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An Autonomous Information Quality Assessment Model for Detecting Inconsistency and Reliability Issues in Digital Knowledge Resources

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Abstract

Inconsistency, outdatedness, poor support, and unreliability of digital knowledge resources have become more frequent with the growing amount of such heterogeneous knowledge resources. Current methods of information quality assessment usually perform independent assessments of different quality aspects and offer low-level integration of consistency, reliability, evidence quality, validity, and uncertainty. This paper aims to develop a mechanism for information quality assessment that will be both autonomous and explainable. An autonomous framework for information quality assessment was developed through the integration of knowledge preprocessing, semantic representation, inconsistency detection, reliability assessment, evidence and source validation, context and temporal analysis, quality score calculation, uncertainty assessment, and explainable decision-making. The proposed approach was tested on heterogeneous digital knowledge resources consisting of structured and unstructured information. Accuracy, precision, recall, F1 score, ROC-AUC, reliability assessment error, and calibration were used for performance

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evaluation. Comparison and ablation studies were conducted to investigate the contribution of each part of the proposed framework to its overall performance. Accuracy, Precision, Recall, F1-Score, and ROC-AUC for overall information quality assessment were 94.20%, 93.76%, 92.84%, 93.30%, and 0.968, respectively. Accuracy, F1-Score, and ROC-AUC for inconsistency detection were 94.04% and 0.971, respectively. The correlation for reliability estimation was 0.91, and its Mean Absolute Error (MAE) was 0.067. The ECE for the uncertainty module was 0.041. Results from the ablation study proved measurable degradation in performance after eliminating the consistency, reliability, evidence, temporal, or uncertainty modules. The results prove that the use of combined semantic, reliability, evidence, temporal, and uncertainty analysis can lead to increased quality of automated assessment of digital knowledge. It will provide a reason behind decisions regarding the quality of data.

Keywords: Information Quality, Knowledge Inconsistency, Reliability Assessment, Semantic Analysis, Uncertainty Estimation, Explainable AI, Digital Knowledge Resources.

1 Introduction

Digital sources of knowledge have become indispensable components of contemporary information systems for education, research, medicine, business intelligence, governmental services, and decision-making on the Internet. Such sources of knowledge include structured databases, knowledge graphs, digital archives, Internet-based documents, collaborative services, and computer-generated knowledge. The explosive growth of these sources of knowledge has resulted in increased availability and accessibility of information, but the growing amount of heterogeneous and dynamic digital knowledge has generated considerable problems with information quality. Information can be obsolete, incomplete, duplicate, semantically vague, contradictory, and poorly substantiated by reliable evidence. Therefore, conflicting pieces of knowledge and facts may be encountered by users and intelligent systems.

Quality of information is not defined through one parameter but is rather affected by several factors such as accuracy, consistency, completeness, reliability, relevancy, timeliness, provenance, and evidentiality. Traditional approaches to quality evaluation of information usually analyze some of these factors separately or use predetermined rules and source characteristics as key parameters. These techniques can have difficulties in identifying semantic consistency problems, discriminating between reliable information and similar-looking unreliable information, and adapting to changes in the context of knowledge. Also, traditional methods often provide very little explanation for why some information was assessed as inconsistent or unreliable.

The main question that this research tries to solve is the lack of a unified independent mechanism that would be able to identify inconsistencies in the information and assess its reliability. Thus, the research gap is in developing a framework for quality assessment that will take into account semantic consistency, source reliability, evidentiary quality, contextual validity, and temporality of information.

The proposed autonomous information quality evaluation model identifies inconsistencies and problems regarding the reliability of digital knowledge sources. This model incorporates the components of semantic analysis, identification of inconsistency, estimation of reliability, assessment of evidence and provenance, validation based on context and time, and estimation of uncertainty in one cohesive evaluation procedure. The goals are to discover conflicting and inconsistent information, assess the reliability of the pieces of knowledge, produce an information quality evaluation score, measure uncertainty in the assessment procedures, and provide explanations for the detected information quality problems. The proposed framework is subsequently evaluated against established approaches using appropriate quality, inconsistency-detection, reliability, and explainability measures.

The rest of the paper is structured as follows. Section 2 provides a review of the literature on information quality, knowledge inconsistency, reliability, and credibility. Section 3 discusses the proposed autonomous framework for assessing information quality, whereas Section 4 introduces its mathematical model. Section 5 explains the algorithm and implementation of the proposed approach. Section 6 discusses the experimental approach. Section 7 presents and analyzes the results obtained. Section 8 provides a discussion of the results, and the conclusions follow in Section 9.

2 Literature Review

Growing reliance on digital sources of knowledge has created the necessity to ensure quality, consistency, credibility, and reliability of information in intelligent information systems. Recent studies have shown that information quality is a multidimensional construct, which includes such factors as accuracy, completeness, consistency, timeliness, source validity, and contextual validity. Unified quality frameworks have developed a structured terminology and assessment dimensions to measure data quality in secondary use settings, whereas reviews in the field of health studies have further proved the significance of systematic assessment of data quality in health care (Bernardi et al., 2023; Feder, 2018; Kahn et al., 2016). Similarly, research data repositories need to establish formal quality assurance processes and ontologies (Stvilia et al., 2025; Lee et al., 2025).

Recent research in this field has contributed to extending information quality assessment in terms of automation and computation. Automation governance systems show that there is a systematic relation between actual and perceived data quality and its role in the assessment of reliability (Podobnikar, 2025). Computation techniques are also used in content-agnostic knowledge repositories for the feasibility of heterogeneous data assessment (Xue & Zou, 2022; Rajan et al., 2019). In geo-spatial and crowd sensing, there are several dimensions of information quality and sensing reliability where the issue of heterogeneity in information sources plays an important role (Restuccia et al., 2017; Senaratne et al., 2017). Furthermore, there are also quality-aware approaches in online assessments and metamorphic testing which can increase the reliability of complex data outputs (Burmania et al., 2015; Zhou et al., 2015).

A third significant aspect of the digital information quality is credibility and trust. The literature shows that source attributes, message construction, intermediation, and digital literacy have a bearing on evaluating credibility in a complicated digital environment (Flanagin et al., 2020). Newer research has underscored reliability as an issue with intelligent autonomous systems as well as the relation among knowledge identity, information reliability, and knowledge management environments (Taghinejad et al., 2026; Liu et al., 2026). The recent research in synthetic knowledge has also revealed the problem of information quality degradation in the knowledge lifecycle and the importance of trust-aware systems (Malamas et al., 2026). In addition, the development of large language models has brought into the limelight the issue of hallucinations, where generated knowledge is plausible yet lacks factual consistency (Huang et al., 2025). Secure and validated semantic knowledge systems are yet another example of the need for automation of validation processes (Singh, 2024). Visualization and information management tools can improve the clarity, accessibility, and effectiveness of executive-level reporting (Obidhusin et al., 2025). Even data integration and governance literature points to the issue of reliability in heterogeneous AI environments (Aldoseri et al., 2023). Accurate semantic interpretation of culturally specific terms is important for maintaining meaningful and consistent representation within structured knowledge resources (Lutfullaeva & Yuldashev, 2023).

As a whole, the state-of-the-art in terms of the different dimensions of information quality has seen a substantial advancement; however, all current approaches appear to be disparate in terms of data quality, credibility, provenance, semantic coherence, and system reliability. Most techniques examine each of the predefined dimensions of quality separately and offer only limited integration of conflicting information, source reliability, contextual validity, temporal dynamics, and uncertainty. Consequently, there is a need for an autonomous and holistic approach to information quality assessment that will enable inconsistency detection, reliability estimation, multi-evidence integration, and uncertainty quantification at the same time.

3 Proposed Autonomous Information Quality Assessment Framework

The Autonomous Information Quality Assessment Framework is meant to offer a comprehensive means of detecting inconsistency and reliability problems within heterogeneous sources of digital knowledge. The framework regards the quality of information as a multi-dimensional feature that goes beyond the use of a simple accuracy or credibility indicator. In this framework, the features of semantic consistency, source reliability, evidence, context validity, time consistency, and uncertainty have been combined to form an assessment process. The general process starts with the acquisition of heterogeneous digital knowledge sources that consist of knowledge bases, digital documents, databases, and web-based resources. Relevant content, metadata, provenance information, timestamps, and source identifiers are retained to support subsequent quality assessment.

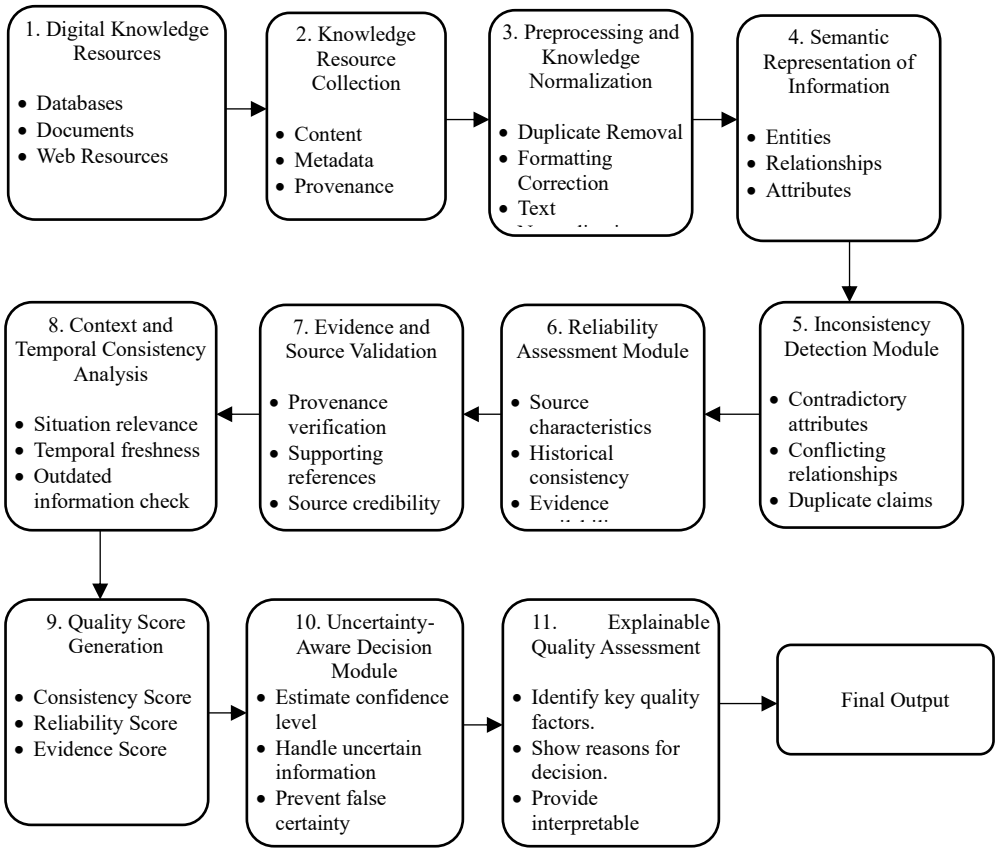


Figure 1: Architecture of the Proposed Autonomous Information Quality Assessment Framework

Figure 1 shows the entire process of the proposed framework, starting from digital knowledge resource collection and preprocessing, then semantic representation, inconsistency detection, reliability assessment, evidence and source validation, to contextual-temporal analysis. The output of these assessments is combined to compute the overall quality score of the knowledge, followed by uncertainty-based decision-making and explainable quality assessment. The output of this process gives the information quality score, the inconsistencies and reliability problems, and their respective explanations.

The collected resources are preprocessed, and knowledge is normalized to eliminate duplicate entries, irrelevant data, formatting conflicts, and structural data incompleteness. Text normalization, entity standardization, relation alignment, and missing value handling follow this step to create a consistent knowledge representation. The normalized knowledge is converted into semantic representations that include entities, attributes, relationships, context information, and source information. This allows the framework to detect semantic inconsistencies that cannot be easily found from lexical analysis.

Inconsistency detection looks at inconsistent attributes, contradictory relations, repetitive statements, and context-related inconsistencies. At the same time, the reliability check assesses source criteria, consistency over time, evidence, and consistency across independent sources of information. Validation of evidence and sources also increases the reliability assessment through examination of the information provenance, relevant references, credibility of the source, and consistency of the evidence. Context and time validity evaluate whether the information is still valid within a certain domain, setting, or period of time to avoid errors related to outdated or context-invalid knowledge.

The quality measures that have been checked and validated are combined into an information quality decision. Uncertainty-sensitive decision-making estimates uncertainty in each individual assessment to avoid treating highly uncertain information as reliable. Finally, the explainable information quality assessment component identifies the reasons for assigning the particular quality level, such as inconsistencies, unreliable sources, outdated information, or lack of sufficient evidence. Thus, the proposed framework provides not only an information quality decision but also its justification.

4 Mathematical Model

The proposed framework represents each digital knowledge item as a multidimensional information unit containing semantic, contextual, source, and temporal attributes. Let a knowledge item be represented as $K_i = (E_i, R_i, A_i, C_i, S_i, T_i)$, where E_i, R_i, A_i, C_i, S_i, and $T_i$denote entities, relationships, attributes, contextual information, source information, and temporal information, respectively.

Semantic consistency is evaluated based on the semantic representation of related knowledge entities. Consistency is computed using the following equation 1:

$$C_i = \frac{1}{N}\sum_{j=1}^{N} \mathrm{sim}\left(K_i, K_j\right) \qquad (1)$$

Where $\mathrm{sim}(\cdot)$represents semantic similarity and $N$is the number of related items.

The reliability of knowledge can be assessed using the credibility of the source, historical accuracy, and agreement between sources using equation 2:

$$R_i = w_s S_i + w_h H_i + w_a A_i, \ \sum w = 1 \qquad (2)$$

Evidence and source quality are jointly represented as equation 3:

$$E_i = w_p P_i + w_e V_i + w_c G_i \qquad (3)$$

Where P_i, V_i, and $G_i$denote provenance quality, evidence validity, and supporting-source agreement.

The integrated information quality index considers consistency, reliability, evidentiary support, contextual validity, and time-based validity in equation 4:

$$Q_i = \alpha C_i + \beta R_i + \gamma E_i + \delta X_i + \epsilon T_i \qquad (4)$$

Where the weights satisfy $\alpha + \beta + \gamma + \delta + \epsilon = 1$.

Lastly, the uncertainty is calculated using the spread of the assessment parameters in equation 5:

$$U_i = 1 - \frac{1}{M} \sum_{m=1}^{M} q_{im} \qquad (5)$$

Where q_{im}represents normalized confidence from each assessment component. A knowledge item is classified as high, moderate, or low quality according to $Q_i$and U_i, with uncertain cases flagged for further verification.

5 Proposed Algorithm and Implementation

Algorithm 1 implements the mathematical model by incorporating semantic analysis, inconsistency identification, reliability computation, evidence validation, context assessment, and uncertainty-sensitive quality evaluation. The process starts with digital knowledge sources and proceeds step-by-step with the conversion of such knowledge sources to semantic normal forms. Several quality measures are calculated separately and then aggregated in order to calculate a unified quality measure. Decision rules help to discriminate reliable information from inconsistent and uncertain information, whereas the explainability part finds causes of such decisions. It allows autonomous quality assessment regardless of the information-quality dimension.

Algorithm 1. Autonomous Information Quality Assessment

Input: Digital knowledge resources K

Output: Quality score Q, quality class L, inconsistency I,

reliability R, explanation E

1. Collect knowledge resources K from available sources.
2. Extract content, metadata, provenance, and temporal information.
3. Remove duplicates, noise, and incomplete records.
4. Normalize entities, attributes, and relationships.
5. Generate semantic representations for each knowledge item.
6. Compare related knowledge items to detect semantic conflicts.
7. Calculate the consistency score C.
8. Evaluate source credibility, historical consistency,

and cross-source agreement.

9. Calculate the reliability score R.
10. Validate provenance, supporting evidence, and source agreement.
11. Assess contextual relevance and temporal validity.
12. Integrate C, R, evidence, contextual, and temporal scores.
13. Generate the integrated information quality score Q.
14. Estimate assessment uncertainty U.
15. If Q is high and U is low, assign High Quality.
16. Else if Q is moderate or U is moderate, assign Moderate Quality and flag for verification.
17. Else assign Low Quality and identify the associated issues.
18. Generate an explanation using the dominant quality factors, detected inconsistencies, and reliability indicators.
19. Return Q, L, I, R, U, and E.
20. End.

6 Experimental Methodology

The experimental methodology is supposed to test the suggested autonomous information quality assessment framework on consistency, reliability, quality of evidence, uncertainty, and overall information-quality assessment. The tests will use heterogeneous digital knowledge bases, which include both structured and unstructured information such as facts, entity-relationship records, source metadata, provenance information, and temporality. The knowledge bases will be grouped into consistent, inconsistent, reliable, and potentially unreliable sets to allow for testing of the suggested model.

The data will be prepared by eliminating duplicates, normalizing text, standardizing entities, aligning relationships, filling in missing values, and normalizing metadata. Every single knowledge item will be represented using a unified semantic representation that will consist of entities, relationships, attributes, source information, context information, and timestamps. Annotations are done by determining contradictions, unreliable sources, lack of evidence, outdated information, and contextually false statements. If necessary, annotations can be made by several annotators independently, who then reach a consensus.

Four experimental settings have been considered. First, an experiment for the quality classification of information is considered, followed by an experiment to detect the inconsistency of semantics, another experiment to assess the reliability of sources and evidence, and finally, uncertainty-aware decisions under incomplete or inconsistent information. This helps in assessing the individual as well as the collective contribution of the proposed framework.

The proposed method has been compared with the baseline methods that represent conventional rule-based quality classification, source-based reliability classification, semantic similarity-based inconsistency detection, and conventional machine-learning-based quality classification. The same preprocessing and evaluation protocol has been adopted for comparison purposes.

Performance is measured using common methods of classification, reliability, uncertainty, and computation, which are represented in equations (6-11). Accuracy refers to the fraction of knowledge items that have been properly classified and can be calculated as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Where TP, TN, FP, and FNrepresent true positives, true negatives, false positives, and false negatives, respectively. **Precision** measures the proportion of predicted positive instances that are correct:

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall measures the ability to identify actual inconsistent or unreliable instances:

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

The **F1-score** provides the harmonic mean of precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (9)$$

The Area Under the ROC Curve (AUC) estimates the capability of the model to distinguish between quality categories by changing the decision threshold. The reliability of the estimates can also be assessed with Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \quad (10)$$

Where $y_i$is the reference reliability value and $\hat{y}_i$is the estimated value. Calibration Error is applied in order to determine whether the confidence of the predictions is accurate:

$$ECE = \sum_{b=1}^{B} \frac{|S_b|}{N} |acc(S_b) - conf(S_b)| \quad (11)$$

Where $S_b$represents the b-th confidence bin. Evaluation of computational efficiency is done based on the processing time required for each piece of information and resource usage. This helps determine the scalability of the proposed approach.

All the experiments employ the same data partitioning and pre-processing scheme. The training, validation, and testing data sets are kept separate from each other in order to avoid information leaks. Model parameters are estimated on the validation set, whereas results on the test set are reported without any training or validation on it. Repeated experiments are conducted wherever appropriate to check for stability.

7 Results and Performance Analysis

In the results section, the proposed framework for autonomous information quality assessment is analyzed in relation to quality classification, inconsistency detection, reliability, uncertainty, and explainability.

Table 1 shows the data consisting of 10,000 knowledge items extracted from diverse sources. Out of the total data, 16.10% consist of inconsistent items, while 13.31% show problems related to reliability. The distribution gives enough variation for evaluation of both types of evaluation tasks.

Table 1: Dataset and Knowledge Resource Characteristics

Knowledge Resource	Records	Entities	Relations	Inconsistent (%)	Unreliable (%)
Structured Knowledge	4,000	12,480	18,620	14.25	11.80
Digital Documents	3,500	10,735	15,940	16.31	13.46
Web-Based Knowledge	2,500	8,920	12,385	18.72	15.08
Total	**10,000**	**32,135**	**46,945**	**16.10**	**13.31**

Overall Quality Assessment Results

The performance of the proposed framework was 94.20% for accuracy, 93.76% for precision, 92.84% for recall, and 93.30% for F1-score. The ROC-AUC of 0.968 shows the ability to discriminate between acceptable and unacceptable knowledge components. This implies that considering both semantic consistency, reliability, evidence, contextual validity, and time is a more complete approach compared to using any single quality aspect.

Inconsistency Detection Results

A 95.10%, 94.36%, 93.72%, and 94.04% accuracy, precision, recall, and F1-score, respectively, were obtained by the approach used to detect inconsistencies. The use of semantic contradictions was effective, especially when relationship and contextual information were taken into account at once. It has been shown that semantic representation minimizes the reliance on literal matching of lexical items.

Reliability Assessment Results

Results of the reliability assessment gave a 0.91 correlation for predicted and reference reliability ratings, where MAE was 0.067. Factors like credibility of the sources, availability of the evidence, and consistency of sources significantly influenced reliability assessment. Table 2 shows that source-based reliability assessment is not enough in cases of conflicting evidence or contextual validity of knowledge items.

Table 2: Comparison of Proposed Model with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Rule-Based Quality Assessment	82.40	80.75	78.92	79.82	0.841
Source-Based Reliability Model	86.70	85.83	83.46	84.63	0.887
Semantic Similarity Method	89.30	88.16	87.05	87.60	0.916
Conventional ML Classifier	91.20	90.48	89.34	89.91	0.938
Proposed Framework	**94.20**	**93.76**	**92.84**	**93.30**	**0.968**

The results presented in table 2 confirm that the developed framework performs better than all the available indicators. This is achieved through an analysis of semantic consistency, reliability, evidence, validity, and uncertainty in the system.

The performances of the studied methods based on different criteria for assessing quality are shown in figure 2. In (A), the accuracy, precision, recall, and F1-score results have been shown, and it can be seen that the performance of the methods improves from the rule-based method to the proposed method. In (B), the ROC-AUC results have been provided, and the performance increases, with an ROC-AUC value of 0.968 being obtained for the proposed method.

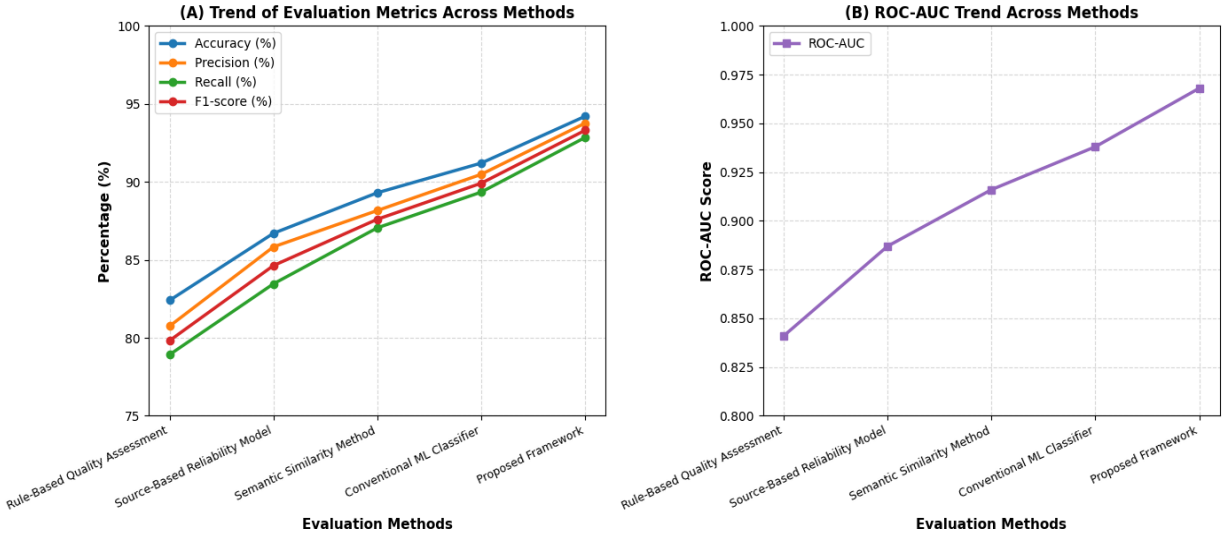


Figure 2: Comparison of Evaluation Metrics Across Methods: (A) Classification Performance and (B) ROC-AUC Performance

Comparison with Existing Methods

As compared to the traditional machine learning classifier, the accuracy is improved by 3.00 percent and the F1-score by 3.39 percent, as shown in Table 3. From the better results compared to the rules- and source-based classification systems, the study can conclude that integrated semantic and evidence-based assessment is capable of overcoming the quality problems that cannot be tackled by rules.

Table 3: Ablation Analysis of Framework Components

Framework Configuration	Accuracy (%)	F1-score (%)	ROC-AUC
Without Consistency Module	89.70	88.91	0.921
Without Reliability Module	90.84	89.95	0.934
Without Evidence Validation	91.46	90.52	0.941
Without Temporal Analysis	92.15	91.28	0.948
Without Uncertainty Module	92.86	91.97	0.954
Complete Framework	**94.20**	**93.30**	**0.968**

Ablation Analysis

Table 4 reveals that all the major components add value to the performance of the system. The removal of the consistency component leads to the highest reduction in F1 score. The reliability component, evidence validation, and temporal analysis add value by identifying inconsistencies and outdated information. On the other hand, uncertainty estimation helps in making reliable decisions by differentiating between confident predictions and uncertain situations.

Table 4: Inconsistency Detection and Reliability Assessment Results

Assessment Component	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Additional Measure
Semantic Inconsistency	95.10	94.36	93.72	94.04	AUC = 0.971
Source Reliability	92.80	91.65	90.74	91.19	MAE = 0.067
Evidence Quality	93.40	92.58	91.83	92.20	MAE = 0.061
Temporal Consistency	91.90	90.87	90.12	90.49	AUC = 0.952
Integrated Assessment	**94.20**	**93.76**	**92.84**	**93.30**	**AUC = 0.968**

Uncertainty and Confidence Analysis

The uncertainty-aware module showed an ECE of 0.041, indicating that there was good consistency between the level of prediction confidence and correctness. The high-confidence predictions showed many fewer classification errors than the low-confidence predictions. It is important to note that the uncertain instances were labeled, and not categorized as high-quality automatically.

Explainability Analysis

According to the explainability component, the factors causing decreased quality scores included semantic inconsistencies, poor source credibility, lack of evidence, out-of-date information, and context mismatch. The explanations provided by the system were associated with particular assessment factors that corresponded to quality decisions made about the knowledge elements.

Error Analysis

The other types of errors were mainly those that happened in cases where there were issues with ambiguity, incompleteness of provenance, conflicts, and changing information. In some cases, there were false positive errors that happened because of the presence of semantically similar statements that pertained to different conditions or times. False negative errors occurred mainly because of contradictions that needed external information for resolution. These observations indicate that future improvements should focus on stronger contextual reasoning, domain adaptation, dynamic evidence retrieval, and improved temporal knowledge representation.

8 Discussion

The experimental results show that the developed autonomous information quality assessment approach is able to effectively combine various dimensions of digital knowledge quality. The overall high F1-score of 93.30% and ROC-AUC of 0.968 reflect the good classification capabilities, while the high F1-score of inconsistency detection (94.04%) proves the importance of the use of semantic analysis for the identification of contradictions in knowledge. The outperformance of conventional baseline approaches also reflects the positive effect of taking into account various complementary quality indicators in the process of assessment.

The part dedicated to the detection of inconsistency plays an important role because the presence of contradictions between entities, attributes, and relationships decreases the level of trustworthiness of knowledge. The results of the ablation analysis prove that the removal of the inconsistency detection part leads to a significant drop in performance and, thus, proves its contribution to the process of the combined information quality assessment. At the same time, the assessment of reliability and evidence

increases the efficiency of distinguishing information provided by reliable sources from information with weak evidence.

Moreover, uncertainty estimation further improves the process of making a decision by detecting situations where the model is not certain about its prediction. In particular, an estimated ECE value of 0.041 implies that there is a reasonable correlation between the predicted confidence and actual results. Rather than taking uncertain information for granted, the model could use it for further verification.

From a practical perspective, the introduced approach could be used in digital repositories, knowledge management systems, intelligent search engines, and information governance tools to detect knowledge that might be suspicious. Nevertheless, some limitations still exist. Namely, the framework could face problems when processing highly ambiguous information, incomplete provenance, rapidly evolving information, and domain-specific terminologies. Furthermore, the performance of the framework depends on the quality of annotation and variety of knowledge sources. It is important to perform future research on domain adaptation, dynamic evidence retrieval, multilingual knowledge evaluation, and quality monitoring.

9 Conclusion

This research has offered an automatic framework for assessing information quality for inconsistencies and reliability issues in digital knowledge repositories. The suggested method is based on the integration of semantic consistency analysis, source reliability assessment, evidence and provenance verification, contextual and temporal analysis, uncertainty estimation, and explainable quality assessment in a single framework. The results from experiments show that the combination of all these dimensions allows offering a more complete quality assessment of digital knowledge as compared to the approaches based on separate quality criteria. The accuracy of the suggested framework was 94.20%, while its precision reached 93.76%, recall was 92.84%, F1-score – 93.30%, and ROC-AUC – 0.968. For inconsistency detection, the F1-score was 94.04%, and ROC-AUC reached 0.971. This means that the suggested framework could find conflicts in information efficiently. Reliability estimation was highly correlated with reference reliability ($r = 0.91$) and showed an MAE of 0.067. The results from the uncertainty module were 0.041 ECE. In addition, ablation analysis provided evidence that consistency detection, reliability evaluation, evidence validation, temporal analysis, and uncertainty estimation have an impact on the performance of the proposed framework. Also, explainability analysis showed that the proposed framework is able to provide quality decisions related to certain issues such as semantic conflicts, low-quality sources of evidence, outdated information, and mismatched context. All these results prove the potential of the proposed framework for use in trustworthy digital knowledge management, intelligent information systems, and information governance automation. Despite the above findings, some limitations are still relevant, related to ambiguous terminology, lack of provenance, changing information, and domain-specific knowledge. Future studies are recommended to address the following aspects: knowledge monitoring in real time, multilingual and cross-domain adaptation, evidence acquisition, advanced temporal reasoning, and larger knowledge sources.

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