Ontology-Grounded Fact-Checking for E-Commerce: A Neuro-Symbolic, Claim-Centric Approach[*]

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Abstract

Misinformation in e-business—discounts based on volatile prices, fictitious stock levels, erroneous certifications, and implausible delivery commitments—erodes trust, competition, and regulatory adherence. This study introduces EBFN-Detect, a neuro-symbolic framework for claim-centric verification that incorporates a domain ontology (EBFN-O), a commercial knowledge graph, and natural language processing models. The pipeline extracts claims from diverse sources, conducts entity linking for products, brands, and sellers, retrieves ontology-guided evidence (RAG on KG), and assesses truthfulness by integrating a claim-evidence aware classifier with symbolic verifications of temporal consistency, price plausibility, and regulatory compliance. The output generates calibrated probabilities and verifiable explanations derived from supported or refuted chains with provenance. The work delineates the method, introduces EBFN-O in accordance with schema.org/GoodRelations/PROV-O, presents a multi-source corpus annotated at three tiers (claim, linking, truth) with reproducible guidelines, describes a RAG+KG pipeline featuring transparent fusion and calibration, and proposes an evaluation protocol that integrates metrics of accuracy, retrieval quality, and explanatory utility. Consequently, EBFN-Detect demonstrates enhancements in macro F1 and Brier/ECE relative to pure neural baselines, exhibiting significant benefits in time-sensitive scenarios and in categories characterized by substantial variant ambiguity, thereby delineating a feasible approach to dependable, traceable, and contestable verification in digital commerce.

1 Introduction

The growing digitization of promotional and sales channels has heightened the exposure of consumers and economic agents to potentially deceptive content. Misinformation in e-business is evident through unrealistic discount calculations based on inflated reference prices, availability claims unsupported by actual inventory, improper use of trademarks or certifications, non-compliant delivery

assurances and return policies, and unsubstantiated technical performance assertions. These practices erode trust in marketplaces, incur compliance costs and sanction risks, and, most importantly, distort competition(Colace, Lombardi, Pascale, & Santaniello, 2018; Gaeta et al., 2024; Grimaldi et al., 2022; Kotonya & Toni, 2020). This study adopts a claim-centric perspective, defining a "claim" as a verifiable assertion about entities within the domain—product, brand, seller, or offer. We classify claims along a truth axis comprising "true," "false," "misleading," and "unverifiable," with the intermediate category encompassing instances where the statement is partially accurate yet presented out of context or in a misleading manner(Casillo et al., 2024; Jiang et al., 2020).

Technological advancements in neural NLP have enhanced the efficacy of text classification; however, they exhibit limitations in scenarios necessitating semantic grounding, numerical-temporal reasoning, and traceable explanations. Standard e-business verifications rely on the exact correspondence between text and entities (SKUs, variants, bundles), jurisdictional and temporal validity constraints, and access to diverse evidence, including unstructured documents, semantic markup (e.g., JSON-LD), historical pricing data, commercial policies, and comparison pages(Gaeta et al., 2025b; Karpukhin et al., 2020). The dynamic nature of promotional language introduces drift phenomena that necessitate robust systems to manage variation in style and communication strategies(Cantone et al., 2023; Gaeta et al., 2025a; Wu et al., 2020).

This research is motivated by the necessity to integrate accuracy, transparency, and robustness: a system is required to identify deceptive statements prevalent in transactional contexts consistently; concurrently, decisions must be explicable and subject to challenge to facilitate internal audits, consumer protection, and regulatory oversight, while minimizing costs associated with complaints, penalties, and erosion of trust.

To tackle these challenges, we propose EBFN-Detect, a neuro-symbolic framework that amalgamates a domain ontology and a knowledge graph with contemporary NLP models (Colace, Lombardi, Pascale, Santaniello, et al., 2018). The primary concept is to integrate the extraction of claims and their association with a knowledge graph alongside semantically guided evidence retrieval (Retrieval-Augmented Generation on graph) and an assessment of veracity achieved by amalgamating neural signals with symbolic rules that delineate constraints of temporal consistency, price plausibility, and regulatory compliance(Cicalese et al., 2024; Colace et al., 2019; Graziuso et al., 2020). This integration enhances the precision and calibration of predictions while generating verifiable explanations through chains of evidence that substantiate or contradict each assertion, facilitating informed audits and disputes(De Simone et al., 2022).

The objectives of this work are fourfold and interrelated: to define and release EBFN-O, an ontology for misinformation in e-business that aligns with established vocabularies (schema.org, GoodRelations, PROV-O) to ensure interoperability and traceability; to construct a multi-source annotated corpus that distinctly differentiates between claim extraction, ontological linking, and truth labeling; to design and assess an architecture that integrates RAG on knowledge graphs with neural classifiers and symbolic checks to achieve explainable and accurately calibrated decisions; and finally, to establish a comprehensive benchmark with metrics for classification, calibration, and evidence retrieval, supplemented by ablation studies and robustness tests to isolate the contributions of individual components.

The proposal facilitates immediate applications. Proactive validation of commercial assertions and subsequent diminution of grievances and sanctions; enhanced consumer transparency through verifiable elucidations; assistance for regulatory bodies with comprehensive traceability of origins. The following chapters delineate related work, methodology, ontology, data collection/annotation decisions, the evaluation protocol accompanied by error analysis, an ethical discourse highlighting primary limitations, and ultimately, the conclusions alongside prospects for real-world implementation.

2   Related works

The way research is done on identifying misinformation and automated fact-checking has evolved. It has moved from being centred on documents and phrases to being centred on claims. It also uses systems that retrieve and verify evidence. The previous approach treated disinformation as a single textual classification issue, achieving favourable results on general datasets, but proving vulnerable when associating with real entities or requiring temporal or numerical reasoning (Clarizia et al., 2020; Zhou & Zafarani, 2021). The claim-centric approach has led to the development of benchmarks and pipelines in which the assertion serves as the analytical unit and truth is evaluated based on external evidence, as demonstrated by FEVER(Thorne et al., 2018) . However, most resources continue to focus on news and politics, paying little attention to the transactional contexts characteristic of e-business.

At the same time, organised knowledge has become increasingly crucial in retrieving evidence and reasoning: knowledge graphs reduce the hallucination of neural models and improve retrieval precision, especially when entity linking is a fundamental part of the process (Hogan et al., 2022). KG-augmented methodologies combine entity linking, structured queries, and neural networks on graphs to disseminate signals among entities and relations (Schlichtkrull et al., 2018), as well as embeddings such as ComplEx for link prediction. However, the integration of e-business is still limited: encyclopedic graphs effectively represent generic entities, but often fail to encapsulate commercial specifics (SKUs, bundles, time-sensitive offers) or the connection between promotional assertions and their regulatory and market origins(Guha et al., 2016; Hepp, 2008).

Advancements in Transformers have facilitated hybrid strategies in which the neural component is 'grounded' by retrieval-augmented pipelines: evidence obtained from document engines or graphs informs generation or classification, thereby reducing reliance on text statistics alone. However, structural issues persist, including the precise alignment of mentions with product, brand, and seller identities, the explicit consideration of temporal factors such as price validity and promotional periods, numerical plausibility concerning historical data, and modelling compliance regulations that differ by jurisdiction. These elements are crucial to e-business, yet they are rarely formalised as symbolic constraints during decision-making (Hogan et al., 2022; Schlichtkrull et al., 2018).

Another issue is explainability and calibration: although techniques and generated explanations improve readability, their accuracy concerning the decision-making process is often questioned. At the same time, metrics such as ECE and Brier score are sometimes disregarded, despite their importance when confidence scores affect operational workflows (Atanasova et al., 2020; BRIER, 1950).

In high-stakes situations like marketplaces, it is crucial that the estimated probability accurately represents the actual risk, and that the explanations are verifiable and traceable(Baker et al., 2013; BRIER, 1950; CHESÑEVAR et al., 2006).

The literature offers essential components—claim-centric verification, KG-enhanced retrieval, ontological standards for commerce, and methods for explainability and calibration—yet reveals a deficiency at the convergence of these domains within e-business. The primary deficiencies pertain to the absence of claim-centric datasets with verifiable provenance and distinct claim categories (price, availability, certifications), the nascent application of ontologies as a cohesive and explicable reasoning framework, and the insufficient focus on calibration in actual decision-making contexts. The proposed framework precisely occupies this domain, integrating ontology and commercial knowledge graphs to facilitate retrieval and consistency verification, amalgamating neural and symbolic elements for truthfulness assessment, and ensuring decision-making is auditable via chains of evidence.

3 Methodology

The proposed methodology, EBFN-Detect, integrates neural and symbolic components within a pipeline comprising distinct yet closely interconnected steps. The concept involves treating each statement as an object extracted from the text, grounding it concerning domain entities and constraints, and verifying it against pertinent and traceable evidence. The pipeline (Fig. 1) initiates with the ingestion of sources (advertisements, product pages, social commerce, comparison sites, press releases), wherein each document is normalized (HTML/JSON-LD), deduplicated, and augmented with temporal and provenance metadata. At this juncture, any semantic markups (e.g., Product, Offer, AggregateOffer, or ClaimReview) are converted into candidate triples and associated with a "commercial" knowledge graph encompassing products, brands, sellers, offers, and domain regulations.

We implement a claim extraction module on the standardized text, functioning in two phases: a language model (seq2seq or classifier with span extraction) detects sentences containing verifiable assertions, followed by a refiner that nominalizes the content into a structured format, delineating the propositional component (e.g., 'Product X is 70% off until Sunday') and semantic arguments (entities, quantities, dates, conditions). This representation is transmitted to semantic linking, which correlates mentions with entities in the graph (SKU, variants, merchants, campaigns) utilizing a hybrid engine: A primary stage of dense/lexical retrieval narrows down the candidates, while a neural reranker functions pairwise between the mention and the entity profile; in cases of ambiguity, the system prefers resolutions that align with binding attributes (category, brand, region, time frame).

Upon alignment of the claim, the system commences ontology-driven evidence retrieval. In this context, formal knowledge functions as a "semantic filter": the category of the assertion (price, availability, certification, delivery promise, returns, warranty) dictates the permissible sources and the constraints that must be adhered to (e.g., for a discount, the validity of the reference price within a prior timeframe; for a delivery promise, the geographical scope of the courier; for a certification, the inclusion of the certificate in recognized registries). The retrieval integrates structured queries on the graph (for relationships and attributes) with document searches on a textual index; the outcomes are consolidated into a "file" of evidence containing citations, timestamps, and provenance chains.

The veracity estimate is obtained from the amalgamation of two signals. The initial component is neural: a claim-evidence aware model assesses the coherence between the assertion and the evidence set, generating a distribution of labels (true, false, misleading, unverifiable). The second is symbolic: a compilation of checks that conducts deterministic or probabilistic validations on domain rules, numerical and temporal consistency, and regulatory adherence. These evaluations produce comprehensible scores (e.g., "reference price unstable for N days" or "lack of certificate in the official registry"), which are consolidated through a straightforward yet transparent fusion function (e.g., a linear combination with optimized weights, or supervised logistic stacking). To render the score applicable in decision-making, we implement a post-hoc calibration that adjusts the estimated probabilities to correspond with the observed empirical frequency, ensuring that thresholds and escalation policies accurately represent actual risk.

Explanations are generated by assembling a concise claim-oriented 'evidence set': the pipeline identifies several representative pieces of evidence and links them through ontological relations (supports/refutes/derivedFrom/validDuring), creating a coherent narrative that justifies the conclusion (e.g. "the 70% reduction is based on a price that lacks stability within the specified timeframe," accompanied by references to excerpts and price charts). When the neural model and symbolic evaluations are incongruent, the system highlights the discrepancy and indicates significant uncertainty, prioritizing human assessment.

The neural models are trained using a composite objective that integrates classification loss, semantic robustness terms (contrastive learning on challenging negatives from similar products), and, when applicable, a penalty for inadequate calibration. To prevent spurious dependencies, the sampling

of negative evidence is regulated: for each claim, pertinent yet inconclusive documents are incorporated, and realistic perturbations (promotional paraphrases, minimal numerical variations) are introduced to enhance resilience against pattern shortcuts. The symbolic component is constructed as a versioned knowledge base: the rules are articulated in declarative format, evaluated through property-based testing on synthetic scenarios, and subjected to canary assessment using simulated real traffic to guarantee that domain evolution (new campaigns, revised legal terms) does not impair performance.

From an infrastructural perspective, the knowledge graph is refreshed via regular ETL processes and quality assurance measures (consistency of identifiers, sameAs relations with external catalogs, management of variants). Entity IDs and page versions facilitate traceability: every decision is reproducible as queries on the graph and indexes are documented alongside the temporal snapshot of the sources. Ultimately, to reduce operational application, the system output comprises the label, the calibrated probability, a structured explanation with citations, and a collection of symbolic flags indicating the checks that have been passed or failed; this framework enables both automation (e.g., obstructing high-risk campaigns) and effective human auditing.
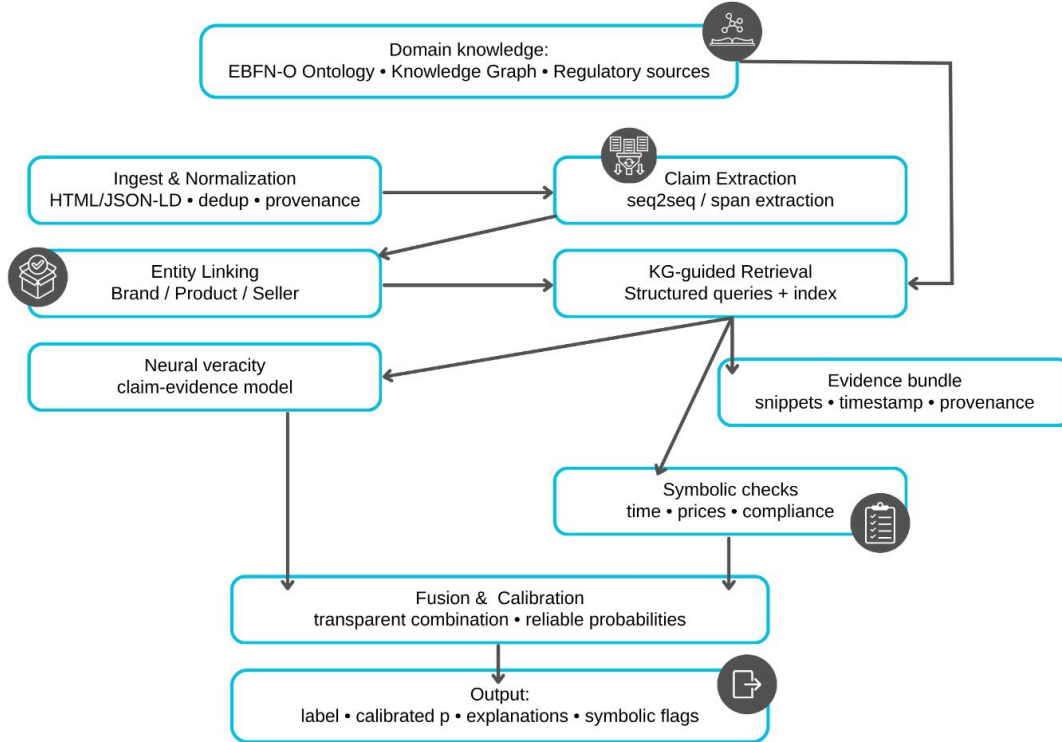

Fig. 1 Pipeline of EBFN-Detect**.**

4 Support ontology

The EBFN-O ontology delineates the concepts and relationships essential for validating standard e-business assertions, preserving connections to sources, context, and constraints for each decision-making process. The core is distinctly claim-centric: each claim pertains to one or more entities within the domain (product, brand, seller, offer) and is associated with evidence that substantiates or contradicts it, maintaining its provenance and temporal relevance. To guarantee interoperability, EBFN-O conforms to recognized vocabularies: schema.org for products, offers, and ClaimReview; GoodRelations for commercial attributes and offer classifications; PROV-O for traceability; AIF for the supports/refutes argumentative framework; SKOS for taxonomy administration (claim types, product categories, source types). The design prioritizes three attributes: (i) Verifiability—each supporting or refuting arc must be substantiated by quotable excerpts and provenance metadata (URI, timestamp, version); (ii) Explicit constraints—temporal factors, pricing, and regulatory compliance are depicted as inspectable relationships and attributes; (iii) Minimal assumption—elementary axioms that facilitate consistency reasoning without enforcing obscure inferences.

The competency questions that direct EBFN-O exemplify our domain: What evidence substantiates or contradicts a discount claim for a particular product within a defined jurisdiction and temporal framework? Has the reference price utilized in the promotion remained consistent for the designated duration? Does the delivery commitment align with logistics capabilities and shipping terms? Addressing these inquiries necessitates classes including Claim, Evidence, Product, Offer, Price, Promotion, Certification, Jurisdiction, Regulation, Source, and MediaItem, along with relationships such as claimsAbout, supports, refutes, derivedFrom, validDuring, hasPrice, hasReferencePrice, soldBy, and sameAs. A statement like "–70% off Product X until Sunday" will be based on the accurate SKU, supplemented with the promotional timeframe, associated with historical pricing data, and verified against the criteria establishing the validity of the price reference.

The ontology facilitates reproducible queries by offering SPARQL query patterns on graphs that integrate structured searches (e.g., obtaining all supporting/refuting evidence along with associated derivedFrom and validDuring) alongside filters for jurisdiction and temporal intervals. The commercial knowledge graph utilized by EBFN-O is informed by product, brand, and seller identities, which correspond to external catalogs (via sameAs) and temporal versions of pages, ensuring verifications align with the web's state at the time of the assertion.

The corpus is constructed by amalgamating various authentic sources: advertising creatives, social commerce posts, product pages, promotional landing pages, official brand press releases, blogs, feeds, price comparison sites, technical data sheets, and fact-checking pages featuring ClaimReview. The ingestion process consolidates formats (HTML, JSON-LD, PDF), implements deduplication and normalization, extracts temporal metadata, preserves snapshots and original URIs for complete reproducibility, and retrieves existing semantic markup (e.g., Product/Offer/AggregateOffer). Without complete markup, automated extraction processes obtain entities, numerical attributes (such as prices, discount percentages, and quantities), and temporal references, which are subsequently aligned with the commercial knowledge graph.

To mitigate bias and leakage, sampling encompasses various product categories, price ranges, and publication channels, while restricting the occurrence of multiple variants of the same product within a single partition. Each document includes metadata specifying language, country/jurisdiction, collection timestamp, and, when applicable, page version.

Annotation occurs in three synchronized phases. Initially, claim extraction involves the annotator identifying the minimal span that conveys a verifiable assertion and documenting a normalized format (subject–predicate–arguments), while also noting the claim type (price, availability, certification, delivery promise, returns/warranty, performance) and contextual elements (date(s), conditions, geographical area). Secondly, ontological linking: the textual reference is anchored to Product/Brand/Seller/Offer within the graph, incorporating pertinent attributes such as

hasPrice/hasReferencePrice, validDuring, inJurisdiction, soldBy, and clarifying ambiguities between SKUs and variants. Third, truth labeling: the assertion is categorized as true, false, misleading, or unverifiable; in cases of dishonesty, the specific factor is identified (e.g., improper calculation basis, lack of context, variant ambiguity, etc.). Every annotation must comprise at least two pieces of evidence accompanied by verifiable citations and a chain of origin (PROV) to facilitate auditing and reanalysis.

An external reviewer assesses Quality through dual annotation and conflict resolution; we evaluate concordance using Cohen's κ or Krippendorff's α for both the claim type and the truth label. Persistent ambiguities necessitate revisions to the guidelines with illustrative positive and negative examples. Regarding compliance, we implement data minimization, pseudonymization of personal data, and a restricted retention policy in accordance with the GDPR; all removal and anonymization decisions are documented in the provenance graph.

The train/dev/test split is conducted by source and product family to enhance robust evaluations, minimizing spurious correlations and promoting generalization. A typical configuration comprises 10,000 documents in the training set (approximately 25,000 claims), 2,000 in the development set (approximately 5,000 claims), and 2,000 in the test set (approximately 5,000 claims), ensuring balanced distributions by claim type and language. Alongside fundamental statistics (document/claim count, average length, label distribution), we will provide metrics on linking coverage (percentage of claims with disambiguated entities), evidence completeness (evidence per claim), and temporal latitude (frequency of verifications necessitating historical data).

ID	Question
CQ1	What evidence supports or refutes a claim of a **discount** on a product in a specific **time frame** and **jurisdiction**?
CQ2	Has the **reference price** used to declare the discount remained **stable** for the period required by applicable legislation?
CQ3	Is a **delivery promise** consistent with the stated **logistical coverage**, **geographical area**, and **conditions**?
CQ4	Is the use of a **certification/mark** supported by a **record in the official register** and is it **valid** for the period indicated?
CQ5	Are the statements regarding **availability** ('in stock') consistent with the seller's **historical stock data** and **lead times**?
CQ6	Are there any **numerical inconsistencies** (unit price vs quantity; discount vs final price) that make the claim **misleading**?

Table 1: Competency Questions (CQs)

4.1 Error assessment and analysis

The assessment of the EBFN-Detect system seeks to quantify predictive accuracy, evidence retrieval quality, probability calibration, and explanatory utility in realistic operational contexts in a balanced fashion. Data partitioning adheres to criteria based on source and product family to prevent overly optimistic estimates, thereby minimizing spurious correlations between training and testing data and promoting generalization to analogous yet distinct domains. All outcomes are presented as means and standard deviations across various seeds, with confidence intervals derived from bootstrap methods and statistical comparisons between models conducted using non-parametric tests when applicable.

The primary metric for veracity classification is the macro F1 score, selected to equilibrate potentially imbalanced classes such as misleading and unverifiable, supplemented by AUC-ROC for a

threshold-independent perspective and micro F1 for overall performance assessment. Given that the system's decisions initiate subsequent actions (campaign suspension, human audit, request for correction), probability calibration is pivotal: we employ the Brier score as a comprehensive metric of probabilistic accuracy and assess the Expected Calibration Error through adaptive binning, supplemented by reliability diagrams that illustrate the disparity between average confidence and empirical frequency. Calibration is conducted post-hoc on the fusion model to represent the behavior of the entire system rather than solely the neural component. It is also validated within specific subgroups (product category, language, jurisdiction) to detect systematic variations.

Evidence retrieval is assessed independently to analyze errors: for each claim, we examine precision@k and nDCG@k concerning a minimal set of snippets identified as necessary and sufficient by the annotators; furthermore, we evaluate recall in greater detail to gauge potential coverage. The quality of explanations is evaluated on two dimensions: fidelity and utility. Fidelity is assessed by examining the alignment between the signals that influenced the decision (activated symbolic rules, significant neural evidence) and the elements presented to the user; usefulness is evaluated through a double-masked human judgment in which expert annotators determine whether the outcome seems justified and verifiable based on the explanations provided. When there are discrepancies between internal reasoning and the provided explanation, the system is deemed under-explained, even if the prediction is accurate, as transparency is essential in regulated environments.

The test defines robustness by incorporating adverse conditions derived from actual instances: promotional paraphrases featuring lexical and rhetorical variations, numerical micro-perturbations altering discounts and prices by minimal percentage points, temporal shifts undermining the validity of promotional windows, and out-of-distribution scenarios in novel product categories. In these situations, we document the relative decline of the primary metrics and the fluctuations in calibration, intending to discern where symbolic rules mitigate the vulnerabilities of the neural model and where, conversely, excessive constraints yield false negatives.

Ablation studies delineate the contributions of various components: by excluding the knowledge graph and retaining solely neural classification, the effects of grounding can be assessed; by omitting symbolic controls, reliance on domain rules can be evaluated; by turning off structured retrieval and substituting it with text-only search, the deficit resulting from the lack of ontological constraints can be quantified. Every configuration undergoes identical calibration protocols to guarantee comparability; when the F1 difference is minimal yet significantly enhances the Brier score and ECE, we favor the better-calibrated variant, as it is more appropriate for systems with fluctuating operating thresholds and priorities.

Error analysis provides a quantitative assessment by identifying prevalent failure types and their underlying causes. The initial group pertains to entity ambiguity, characteristic of products with closely resembling variants: linking errors result in the acquisition of accurate evidence for an incorrect SKU, yielding deceptive outcomes; in such instances, the incorporation of distinguishing attributes (capacity, color, bundle) in the entity profile mitigates confusion. A second category pertains to temporal dynamics: the disparity between the page timestamp and the discount regulatory window may render a claim seemingly valid that was not valid at the time of publication; thus, the explicit indication of validity throughout the entire evidence chain is essential. A third category pertains to numerical reasoning: discrepancies arising from rounding, taxes, or ancillary costs omitted from the final price may cause the neural model to classify true outcomes as false erroneously; the resolution entails the application of symbolic rules to standardize the calculation basis. A considerable number of errors arise from explanations that, while formally accurate, are deemed inadequate by annotators. Modifying the evidence selector to prioritize more self-sufficient snippets and contextually relevant citations enhances utility without affecting the decision-making process.

5 Discussions and limitations

Implementing EBFN-Detect in e-business environments necessitates stringent oversight of privacy, equity, transparency, and governance, alongside a comprehensive understanding of technical and operational constraints. Data collection adheres to the minimization principle: only the information essential for claim verification is obtained, retention periods are established, and accesses and modifications are monitored. The traceability of origin, structured with PROV, renders each verification auditable yet necessitates vigilance to prevent re-identification; consequently, quotable excerpts are segregated from comprehensive snapshots, modifying visibility according to usage. Fairness is evaluated through disaggregated assessments by product category, language, and channel; when discrepancies arise, adjustments are made for subgroups, and human intervention is implemented in areas of heightened uncertainty. Ontology is a focal point: taxonomies and mappings are versioned and documented to mitigate market or linguistic bias, and modification proposals are accepted via a formal review process.

Operational transparency entails that each decision is accompanied by a quantified probability, a verifiable rationale, and a disclosure of any informational deficiencies; individuals disputing the decision may present supplementary evidence, and the appeals results are integrated into the learning process to rectify persistent error patterns. Governance distinctly delineates the analytical engine from enforcement policies: the obstruction or moderation of campaigns is externally regulated, whereas modifications to ontology and graph undergo a request for alteration, review, and non-regression testing, with temporal versioning of the regulatory sources implemented.

There are definitive technical constraints. Regulations can be delicate: overly stringent rules produce false negatives, while excessively vague ones diminish their discriminatory efficacy. Synthetic test suites and progressive releases with canaries are therefore maintained. Domain drift—page formats, promotional language, regulatory frameworks—necessitates ongoing monitoring, regular retraining, and validity assessments for expiring claims. Numerical reasoning regarding prices and discounts is influenced by implementation specifics (rounding, taxes, additional costs): the symbolic element standardizes calculation foundations and clarifies assumptions, diminishing ambiguity among reference price, discount percentage, and final price. Reliance on external data, such as certification registries or stock feeds, results in delays and information deficiencies; in the absence of updates, the system generates conditional outcomes and refrains from excessively aggressive automation. Ultimately, adversarial risks exist, such as "price pulsing" or duplications with micro-linguistic variations, which are mitigated through anti-gaming controls, inter-source correlations, and semantic de-duplication.

Operational scalability necessitates a graph that is continuously updated through incremental ETL, curated sameAs alignments, and temporal page versions, alongside a stratified approach: employing light pre-filters for typical scenarios, conducting thorough checks beyond the risk threshold, and utilizing caching and materialized views for recurring evidence. All decisions are reproducible due to the documentation of queries, snapshots, and version parameters alongside the output. The roadmap anticipates the implementation of multilingual and multimodal extensions (including creative images, comparison tables, and visual badges), the enhancement of structured sources and ontological alignments, the fortification of numerical normalizations, and a regular red-teaming initiative to evaluate the system against real-world manipulation scenarios. This approach integrates specific practices—data minimization, disaggregated assessments, verifiable explanations, appeal mechanisms, and formalized governance—with a continuous improvement cycle that acknowledges existing limitations and converts them into a verifiable action plan.

6 Conclusions and future outcomes

This study introduced EBFN-Detect, a neuro-symbolic methodology for validating assertions in e-business, integrating domain ontology, knowledge graphs, and NLP models to generate precise, calibrated, and elucidated decisions. The salient characteristic is the transition from "isolated" textual classification to a claim-centric methodology, anchored in domain entities and constraints, and substantiated by verifiable evidence. The EBFN-O ontology offers the lexicon and constraints necessary to correlate discounts, availability, certifications, and delivery promises to queryable frameworks; the knowledge graph operationalizes these frameworks, facilitating a semantically informed retrieval that diminishes ambiguity and enhances the relevance of the evidence. Integrating neural elements and symbolic controls facilitates navigation through the ambiguities inherent in promotional marketing. At the same time, probabilistic calibration renders the outputs applicable in decision-making processes with varying thresholds and priorities. The methodological contribution includes a data quality initiative: a three-tier annotated corpus (claim, linking, truth) and an evaluation protocol that assesses not only accuracy and AUC but also Brier score, ECE, retrieval quality, and the utility of explanations, alongside robustness analysis and error taxonomy. The proposal incorporates operational practices concerning privacy, fairness, transparency, and governance, essential for adoption in regulated environments, alongside its technical components.

Future advancements proceed along three interrelated trajectories. The primary focus is on coverage: broadening the system to encompass additional languages and markets, incorporating multimodal signals (such as creative images, graphic badges, comparison tables, and screenshots with advanced OCR), and enhancing structured sources, including certification registers and vertical industry catalogs, to augment the breadth and precision of retrieval. The second aspect pertains to the rationality of reasoning: enhancing numerical standardization for pricing, discounts, and units of measurement; implementing anti-gaming mechanisms and inter-source correlations to mitigate strategies like price pulsing; investigating counterfactual explanations and more nuanced measures of uncertainty to provide the label with credible alternatives and absent conditions. The third guideline pertains to operational maturity: implement systematic retraining and drift monitoring, formalize synthetic and canary testing before each release, establish a closed-loop system of contestation and learning that converts appeals into new annotated examples; concurrently, design controlled studies (A/B) to assess the impact on complaints, audit durations, and erroneous removal rates, thereby informing the system's evolution with empirical evidence. In the future, a public, claim-oriented benchmark tailored to e-business, featuring traceable provenance and distinct product categories, is essential for consolidating results and enabling transparent method comparisons.

In conclusion, EBFN-Detect illustrates that integrating explicit knowledge and statistical learning is not merely an architectural decision, but a necessity for transitioning fact-checking from the "news" domain to the mechanisms that regulate trust in digital commerce. The trajectory is evident: enhanced structured and multimodal data, improved normalization; increased declarative reasoning, superior verifiability; augmented measures of uncertainty, enhanced usability. The objective is to develop a system that determines its veracity upon encountering any assertion while elucidating the rationale, degree of confidence, and supporting evidence—representing a tangible advancement towards a more transparent, competitive, and dependable e-business environment.

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