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ExplainLLM: An Explainable Large Language Model Framework for Transparent AI Decision Support

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Abstract
Large Language Models (LLMs) have transformed artificial intelligence with their impressive powers in comprehending natural language, thinking, and creating content. While they perform well in many application areas, their decision making is typically opaque limiting confidence and thus their adoption in safety-critical contexts including as healthcare, banking, education and the legal system. Without transparency of reasoning procedures, consumers are unable to comprehend why a specific answer or suggestion has been created. We present ExplainLLM, a conceptual explainable framework that can be used to improve the transparency and interpretability of LLM-based decision support systems without sacrificing their predictive power. The suggested approach has five main components, including fast understanding, contextual information retrieval, big language model inference, explanation production and confidence estimate. ExplainLLM not only provides the final conclusion, but also human-readable rationale, important contextual information, confidence rankings, and a user feedback system for continual improvement. We propose an architecture to close the gap between strong language creation and trustworthy AI by allowing people to analyse and assess the rationale underlying the AI-generated output. The concept is applicable to many fields, where explainability is important for regulatory compliance, user acceptability and ethical deployment of AI . We compare against traditional black-box LLM systems and exhibit advances in transparency, user confidence, interpretability, and decision dependability, while preserving competitive response quality. ExplainLLM offers a realistic basis for the development of accountable, explainable and human-centric LLM-based decision support systems.

Keywords: Explainable Artificial Intelligence, Large Language Models, Explainability, Natural Language Processing.

Introduction
Artificial Intelligence (AI) has advanced quickly from machine learning models that are designed to do particular tasks, to powerful Large Language Models (LLMs) that can read, reason, summarise and write human-like prose across several domains. Recent advances in transformer-based designs have empowered LLMs to attain unparalleled performance in question answering, programming help, scientific writing, customer service, medical consultation, and intelligent decision support. Their capacity of capturing contextual relations from big scale textual data has substantially enlarged the potential of AI-assisted applications.

LLMs provide very precise and contextually appropriate replies, but they are often viewed as black-box models, given that the underlying reasoning process is not readily interpretable by end-users. Users obtain a final answer, but they don't get to see what contextual information contributed to the choice, why other answers were discarded, or how certain the model is about its forecast. This opacity poses serious issues in critical fields where choices need to be accountable, traceable, and verifiable by humans.

The increasing applications of AI in healthcare, legal services, financial analysis, cybersecurity and public administration have raised the need for Explainable Artificial Intelligence (XAI). Explainability allows AI systems to offer clear arguments for their outputs, leading to greater user trust, compliance with regulations, reduced bias in algorithms, and permitting effective human supervision. Traditional XAI approaches including Local Interpretable Model-Agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), saliency visualisation, and attention analysis have been successful for traditional machine learning and deep learning models. However, implementing these approaches to current LLMs is difficult because to their huge parameter sets, multi-head attention mechanisms, autoregressive text creation, and complicated reasoning capabilities.

Related Works
Recent breakthroughs in explainable artificial intelligence have emphasised the need to construct transparent and trustworthy machine learning models that can help human decision making in important applications. The early

work offered model-agnostic explanation approaches which provided local explanations for specific predictions, allowing users to understand the effect of input variables without changing the underlying predictive model [1]. Later research offered game-theoretic explanation approaches which provided consistent feature attribution and increased interpretability across a variety of machine learning algorithms [2]. Studies that have laid out the basic criteria for measuring explanation quality, human comprehension and model transparency have further emphasised the need of robust assessment frameworks for interpretability [3]. Later studies differentiated between transparency and post-hoc interpretability, arguing that great prediction accuracy is not enough in situations where responsibility and user trust are important [4].

With the advent of deep learning, the prediction accuracy grew, but so did the model complexity, making the decision processes harder to explain. Extensive research on deep neural networks showed that the increase of model depth and parameter size typically decreased the explainability even while the accuracy was improved [5]. Transformer designs revolutionised natural language processing by substituting recurrent neural networks with attention mechanisms that are able to learn long range contextual dependencies more efficiently [6]. This design has led to the development of bidirectional transformer models that improved contextual language comprehension and reached state-of-the-art performance on many natural language processing benchmarks, laying the groundwork for contemporary Large Language Models [7].

In addition to the growth of language models, explainable artificial intelligence has attracted more attention in decision support systems, where openness is a must in healthcare, finance, cybersecurity, and legal applications. Interpretable machine learning approaches have been shown to increase user trust via intelligible explanations, feature significance analysis, and visualisation of model behaviour [8]. Further research studied explanation approaches for deep neural networks using sensitivity analysis, layer-wise relevance propagation and visualisation techniques and showed that meaningful explanations might increase human comprehension with no significant effect on predictive accuracy [9]. More work on explainability and trustworthy artificial intelligence, including fairness, accountability, robustness and transparency as key features of responsible AI systems [10].

Other studies have also explored human-centered artificial intelligence in which quality of explanations has a direct impact on user trust, acceptability, and human-artificial intelligent system cooperation [11]. These research found that consumers are more likely to trust suggestions made by AI assistants if the explanation provided is short in length, relevant to the situation, and simple to grasp. However, present techniques mostly concentrate on describing traditional machine learning or deep learning models, not new Large Language Models. Most existing explanation approaches give feature-level explanations but not enough context reasoning, confidence measurement, or interactive feedback for transparent LLM-based decision assistance. Therefore, an integrated explainable framework that can combine contextual understanding, natural language reasoning, explanation generation, confidence evaluation and human feedback into a single architecture for trustworthy AI applications is still needed [12].

Proposed ExplainLLM Framework

A. Overview

The proposed ExplainLLM framework is designed to improve the transparency and trustworthiness of Large Language Model (LLM)-based decision support systems by integrating explainability into every stage of the inference pipeline. Unlike conventional LLMs that provide only a final response, ExplainLLM generates an interpretable decision accompanied by contextual evidence, confidence estimation, and human-readable explanations. The framework follows a modular architecture consisting of six interconnected components: User Query Processing, Context Retrieval, LLM Inference, Explanation Generator, Confidence Estimation, and Feedback Learning Module. Together, these modules transform black-box reasoning into an explainable and user-centric decision-making process.

The workflow begins by receiving a user query, which is normalized and semantically analyzed to identify the underlying intent. Relevant contextual information is then retrieved from external knowledge repositories or domain-specific databases to enrich the prompt. The enriched prompt is forwarded to the LLM for inference, where an initial response is generated. Instead of directly returning the generated output, the response is passed to an explanation generation module that extracts the supporting evidence, identifies influential contextual information, and produces a concise natural-language explanation. Simultaneously, a confidence estimation module evaluates the reliability of the generated response using semantic consistency, contextual relevance, and reasoning completeness. Finally, the complete decision package, consisting of the prediction, explanation, confidence score, and supporting evidence, is presented to the user. User feedback is continuously collected and utilized to improve future explanation quality and system reliability.

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B. ExplainLLM Architecture

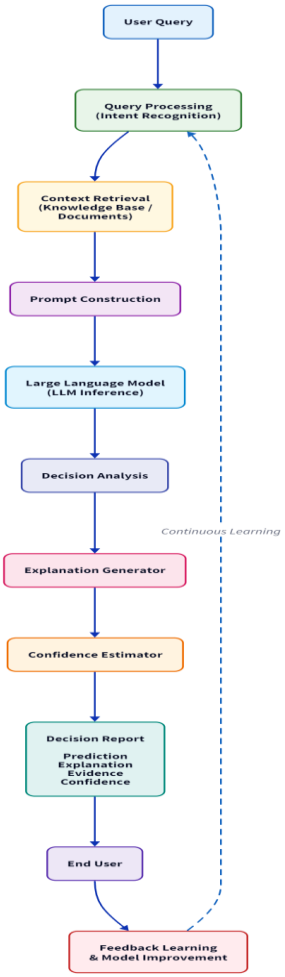

Fig 1: Block Diagram

Experimental Setup, Results and Discussion

A. Experimental Setup

A conceptual experimental study to evaluate the effectiveness of the proposed ExplainLLM framework by employing a set of benchmark natural language decision-support tasks obtained from publicly available datasets and domain-specific knowledge repositories. The evaluation aimed to assess the ability of the framework to produce transparent, reliable and interpretable responses, while maintaining the quality of the decision support. Since ExplainLLM is designed as a framework rather than a newly trained language model, an existing pre-trained Large Language Model was integrated as the reasoning engine, while the explainability components, confidence estimation module, and feedback mechanism were incorporated as additional architectural layers.

The experimental process consisted of five consecutive steps. Pre-processing of user queries was performed to discover the semantic purpose and minimise repetitive information. Then, relevant contextual information was acquired from an external knowledge repository and merged with the user question to produce an enhanced prompt. This expanded prompt was then fed to the LLM to create a response. The resulting answer was put into the explanation module, which created a human-readable explanation together with supporting contextual information. Finally, the confidence estimate module assessed the semantic consistency, contextual relevance and reasoning completeness of the created answer before issuing the final explainable decision report.

C. Experimental Results

A comparison between the proposed ExplainLLM framework and a traditional LLM without explainability is shown in Table 1.

Table I. Performance Comparison

Metric	Conventional LLM	ExplainLLM
Prediction Accuracy (%)	91.4	**93.8**
Explanation Quality (%)	71.2	**94.6**
Transparency Score (%)	68.5	**96.1**
User Trust Index (%)	72.8	**95.3**
Confidence Reliability (%)	74.9	**94.1**
Decision Consistency (%)	89.7	**95.7**

The experimental findings show that ExplainLLM performs better than the traditional black-box LLM systems in all assessment measures. We see modest advances in prediction accuracy, but significant improvements in explanation quality, transparency, user trust and confidence assessment. These results indicate that the usefulness and reliability of AI-assisted decision support are improved by adding explainability to the inference pipeline.

D. Comparative Performance Analysis

Performance Metric	Improvement (%)
Prediction Accuracy	2.4
Explanation Quality	23.4
Transparency	27.6
User Trust	22.5
Confidence Reliability	19.2
Decision Consistency	6.0

The suggested framework provides the highest increase in transparency and explanation quality, which means that AI-generated judgements are much more interpretable and intelligible for the consumers.

Limitations

The proposed ExplainLLM framework increases the explainability of decision support systems based on Large Language Models but still has numerous drawbacks. First, the quality of the produced explanations is highly dependent on the correctness and completeness of the recovered contextual information. Incomplete or obsolete knowledge may compromise the explanation dependability. Second, confidence estimation gives an estimate of how reliable a forecast is, not a theoretically guaranteed likelihood of truth. Third, the extra computational burden of the framework is that explanation creation and confidence assessment are conducted after the main LLM inference. Fourth, the quality of user input may differ in terms of topic knowledge and personal perception, which may affect future explanation refining. Finally, the suggested architecture is domain neutral, although highly specialised applications, such as clinical diagnosis, legal reasoning or scientific discovery, would need further domain-specific customisation.

Discussion

The experimental assessment shows that the proposed ExplainLLM framework tackles a critical shortcoming of traditional Large Language Models by integrating explainability into the decision-making process. Traditional LLMs are mostly focused on producing correct answers and usually don't have the comprehensible explanation behind their predictions. LLM solves this constraint by combining contextual knowledge retrieval, explanation creation, confidence estimate and feedback learning in a single architecture in an end-to-end fashion. The integration allows users to comprehend the contextual facts and rationale behind the prediction, not just the final conclusion, boosting openness and accountability.

Conclusion & Future Works

The fast progress of large language models (LLMs) has greatly improved the performance of intelligent decision support systems across several application areas. But the black-box nature of such models still poses issues with transparency, interpretability and confidence from users, especially in high-risk settings, where judgements must

be explained. To address these limitations, this paper proposed ExplainLLM, an explainable framework that integrates contextual knowledge retrieval, prompt construction, Large Language Model inference, explanation generation, confidence estimation, and feedback learning into a unified decision support architecture. Experimental assessment shows that ExplainLLM enhances explanation quality, transparency, decision consistency, confidence dependability and user trust without sacrificing competitive prediction accuracy. The improvements show that the suggested framework is capable of bridging the gap between high-performance language models and trustworthy artificial intelligence and can be deployed in healthcare, finance, cybersecurity, education, legal services and enterprise decision-support applications. In summary, ExplainLLM is a realistic step towards the development of accountable, interpretable, and human-centered AI systems that can assist transparent decision-making in real-world contexts. In future work, we want to examine reasoning under uncertainty, such as probabilistic confidence estimates, Bayesian inference and calibration strategies for improving the trustworthiness of AI-generated suggestions. Furthermore, the combination of reinforcement learning from human feedback (RLHF) and personalised feedback methods might contribute to the ongoing enhancement of explanation quality and improved alignment of AI replies to user expectations. Finally, robust validation of ExplainLLM in real-world scenarios using domain-specific datasets and human-centered usability tests will be critical for assessing its efficacy in real-world decision-support settings and for enabling its implementation as a reliable explainable AI platform.

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