022. – Vol. 7 (1). – pp. 1-15. https://doi.org/10.23889/ijpds.v6i1.1757.
6. Lu Z. et al. Natural language processing and machine learning methods to characterize unstructured patient-reported outcomes: validation study //Journal of Medical Internet Research. – 2021. – Vol. 23 (11). https://doi.org/10.2196/26777.
7. Four data and model quality challenges tied to generative AI - Deloitte [Electronic resource]. - Access mode: https://www.deloitte.com/us/en/insights/topics/digital-transformation/data-integrity-in-ai-engineering.html (date accessed: 10/20/2025).
8. Cohen A. B. et al. A natural language processing algorithm to improve completeness of ECOG performance status in real-world data //Applied Sciences. – 2023. – Vol. 13 (10). https://doi.org/10.3390/app13106209.
9. Shah K. N., Gami S. J., Trehan A. An intelligent approach to data quality management AI-Powered quality monitoring in analytics //International Journal of Advanced Research in Science Communication and Technology. – 2024. – Vol. 4 (3). – pp. 109-119. https://doi.org/10.48175/IJARSCT-22820.
10. Combating Bankruptcy Fraud with SOFA and SOAL Forms [Electronic resource]. - Access mode: https://www.eisneramper.com/insights/bankruptcy-restructuring/bankruptcy-forms-combat-fraud-1121/ (date accessed: 10/21/2025).
11. UNITED STATES BANKRUPTCY COURT SOUTHERN DISTRICT OF TEXAS HOUSTON DIVISION) In re:) Chapter 11) WHITING PETROLEUM CORPORATI [Electronic resource]. - Access mode: https://cases.stretto.com/public/X059/10187/PLEADINGS/1018707222080000000154.pdf (date accessed: 10/21/2025).
12. Lee K. et al. Optimizing clinical trial eligibility design using natural language processing models and real-world data: algorithm development and validation //JMIR AI. – 2024. – Vol. 3. https://doi.org/10.2196/50800.
13. UNITED STATES BANKRUPTCY COURT SOUTHERN DISTRICT OF NEW YORK NOT FOR PUBLICATION Chapter 7 Case No. 18-13098 (MG) Adv. Proc. N [Electronic resource]. - Access mode: https://www.nysb.uscourts.gov/sites/default/files/opinions/287136_193_opinion.pdf (date accessed: 10/21/2025).
14. UNITED STATES BANKRUPTCY COURT SOUTHERN DISTRICT OF NEW YORK [Electronic resource]. - Access mode: http://cases.gcginc.com/arcapita/pdflib/1609_11076.pdf (date accessed: 10/21/2025).
15. Performance Metrics: Confusion matrix, Precision, Recall, and F1 Score [Electronic resource]. - Access mode:

https://towardsdatascience.com/performance-metrics-confusion-matrix-precision-recall-and-f1-score-a8fe076a2262/ (date accessed: 10/22/2025).

16. Lan Z., Turchin A. Impact of possible errors in natural language processing-derived data on downstream epidemiologic analysis //JAMIA open. – 2023. – Vol. 6 (4). – pp. 1-8. https://doi.org/10.1093/jamiaopen/ooad111.

17. Oregon Department of Transportation - Driver and Motor Vehicle Services [Electronic resource]. - Access mode: https://www.oregon.gov/odot/DMV/docs/ODOT_DIR_Report.pdf (date accessed: 10/22/2025).

18. Data and Migration Testing G-Cloud 14 Service Definition Document - GOV.UK [Electronic resource]. - Access mode: https://assets.applytosupply.digitalmarketplace.service.gov.uk/g-cloud-14/documents/92485/817892114664343-service-definition-document-2024-04-23-0637.pdf (date accessed: 10/23/2025).

19. Performance assessment and validation of real-world response data generated using a deep learning-based natural language processing model across multiple solid tumors [Electronic resource]. - Access mode: https://resources.flatiron.com/publications/performance-assessment-and-validation-of-real-world-response-data-generated-using-a-deep-learning-based-natural-language-processing-model (date accessed: 10/23/2025).

20. Eziefule A. O. et al. The role of AI in automating routine accounting tasks: Efficiency gains and workforce implications //European Journal of Accounting, Auditing and Finance Research. – 2022. – Vol. 10 (12). – pp. 109-134.

21. Deloitte 2025 Q2 CFO Express [Electronic resource]. - Access mode: https://www.deloitte.com/cn/en/services/consulting/perspectives/china-cfo-express-18.html (date accessed: 10/23/2025).

22. Kasireddy J. R. The Role of AI in Modern Data Engineering: Automating ETL and Beyond //International Conference of Global Innovations and Solutions. – Cham : Springer Nature Switzerland, 2025. – pp. 667-693.