# Explainability in Practice: A Survey of Explainable NLP Across Various Domains

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#### **Abstract**

Natural Language Processing (NLP) has become a cornerstone in many critical sectors, including healthcare, finance, Customer Relationship Management, etc. This is particularly true with the development and use of advanced models like GPT-4o, Gemini, and BERT, which are now widely used for decision-making processes. However, the black-box nature of these advanced NLP models has created an urgent need for transparency and explainability. This review provides an exploration of explainable NLP (XNLP) with a focus on its practical deployment and real-world applications, examining how these can be applied and what the challenges are in domain-specific contexts. The paper underscores the importance of explainability in NLP and provides a comprehensive perspective on how XNLP can be designed to meet the unique demands of various sectors, from healthcare's need for clear insights to finance's focus on fraud detection and risk assessment. Additionally, the review aims to bridge the knowledge gap in XNLP literature by offering a domain-specific exploration and discussing underrepresented areas such as real-world applicability, metric evaluation, and the role of human interaction in model evaluation. The paper concludes by suggesting future research directions that could lead to a better understanding and broader application of XNLP.

#### Keywords

Natural Language Processing (NLP), Explainable Natural Language Processing (XNLP), Transparency, Interpretability, Ethical Al

#### Introduction

Natural Language Processing (NLP) and, more recently, Large Language Models (LLMs) have transformed machinehuman interaction by enabling systems to process and generate human language more effectively. Although newer models like OpenAI's GPT-40 and Google's Gemini have pushed the boundaries of language understanding, slightly older architectures such as BERT Devlin et al. (2019) continue to influence modern NLP pipelines. Indeed, these models have found applications across diverse domains, including healthcare, finance, and Customer Relationship Management (CRM) Shrivastava (2022), leading to reduced processing times and enhanced automation Ribeiro et al. (2016b); Guidotti et al. (2018). For instance, a study by Oniani et al. (2024) showed that using Clinical Practice Guidelines (CPGs) in conjunction with LLMs can produce more precise and contextually relevant treatment recommendations, thus improving clinical decision support (CDS) Li et al. (2023). By streamlining such processes, NLP systems offer significant benefits, including rapid analysis, user-friendly interfaces, and the ability to handle substantial amounts of data efficiently Zhao et al. (2023).

Despite these advances, most high-performing NLP models operate as "black boxes." The underlying challenge is not merely the large number of parameters in models like GPT-40 or Gemini, but the lack of transparent, human-interpretable decision pathways in neural architectures Rudin and Radin (2019). In simpler models such as linear regression, it is relatively easier to track how each input feature contributes to a prediction. By contrast, deep neural

networks capture complex, non-linear relationships that are difficult to decode, whether they contain millions or billions of parameters. Moreover, these networks are frequently trained on massive datasets where historical or societal biases may be embedded Bolukbasi et al. (2016); Caliskan et al. (2017), creating a risk of perpetuating discrimination in downstream predictions Barocas et al. (2016). In practice, such biases have been detected in various sectors, including hiring algorithms Dastin (2018), medical diagnostics Igoe (2021), and financial services Andrews (2021). When left unexamined, these biases can lead to adverse outcomes, such as unfair treatment of job applicants, unequal access to credit, or suboptimal healthcare recommendations.

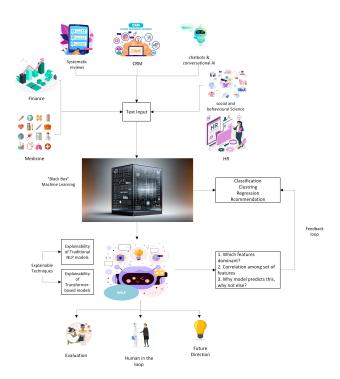
Explainable AI (XAI) initiatives provide a collection of methods and tools to make these "black-box" processes more transparent. Within XAI, XNLP specifically addresses the interpretability of language-based models, focusing on features like word embeddings, attention mechanisms, and textual rationales. As illustrated in Figure 1, a typical XNLP pipeline begins with an input text, processes it through a model, and then employs an explanation layer (e.g., highlighting key tokens or visualizing attention weights) to

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**Figure 1.** Pipeline for XNLP. The input text is processed by a model (e.g., a neural network), and an explanation mechanism highlights important tokens or latent representations. This helps stakeholders, such as clinicians, financial analysts, or end-users, interpret the model's decision-making.

clarify how the final output is derived. XNLP aims to tackle distinct linguistic challenges, such as contextual details, synonyms, or domain-specific jargon, that do not always arise in other modalities like images or tabular data Gurrapu et al. (2023); Qian et al. (2021).

Existing literature on XNLP methods, including Local Interpretable Model-Agnostic Explanations (LIME) Ribeiro et al. (2016b), SHapley Additive exPlanations (SHAP) Jain et al. (2023); Gramegna and Giudici (2021), and attentionbased explanations Tenney et al. (2020), has made considerable progress in unpacking model decisions. Still, much remains to be explored, especially in domain-specific contexts. In healthcare, for instance, NLP systems must provide clinically relevant insights that integrate seamlessly into physicians' workflows Islam et al. (2022). This necessity extends to mental health applications, where language models may assist in monitoring depressive or suicidal ideation through social media posts or electronic health records (EHRs) Zirikly et al. (2019). In finance, explanations must address both the complexity of specialized terminology and the high stakes of compliance and fraud detection Černevičienė and Kabašinskas (2024). Similarly, chatbots and conversational AI systems raise new challenges regarding user trust, especially if the system's responses are critical for customer support or emergency services.

Although general XAI frameworks Tjoa and Guan (2020); Arrieta et al. (2020); Puiutta and Veith (2020) provide broad guidelines, there is a gap in how these methods directly translate into *domain-tailored* XNLP solutions. Recent surveys such as Ali et al. (2023); Danilevsky et al. (2020); Islam et al. (2022) underscore the importance of interpretable

NLP but tend to focus on the technical aspects rather than the nuances of real-world deployment. In response, this survey offers the following main contributions:

- Domain-Specific Analysis: We compile and examine research across various domains (healthcare, finance, CRM, etc.), including mental health under the medical umbrella, to highlight how XNLP can be adapted for different regulatory and practical requirements.
- Evaluation Techniques and Metrics: We examine the full range of evaluation approaches for XNLP from both quantitative and qualitative perspectives. For quantitative assessment, we introduce mathematical equations for key metrics such as fidelity, providing a more rigorous understanding of model performance. On the qualitative side, we discuss metrics like user trust, highlighting methods that capture human-centered insights into model explanations.
- Critical Challenges and Trade-offs: We address open questions regarding bias, privacy, data availability, and the balance between performance and interpretability.
- Future Directions: Building on the limitations found in existing literature, we propose potential research avenues, such as personalized explanations, human-in-the-loop evaluations, and mechanistic interpretability for LLMs.

The remainder of the paper is organized as follows: Modeling Techniques for XNLP section reviews foundational NLP techniques and transitions to modern transformerbased methods and LLMs, highlighting their explainability mechanisms. Applications and Domains of XNLP section explores the application of XNLP methods in diverse fields, including Medicine, where we also delve into mental health applications, Finance, Systematic Reviews, CRM, Chatbots and Conversational AI, Social and Behavioral Science, Human Resources (HR), and other emerging use cases. Critical Aspects of XNLP section addresses the critical aspects of XNLP, including evaluation metrics, trade-offs, rationalization techniques, human evaluation, and data/code availability. Future Directions and Research Opportunities in XNLP section outlines promising directions for further investigation, such as personalized and mechanistic explanations. Finally, Conclusion section concludes with a summary of the survey's key insights.

#### **Modeling Techniques for XNLP**

#### Explainability of Traditional NLP Models

Traditional NLP models, notably Bag of Words (BoW) and its variants such as term frequency (TF) and term frequency-inverse document frequency (TF-IDF), provide foundational approaches to textual representation. A BoW model encodes a document as a set of token counts without preserving word order or contextual usage. When coupled with transparent classifiers (e.g., logistic regression), the model's coefficients help uncover each word's influence on the prediction outcome. For instance, if a logistic regression

classifier assigns a large positive coefficient to the token "excellent" in a sentiment analysis task, it signals a strong correlation between that token and a positive sentiment Heap et al. (2017); Liu et al. (2020).

TF-IDF further refines this representation by assigning greater importance to words that appear frequently in a document but are relatively rare across the entire corpus Shimomoto et al. (2018); Zubiaga (2020). While these methods are simple and often interpretable, they struggle to encode contextual and syntactic relationships DAGAN et al. (1995); Jurafsky and Martin (2019); Zubiaga (2020). Moreover, in TF and TF-IDF systems, interpretability can still be unintuitive: if multiple words frequently co-occur and jointly predict an outcome (e.g., disease codes in discharge letters), each word might receive a small coefficient, even smaller than another word that is less important but does not cooccur as often. Although early in conception, these classical representations paved the way for more complex models that better capture semantic relationships. The drive to incorporate contextual meaning has led researchers toward advanced embedding techniques that combine high performance with more transparent decision processes.

### Explainability of Embedding Models

Embedding models revolutionized NLP by mapping words, phrases, or sentences into continuous vector spaces. In contrast to BoW-based approaches, these dense representations capture subtler semantic and syntactic details Song and Raghunathan (2020). Word2Vec Mikolov et al. (2013) and GloVe Pennington et al. (2014), for example, produce vectors where semantically similar words (e.g., "king" and "queen") reside close together, a property earlier BoW variants could not achieve Sileo and Moens (2022). Sentence-level embeddings (e.g., Universal Sentence Encoder Cer et al. (2018)) extend this idea by encoding entire clauses or paragraphs into fixed-dimensional vectors. Despite performance gains, these embedding models add complexity that can obscure their decision-making. Accordingly, researchers employ several explainability strategies:

- Visualization of Vector Spaces: Tools like Tensor-Board Vogelsang and Erickson (2020) and Embedding Vis Li et al. (2018) map high-dimensional embeddings into 2D or 3D layouts, enabling users to visually inspect semantic clusters and language structures. Dimensionality reduction methods such as t-SNE Van der Maaten and Hinton (2008) and PCA Jolliffe and Cadima (2016) are commonly employed to reveal meaningful relationships among words or sentences Braşoveanu and Andonie (2022); Wang (2019).
- Gradient-Based Methods: Saliency maps, adapted from computer vision Simonyan et al. (2013), highlight input tokens that produce the largest gradient magnitudes with respect to an embedding layer. By tracing which tokens trigger the strongest change in output, these methods provide local explanations for model predictions.
- Attention Mechanisms: Some embedding-based architectures incorporate attention layers, granting insight into how much "focus" the model places

on particular words or sub-phrases Bahdanau et al. (2014); Vaswani et al. (2017). Unlike gradient-based methods, attention is computed during the forward pass, inherently supporting interpretability.

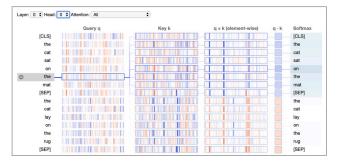
Balancing interpretability and performance remains challenging as models grow increasingly complex Sonkar et al. (2020). The notion of "explanation" is also context-dependent. Visualizations like PCA or t-SNE may suffice for intuitive overviews, particularly in less technical scenarios Conklin et al. (2021); Wattenberg et al. (2016). However, in high-stakes domains such as medicine or finance, stakeholders often demand deeper, more granular rationales behind each prediction. Consequently, embedding-based NLP poses an ongoing tension: how to develop representations that remain robust and powerful while offering sufficiently transparent insights into their internal structures.

#### Explainability of Transformer-Based Models

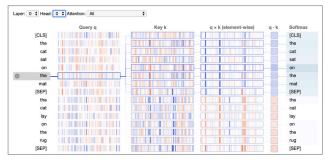
Transformers have reshaped modern NLP through *self-attention* mechanisms that handle long-range dependencies without recurrent networks Kalyan et al. (2021). A classic example is BERT Devlin et al. (2019), which, by using multi-head self-attention, can be pre-trained on massive corpora and then fine-tuned for tasks like sentiment analysis, question answering, or named entity recognition McCann et al. (2018). Its successors, such as RoBERTa Liu et al. (2019) and ALBERT Lan et al. (2020), continue this trend, delivering improvements in various NLP benchmarks.

Although Transformer architectures achieve strong results on NLP tasks, they present unique interpretability challenges. A widely adopted strategy is **attention-weight visualization**, as illustrated in Figure 2. Tools like BERTViz enable multiscale inspection of attention patterns across layers and heads, helping researchers and practitioners understand which input tokens the model attends to when generating its predictions Vig (2019). This form of visualization facilitates the interpretation of token interactions and can reveal model reasoning for specific linguistic phenomena. Other notable methods for unpacking transformer-based decisions include:

- **Probing Tasks**: Simplified linguistic evaluations designed to reveal what grammatical or semantic properties the model retains **Hewitt and Liang** (2019).
- **Feature Visualization**: Techniques that visualize learned features or activation patterns, aiding our understanding of which elements are activated by particular words or phrases Olah et al. (2017).
- Attribution Methods: Integrated Gradients Sundararajan et al. (2017) and similar tools offer tokenlevel importance scores by accumulating gradients over input perturbations.
- Model Simplification & Distillation: Training smaller, more interpretable student networks to replicate large model outputs, thereby bridging the gap between high performance and clarity Hinton et al. (2015).



(a) BERT architecture: transformer encoder stack with bidirectional attention.



**(b)** GPT-2 architecture: transformer decoder stack with causal (unidirectional) attention.

Figure 2. Illustrative comparison of transformer-based model structures and their role in explainability. (a) BERT uses a stack of transformer encoders with bidirectional attention, enabling context-aware explanations for each token. (b) GPT-2 employs a stack of transformer decoders with causal attention, focusing on left-to-right context for generative tasks. Visualizations such as attention maps help interpret which input tokens are most influential in the model's predictions Vig (2019).

Local interpretation approaches, such as LIME Ribeiro et al. (2016a), and global methods, including SHAP Lundberg and Lee (2017), are also frequently integrated with transformers. Perturbation-based techniques Liang et al. (2018) systematically alter input text to identify critical words or phrases, while contextual decomposition Murdoch et al. (2018) breaks down output scores into contributions from individual tokens or token interactions. Despite the proliferation of these tools, no single best practice exists for all contexts. Moreover, attention-weight visualization can sometimes be misleading: in sentiment analysis, weights could highlight neutral tokens (e.g., "the"), downplaying salient words like "hate" Jain and Wallace (2019); Wiegreffe and Pinter (2019). As a result, any claim of interpretability demands careful validation against the model's actual decision-making mechanisms and the end-user's needs.

Transformer models like BERT Devlin et al. (2019) and GPT-x Radford et al. (2019) have led to major advances in NLP, but their large size and complex inner workings make it hard to understand how they work. Critical Aspects of XNLP section discusses many of these explainability challenges in practice. We also expect that future XNLP methods will include better built-in ways to make their decisions easier to understand.

#### LLMs and Mechanistic Interpretability

Building on transformer foundations, recent LLMs like Claude 3, GPT-40, and Gemini have started a new trend in interpretability research, often called *mechanistic* or *feature-level* interpretability. An anthropic's project\* shows that sparse, yet human-interpretable, features (e.g., "sycophancy," "Golden Gate Bridge") can be extracted from millions of neurons in Claude 3. Tracing how these features emerge and how they collectively shape token predictions provides unprecedented insight into an LLM's internal reasoning.

Parallel techniques, such as *B-cosification* Arya et al. (2024), retrofit transformers with constrained linear layers so that each weight contributes a *signed*, *additive explanation* of the output. This architectural shift pushes XNLP beyond conventional post-hoc saliency maps, advocating for *explainability-by-design* in large models. Moreover, *explanation-distillation* methods Fang et al. (2025) train smaller student models to replicate both the task outputs *and* the rationales of an LLM teacher, enabling compact models that remain faithful to the original model's reasoning. This twofold objective, accuracy *and* interpretable justifications, illustrates a growing trend in modern NLP: bridging state-of-the-art performance with human-centric explanatory frameworks.

These lines of research collectively indicate a shift toward deeper, more granular transparency in LLMs. Instead of solely relying on post-hoc methods like attention or gradient-based saliency, designers increasingly embed interpretability directly into model architectures and training regimes. As LLMs advance in complexity and capability, mechanistic interpretability stands out as a crucial avenue for ensuring that these systems remain accountable, trustable, and aligned with human values.

# Applications and Domains of XNLP

AI-based applications have been extensively adopted across multiple facets of modern life, including social media, medicine, commerce, customer service, and finance. Common tasks like machine translation, text summarization, and sentiment analysis aim to automate routine processes and improve user experiences Vaswani et al. (2017); Covington et al. (2016). In these generic contexts, performance often takes precedence over the transparency of how a model arrives at its conclusions. However, in more sensitive fields such as medicine, or in high-stakes areas like finance, achieving explainability is critical. For instance, clinicians analyzing EHRs must trust not only the accuracy but also the reasoning behind a model's predictions, given that such insights directly influence patient treatment plans. Unlike traditional AI systems that can provide only "Yes" or "No" type answers, XNLP frameworks offer "Wh-questions" (e.g., "Why," "When," and "Where"), enabling richer rationales for model outputs. These rationales must be clear and actionable so that healthcare providers, financial analysts, and other key stakeholders can have confidence in the system.

<sup>\*</sup>Mapping the Mind of a Large Language Model Templeton et al. (2024)

Beyond interpretability, **fairness** and **equity** rank highly in domains where decisions can drastically impact individuals or communities Ledro et al. (2022). In medicine, for example, demonstrating how a patient is flagged for a specific intervention is crucial to ensuring unbiased healthcare. Similarly, in CRM, AI-driven personalization should not discriminate based on sensitive attributes. As shown by Brandl et al. (2024), balancing fairness and explainability can promote greater trust in AI systems. This aligns with the principle that if logical and scientifically grounded arguments reinforce current knowledge, users are more inclined to trust an AI's conclusions Islam et al. (2021).

XNLP also benefits human-AI collaboration. When an AI exceeds human capability in certain tasks, such as strategic game play, e.g., AlphaGo Silver et al. (2016), transparent explanations allow individuals to glean novel strategies or insights. Conversely, if an AI achieves performance comparable to a human expert, interpretability reinforces end-user trust in the system Glikson and Woolley (2020). In finance, for example, a model predicting firm valuations must provide transparent justifications so that shareholders can audit its outputs. Absent transparency, the model could be manipulated to favor particular interests. Similarly, chatbots in customer service must not only respond to user queries but also justify those responses to cultivate user trust and satisfaction.

Table 1 offers an overview of some of the key application domains where XNLP has proven to be a game-changer. These domains range from *medicine* and *finance* to *systematic reviews*, *CRM*, *chatbots*, and *social and behavioral science*, each with distinct subcategories and challenges. HR is also included as a growing domain where XNLP can augment processes like recruitment and performance evaluation.

#### Medicine

XNLP has become particularly valuable in the medical domain, where decisions can be life-altering. From analyzing patient histories in EHRs to processing physician notes for disease risk assessments, explainability is key because it clarifies the logic behind a model's prediction. For example, Choi et al. (2016) devised an interpretable recurrent neural network (RNN) model for heart failure prediction, explicitly highlighting which medical codes contributed most to the risk factors. Similar rule-based approaches have been used to extract clinical evidence from randomized controlled trials Kang et al. (2017); Weng et al. (2017), ensuring transparency in processes that directly influence patient care.

Recent initiatives also extend to mental health, a critical area of medicine that relies on sensitive textual data, often collected from social media platforms or patient narratives. For instance, LLM-based analyses have been proposed to detect early signs of depression or suicidal ideation, using model explanations to reassure clinicians and researchers about the validity of identified risk factors Yang et al. (2023a). Table 2 provides a concise overview of major XNLP applications in medicine, showing the interplay among model architectures, explainability techniques, and evaluation metrics.

Alongside EHR classification and rule-based extraction, contemporary work uses deep learning methods, e.g., word embeddings, transformers, to produce more robust predictive power in domains like cancer diagnostics Alabi et al. (2023), disease progression modeling Yang et al. (2021), and ICD-10 coding Mullenbach et al. (2018). Nonetheless, the need for interpretability remains pressing, as stakeholders require transparent models to validate medical recommendations and address concerns about potential biases. XAI enhances trust among healthcare professionals by elucidating AI-driven decisions, thereby meeting regulatory transparency requirements and promoting fairness and safety in clinical settings Abgrall et al. (2024).

Research on mental health analysis via XNLP further underscores the domain's complexity and sensitivity. For instance, LLM-based strategies to detect distress patterns depend on clear, faithful explanations that can be passed to mental health practitioners Yang et al. (2023a). Ensuring patient privacy, dealing with text de-identification Bagheri et al. (2023), and mitigating data biases remain crucial obstacles in this space. Overall, integrating XNLP in the medical domain holds the promise of safer clinical decision support, faster literature reviews, and more equitable patient care by revealing how and why a system recommends certain treatments or diagnoses.

#### Finance

Financial decision-making involves intricate processes such as risk assessment, fraud detection, and firm valuation, all of which require both accurate and transparent AIdriven insights. Recent studies show that incorporating NLP techniques to analyze financial reports, news articles, or transaction logs can effectively flag risk factors and provide timely alerts Wang et al. (2024b). However, traditional NLP-based models often lack explainability, which is critical when end users, be they financial experts or customers, need to understand why a model has flagged a transaction as fraudulent or assigned a particular credit score. XAI addresses this gap by providing interpretable insights that can build trust in the system's outputs. For instance, integrating XAI techniques into credit scoring models enhances transparency and compliance with regulations like the General Data Protection Regulation (GDPR) and the Equal Credit Opportunity Act (ECOA), ensuring that algorithmic decisions are understandable and coherent Demajo et al. (2020). Additionally, employing model-agnostic explanation methods such as SHAP and LIME in credit risk management helps stakeholders comprehend the reasoning behind model predictions, thereby fostering trust and facilitating informed decisionmaking Misheva et al. (2021).

Risk assessment underpins pivotal tasks in the financial sector, such as loan approvals, insurance rate settings, and investment decisions. Inaccuracies or lack of transparency in this process can have significant ramifications, from unfair interest rates to systemic risks. XNLP can help by elucidating which textual factors, like specific keywords in a credit application or trends in financial reports, contribute to elevated risk scores Fritz-Morgenthal et al. (2022); Wallace et al. (2019). For example, Wallace et al. (2019) proposed a graph-based attention model for credit risk assessment,

Table 1. Overview of XNLP Applications, Subcategories, and Case Studies.

XNLP Applications	Subcategories	Studies
Medicine	EHRs	Choi et al. (2016); Alabi et al. (2023)
	Medical Documents Analysis	Li et al. (2022); Moradi and Samwald (2022); Kang et al. (2017); Weng et al. (2017)
Finance	Risk Assessment	Fritz-Morgenthal et al. (2022); Wallace et al. (2019)
	Fraud Detection	Psychoula et al. (2021); Fritz- Morgenthal et al. (2022); Varshney and Alemzadeh (2017);
	Firm Valuation	Cirqueira et al. (2021) Rizinski et al. (2024); Bagga and Stathis (2023)
Systematic Reviews	Review Automation Text Summarization	Rosemblat et al. (2019) Marshall et al. (2016)
CRM	Sentiment Analysis	Capuano et al. (2021); Du et al.
	Customer Support Automation	(2019); Bacco et al. (2021) Bar-Haim et al. (2020); Jenneboer et al. (2022)
Chatbots and Conversational AI	Conversational Agents	Bar-Haim et al. (2020); COPPO and GUIDOTTI (2018)
	Context-Aware Recommendations	Zhang et al. (2019a)
Social and Behavioral Science	Sexism and Hate Speech Detection	Mozafari et al. (2020); Saleh et al. (2023); Plaza et al. (2023); Kirk et al. (2023); Mohammadi et al. (2023b, 2024); Anjum and Katarya (2023)
	Fake News and AI Generative Detection	Capuano et al. (2023); Mohammadi et al. (2023a)
Human Resources	Talent Acquisition and Recruitment	Patwardhan et al. (2023); Gurrapu et al. (2023)
	Employee Sentiment Analysis	Jim et al. (2024); Pluciński (2022)
	Performance Evaluation	Chang (2023); Herrewijnen et al. (2023)
	Diversity and Inclusion	Longo (2023)

Table 2. Summary of XNLP Applications in Medicine

PaperApplication	Model	Explainability Method	Dataset	Metrics
Choi Heart Failet al. ure Predic- (2016)tion	RNN	Feature Importance	EHRs	Accuracy, AUC-ROC
Muller HAR's Claset al. sification (2018)	CNN	Rationale- based explana- tions	MIMIC- III	Precision, Recall, F1-score
Kang RCT et al. Analysis & (2017)Extraction	Rule- based NLP	Transparent Rule Extraction	Clinical Trials	Extraction Accuracy
ZhangBiomedical et al. Word (2019B)mbed- dings	fastText + MeSH	MeSH- Based Interpreta- tions	UMNSRS- Sim, UMNSRS- Rel	Embedding Quality
Yang Disease et al. Progression (2021)Prediction	Transformer	Attention Mechanism	Public EHRs	RMSE, MAE
Alabi Cancer et al. Diagnosis (2023)	BERT	LIME and SHAP	Cancer Registry	F1-score, Precision, Recall

highlighting how interactions and transactions shape the final score. Such clarity is essential not only to justify decisions to regulators and auditors but also to empower clients to take corrective steps to mitigate risk, thereby fostering increased trust in financial institutions Rudin et al. (2022).

Fraud detection systems have traditionally operated as opaque "black boxes," leaving end users uncertain about what triggers a fraud alert. XNLP tools shine a light on

relevant textual features, possibly certain transaction notes or unusual patterns in communications, to clarify why a specific transaction has been flagged Psychoula et al. (2021); Fritz-Morgenthal et al. (2022); Varshney and Alemzadeh (2017); Cirqueira et al. (2021). Interpretable machine learning frameworks, such as decision trees, can provide feature-importance scores, while neural architectures can integrate attention layers that visually highlight suspicious keywords. For instance, Cirqueira et al. (2021) introduced an XAI approach for fraud detection, aligning fraud experts' investigative tasks with model-generated explanations. Enhancing user comprehension of these flags not only minimizes false positives but also strengthens collaboration between human fraud analysts and AI systems.

XNLP methods are also gaining traction in firm valuation, a high-stakes arena of finance where annual reports, market data, and corporate disclosures must be parsed to determine a company's worth. A key challenge lies in distinguishing relevant signals from strategic or even misleading language. More advanced NLP models, including *transformerbased* architectures, attempt to capture long-range dependencies and contextual nuances Bagga and Stathis (2023). Yet context-dependent meanings, sarcasm, and subtle cues remain challenging to detect, raising concerns that companies might "game the system" by inserting specific words likely to inflate valuations Abro et al. (2023). To address this, XNLP solutions like the one proposed by Bagga and Stathis (2023) incorporate interpretability mechanisms (e.g.,

attention-based explanations) to show precisely which textual segments influenced a model's valuation output. Similarly, Rizinski et al. (2024) found that combining explainable lexicon models with sentiment analysis in financial texts improves both accuracy and interpretability, allowing investors and auditors to discern exactly how sentiment-laden phrases affect overall firm valuation.

Table 3. Summary of XNLP Applications in Finance

PaperApplication	Model	Explainability Method	Dataset	Metrics
Ghai Risk et al. Assessment (2021)Classifica- tion	BERT	Layer-wise relevance propagation	20 News- groups	Accuracy, F1-score, Precision, Recall
Walla@redit Risk et al. Assessment (2019)	Graph- based Attention	Probing Methodol- ogy	Financial Transac- tions	Evaluation Metrics
Varshrægaud Alert and Explanation Alemzadeh (2017)	ML Models (e.g., Decision Trees, SVM)	Feature Importance	Transaction Data	Precision, Recall, AUC
CirqudFraudulent et al. Trans- (2021)actions Justification	XAI Methods	Explanation Generation	Financial Transac- tions	Accuracy, F1-score, Precision, Recall
BaggaFirm Valua- and tion Stathis (2023)	Transformer- based Model	Explanation Generation	Financial Docu- ments	ROUGE, BLEU
RizinsSentiment et al. Analysis for (2024)Valuation	Explainable Lexicon Model	SHAP Explain- ability	Financial Texts	Accuracy, F1-score, Precision, Recall

In summary, XNLP is reshaping key finance processes by injecting interpretability into risk analyses, fraud alerts, and valuation metrics. Explainable risk assessments help users manage their creditworthiness more effectively, while transparent fraud detection can strengthen the reliability and acceptance of AI-driven alerts. Meanwhile, interpretable firm valuation models demystify how textual content in financial disclosures influences market perceptions. As Table 3 illustrates, the state of the art spans various architectures (from decision trees to transformers) and explanation frameworks (from feature-importance scores to saliency maps), reflecting a rapidly evolving field. Going forward, deeper integration of XNLP principles, coupled with robust evaluation metrics, will be pivotal in boosting stakeholder confidence and ensuring more equitable, auditable financial ecosystems.

#### Systematic Reviews

Systematic reviews are a cornerstone of evidence-based decision-making in various fields. The process commonly involves screening large volumes of research literature, extracting relevant data, and synthesizing key findings. Although AI-based automation can accelerate tasks such as study identification or data extraction, explainability plays a crucial role in ensuring researchers understand why specific studies are included or excluded. Techniques derived from *XNLP* help demystify this process, offering transparency and trust in the automated workflow.

For instance, some approaches such as Rosemblat et al. (2019) use Support Vector Machines (SVMs) and specialized explanation frameworks to elucidate which textual features contributed most to including or excluding a study. These methods, collectively, allow reviewers to focus on interpreting potentially significant papers rather than sifting through thousands of irrelevant ones.

Marshall et al. (2016) likewise developed RobotReviewer<sup>†</sup>, which addresses bias assessment within systematic reviews. By using text analysis for bias detection in clinical trials, RobotReviewer can automatically surface key phrases or patterns indicative of methodological flaws. When combined with an explainable component, this process not only speeds up bias assessment but also clarifies the reasons behind each flagged instance. Table 4 highlights notable XNLP applications in systematic reviews, detailing the associated models, explainability methods, data sources, and relevant metrics.

Table 4. Summary of XNLP Applications in Systematic Reviews

PaperApplication	Model	Explainability Method	Dataset	Metrics
RosenRéxiew et al. Automation (2019)	SVM	Explanation Framework	PubMed	WSS <sup>‡</sup> , RRF <sup>§</sup>
MarshBilas et al. Assessment (2016)	RobotReviewe	rText Analysis for Bias Detection	Clinical Trials	Bias Assess- ment Metrics, Accuracy
Chen Model et al. Interpreta- (2018)tion	LSTM	Information Bottleneck	SST-2, IMDb	Accuracy, Mutual Informa- tion

Recent large-scale simulation studies have shown that active learning models enhance the efficiency of systematic review screening processes. By prioritizing the most relevant records, these models reduce the manual workload required for reviewing literature. For instance, Teijema et al. (2025) conducted over 29,000 simulations across various model configurations and datasets, consistently finding that active learning outperformed random screening strategies in identifying pertinent studies. As the volume of global research continues to grow, incorporating XNLP into automated reviewing workflows stands as a promising strategy to enhance speed, clarity, and consistency in evidence synthesis.

# Customer Relationship Management (CRM)

CRM involves diverse functions such as tracking user sentiment, generating automated summaries of user feedback, and providing responsive customer support. Recent advances in XNLP have shown promise in improving the transparency and effectiveness of these processes. By revealing the underlying factors that drive model outputs, organizations can better trust, refine, and act upon AI-generated insights.

A key role for XNLP in CRM emerges in **text sum-marization**, where textual data from various sources, such as product reviews or user comments, must be condensed into concise, informative summaries. For instance, Nye

<sup>†</sup>https://www.robotreviewer.net/

et al. (2018) used BERT for extractive summarization in biomedical literature, employing attention visualization to demonstrate how certain sentences contribute to the final output. This approach not only highlights important segments of text but also helps stakeholders understand why particular sentences were chosen. Similarly, the inclusion of attention-based or rationale-based explanations promotes transparency, enabling decision-makers to trust automated summaries in areas like market research or product feedback analysis.

Another core application is **sentiment analysis**, which is vital for gauging public perception and refining marketing strategies. Although sentiment analysis can detect emotions or opinions in large-scale text data, it often operates as a "black box." By applying explainability methods such as LIME (LIME), Layer-wise Relevance Propagation (LRP), or attention-based heatmaps, organizations can better interpret why a particular sentiment label was assigned Capuano et al. (2021); Du et al. (2019); Bacco et al. (2021). For example, Du et al. (2019) integrated LRP into a BiLSTM model to show which words triggered specific sentiment predictions, and Bacco et al. (2021) used SHAP explanations to reveal token-level contributions, boosting user confidence in the underlying sentiment classification.

Beyond sentiment analysis, XNLP also enhances customer support automation, including chatbots and self-service platforms that respond to consumer inquiries in real time. By making these systems explainable, companies can pinpoint why certain answers or suggestions were given, reducing user frustration and building trust Bar-Haim et al. (2020); Jenneboer et al. (2022). For example, Jenneboer et al. (2022) integrated explainability in a transformer-based chatbot, visualizing attention weights to show customers how their queries influenced responses. Table 5 illustrates various CRM-related applications, outlining the models, explainability techniques, datasets, and performance metrics used.

Overall, XNLP's integration into CRM marks a key shift in how businesses collect, interpret, and act on text data. By offering transparent rationales for automated summarization, sentiment detection, and response generation, these systems help organizations forge deeper connections with their customers. Moreover, explainability not only enhances user trust but also empowers developers and stakeholders to refine their NLP pipelines for improved accuracy and reliability. As shown in Table 5, a variety of architectures and techniques, ranging from BiLSTM to Transformer-based models, are being equipped with explainability features, enabling more interpretable and user-aligned CRM solutions.

### Chatbots and Conversational AI

Chatbots and conversational AI systems have become increasingly prevalent in areas such as virtual assistance, customer support, and information retrieval. By using XNLP, these systems can offer more transparent and user-centric interactions, as their generated responses or recommendations can be coupled with clear rationales. This transparency fosters greater user trust, enabling individuals to understand the *why* behind the bot's outputs and to feel more confident in adopting its suggestions or insights.

Table 5. Summary of XNLP Applications in CRM

PaperApplication	Model	Explainability Method	Dataset	Metrics
Nye Text Sumet al. marization (2018)	BERT	Attention Visualiza- tion	Biomedical Articles	ROUGE, BLEU
CapuaSentiment et al. Analysis (2021)	BERT	LIME	Yelp Reviews	Accuracy, F1-score
Du Sentiment et al. Analysis (2019)	BiLSTM	Layer-wise Relevance Propagation	Amazon Reviews	Accuracy, Precision, Recall
BaccoSentiment et al. Analysis (2021)	BiLSTM	SHAP	Movie Reviews	Accuracy, F1-score, Precision
Bar- Customer Haim Support et al. Automation (2020)	Seq2Seq	Explanation- by- Example	Customer Service Logs	Customer Satisfac- tion Score
Jennel@ustomer et al. Support (2022)Automation	Transformer- based Chatbot	Attention Visualiza- tion	Customer Service Logs	Response Time, User Satisfac- tion
Lei Text et al. Classifi- (2016)cation, Info Extraction	LSTM	Rationale- based Explana- tions	Beer Review, CoNLL- 2003	Accuracy, F1-score
Lage Sentiment et al. Analysis (2018)	BERT	Feature Visualiza- tion	Yelp Polarity	Accuracy, Precision, Recall, F1-score
Tsai Review et al. Automation (2023)	LSTM	Shapley Interaction Index	IMDb	Accuracy, F1-score, Precision, Recall
Rana Fact Verifiet al. cation (2022)	BiGRU + Attention	Attention Heatmaps, Explainable Fact- Checking	LIAR, PolitiFact	Accuracy, Precision, Recall, F1-score
Yu Sentiment et al. Analysis (2021)	CNN, BiGRU	Attention Heatmaps, Ablation	Amazon, BeerAd- vocate	Accuracy, Precision, Recall, F1-score
AntogSentiment and Analysis Falt- ings (2021)	RL + RNN	Rationalization Generation	TripAdvisor, RateBeer	Accuracy, F1-score

Context-aware recommendation systems aim to deliver personalized suggestions by incorporating elements of user intent, interaction history, or external data. Incorporating XNLP techniques into these recommenders can enhance user confidence by explicitly showing which contextual cues led to particular recommendations. For instance, Zhang et al. (2019a) proposed a context-aware recommendation model that provides explanations about how user-item interactions influenced its outputs, leading to higher satisfaction. Similarly, COPPO and GUIDOTTI (2018) demonstrated how a chatbot could justify its decisions, improving user trust and engagement.

In 2023, conversational AI took a significant leap with the introduction of GPT-4, known for its larger context window and improved accuracy in both English and code-based tasks. OpenAI's GPT-40 ("o" for "omni") extended these advantages, matching GPT-4 Turbo performance in English while showing further gains in non-English languages TechTarget (2024a); OpenAI (2024b,a); TechTarget (2024b). Although these advanced models can generate more coherent and

context-aware dialogue, they still require effective *explainability* strategies to clarify the internal reasoning paths or chain-of-thought that lead to each response. XNLP methods thus remain vital for building user trust, especially as chatbot complexity and capabilities continue to grow.

Recent studies underscore the importance of explainable conversational AI for enhancing user satisfaction, transparency, and overall effectiveness Matellio (2024); Seminck (2023); Miglani et al. (2023). While AI chatbots increasingly excel at generating swift, personalized responses, embedding XNLP capabilities can reveal how the system arrives at each answer. This can be accomplished through mechanisms like attention distributions, rationale highlighting, or feature visualization, each of which helps users grasp the underlying logic. Such interpretability also aids in detecting potential biases or inconsistencies, enabling developers to refine their models and ensuring the system behaves reliably under different conditions Soni and Dubey (2024); Dxwand (2024); Threado (2024).

Table 6 highlights a range of applications in chatbots and conversational AI, detailing the models, explainability techniques, datasets, and evaluation metrics employed. These examples demonstrate how integrating transparency can bolster user trust, streamline recommendation processes, and refine user engagement strategies.

**Table 6.** Summary of XNLP Applications in Chatbots and Conversational AI

PaperApplication	n Model	Explainability Method	Dataset	Metrics
Jain Conversation and Agents Wallace (2019)	nal BiLSTM, CNN	Attention Distribu- tions	SST-5	Accuracy, F1-score
Bar- Automated Haim Customer et al. Service (2020)	Transformer Models	Justifications for Responses	IMDb	Efficacy
COPPChatbots and GUIDOTTI (2018)	Various	Explainability	AG News	User Trust, Engage- ment
ZhangRecommene et al. Systems (2019a)	datio Deep Learning- based	Attention Mechanism	MovieLens, Amazon Product	User Satis- faction
SeminConversation (2023)Agents	nal GPT-4	Transparency	MovieLens, Amazon, Goodreads	User Engage- ment, Accuracy
MatellChatbots in (2024)Business	n Various	Transparency in Decision- Making	General Business Data	User Trust Satisfac- tion
Ghazv <b>Taisle</b> jad et al. Oriented (2018)Dialogue	Seq2Seq	External DB Integration	MovieLens, Reddit	Response Accuracy

Overall, the integration of XNLP into conversational AI has the potential to reshape user interactions by providing richer, more transparent exchanges. As large-scale models like GPT-40 continue to grow in complexity, designing robust *explainability* mechanisms will be central to maintaining user trust and improving dialogue outcomes. From clarifying context-aware recommendations to justifying chatbot responses, XNLP methods play a pivotal role in the future trajectory of conversational systems.

#### Social and Behavioral Science

Social and behavioral science research often addresses highly complex societal challenges, such as hate speech, sexism, misinformation, and emotional well-being. *XNLP* provides valuable tools for enhancing the reliability of automated methods in this domain, enabling clearer rationales behind model outputs. This transparency allows researchers and practitioners to gain deeper insights into underlying language patterns and the decision-making processes of NLP models.

Transformer-based architectures, including BERT, have significantly advanced the detection of offensive language. Mozafari et al. (2020) relied on BERT to accurately analyze annotated data for hate speech, improving both detection performance and interpretability. Likewise, Saleh et al. (2023) developed domain-specific word embeddings focused on hate speech data, offering nuanced insights into how such content manifests linguistically. Efforts such as the sEXism Identification in Social neTworks (EXIST) and SemEval-2023 Task 10 competitions demonstrate the multilingual capabilities of XNLP for tackling sexist or hateful content in English and Spanish Plaza et al. (2023); Kirk et al. (2023); Mohammadi et al. (2023b, 2024). These studies highlight the value of *human-in-the-loop* validation, where user feedback helps align model outputs with human judgments and mitigate biases Anjum and Katarya (2023).

Misinformation poses an escalating threat in digital communication. XNLP offers robust techniques to identify fabricated or AI-generated text, thereby safeguarding the integrity of online information. Capuano et al. (2023) illustrate the efficacy of XNLP in distinguishing genuine content from deceptive or machine-generated posts. Similarly, Mohammadi et al. (2023a) created a multilingual ensemble model, tested under a shared task by Computational Linguistics in the Netherlands (CLIN), to discern AI-generated text from human-authored writing Fivez et al. (2024). Beyond purely text-based strategies, multimodal systems like SceneFND integrate textual, contextual, and visual cues, showing enhancements in identifying misinformation across diverse datasets Zhang et al. (2024).

Though frequently classified under *medicine* (see Medicine section), research in social and behavioral contexts also applies XNLP to assess mental health conditions and public sentiment. Han et al. (2023) employed NLP features from social media posts to predict emotional or psychological well-being. Meanwhile, Ahmed et al. (2024) experimented with transformer-based architectures to classify depression severity, illustrating how explainable output can guide mental health interventions. Additionally, Ali et al. (2022) leveraged large-scale XNLP methods for real-time analysis of political sentiment on Twitter during the 2020 U.S. Presidential Elections, demonstrating how these techniques can capture public opinion dynamics.

Wang et al. (2024a) introduce *L-Defense*, a framework that partitions crowd discourse on a news claim into two opposing camps. It then extracts salient evidence for each side and prompts a large language model (LLM) to debate and defend their respective narratives. The "winning" defenseproduces a concise natural-language explanation along with the final veracity label, achieving higher detection

accuracy than previous methods and offering users a transparent, evidence-based rationale.

Schmidl et al. (2024) compare GPT-4 and Claude 3 in a tumor-board scenario, finding that both models produce expert-level treatment plans, each accompanied by step-by-step rationales that clinicians can readily audit. In parallel, Wang et al. (2024a) study social-media language to evaluate depression severity, identifying the phrases that most influenced each assessment. Such research underscores an emerging focus on verifying not only the plausibility but also the *practical utility* of XNLP explanations in real-world healthcare settings.

**Table 7.** Summary of XNLP Applications in Social and Behavioral Science

PaperApplication	Model	Explainability Method	Dataset	Metrics
MozafHate et al. Speech (2020)Detection	BERT	Transformer Models	Annotated Datasets	Detection Accuracy
Saleh Hate et al. Speech (2023)Analysis	Domain- Specific Models	Word Embedding	Hate Speech Websites	Delicate Language Insights
Plaza Sexism et al. Detection (2023)	ML Algo- rithms	EXIST Competi- tion	EXIST- 2023	Classification Accuracy
Mozafhhate et al. Speech (2020)Detection	BERT + Bias Mitigation	Bias Mitigation Mechanism	Davidson & Waseem	F1- measure
Saleh Hate et al. Speech (2023)Detection	BERT & Deep Models	LIME	Hate Speech Word Embed- ding	Detection Accuracy
Kirk Explainable et al. Online (2023)Sexism Detection	BERT	SHAP	SemEval- 2023 Task 10, EXIST- 2023	F1 Score
MoharEmpldinable et al. Sexism (2024)Detection	Ensemble (BERT, XLM-R, Distil- BERT)	SHAP	EXIST- 2023	Token Influence Analysis
MoharAthadi et al. Generated (2023affext Detection	Ensemble + Multilin- gual BERT	SHAP	Various Genres	Detection Accuracy
Han Mental et al. Health (2023)Analysis	NLP Tech- niques	Feature Importance	Social Media Posts	Predictive Power
Wang Fake-News et al. Detection (2024a/L- Defense)	LLM- based Debate	Natural- Language Justification	Crowd Discourse	Detection Accuracy
Schmi <b>T</b> lumoret al. Board (2024)Treatment Plans	GPT-4, Claude 3	Step- by-step Rationales	Clinical Case Reports	Expert- Level Validity
Wang Depression et al. Severity (2024a) ssessment	Transformer- based	Highlighted Key Phrases	Social Media Posts	Clinical Utility

Overall, integrating XNLP into social and behavioral science marks a significant advance in addressing issues such as hate speech, sexism, misinformation, and mental health monitoring Mathew et al. (2021); Yang et al. (2023b). By using the interpretability features of advanced transformer models, domain-specific embeddings, and multilingual

datasets, researchers can develop classifiers that not only identify problematic content or behaviors but also explain their predictions. This approach reinforces the credibility of automated systems and aids stakeholders, ranging from social scientists to clinicians, in better understanding the nuanced language patterns that drive complex social phenomena.

### Human Resources (HR)

HR encompasses processes ranging from talent acquisition and employee sentiment analysis to performance reviews and diversity initiatives. XNLP has recently gained traction in optimizing these functions, offering transparent decision-making tools that can build trust, reduce biases, and streamline various HR operations.

Transformer-based architectures like BERT and GPT are increasingly used to automate the resume-screening and candidate-ranking process, matching required skills more effectively with job descriptions. For instance, Patwardhan et al. (2023) demonstrate how attention mechanisms within BERT can make the initial recruitment phase more efficient and less prone to subjective bias. In parallel, Gurrapu et al. (2023) show how attention visualization explains model outputs, thereby enhancing stakeholder trust in the screening process. Akkasi (2024) further highlight how a transformer-based ensemble model can accurately extract both technical and non-technical competencies, significantly boosting the precision and transparency of candidate matching.

In understanding workforce morale, XNLP provides robust sentiment analysis techniques to analyze feedback from surveys, internal forums, and social media. Using transformer-based models like RoBERTa, Jim et al. (2024) process large volumes of employee comments, pinpointing negative sentiments and emerging workplace issues. Additionally, attention-driven methods clarify which textual factors influenced each sentiment label, allowing HR departments to better understand employee concerns Pluciński (2022).

Traditional performance reviews often lack consistency and can harbor biases. By incorporating XNLP to analyze written feedback and performance data, organizations achieve more objective and transparent evaluations. Chang (2023) demonstrate how attention mechanisms in transformer models highlight the most relevant textual feedback, providing a clear rationale for each performance score. Recent work by Herrewijnen et al. (2023) similarly suggests that integrating explainabilityproduces more equitable outcomes, as HR managers can interpret the exact factors driving each model's assessment.

XNLP further contributes to fostering diversity and inclusion within companies by detecting linguistic biases in job postings, internal policies, and employee communications. For example, Longo (2023) propose an XNLP framework that not only flags biased content but also clarifies its reasoning through interpretable outputs. This transparency helps organizations address the root causes of inequality and maintain more inclusive hiring practices.

As illustrated in Table 8, the use of XNLP across various HR functions, from screening resumes to promoting inclusivity, underscores its capacity to bring objectivity, transparency, and efficiency to people-centric tasks. Studies consistently

Table 8. Summary of XNLP Applications in HR

PaperApplication	Model	Explainability Method	Dataset	Metrics
PatwaiRearuitment et al. Automation (2023)	BERT	Attention Mecha- nisms	Resume Data	Match Accuracy
GurrapRecruitment et al. (2023)	BERT	Attention Visualiza- tion	Resume Data	Bias Reduction
AkkasSkill (2024)Extraction	Transformer Ensemble	Attention Mecha- nisms	Job Descrip- tions	Precision, Recall
Jim Employee et al. Sentiment (2024)Analysis	RoBERTa	Attention Mecha- nisms	Employee Feedback	Sentiment Insights
Pluciń <b>Se</b> ntiment (2022)Analysis	RoBERTa	Attention Mecha- nisms	Employee Feedback	Sentiment Accuracy
ChangPerformance (2023)Evaluation	Transformer Models	XAI	Performance Reviews	Objectivity Scores
HerrevPerformance et al. Evaluation (2023)	Transformer Models	XAI	Performance Reviews	Fairness Scores
LongoDiversity (2023)	Custom NLP	XAI	Company Policies	Bias Detection

show that leveraging explainability features (e.g., attention heatmaps, rationale generation) not only strengthens user trust but also aligns HR strategies more closely with organizational values. Looking ahead, ongoing research into transformer-based and explainable methods promises further refinements in reducing biases, understanding employee concerns, and improving overall talent management.

# Other Applications

Beyond the domains discussed earlier, XNLP finds utility in a wide range of tasks and sectors. These include language generation, text classification, machine translation, summarization, visual question answering, and more. In such contexts, explainability is vital for understanding how and why a model produces specific outputs, offering transparency and trustworthiness in settings that may require critical decision-making or that deal with large-scale user interactions.

Sheng et al. (2019) employed Transformer-based models (e.g., GPT-2) to visualize attention mechanisms and detect biases in generated language. Such visualization not only reveals which tokens or phrases drive certain outputs but also highlights how societal or dataset biases might surface in generation processes.

DeYoung et al. (2020) proposed rationale-based explanations for text classification tasks across multiple datasets (BoolQ, e-SNLI, etc.), evaluating the quality of explanations on fidelity, comprehensiveness, and sufficiency. Similarly, Jacovi and Goldberg (2020) and Ayyubi et al. (2020) extended the discussion to machine translation, summarization, and visual question answering, using (multi)transformer models for *faithfulness* and *rationale generation*, respectively.

Several works have delved into annotation of word importance and visualization of model internals. For instance, He et al. (2019) and Alishahi et al. (2019) examined neural machine translation and reading comprehension using BERT and Transformer-based architectures, annotating tokens with

importance weights and generating explanations tested on datasets such as 20NG, AGNews, IMDB, SQuAD, and e-SNLI. Likewise, Zhou et al. (2020) and Hoover et al. (2020) employed BERT and other Transformer variants to study learned self-attention, providing interactive visual analyses of attention patterns. Beyond purely text-based challenges, multimodal Transformer approaches such as Ayyubi et al. (2020) and Tang et al. (2021) addressed visual commonsense reasoning, indicating how explainable components can strengthen cross-domain understanding.

Commonsense-related tasks and interpretability-oriented methods have also drawn increasing attention. For example, Lakhotia et al. (2020) introduced FiD-Ex to generate extractive rationales, while Wiegreffe et al. (2020) used T5-based joint models to produce free-text explanations in tasks like commonsense question-answering and natural language inference. Additional works by Plyler et al. (2021), Fomicheva et al. (2022), and Chan et al. (2022) concentrated on translation quality estimation, text classification, and universal rationalization frameworks, respectively. Table 9 highlights diverse XNLP applications along with key models, methods, datasets, and metrics.

XNLP's application in these diverse areas underscores its growing impact, including tasks that may not carry as high a risk as medical or financial domains but still benefit from transparency (e.g., language bias detection, rationale generation, and VQA). By illuminating *how* decisions are reached, XNLP fosters trust and reliability in NLP-driven solutions, particularly in critical endeavors such as summarization, machine translation, or text classification, where hidden biases could otherwise remain undiscovered. The consistent theme across studies is that explainability strengthens user confidence and supports auditing and refining model performance.

From the compiled studies, we observe that *risk-sensitive* areas (e.g., healthcare) rely strongly on actionable explanations (feature importance, rule extraction) to ensure trustworthy decision-making. In contrast, sectors like finance emphasize attention-based methods for spotting anomalies in vast data streams. CRM and chatbot applications often focus on generating user-facing explanations, thereby building trust in real-time interactions. Regardless of domain, the shared principle is that *explainability* underpins system reliability and user acceptance, paving the way for broader adoption of NLP-based automation.

#### Critical Aspects of XNLP

# Evaluation Metrics: Quantifying Understanding

What does it mean to *understand* a model's output? In order to evaluate the effectiveness of XNLP techniques, it is necessary to *quantify* the level of comprehension provided by the model's explanations, typically through a blend of quantitative and qualitative metrics Fan et al. (2020). While many of these metrics can be described conceptually, formalizing them mathematically can offer a more precise view of how such measures are actually computed.

Quantitative Metrics These approaches aim to measure how closely an explanation mirrors a model's underlying reasoning, often focusing on the following concepts:

Table 9. Summary of XNLP Applications in Other Domains

	.,	- In In the second second		
PaperTask	Model	Explainability Method	Dataset	Metrics
ShengLanguage et al. Generation (2019)	GPT-2, etc.	Attention Visualiza- tion	WebText	Automated Bias Metrics
He Neural et al. Machine (2019)Γranslation	BERT	Word Importance Annotation	Various (20NG, AGNews, IMDb)	Accuracy, F1
DeYoulhaxt Claset al. sification & (2020)Rationale	Various Models	Rationale- based Explana- tions	BoolQ, e-SNLI, etc.	Fidelity, Compre- hensive- ness
JacoviMachine and Translation, Gold-Summ. berg (2020)	Transformer Models	QA for Faithfulness	CNN/Daily Mail, XSum	Fidelity Score
AyyubVisual et al. Question (2020)Answering	Multimodal Trans- former	Rationale Generation	VQA v2.0, VizWiz	Answer Accuracy
AlishaMachine et al. Reading (2019)Compre- hension	Transformer- based	Explanation Generation	SQuAD 1.1, e- SNLI	Fidelity, Sensibility
Zhou Natural et al. Language (2020)Under- standing	BERT	Activation & Attention Visualiza- tion	BERT- based Tasks	(Varied)
HooveFransformer et al. Model (2020)Analysis	BERT, etc.	Visualization, Self- Attention	Not Speci- fied	Not Speci- fied
LakhoExtractive et al. Rationale (2020)Generation	LSTM, BERT	FiD-Ex	VCR	Exact Match, Rationale F1
Tang Visual et al. Com- (2021)monsense Reasoning	DMVCR	Dynamic Working Memory	VCR, Revisited- VQA	(Task- Specific)
Wiegr-Fifee-text et al. Rationales (2020)	T5-based Joint Models	Natural Language Rationales	Commonsense QA, NLI	Feature Impor- tance Agreement
Plyler NMT Qualet al. ity Estima- (2021)tion	Transformer	LIME, Integrated Gradients	MLQE-PE	Pearson, Spearman, MAE
FomicNeural et al. Machine (2022)Translation	BERT- based	Feature Visualiza- tion	WMT Metrics Shared Task	Pearson, Kendall's Tau
Chan Text Classiet al. fication (2022)	UniREX	Rationalization	FEVER, Movie Reviews	Precision, Recall, F1

**Fidelity** reflects how accurately an explanation captures the *true* behavior of a model. High-fidelity explanations yield the same predictions as the original model across an evaluation set. Formally, suppose  $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^n$  is a dataset of n instances, where  $x_i$  is an input and  $y_i$  is the model's predicted label. Let M be the black-box model and E be the explainability function (e.g., a local surrogate or rationale generator). One way to measure fidelity is to track how well the surrogate's output  $\hat{y}_i = E(x_i)$  aligns with  $y_i = M(x_i)$ . A simplified discrete version might be:

$$\mathrm{Fidelity}(E,M,\mathcal{D}) \; = \; \frac{1}{|\mathcal{D}|} \sum_{(x_i,y_i) \in \mathcal{D}} \mathbf{1} \big[ \hat{y}_i = y_i \big], \tag{1}$$

where  $\mathbf{1}[\cdot]$  is the indicator function. The higher this value, the more the explanation's outcomes match the original

model's predictions. For instance, LIME Ribeiro et al. (2016b) can approximate M locally with a simpler model to gauge this agreement.

**Coherence** assesses the logical consistency or readability of an explanation in natural language form. Established language metrics (e.g., BLEU Papineni et al. (2002), ROUGE Lin (2004), BERTScore Kaster et al. (2021)) are commonly used. For instance, the BLEU score between an automatically generated explanation E(x) and a reference explanation R(x) can be expressed as:

BLEU = 
$$\exp\left(\min\left(0, 1 - \frac{r}{c}\right) + \sum_{n=1}^{N} w_n \ln p_n\right),$$
 (2)

where r is the reference length, c is the candidate length,  $p_n$  is the precision of matched n-grams, and  $w_n$  are weights (often uniform). Higher BLEU scores indicate closer alignment between generated explanations and reference texts.

**Completeness** determines whether an explanation includes all salient factors behind a decision. One example arises in SHAP Lundberg and Lee (2017), where each feature contribution  $\phi_i$  in a set of N features is aggregated to reconstruct the model's prediction M(x). A simplified Shapley-based formula is:

$$\phi_i(M, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! (|N| - |S| - 1)!}{|N|!} \Big( M(S \cup \{i\}) - M(S) \Big).$$
(3)

Here, completeness implies that  $\sum_{i=1}^{N} \phi_i = M(x)$ , capturing each feature's marginal contribution. Explanations lacking key contributions may have lower completeness scores.

Qualitative Metrics While quantitative metrics address how well the explanation aligns with the model's internal logic or reference texts, qualitative measures focus on user perceptions and real-world usability:

User trust Lipton (2018) gauges how confident users feel about an explanation. It can be approached via questionnaires or controlled user tests, but is not usually reduced to a single formula. Instead, a rating scale (e.g., 1–5) is often used to approximate trust. Satisfaction deals with how helpful or intuitive users find an explanation Doshi-Velez and Kim (2017). It may be measured as a difference in user performance or preference when they have access to explanations versus when they do not. Transparency captures whether users believe they understand the model's reasoning. This can be elicited via self-report items: for instance, "On a scale of 1–7, rate how well you grasp the model's decision rationale." Lipton (2018). Aggregated responses create a transparency index, though it remains subjective by nature.

In practice, both quantitative and qualitative assessments are needed to create a holistic view of an explanation's quality Hoffman et al. (2018); Mohseni et al. (2021). However, the reliance on subjective judgments can introduce bias, and users may feel satisfied with explanations that *appear* coherent but are not causally accurate Miller (2019). This tension underscores the complexity of evaluating XNLP methods in real-world contexts. Søgaard (2021) emphasizes that context-aware metrics, those tailored to specific domain

Table 10. Overview of Evaluation Metrics for XNLP Techniques

Type	Metric	Description	Study
	Fidelity	Measures how accurately the explanations reflect the model's	(Ribeiro et al.
Quantitative	Coherence	behavior; see Eq. 1 for a simplified version.  Assesses clarity and logical consistency in generated explanations	2016b) (Papineni et al.
	Completeness	(e.g., BLEU in Eq. 2). Evaluates whether all relevant factors are included, e.g., Shapley-based sums in Eq. 3.	2002) (Lundberg and Lee 2017)
0 11 1	User Trust	Measures the confidence users have in the model's explanations	(Lipton 2018)
Qualitative	Satisfaction	(often via surveys).  Gauges user acceptance and perceived usefulness; frequently collected through rating scales.	(Doshi-Velez and Kim 2017)
	Transparency	Evaluates whether users feel they understand the model's reasoning.	(Lipton 2018)

needs, may further improve the relevance and robustness of XNLP evaluations.

Building XNLP systems often entails balancing model performance with interpretability. Although simpler models (e.g., linear regression, decision trees) are more transparent, they may fail to capture the complexities of language data as accurately as neural networks Doshi-Velez and Kim (2017). In high-stakes domains like healthcare and finance, navigating this *explainability-performance* trade-off is critical; inaccurate predictions can have serious real-world consequences, but opaque models are less likely to be trusted by stakeholders.

Time Complexity. Some XNLP methods, such as gradientbased approaches (e.g., SHAP in Eq. 3), require computational overhead comparable to the training phase itself. Others, like attention-based mechanisms, exploit existing model components to highlight important tokens with less added cost. As model sizes grow (e.g., GPT-4-level architectures), computational demands for generating explanations increase significantly Brown et al. (2020). Scalability thus becomes a key bottleneck for widespread adoption of XNLP, particularly when handling large datasets or complex tasks. Scalability and Standardization. Large-scale LLMs have heightened concerns about the feasibility of real-time explanations Singh et al. (2016). Ongoing research focuses on optimizing explanation modules, exploring ways to produce faithful insights without unduly burdening memory or compute cycles Søgaard (2021). Meanwhile, standardized evaluation protocols are needed to compare XNLP approaches across domains, ensuring consistency in how metrics (e.g., fidelity, completeness) are applied. Moreover, effective knowledge management practices are shown to enhance software development outcomes, in part by improving software processes Chugh et al. (2020)

# Rationalization Techniques: Current Approaches and Challenges

As NLP models become more intricate, providing explicit *rationales* for their outputs has garnered growing attention Atanasova (2024); Rajani et al. (2019). Often referred to as Rational NLP (RNLP), this subfield seeks to generate human-readable *explanations* of model decisions. While the foundational concept dates back to Zaidan et al. (2007), the surge in interest follows the wider availability of neural methods that can produce or highlight textual justifications. Extractive Rationalization. Techniques like LIME, Grad-CAM, or SHAP highlight the parts of the input most influential for a model's prediction Ribeiro et al. (2016b); Lei

et al. (2016). These methods are relatively straightforward to implement but can oversimplify the decision process. As models scale (e.g., large transformers), ensuring that these extractive saliency maps remain faithful is a growing challenge Majumder et al. (2021).

Abstractive Rationalization. Future directions in rationalization include generating free-form natural language explanations that may deviate from the exact phrasing of the input text Gurrapu et al. (2022); Sha et al. (2023). This approach allows for more context-rich narratives but risks producing plausible yet inaccurate summaries if not rigorously tested for alignment with the model's internal states. Ribeiro et al. (2018) introduced ideas like Semantically Equivalent Adversarial Rules to refine rationalization by ensuring the model's textual explanations genuinely mirror its decision boundary.

Despite these advances, *post-hoc* rationalizations can still be misleading if they do not reflect the true causal pathways in the model Siddhant and Lipton (2018). Furthermore, widely used metrics often emphasize precision but rarely capture coherence, consistency, or domain relevance Jacovi and Goldberg (2020). Tackling these gaps is crucial for developing dependable rationalization frameworks.

Advances in Evaluation Metrics and Benchmarks Two large-scale meta-evaluation suites are shaping how researchers assess XNLP methods:

- LATEC Klein et al. (2024): Benchmarks 17 explainers on 20 metrics across 7,500 settings, revealing frequent metric disagreements and advocating a multi-faceted evaluation approach.
- BEExAI Sithakoul et al. (2024): An open leaderboard where contributors upload saliency maps or rationales, receiving a comprehensive scorecard on fidelity, interpretability, and compute cost.

On the user side, Kim et al. (2024) compiled a systematic review of 73 user studies in XAI, highlighting the need to merge objective performance metrics with subjective user assessments. Collectively, these efforts signal a shift toward reasoning-aware, user-centered evaluation protocols that extend beyond single numeric proxies.

# Data and Code Availability: The Role of Open Science

In parallel with technical innovations, open science principles significantly affect the transparency and reproducibility

of XNLP studies Seminck (2023); Brinkman et al. (2021). Public release of datasets and code fosters rigorous validation, enabling other researchers to replicate, critique, or extend the work. Tools like Ecco Alammar (2021) facilitate the interpretation of transformer activations, aligning with open-source philosophies that lower barriers for scientific collaboration. Nonetheless, partial access or commercial constraints (e.g., proprietary GPT-4 models) can hamper indepth analysis. During this survey, many XNLP projects provided open-source code on GitHub or Zenodo, but far fewer offered publicly accessible datasets, underscoring a persistent bottleneck. Søgaard (2021) further highlights the value of standardized tasks and benchmarks, promoting fair comparisons across various XNLP domains.

# Future Directions and Research Opportunities in XNLP

Reinforcement learning (RL) and Chain-of-Thought Reasoning. RL increasingly intersects with advanced models like GPT, creating opportunities to refine both performance and interpretability Li et al. (2016); Liu et al. (2016). Chain-of-thought prompting Wei et al. (2022), wherein a model articulates its intermediate reasoning steps, can bolster interpretability—though these intermediate rationales are not always genuinely employed by the model's internal mechanics Lanham et al. (2023). Future research may embed *faithfulness tests* into the training objective, penalizing spurious or ungrounded reasoning steps.

Hybrid Neuro-Symbolic Systems. Combining neural networks with rule-based logic canproduce interpretable, high-performing NLP pipelines. Weber et al. (2019) illustrate a question-answering system that merges Prolog-style inferences with neural expansions, balancing explicit symbolic reasoning with the flexibility of learned representations. Similarly, NELLIE Weir et al. (2024) uses a Prolog-like proof tree guided by an LLM retriever, demonstrating how symbolic inference can offer auditable explanations while preserving neural adaptability.

Explainable Dialogue and Social Media Analytics. Sarkar et al. (2023) showcases an explainable transformer-based dialogue system capable of clarifying its reasoning, improving user trust. In social media contexts, XNLP can disclose the driving motivations behind viral content Bovet and Makse (2019), interpret emotional or political trends, and combat fake news. Here, personalized or context-driven explanations can play a pivotal role in aligning NLP outputs with diverse user needs.

**Personalized and Adaptive Explainability.** As user demographics and tasks grow more diverse, one-size-fits-all explanations may not suffice Kuhl et al. (2020). Systems like TELL-ME Jeck et al. (2025) let users specify whether they prefer analogical or factual styles, adapting future explanations accordingly. Tailoring the level of detail or communication style to match user domain expertise or cultural nuances can boost comprehension and adoption across varied environments.

**Rational AI (RAI).** Ongoing work in rational AI moves beyond surface-level justification, aiming to ensure that textual or visual rationales truly align with the model's

underlying logic Yu et al. (2019). Verified chain-of-thought reasoning, step-by-step evaluation, and semantically consistent rationales all converge to make model outputs not merely comprehensible but also trustworthy in real operational settings.

In sum, XNLP's future hinges on bridging performance and transparency, leveraging advanced techniques (e.g., chain-of-thought, RL) while upholding robust evaluation and open-science practices. Continued progress will likely depend on refining how we measure explanation quality, adapt them to user needs, and ensure that rationales faithfully mirror model processes.

#### Conclusion

In this paper, we explored the landscape of XNLP by focusing on how it can be effectively applied across multiple domains to enhance user understanding, transparency, and trust in machine learning models. We began by examining the increasing sophistication of NLP systems and the intrinsic opacity of advanced architectures such as transformers. Particularly in high-stakes sectors like healthcare and finance, understanding *why* a model predicts certain outcomes is often as crucial as the predictions themselves.

We then traced the evolution of XNLP modeling techniques, starting from traditional methods like BoW and TF-IDF and advancing to embedding-based and transformer architectures. We highlighted various interpretability approaches, attention visualization, gradient-based explanations, and rationalization methods, that aim to demystify the inner workings of NLP systems. Additionally, we demonstrated how these techniques can be employed to align complex models with end-user requirements for clarity and reliability.

From here, we examined XNLP's implementation in distinct domains:

- **Medicine:** Deployments in EHRs and clinical text analysis illustrate how XNLP can generate actionable insights for patient care. It provides interpretable outputs that can strengthen medical decision-making and build confidence among clinicians.
- **Finance:** We explored XNLP solutions for risk assessment, fraud detection, and firm valuation, underscoring the need for transparent predictive models in a domain where accountability is critical.
- **Systematic Reviews:** By explaining which studies are included or excluded, XNLP can enhance both the efficiency and clarity of evidence-based research.
- **CRM and Chatbots:** Employing XNLP to boost sentiment analysis or to create context-aware chatbot-sproduces more trustworthy and user-friendly systems, emphasizing customer satisfaction.
- Social and Behavioral Science: We saw how XNLP can detect hate speech, sexism, misinformation, and mental health signals, thus promoting ethical and transparent analysis of social data.

- Human Resources: In HR, XNLP can automate tasks like recruitment or performance evaluation, offering explicit rationales that foster fair and unbiased decisions.
- Other Applications: Tasks like language generation, machine translation, and visual question answering demonstrate the breadth of XNLP's impact and the diverse challenges in making advanced models interpretable.

We then delved into *critical aspects* of XNLP, discussing evaluation metrics (both quantitative and qualitative), potential trade-offs in model complexity and interpretability, and rationalization methods that strive for transparency while maintaining performance. We also highlighted the pivotal role of human-in-the-loop designs—where user feedback, bias detection, and user satisfaction can refine explanations, as well as the importance of open science practices for data and code availability. Finally, we outlined future research directions, including RL integrations, chain-of-thought reasoning, hybrid neuro-symbolic architectures, explainable dialogue systems, and personalized or adaptive explainability. These frontiers show how XNLP may further develop to meet real-world needs for trustworthy, useraligned natural language solutions.

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#### **Declarations**

#### Data availability

No primary data were generated; all sources are cited in the reference list.

#### Conflict of interest

The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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# Glossary of Terms and Abbreviations Research Methodology

To initiate our review, we conducted an extensive search of reputable databases such as *Google Scholar*, *IEEE Xplore*, *ACL*, and *ACM Digital Library*, using keywords related to *explainable AI* and *natural language processing*. This initial search provided a broad corpus of relevant academic work, which we subsequently refined through a **bibliometric analysis** performed with *VOSviewer*. This tool facilitated the identification of core articles, keywords,

Table 11. Common Definitions and Abbreviations

Term/Abbrev.	Definition	
SVM	Support Vector Machine	
CNN	Convolutional Neural Network	
LSTM	Long Short-Term Memory	
Transformer	A neural network architecture using self- attention	
BERT	Bidirectional Encoder Representations from Transformers	
DistilBERT	A smaller, distilled version of BERT	
XLM-R	A multilingual variant of RoBERTa	
BiGRU	Bidirectional Gated Recurrent Unit	
BiLSTM	Bidirectional Long Short-Term Memory	
Ensemble Model	A combination of multiple models (e.g., BERT, XLM-R, DistilBERT)	
GPT-4	Generative Pre-trained Transformer 4, a large language model by OpenAI	
MAE	Mean Absolute Error	
AUC / AUC-ROC	Area Under the ROC (Receiver Operating Characteristic) Curve	
Accuracy	Ratio of correct predictions to total predictions	
Precision	True Positives	
Recall	True Positives + False Positives True Positives + False Negatives True Positives + False Negatives	
F1-score	Harmonic mean of Precision and Recall	
RMSE	Root Mean Squared Error	
ROUGE	Recall-Oriented Understudy for Gisting Eval-	
ROUGE	uation (a summarization metric)	
XAI	Explainable Artificial Intelligence	
LIME	Local Interpretable Model-agnostic Explana-	
SHAP	SHapley Additive exPlanations	
MLQE-PE	Machine Translation Quality Estimation - Post Editing dataset	
NMT	Neural Machine Translation	
Probing Methodology	Analyzing internal representations (e.g., attention) to assess model behavior	
RCT	Randomized Controlled Trial	
SST-2 / SST-5	Stanford Sentiment Treebank (binary/5-class)	
UMNSRS	University of Minnesota Semantic Related-	
WSS	ness Set Work Saved over Sampling (systematic review metric)	

and research interconnections, thereby producing a more coherent keyword set for our dataset.

Following this, we employed the open-source tool *ASReview*, which leverages active learning, to further sift through our refined collection of papers. By iteratively screening them, ASReview helped pinpoint the most pertinent articles for each specific application domain in XNLP. This dual-stage methodology—*VOSviewer* for visual bibliometric insights and *ASReview* for targeted article retrieval—proved robust and efficient in capturing the breadth and depth of XNLP research. Below is a concise summary of the methodological steps:

- Data Sources: We scoured databases like Google Scholar, IEEE Xplore, ACL, and ACM Digital Library, focusing on publications from 2018 to 2025.
- 2. Search Strategy: Relevant terms ('`explainable AI'' and '`natural language processing'') were searched within titles, abstracts, and keywords.

<sup>¶</sup>https://www.vosviewer.com/

https://asreview.nl/

 Bibliometric Analysis: Using VOSviewer, we built cooccurrence networks of keywords and identified major thematic clusters.

- 4. *Initial Results:* We initially obtained 217 candidate papers, forming a provisional survey of the XNLP landscape.
- 5. *Data Cleaning:* Duplicates and marginally related items were removed, resulting in a streamlined dataset of 135 papers.
- Targeted Literature Retrieval: Through ASReview, we systematically screened the dataset to isolate articles that offered the most relevant insights for each XNLP application.

Cross-referencing these tools (VOSviewer for bibliometric visualization and ASReview for systematic screening) offered a balanced approach that sped up the literature analysis and clarified the focal points in XNLP research. In particular, this methodology aided in revealing the primary ways XNLP is applied, the challenges observed, and the prospective frontiers for further inquiry.

Table 12 displays the final distribution of papers across different XNLP application domains, illustrating how we curated a representative yet succinct overview of current research. This approach not only streamlined the literature survey but also enabled a sharper focus on the domains covered in this review.

**Table 12.** Number of Final Related Papers in Different Applications

No.	Application	No. Papers
1	Medicine	26
2	Finance	22
3	Systematic Reviews	14
4	CRM	31
5	Chatbots and Conversational AI	17
6	Social and Behavioral Science	29
7	HR	18
8	Other Applications	34

# Terminology

To ensure clarity throughout the paper, we define the key terms that frequently appear in our discussions:

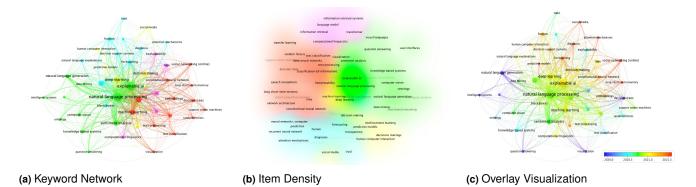
- Natural Language Processing (NLP): A field of AI involving the interpretation and generation of human language by computational means.
- XNLP: A specific domain within NLP emphasizing transparent and interpretable machine learning models.
   Its purpose is to clarify how models arrive at their conclusions.
- Rational NLP (RNLP): An extension of NLP focusing on generating explicit logical justifications or rationales for model decisions.
- Explainability-Performance Balance: The tension between maximizing predictive accuracy and preserving interpretability in model design.

- Human-in-the-Loop (HITL): A paradigm where human feedback is integrated into model training and validation to ensure alignment with practical, ethical, or domainspecific criteria.
- Interpretability Metrics: Quantitative measures (e.g., fidelity, completeness) used to assess how well an explanation reflects the internal logic of a model or informs end-users.
- Explanatory Visualization: Approaches (e.g., attention heatmaps, saliency maps) that visually clarify which features or tokens influence a model's decision-making process.

Together, these definitions and methodological steps underlie our exploration of XNLP across various application domains, shaping the paper's discussion on explainability, transparency, and the evolving research directions in this field.

#### References

- Gwénolé Abgrall, Andre L Holder, Zaineb Chelly Dagdia, Karine Zeitouni, and Xavier Monnet. Should ai models be explainable to clinicians? *Critical Care*, 28(1):301, 2024.
- Abdul Ahad Abro, Mir Sajjad Hussain Talpur, and Awais Khan Jumani. Natural language processing challenges and issues: A literature review. *Gazi University Journal of Science*, pages 1–1, 2023.
- Tasnim Ahmed, Shahriar Ivan, Ahnaf Munir, and Sabbir Ahmed. Decoding depression: Analyzing social network insights for depression severity assessment with transformers and explainable ai. *Natural Language Processing Journal*, 7: 100079, 2024. ISSN 2949-7191. doi: https://doi.org/10.1016/j.nlp.2024.100079. URL https://www.sciencedirect.com/science/article/pii/S294971912400027X.
- Abbas Akkasi. Job description parsing with explainable transformer based ensemble models to extract the technical and non-technical skills. *Natural Language Processing Journal*, 9: 100102, 2024. ISSN 2949-7191. doi: https://doi.org/10.1016/j.nlp.2024.100102. URL https://www.sciencedirect.com/science/article/pii/S2949719124000505.
- Rasheed Omobolaji Alabi, Mohammed Elmusrati, Ilmo Leivo, Alhadi Almangush, and Antti A Mäkitie. Machine learning explainability in nasopharyngeal cancer survival using lime and shap. Scientific Reports, 13(1):8984, 2023.
- J Alammar. Ecco: An open source library for the explainability of transformer language models. In Heng Ji, Jong C. Park, and Rui Xia, editors, *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 249–257, Online, August 2021. ACL Anthology. doi: 10.18653/v1/2021.acl-demo.30. URL https://aclanthology.org/2021.acl-demo.30.
- Rao Hamza Ali, Gabriela Pinto, Evelyn Lawrie, and Erik J Linstead. A large-scale sentiment analysis of tweets pertaining to the 2020 us presidential election. *Journal of big Data*, 9(1):79, 2022.
- Sajid Ali, Tamer Abuhmed, Shaker El-Sappagh, Khan Muhammad, Jose M Alonso-Moral, Roberto Confalonieri, Riccardo



**Figure 3.** VOSviewer-based visualizations of the bibliometric data: **(a)** Network of co-occurring keywords, **(b)** Item density revealing concentrated regions of research interest, **(c)** Overlay map where color corresponds to average publication year (blue = earlier, red = more recent).

Guidotti, Javier Del Ser, Natalia Díaz-Rodríguez, and Francisco Herrera. Explainable artificial intelligence (xai): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion*, 99:101805, 2023.

Afra Alishahi, Grzegorz Chrupała, and Tal Linzen. Analyzing and interpreting neural networks for nlp: A report on the first blackboxnlp workshop. *Natural Language Engineering*, 25(4): 543–557, 2019.

E Andrews. How flawed data aggravates inequality in credit, 2021. Anjum and Rahul Katarya. Hate speech, toxicity detection in online social media: a recent survey of state of the art and opportunities. *International Journal of Information Security*, pages 1–32, 2023.

Diego Antognini and Boi Faltings. Rationalization through concepts. *ArXiv*, abs/2105.04837, 2021. URL https://api.semanticscholar.org/CorpusID:234357794.

Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, Richard Benjamins, et al. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information fusion*, 58:82–115, 2020.

Shreyash Arya, Sukrut Rao, Moritz Boehle, and Bernt Schiele. B-cosification: Transforming deep neural networks to be inherently interpretable. In 38th Conference on Neural Information Processing Systems, 2024.

Pepa Atanasova. *Generating Fact Checking Explanations*, pages 83–103. Springer Nature Switzerland, Cham, 2024. ISBN 978-3-031-51518-7. doi: 10.1007/978-3-031-51518-7\_4. URL https://doi.org/10.1007/978-3-031-51518-7\_4.

Hammad A Ayyubi, Md Mehrab Tanjim, Julian J McAuley, and Garrison W Cottrell. Generating rationales in visual question answering. *arXiv preprint arXiv:2004.02032*, 2020.

Luca Bacco, Andrea Cimino, Felice Dell'Orletta, and Mario Merone. Explainable sentiment analysis: a hierarchical transformer-based extractive summarization approach. *Electronics*, 10(18):2195, 2021. ISBN: 2079-9292 Publisher: MDPI.

Pallavi Bagga and Kostas Stathis. Towards explainable strategy templates using nlp transformers. *arXiv preprint* arXiv:2311.14061, 2023.

Ayoub Bagheri, Anastasia Giachanou, Pablo Mosteiro, and Suzan Verberne. *Natural Language Processing* 

 and
 Text
 Mining
 (Turning
 Unstructured
 Data

 into
 Structured)
 pages
 69–93
 Springer
 International

 Publishing
 Cham
 2023
 ISBN
 978-3-031-36678-9

 9
 doi:
 10.1007/978-3-031-36678-9\_5
 URL
 https:

 //doi.org/10.1007/978-3-031-36678-9\_5
 https:

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473, 2014. URL https://api.semanticscholar.org/CorpusID:11212020.

Roy Bar-Haim, Lilach Eden, Roni Friedman, Yoav Kantor, Dan Lahav, and Noam Slonim. From Arguments to Key Points: Towards Automatic Argument Summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4029–4039, Online, July 2020. ACL Anthology. doi: 10.18653/v1/2020. acl-main.371. URL https://aclanthology.org/2020.acl-main.371.

Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness in machine learning*. NIPS Tutorial, 2016.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in neural information processing systems, 29, 2016.

Alexandre Bovet and Hernán A. Makse. Influence of fake news in Twitter during the 2016 US presidential election. *Nature communications*, 10(1):7, 2019. ISBN: 2041-1723 Publisher: Nature Publishing Group UK London.

Stephanie Brandl, Emanuele Bugliarello, and Ilias Chalkidis. On the interplay between fairness and explainability. In Anaelia Ovalle, Kai-Wei Chang, Yang Trista Cao, Ninareh Mehrabi, Jieyu Zhao, Aram Galstyan, Jwala Dhamala, Anoop Kumar, and Rahul Gupta, editors, *Proceedings of the 4th Workshop on Trustworthy Natural Language Processing (TrustNLP 2024)*, pages 94–108, Mexico City, Mexico, June 2024. ACL Anthology. doi: 10.18653/v1/2024. trustnlp-1.10. URL https://aclanthology.org/2024.trustnlp-1.10.

Adrian MP Braşoveanu and Răzvan Andonie. Visualizing and explaining language models. In *Integrating Artificial Intelligence and Visualization for Visual Knowledge Discovery*, pages 213–237. Springer, 2022.

L Brinkman, Judith J de Haan, Daniël van Hemert, Joost de Laat, Dominique Rijshouwer, Sander Thomaes, and Ruth van Veelen. Open science monitor 2020 utrecht

university: commissioned by the utrecht university open science programme. 2021.

- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language Models are Few-Shot Learners. In Advances in Neural Information Processing Systems, volume 33, pages 1877-1901. Curran Associates, Inc., 2020. URL https: //proceedings.neurips.cc/paper/2020/hash/ 1457c0d6bfcb4967418bfb8ac142f64a-Abstract. html.
- Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186, 2017.
- Nicola Capuano, Luca Greco, Pierluigi Ritrovato, and Mario Vento. Sentiment analysis for customer relationship management: an incremental learning approach. *Applied Intelligence*, 51:3339– 3352, 2021.
- Nicola Capuano, Giuseppe Fenza, Vincenzo Loia, and Francesco David Nota. Content based fake news detection with machine and deep learning: a systematic review. Neurocomputing, 2023.
- Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Brian Strope, and Ray Kurzweil. Universal sentence encoder for English. In Eduardo Blanco and Wei Lu, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 169–174, Brussels, Belgium, November 2018. ACL Anthology. doi: 10.18653/v1/D18-2029. URL https://aclanthology.org/D18-2029.
- Jurgita Černevičienė and Audrius Kabašinskas. Explainable artificial intelligence (xai) in finance: a systematic literature review. *Artificial Intelligence Review*, 57(8):216, 2024.
- Aaron Chan, Maziar Sanjabi, Lambert Mathias, Liang Tan, Shaoliang Nie, Xiaochang Peng, Xiang Ren, and Hamed Firooz. Unirex: A unified learning framework for language model rationale extraction. In *International Conference on Machine Learning*, pages 2867–2889. PMLR, 2022.
- Kuei-Hu Chang. Natural language processing: Recent development and applications, 2023.
- Jianbo Chen, Le Song, Martin Wainwright, and Michael Jordan. Learning to explain: An information-theoretic perspective on model interpretation. In *International conference on machine learning*, pages 883–892. PMLR, 2018.
- Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F. Stewart, and Jimeng Sun. Doctor AI: Predicting Clinical Events via Recurrent Neural Networks. In *Proceedings of the 1st Machine Learning for Healthcare Conference*, pages 301–318. PMLR, December 2016. URL https://proceedings.mlr.press/v56/Choi16.html. ISSN: 1938-7228.

- Mitali Chugh, Nitin Chanderwal, Rajesh Upadhyay, and Devendra Kumar Punia. Effect of knowledge management on software product experience with mediating effect of perceived software process improvement: An empirical study for indian software industry. *Journal of Information Science*, 46(2):258–272, 2020.
- Douglas Cirqueira, Markus Helfert, and Marija Bezbradica. Towards design principles for user-centric explainable AI in fraud detection. In Artificial Intelligence in HCI: Second International Conference, AI-HCI 2021, Held as Part of the 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings, pages 21–40. Springer, 2021.
- Austin C Conklin, Hitoo Nishi, Florencia Schlamp, Tiit Örd, Kadri Õunap, Minna U Kaikkonen, Edward A Fisher, and Casey E Romanoski. Meta-analysis of smooth muscle lineage transcriptomes in atherosclerosis and their relationships to in vitro models. *Immunometabolism*, 3(3), 2021.
- FRANCESCO COPPO and ANDREA GUIDOTTI. Artificial intelligence: analysis and evolution of the international startup ecosystem. 2018.
- Paul Covington, Jay Adams, and Emre Sargin. Deep neural networks for youtube recommendations. In *Proceedings of the 10th ACM conference on recommender systems*, pages 191–198, 2016.
- I DAGAN, S. MARCUS, and S. MARKOVITCH. Contextual word similarity and estimation from sparse data. *Comput. speech lang. (Print)*, 9(2):123–152, 1995. ISSN 0885-2308. Place: Oxford Publisher: Elsevier.
- Marina Danilevsky, Kun Qian, Ranit Aharonov, Yannis Katsis, Ban Kawas, and Prithviraj Sen. A Survey of the State of Explainable AI for Natural Language Processing. In Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing, pages 447–459, Suzhou, China, December 2020. ACL Anthology. URL https://aclanthology.org/2020.aacl-main.46.
- Jeffrey Dastin. Amazon scraps secret AI recruiting tool that showed bias against women. https://www.reuters.com/article/us-amazon-com-jobs-automation, note=Accessed: 2024-09-03, 2018.
- Lara Marie Demajo, Vince Vella, and Alexiei Dingli. Explainable ai for interpretable credit scoring. *arXiv preprint arXiv:2012.03749*, 2020.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In North American Chapter of the Association for Computational Linguistics. ACL Anthology, 2019. URL https://api.semanticscholar. org/CorpusID:52967399.
- Jay De Young, Sarthak Jain, Nazneen Fatema Rajani, Eric Lehman, Caiming Xiong, Richard Socher, and Byron C. Wallace. ERASER: A benchmark to evaluate rationalized NLP models. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4443– 4458, Online, July 2020. ACL Anthology. doi: 10.18653/ v1/2020.acl-main.408. URL https://aclanthology. org/2020.acl-main.408.

Finale Doshi-Velez and Been Kim. Towards a rigorous science of interpretable machine learning. *arXiv preprint* arXiv:1702.08608, 2017.

- Mengnan Du, Ninghao Liu, and Xia Hu. Techniques for interpretable machine learning. *Communications of the ACM*, 63(1):68–77, 2019. ISBN: 0001-0782 Publisher: ACM New York, NY, USA.
- Dxwand. Improve customer satisfaction with chatbots, 2024. URL https://.com/blog/improve-customer-satisfaction-chatbots.

  Accessed: 2024-08-04.
- Fenglei Fan, Jinjun Xiong, Mengzhou Li, and Ge Wang. On interpretability of artificial neural networks: A survey. *IEEE Transactions on Radiation and Plasma Medical Sciences*, 5:741–760, 2020. URL https://api.semanticscholar.org/CorpusID:227240484.
- Luyang Fang, Xiaowei Yu, Jiazhang Cai, Yongkai Chen, Shushan Wu, Zhengliang Liu, Zhenyuan Yang, Haoran Lu, Xilin Gong, Yufang Liu, et al. Knowledge distillation and dataset distillation of large language models: Emerging trends, challenges, and future directions. arXiv preprint arXiv:2504.14772, 2025.
- Pieter Fivez, Walter Daelemans, Tim Van de Cruys, Yury Kashnitsky, Savvas Chamezopoulos, Hadi Mohammadi, Anastasia Giachanou, Ayoub Bagheri, Wessel Poelman, Juraj Vladika, et al. The clin33 shared task on the detection of text generated by large language models. Computational Linguistics in the Netherlands Journal, 13:233–259, 2024.
- Marina Fomicheva, Lucia Specia, and Nikolaos Aletras. Translation error detection as rationale extraction. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, *Findings of the Association for Computational Linguistics: ACL 2022*, pages 4148–4159, Dublin, Ireland, May 2022. ACL Anthology. doi: 10.18653/v1/2022.findings-acl.327. URL https://aclanthology.org/2022.findings-acl.327.
- Sebastian Fritz-Morgenthal, Bernhard Hein, and Jochen Papenbrock. Financial Risk Management and Explainable, Trustworthy, Responsible AI. Frontiers in Artificial Intelligence, 5, 2022. ISSN 2624-8212. URL https://www.frontiersin.org/articles/10.3389/frai.2022.779799.
- Bhavya Ghai, Q Vera Liao, Yunfeng Zhang, Rachel Bellamy, and Klaus Mueller. Explainable active learning (xal) toward ai explanations as interfaces for machine teachers. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW3):1–28, 2021.
- Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley. A knowledge-grounded neural conversation model. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018.
- Ella Glikson and Anita Williams Woolley. Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2):627–660, 2020.
- Alex Gramegna and Paolo Giudici. Shap and lime: an evaluation of discriminative power in credit risk. *Frontiers in Artificial Intelligence*, 4:752558, 2021.
- Riccardo Guidotti, Anna Monreale, Salvatore Ruggieri, Franco Turini, Fosca Giannotti, and Dino Pedreschi. A survey of methods for explaining black box models. *ACM computing*

- surveys (CSUR), 51(5):1-42, 2018.
- Sai Gurrapu, Lifu Huang, and Feras A. Batarseh. Exclaim: Explainable neural claim verification using rationalization. 2022 IEEE 29th Annual Software Technology Conference (STC), pages 19–26, 2022. URL https://api.semanticscholar.org/CorpusID:253629794.
- Sai Gurrapu, Ajay Kulkarni, Lifu Huang, Ismini Lourentzou, and Feras A Batarseh. Rationalization for explainable nlp: A survey. *Frontiers in Artificial Intelligence*, 6, 2023.
- Nuo Han, Sijia Li, Feng Huang, Yeye Wen, Xiaoyang Wang, Xiaoqian Liu, Linyan Li, and Tingshao Zhu. Sensing psychological well-being using social media language: Prediction model development study. *Journal of Medical Internet Research*, 25:e41823, 2023.
- Shilin He, Zhaopeng Tu, Xing Wang, Longyue Wang, Michael R Lyu, and Shuming Shi. Towards understanding neural machine translation with word importance. *arXiv preprint* arXiv:1909.00326, 2019.
- Bradford Heap, Michael Bain, Wayne Wobcke, Alfred Krzywicki, and Susanne Schmeidl. Word vector enrichment of low frequency words in the bag-of-words model for short text multi-class classification problems. *arXiv preprint arXiv:1709.05778*, 2017.
- Elize Herrewijnen, Dong Nguyen, Kees Van Deemter, and Floris Bex. Human-annotated rationales and explainable text classification: A survey. *Frontiers in Artificial Intelligence*, 7: 1260952, 2023.
- John Hewitt and Percy Liang. Designing and interpreting probes with control tasks. arXiv preprint arXiv:1909.03368, 2019.
- Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint* arXiv:1503.02531, 2015.
- Robert R Hoffman, Shane T Mueller, Gary Klein, and Jordan Litman. Metrics for explainable ai: Challenges and prospects. *arXiv preprint arXiv:1812.04608*, 2018.
- Benjamin Hoover, Hendrik Strobelt, and Sebastian Gehrmann. exBERT: A Visual Analysis Tool to Explore Learned Representations in Transformer Models. In Asli Celikyilmaz and Tsung-Hsien Wen, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 187–196, Online, July 2020. ACL Anthology. doi: 10.18653/v1/2020. acl-demos.22. URL https://aclanthology.org/2020.acl-demos.22.
- KJ Igoe. Algorithmic bias in health care exacerbates social inequities—how to prevent it. *Executive and Continuing Professional Education*, 2021.
- Mir Riyanul Islam, Mobyen Uddin Ahmed, and Shahina Begum. Local and global interpretability using mutual information in explainable artificial intelligence. In 2021 8th International Conference on Soft Computing & Machine Intelligence (ISCMI), pages 191–195. IEEE, 2021.
- Mir Riyanul Islam, Mobyen Uddin Ahmed, Shaibal Barua, and Shahina Begum. A systematic review of explainable artificial intelligence in terms of different application domains and tasks. *Applied Sciences*, 12(3):1353, 2022.
- Alon Jacovi and Yoav Goldberg. Towards faithfully interpretable nlp systems: How should we define and evaluate faithfulness? In *Annual Meeting of the Association for Computational Linguistics*. ACL Anthology, 2020. URL https://api.

#### semanticscholar.org/CorpusID:215416110.

- Rachna Jain, Ashish Kumar, Anand Nayyar, Kritika Dewan, Rishika Garg, Shatakshi Raman, and Sahil Ganguly. Explaining sentiment analysis results on social media texts through visualization. *Multimedia Tools and Applications*, pages 1–17, 2023.
- Sarthak Jain and Byron C. Wallace. Attention is not Explanation. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 3543–3556, Minneapolis, Minnesota, June 2019. ACL Anthology. doi: 10.18653/v1/N19-1357. URL https://aclanthology.org/N19-1357.
- Jakub Jeck, Florian Leiser, Anne Hüsges, and Ali Sunyaev. Tell-me: Toward personalized explanations of large language models. In Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems, pages 1–18, 2025.
- Liss Jenneboer, Carolina Herrando, and Efthymios Constantinides. The impact of chatbots on customer loyalty: A systematic literature review. *Journal of theoretical and applied electronic commerce research*, 17(1):212–229, 2022.
- Jamin Rahman Jim, Md Apon Riaz Talukder, Partha Malakar, Md Mohsin Kabir, Kamruddin Nur, and MF Mridha. Recent advancements and challenges of nlp-based sentiment analysis: A state-of-the-art review. Natural Language Processing Journal, page 100059, 2024.
- Ian T. Jolliffe and Jorge Cadima. Principal component analysis: a review and recent developments. *Philosophical transactions of* the royal society A: Mathematical, Physical and Engineering Sciences, 374(2065):20150202, 2016. ISBN: 1364-503X Publisher: The Royal Society Publishing.
- Daniel Jurafsky and James H. Martin. Vector semantics and embeddings. Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition, pages 270–85, 2019.
- Katikapalli Subramanyam Kalyan, Ajit Rajasekharan, and Sivanesan Sangeetha. Ammus: A survey of transformer-based pretrained models in natural language processing. *arXiv preprint arXiv:2108.05542*, 2021.
- Tian Kang, Shaodian Zhang, Youlan Tang, Gregory W Hruby, Alexander Rusanov, Noémie Elhadad, and Chunhua Weng. EliIE: An open-source information extraction system for clinical trial eligibility criteria. *Journal of the American Medical Informatics Association*, 24(6):1062–1071, November 2017. ISSN 1067-5027. doi: 10.1093/jamia/ocx019. URL https://doi.org/10.1093/jamia/ocx019.
- Marvin Kaster, Wei Zhao, and Steffen Eger. Global explainability of BERT-based evaluation metrics by disentangling along linguistic factors. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 8912–8925, Online and Punta Cana, Dominican Republic, November 2021. ACL Anthology. doi: 10.18653/v1/2021.emnlp-main.701. URL https://aclanthology.org/2021.emnlp-main.701.
- Jenia Kim, Henry Maathuis, and Danielle Sent. Human-centered evaluation of explainable ai applications: a systematic review. *Frontiers in Artificial Intelligence*, 7:1456486, 2024.

- Hannah Kirk, Wenjie Yin, Bertie Vidgen, and Paul Röttger. Semeval-2023 task 10: Explainable detection of online sexism. In Proceedings of the 17th International Workshop on Semantic Evaluation (SemEval-2023), pages 2193–2210, 2023.
- Lukas Klein, Carsten Lüth, Udo Schlegel, Till Bungert, Mennatallah El-Assady, and Paul Jäger. Navigating the maze of explainable ai: A systematic approach to evaluating methods and metrics. Advances in Neural Information Processing Systems, 37:67106–67146, 2024.
- NIklas Kuhl, Jodie Lobana, and Christian Meske. Do you comply with ai?—personalized explanations of learning algorithms and their impact on employees' compliance behavior. *arXiv* preprint arXiv:2002.08777, 2020.
- Isaac Lage, Andrew Ross, Samuel J Gershman, Been Kim, and Finale Doshi-Velez. Human-in-the-Loop Interpretability Prior. In Advances in Neural Information Processing Systems, volume 31. Curran Associates, Inc., 2018. URL https://proceedings.neurips.cc/paper\_files/paper/2018/hash/ 0a7d83f084ec258aefd128569dda03d7-Abstract.html.
- Kushal Lakhotia, Bhargavi Paranjape, Asish Ghoshal, Wen tau Yih, Yashar Mehdad, and Srini Iyer. Fid-ex: Improving sequenceto-sequence models for extractive rationale generation. In Conference on Empirical Methods in Natural Language Processing, 2020. URL https://api.semanticscholar. org/CorpusID:229923145.
- Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=H1eA7AEtvS.
- Tamera Lanham, Anna Chen, Ansh Radhakrishnan, Benoit Steiner, Carson Denison, Danny Hernandez, Dustin Li, Esin Durmus, Evan Hubinger, Jackson Kernion, et al. Measuring faithfulness in chain-of-thought reasoning. arXiv preprint arXiv:2307.13702, 2023.
- Cristina Ledro, Anna Nosella, and Andrea Vinelli. Artificial intelligence in customer relationship management: literature review and future research directions. *Journal of Business & Industrial Marketing*, 37(13):48–63, 2022.
- Tao Lei, Regina Barzilay, and Tommi Jaakkola. Rationalizing neural predictions. In Jian Su, Kevin Duh, and Xavier Carreras, editors, *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 107–117, Austin, Texas, November 2016. ACL Anthology. doi: 10.18653/v1/D16-1011. URL https://aclanthology.org/D16-1011.
- Binbin Li, Tianxin Meng, Xiaoming Shi, Jie Zhai, and Tong Ruan. Meddm: Llm-executable clinical guidance tree for clinical decision-making. *ArXiv*, abs/2312.02441, 2023. URL https://api.semanticscholar.org/CorpusID:265658947.
- Irene Li, Jessica Pan, Jeremy Goldwasser, Neha Verma, Wai Pan Wong, Muhammed Yavuz Nuzumlalı, Benjamin Rosand, Yixin Li, Matthew Zhang, David Chang, R. Andrew Taylor, Harlan M. Krumholz, and Dragomir Radev. Neural natural language processing for unstructured data in electronic health records: A review. Computer Science Review, 46:100511,

2022. ISSN 1574-0137. doi: https://doi.org/10.1016/j.cosrev. 2022.100511. URL https://www.sciencedirect.com/science/article/pii/S1574013722000454.

- Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. Deep reinforcement learning for dialogue generation. In Jian Su, Kevin Duh, and Xavier Carreras, editors, *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202, Austin, Texas, November 2016. ACL Anthology. doi: 10. 18653/v1/D16-1127. URL https://aclanthology.org/D16-1127.
- Quan Li, Kristanto Sean Njotoprawiro, Hammad Haleem, Qiaoan Chen, Chris Yi, and Xiaojuan Ma. Embeddingvis: A visual analytics approach to comparative network embedding inspection. In 2018 IEEE Conference on Visual Analytics Science and Technology (VAST), pages 48–59. IEEE, 2018.
- Bin Liang, Hongcheng Li, Miaoqiang Su, Pan Bian, Xirong Li, and Wenchang Shi. Deep text classification can be fooled. In *Proceedings of the 27th International Joint Conference on Artificial Intelligence*, IJCAI'18, page 4208–4215. AAAI Press, 2018. ISBN 9780999241127.
- Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81, 2004.
- Zachary C Lipton. The mythos of model interpretability: In machine learning, the concept of interpretability is both important and slippery. *Queue*, 16(3):31–57, 2018.
- Chia-Wei Liu, Ryan Lowe, Iulian Serban, Mike Noseworthy, Laurent Charlin, and Joelle Pineau. How NOT To Evaluate Your Dialogue System: An Empirical Study of Unsupervised Evaluation Metrics for Dialogue Response Generation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2122–2132, Austin, Texas, November 2016. ACL Anthology. doi: 10.18653/v1/D16-1230. URL https://aclanthology.org/D16-1230.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- Zhiyuan Liu, Yankai Lin, and Maosong Sun. Representation learning for natural language processing. Springer Nature, 2020. ISBN 9811555737.
- Luca Longo. Explainable Artificial Intelligence: First World Conference, xAI 2023, Lisbon, Portugal, July 26–28, 2023, Proceedings, Part II. Springer Nature, 2023.
- Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. Advances in neural information processing systems, 30, 2017.
- Bodhisattwa Prasad Majumder, Oana-Maria Camburu, Thomas Lukasiewicz, and Julian McAuley. Knowledge-grounded self-rationalization via extractive and natural language explanations. In *International Conference on Machine Learning*, 2021. URL https://api.semanticscholar.org/CorpusID:248963782.
- Iain J. Marshall, Joël Kuiper, and Byron C. Wallace. RobotReviewer: evaluation of a system for automatically assessing bias in clinical trials. *Journal of the American Medical Informatics Association*, 23(1):193–201, 2016. ISBN: 1527-974X Publisher: Oxford University Press.

Matellio. Explainable ai chatbot development, 2024.

URL https://www.matellio.com/blog/explainable-ai-chatbot-development/.

Accessed: 2024-08-04.

- Binny Mathew, Punyajoy Saha, Seid Muhie Yimam, Chris Biemann, Pawan Goyal, and Animesh Mukherjee. Hatexplain: A benchmark dataset for explainable hate speech detection. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pages 14867–14875, 2021.
- Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*, 2018.
- Vivek Miglani, Aobo Yang, Aram Markosyan, Diego Garcia-Olano, and Narine Kokhlikyan. Using captum to explain generative language models. In Liling Tan, Dmitrijs Milajevs, Geeticka Chauhan, Jeremy Gwinnup, and Elijah Rippeth, editors, *Proceedings of the 3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS 2023)*, pages 165–173, Singapore, December 2023. ACL Anthology. doi: 10.18653/v1/2023.nlposs-1.19. URL https://aclanthology.org/2023.nlposs-1.19.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed Representations of Words and Phrases and their Compositionality. In Advances in Neural Information Processing Systems, volume 26. Curran Associates, Inc., 2013. URL https://proceedings.neurips.cc/paper/2013/hash/9aa42b31882ec039965f3c4923ce901b-Abstract.html.
- Tim Miller. Explanation in artificial intelligence: Insights from the social sciences. *Artificial intelligence*, 267:1–38, 2019.
- Branka Hadji Misheva, Joerg Osterrieder, Ali Hirsa, Onkar Kulkarni, and Stephen Fung Lin. Explainable ai in credit risk management. *arXiv preprint arXiv:2103.00949*, 2021.
- Hadi Mohammadi, Anastasia Giachanou, and Ayoub Bagheri. AI-Generated Text Detection Using Ensemble and Combined Model Training, November 2023a. URL https://doi.org/10.5281/zenodo.10079010.
- Hadi Mohammadi, Anastasia Giachanou, Ayoub Bagheri, et al. Towards robust online sexism detection: a multi-model approach with bert, xlm-roberta, and distilbert for exist 2023 tasks. In Working Notes of the Conference and Labs of the Evaluation Forum (CLEF 2023), volume 3497, pages 1000– 1011. CEUR Workshop Proceedings, 2023b.
- Hadi Mohammadi, Anastasia Giachanou, and Ayoub Bagheri. A transparent pipeline for identifying sexism in social media: Combining explainability with model prediction. *Applied Sciences*, 14(19):8620, 2024.
- Sina Mohseni, Niloofar Zarei, and Eric D Ragan. A multidisciplinary survey and framework for design and evaluation of explainable ai systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 11(3-4):1–45, 2021.
- Milad Moradi and Matthias Samwald. Deep learning, natural language processing, and explainable artificial intelligence in the biomedical domain. *arXiv preprint arXiv:2202.12678*, 2022
- Marzieh Mozafari, Reza Farahbakhsh, and Noël Crespi. Hate speech detection and racial bias mitigation in social media based on bert model. *PloS one*, 15(8):e0237861, 2020.

James Mullenbach, Sarah Wiegreffe, Jon Duke, Jimeng Sun, and Jacob Eisenstein. Explainable prediction of medical codes from clinical text. In Marilyn Walker, Heng Ji, and Amanda Stent, editors, Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1101-1111, New Orleans, Louisiana, June 2018. ACL Anthology. doi: 10.18653/v1/N18-1100. URL https://aclanthology.org/N18-1100.

- W James Murdoch, Peter J Liu, and Bin Yu. Beyond word importance: Contextual decomposition to extract interactions from lstms. arXiv preprint arXiv:1801.05453, 2018.
- Benjamin Nye, Junyi Jessy Li, Roma Patel, Yinfei Yang, Iain J. Marshall, Ani Nenkova, and Byron C. Wallace. A corpus with multi-level annotations of patients, interventions and outcomes to support language processing for medical literature. Proceedings of the conference. Association for Computational Linguistics. Meeting, volume 2018, page 197. NIH Public Access, 2018.
- Chris Olah, Alexander Mordvintsev, and Ludwig Schubert. Feature visualization. Distill, 2(11):e7, 2017.
- David Oniani, Xizhi Wu, Shyam Visweswaran, Sumit Kapoor, Shravan Kooragayalu, Katelyn Polanska, and Yanshan Wang. Enhancing large language models for clinical decision support by incorporating clinical practice guidelines. 12th International Conference on Healthcare Informatics (ICHI), pages 694-702, 2024. URL https://api. semanticscholar.org/CorpusID:267069462.
- OpenAI. Hello gpt-4o, 2024a. URL https://openai.com/ index/hello-gpt-4o/. Accessed: 2024-08-04.
- OpenAI. Gpt-40 mini: Advancing cost-efficient intelligence, 2024b. https://openai.com/index/ URL Accessed: 2024-08-04.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 311-318, 2002.
- Narendra Patwardhan, Stefano Marrone, and Carlo Sansone. Transformers in the real world: A survey on nlp applications. Information, 14(4):242, 2023.
- Jeffrey Pennington, Richard Socher, and Christopher Manning. GloVe: Global Vectors for Word Representation. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532-1543, Doha, Qatar, October 2014. ACL Anthology. 10.3115/v1/D14-1162. URL https://aclanthology. org/D14-1162.
- Laura Plaza, Jorge Carrillo-de Albornoz, Roser Morante, Enrique Amigó, Julio Gonzalo, Damiano Spina, and Paolo Rosso. Overview of exist 2023: sexism identification in social networks. In European Conference on Information Retrieval, pages 593-599. Springer, 2023.
- Kamil Pluciński. Overview of explainable AI methods in NLP, 2022. URL https://deepsense.ai/ overview-of-explainable-ai-methods-in-nlp/. Section: Artificial Intelligence.
- Mitchell Plyler, Michael Green, and Min Chi. Making a (counterfactual) difference one rationale at a time. Advances in Neural Information Processing Systems, 34:28701-28713,

2021.

- Ismini Psychoula, Andreas Gutmann, Pradip Mainali, Sharon H. Lee, Paul Dunphy, and Fabien Petitcolas. Explainable Machine Learning for Fraud Detection. Computer, 54(10):49–59, October 2021. ISSN 1558-0814. doi: 10.1109/MC.2021. 3081249. Conference Name: Computer.
- Erika Puiutta and Eric MSP Veith. Explainable reinforcement learning: A survey. In International cross-domain conference for machine learning and knowledge extraction, pages 77–95. Springer, 2020.
- Kun Qian, Marina Danilevsky, Yannis Katsis, Ban Kawas, Erick Oduor, Lucian Popa, and Yunyao Li. Xnlp: A living survey for xai research in natural language processing. In 26th International Conference on Intelligent User Interfaces-Companion, pages 78-80, 2021.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.
- Nazneen Fatema Rajani, Bryan McCann, Caiming Xiong, and Richard Socher. Explain yourself! leveraging language models for commonsense reasoning. arXiv preprint arXiv:1906.02361, 2019.
- Ashish Rana, Deepanshu Khanna, Tirthankar Ghosal, Muskaan Singh, Harpreet Singh, and Prashant Singh Rana. Rerrfact: Reduced evidence retrieval representations for scientific claim verification. arXiv preprint arXiv:2202.02646, 2022.
- Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. Modelagnostic interpretability of machine learning. arXiv preprint arXiv:1606.05386, 2016a.
- Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "Why Should I Trust You?": Explaining the Predictions of Any In Proceedings of the 22nd ACM SIGKDD gpt-4o-mini-advancing-cost-efficient-intelligentational Conference on Knowledge Discovery and Data Mining, KDD '16, pages 1135-1144, New York, NY, USA, August 2016b. Association for Computing Machinery. ISBN 978-1-4503-4232-2. doi: 10.1145/2939672.2939778. URL https://doi.org/10.1145/2939672.2939778.
  - Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. Semantically Equivalent Adversarial Rules for Debugging NLP models. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 856-865, Melbourne, Australia, July 2018. ACL Anthology. doi: 10.18653/v1/P18-1079. URL https: //aclanthology.org/P18-1079.
  - Maryan Rizinski, Hristijan Peshov, Kostadin Mishev, Milos Jovanovik, and Dimitar Trajanov. Sentiment analysis in finance: From transformers back to explainable lexicons (xlex). IEEE Access, 2024.
  - Graciela Rosemblat, Marcelo Fiszman, Dongwook Shin, and Halil Kilicoglu. Towards a characterization of apparent contradictions in the biomedical literature using context analysis. J Biomed Inform, 98:103275, October 2019. ISSN 1532-0480. doi: 10.1016/j.jbi.2019.103275.
  - Cynthia Rudin and Joanna Radin. Why are we using black box models in ai when we don't need to? a lesson from an explainable ai competition. Harvard Data Science Review, 1 (2):1-9,2019.
  - Cynthia Rudin, Chaofan Chen, Zhi Chen, Haiyang Huang, Lesia Semenova, and Chudi Zhong. Interpretable machine learning: Fundamental principles and 10 grand challenges. Statistic

- Surveys, 16:1-85, 2022.
- Hind Saleh, Areej Alhothali, and Kawthar Moria. Detection of hate speech using bert and hate speech word embedding with deep model. Applied Artificial Intelligence, 37(1):2166719, 2023.
- Surjodeep Sarkar, Manas Gaur, L Chen, Muskan Garg, Biplav Srivastava, and Bhaktee Dongaonkar. Towards explainable and safe conversational agents for mental health: A survey. arXiv preprint arXiv:2304.13191, 2023.
- Benedikt Schmidl, Tobias Hütten, Steffi Pigorsch, Fabian Stögbauer, Cosima C Hoch, Timon Hussain, Barbara Wollenberg, and Markus Wirth. Assessing the use of the novel tool claude 3 in comparison to chatgpt 4.0 as an artificial intelligence tool in the diagnosis and therapy of primary head and neck cancer cases. European Archives of Oto-Rhino-Laryngology, 281(11):6099-6109, 2024.
- Olga Seminck. Conversational ai: Dialogue systems, conversational agents, and chatbots by michael mctear. Computational Linguistics, 49(1):257-259, 2023.
- Lei Sha, Oana-Maria Camburu, and Thomas Lukasiewicz. Rationalizing predictions by adversarial information calibra-Artificial Intelligence, 315:103828, 2023. 0004-3702. doi: https://doi.org/10.1016/j.artint.2022.103828. URL https://www.sciencedirect.com/science/ article/pii/S0004370222001680.
- Emily Sheng, Kai-Wei Chang, Premkumar Natarajan, and Nanyun The woman worked as a babysitter: On biases in language generation. arXiv preprint arXiv:1909.01326, 2019.
- Erica K. Shimomoto, Lincon S. Souza, Bernardo B. Gatto, and Kazuhiro Fukui. Text classification based on word subspace with term-frequency. In 2018 International Joint Conference on Neural Networks (IJCNN), pages 1-8. IEEE, 2018. ISBN 1-5090-6014-6.
- Vedansh Shrivastava. Innovation Unleashed: The Hottest NLP Technologies of 2022, December 2022. URL https: //www.analyticsvidhya.com/blog/2022/12/ innovation-unleashed-the-hottest-nlp-technologi2021, Proceedings 23, pages 81-93. Springer, 2021.
- Aditya Siddhant and Zachary C. Lipton. Deep Bayesian active learning for natural language processing: Results of a large-In Ellen Riloff, David Chiang, scale empirical study. Julia Hockenmaier, and Jun'ichi Tsujii, editors, Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2904-2909, Brussels, Belgium, October-November 2018. ACL Anthology. doi: 10.18653/ v1/D18-1318. URL https://aclanthology.org/ D18-1318.
- Damien Sileo and Marie-Francine Moens. Analysis and prediction of NLP models via task embeddings. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Jan Odijk, and Stelios Piperidis, editors, Proceedings of the Thirteenth Language Resources and Evaluation Conference, pages 633-647, Marseille, France, June 2022. European Language Resources Association. URL https://aclanthology. org/2022.lrec-1.67.
- David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, et al. Mastering the game of go with deep neural networks and tree search. Nature, 529(7587):484-489, 2016.

- Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Deep inside convolutional networks: Visualising image classification models and saliency maps. CoRR, abs/1312.6034, 2013. URL https://api.semanticscholar.org/ CorpusID: 1450294.
- Sameer Singh, Marco Tulio Ribeiro, and Carlos Guestrin. Programs as black-box explanations. ArXiv, abs/1611.07579, 2016. URL https://api.semanticscholar.org/ CorpusID:13345472.
- Samuel Sithakoul, Sara Meftah, and Clément Feutry. Beexai: Benchmark to evaluate explainable ai. In World Conference on Explainable Artificial Intelligence, pages 445-468. Springer, 2024.
- Anders Søgaard. Explainable natural language processing. Morgan & Claypool Publishers, 2021.
- Congzheng Song and Ananth Raghunathan. Information leakage in embedding models. In Proceedings of the 2020 ACM SIGSAC conference on computer and communications security, pages 377-390, 2020.
- A. Soni and S. Dubey. The impact of ai-powered chatbots on customer satisfaction in e-commerce marketing (tam approach). Journal of Public Relations and Advertising, 3(1): 12-18, 2024.
- Shashank Sonkar, Andrew E. Waters, and Richard Baraniuk. Attention word embedding. In International Conference on Computational Linguistics, 2020. URL https://api. semanticscholar.org/CorpusID:219176825.
- Mukund Sundararajan, Ankur Taly, and Qiqi Yan. Axiomatic attribution for deep networks. In International conference on machine learning, pages 3319-3328. PMLR, 2017.
- Xuejiao Tang, Xin Huang, Wenbin Zhang, Travers B Child, Qiong Hu, Zhen Liu, and Ji Zhang. Cognitive visual commonsense reasoning using dynamic working memory. In Big Data Analytics and Knowledge Discovery: 23rd International Conference, DaWaK 2021, Virtual Event, September 27-30,
- TechTarget. Context window, 2024a. URL https: //www.techtarget.com/whatis/definition/ context-window. Accessed: 2024-08-04.
- TechTarget. Gpt-4o explained: Everything need to know, 2024b. URL https:// www.techtarget.com/whatis/feature/ GPT-4o-explained-Everything-you-need-to-know. Accessed: 2024-08-04.
- Jelle Jasper Teijema, Jonathan de Bruin, Ayoub Bagheri, and Rens van de Schoot. Large-scale simulation study of active learning models for systematic reviews. International Journal of Data Science and Analytics, pages 1-22, 2025.
- Adly Templeton, Tom Conerly, Jonathan Marcus, Jack Lindsey, Trenton Bricken, Brian Chen, Adam Pearce, Craig Citro, Emmanuel Ameisen, Andy Jones, Hoagy Cunningham, Nicholas L. Turner, Callum McDougall, Monte MacDiarmid, Alex Tamkin, Esin Durmus, Tristan Hume, Francesco Mosconi, C. Daniel Freeman, Theodore R. Sumers, Edward Rees, Joshua Batson, Adam Jermyn, Shan Carter, Chris Olah, and Tom Henighan. Scaling monosemanticity: Extracting interpretable features from claude 3 sonnet. https://transformer-circuits.pub/2024/ scaling-monosemanticity/, 2024. Accessed: 2025-05-26.

- Ian Tenney, James Wexler, Jasmijn Bastings, Tolga Bolukbasi, Andy Coenen, Sebastian Gehrmann, Ellen Jiang, Mahima Pushkarna, Carey Radebaugh, Emily Reif, and Ann Yuan. The language interpretability tool: Extensible, interactive visualizations and analysis for NLP models. In Qun Liu and David Schlangen, editors, Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 107-118, Online, October 2020. ACL Anthology. doi: 10.18653/v1/2020. emnlp-demos.15. URL https://aclanthology.org/ 2020.emnlp-demos.15.
- Threado. How ai chatbots improve customer engagement and retention, 2024. URL https://www.threado.com/blogs/ Accessed: 2024-08-04.
- Erico Tjoa and Cuntai Guan. A survey on explainable artificial intelligence (xai): Toward medical xai. IEEE transactions on neural networks and learning systems, 32(11):4793-4813, 2020.
- Che-Ping Tsai, Chih-Kuan Yeh, and Pradeep Ravikumar. Faithshap: The faithful shapley interaction index. Machine Learning Research, 24(94):1–42, 2023.
- Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-SNE. Journal of machine learning research, 9(11), 2008. ISBN: 1532-4435.
- Kush R. Varshney and Homa Alemzadeh. On the safety of machine learning: Cyber-physical systems, decision sciences, and data products. Big data, 5(3):246-255, 2017. ISBN: 2167-6461 Publisher: Mary Ann Liebert, Inc. 140 Huguenot Street, 3rd Floor New Rochelle, NY 10801 USA.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in neural information processing systems, 30, 2017.
- Jesse Vig. A multiscale visualization of attention in the transformer model. ACL 2019, page 37, 2019.
- David C Vogelsang and Bradley J Erickson. Magician's corner: 6. tensorflow and tensorboard, 2020.
- Eric Wallace, Yizhong Wang, Sujian Li, Sameer Singh, and Matt Gardner. Do nlp models know numbers? probing numeracy in embeddings. In Conference on Empirical Methods in Natural Language Processing, 2019. URL https://api. semanticscholar.org/CorpusID:202583694.
- Bo Wang, Jing Ma, Hongzhan Lin, Zhiwei Yang, Ruichao Yang, Yuan Tian, and Yi Chang. Explainable fake news detection with large language model via defense among competing wisdom. In Proceedings of the ACM Web Conference 2024, pages 2452– 2463, 2024a.
- Liyang Wang, Yu Cheng, Ao Xiang, Jingyu Zhang, and Haowei Yang. Application of natural language processing in financial risk detection. arXiv preprint arXiv:2406.09765, 2024b.
- Yu Wang. Single training dimension selection for word embedding with pca. arXiv preprint arXiv:1909.01761, 2019.
- Martin Wattenberg, Fernanda Viégas, and Ian Johnson. How to use t-sne effectively. Distill, 1(10):e2, 2016.
- Leon Weber, Pasquale Minervini, Jannes Munchmeyer, Ulf Leser, and Tim Rocktäschel. Nlprolog: Reasoning with weak unification for question answering in natural language. In Annual Meeting of the Association for Computational Linguistics. ACL Anthology, 2019. URL https://api.

#### semanticscholar.org/CorpusID:189898046.

- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-ofthought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824– 24837, 2022.
- Nathaniel Weir, Peter Clark, and Benjamin Van Durme. Nellie: a neuro-symbolic inference engine for grounded, compositional, and explainable reasoning. In Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, pages 3602-3612, 2024.
- Wei-Hung Weng, Kavishwar B. Wagholikar, Alexa T. McCray, Peter Szolovits, and Henry C. Chueh. Medical subdomain  $\verb|how-ai-chatbots-improve-customer-engagement-and \verb|dassfinear| foi holds | local modes | using a machine | learning-learning | local modes | local modes$ based natural language processing approach. BMC Medical Informatics and Decision Making, 17(1):155, December 2017. ISSN 1472-6947. doi: 10.1186/s12911-017-0556-8. URL https://doi.org/10.1186/s12911-017-0556-8.
  - Sarah Wiegreffe and Yuval Pinter. Attention is not not explanation. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 11-20, Hong Kong, China, November 2019. ACL Anthology. doi: 10.18653/ v1/D19-1002. URL https://aclanthology.org/ D19-1002.
  - Sarah Wiegreffe, Ana Marasović, and Noah A. Smith. Measuring association between labels and free-text rationales. In Conference on Empirical Methods in Natural Language Processing, 2020. URL https://api.semanticscholar.org/ CorpusID: 225068329.
  - Kailai Yang, Shaoxiong Ji, Tianlin Zhang, Qianqian Xie, Ziyan Kuang, and Sophia Ananiadou. Towards interpretable mental health analysis with large language models. Houda Bouamor, Juan Pino, and Kalika Bali, editors, Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, pages 6056–6077, Singapore, December 2023a. ACL Anthology. doi: 10.18653/v1/2023. emnlp-main.370. URL https://aclanthology.org/ 2023.emnlp-main.370.
  - Liuqing Yang, Xifeng Wang, Qi Guo, Scott Gladstein, Dustin Wooten, Tengfei Li, Weining Z Robieson, Yan Sun, Xin Huang, and Alzheimer's Disease Neuroimaging Initiative. Deep learning based multimodal progression modeling for alzheimer's disease. Statistics in Biopharmaceutical Research, 13(3):337-343, 2021.
  - Yongjin Yang, Joonkee Kim, Yujin Kim, Namgyu Ho, James Thorne, and Se-Young Yun. Hare: Explainable hate speech detection with step-by-step reasoning. arXiv preprint arXiv:2311.00321, 2023b.
  - Mo Yu, Shiyu Chang, Yang Zhang, and T. Jaakkola. Rethinking cooperative rationalization: Introspective extraction and complement control. In Conference on Empirical Methods in Natural Language Processing, 2019. URL https://api. semanticscholar.org/CorpusID:202235037.
  - Mo Yu, Yang Zhang, Shiyu Chang, and Tommi Jaakkola. Understanding interlocking dynamics of cooperative rationalization. Advances in Neural Information Processing Systems, 34: 12822-12835, 2021.

Omar Zaidan, Jason Eisner, and Christine Piatko. Using "annotator rationales" to improve machine learning for text categorization. In Human language technologies 2007: The conference of the North American chapter of the association for computational linguistics; proceedings of the main conference, pages 260–267. ACL Anthology, 2007.

- Guobiao Zhang, Anastasia Giachanou, and Paolo Rosso. Scenefnd: Multimodal fake news detection by modelling scene context information. *Journal of Information Science*, 50(2):355–367, 2024
- Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. Deep learning based recommender system: A survey and new perspectives. *ACM computing surveys (CSUR)*, 52(1):1–38, 2019a. ISBN: 0360-0300 Publisher: ACM New York, NY, USA.
- Yijia Zhang, Qingyu Chen, Zhihao Yang, Hongfei Lin, and Zhiyong Lu. Biowordvec, improving biomedical word embeddings with subword information and mesh. *Scientific data*, 6(1):52, 2019b.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Z. Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jianyun Nie, and Ji rong Wen. A survey of large language models. *ArXiv*, abs/2303.18223, 2023. URL https://api.semanticscholar.org/CorpusID:257900969.
- Wangchunshu Zhou, Jinyi Hu, Hanlin Zhang, Xiaodan Liang, Maosong Sun, Chenyan Xiong, and Jian Tang. Towards interpretable natural language understanding with explanations as latent variables. Advances in Neural Information Processing Systems, 33:6803–6814, 2020.
- Ayah Zirikly, Philip Resnik, Ozlem Uzuner, and Kristy Hollingshead. Clpsych 2019 shared task: Predicting the degree of suicide risk in reddit posts. In *Proceedings of the sixth workshop on computational linguistics and clinical psychology*, pages 24–33, 2019.
- Arkaitz Zubiaga. Tf-cr: Weighting embeddings for text classification. arXiv preprint arXiv:2012.06606, 2020.