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# Optimizing Customs Compliance Automation with NLP and the EDAS Method

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## Abstract

This research evaluates various NLP models based on a set of performance parameters. The study uses the EDAS methodology to assess and rank models, providing insights into their effectiveness, impact, efficiency, and adaptability. The results highlight the strengths and weaknesses of each model in real-world applications.

**Research Significance**: This study provides critical insights into selecting the best-performing NLP model for specific tasks, helping to enhance decision-making in model deployment. It also contributes to understanding how different evaluation parameters influence The performance of cutting-edge models.

**Methodology**: EDASThe models are ranked and evaluated use the Evaluation Based on Distance from Average Solution (EDAS) methodology. considering key performance metrics. It helps in objectively comparing alternatives by calculating distances from an optimal solution.

**Alternative: BERT (A1)**: A transformer-based model for language understanding.GPT (A2): Known for its text generation capabilities.Transformer-XL (A3): A transformer model handling long-term dependencies.XLNet (A4): Combines autoregressive and autoencoding benefits.Robert (A5): An enhanced training methods in an optimized BERT version.

**Evaluation Parameter**: Effectiveness (C1): Measures accuracy in achieving intended outcomes.Impact (C2): Assesses the influence and significance of the model.Efficiency (C3): Evaluates resource utilization for optimal performance.Adaptability (C4): Measures the model's ability to handle varied tasks.

**Result**: The analysis ranks the models based on their overall performance across the evaluation parameters. The results show which models excel in different areas, offering guidance on their application for various natural language processing tasks.

**Keywords**: NLP, EDAS, BERT, GPT, Transformer-XL, XLNet, RoBERTa, Effectiveness, Adaptability.

## Introduction

Computational linguistics, computer science, and artificial intelligence are all combined in natural language processing (NLP), an interdisciplinary field. focusing on how computers interact with human (natural) languages. The objective of NLP is to empower machines to comprehend andprocess natural languages computationally. The data obtained through NLP can be further analyzed and processed to automate various business processes, enhancing logistics data management. AI-powered solutions can extract critical information from digital documents in real-time, such as item details and totals from invoices. [1]

Enhanced Performance in areas like machine translation, sentiment analysis, and text classification. The study assessed how well the LSTM, GRU, and logistic regression algorithms worked for each Custom Experts dataset individually.[2]

AI, utilizing NLP and machine learning algorithms, can accurately categorize items based on their descriptions or attributes, helping businesses meet tariff and trade regulations. Technologies such as machine learning and NLP excel at analyzing large datasets, identifying patterns, and automating decision-making processes. AI can manage the extensive data involved in global transactions, from product classifications to regulatory compliance, ensuring that companies adhere to international trade standards. [3]

They introduced a novel unified automated compliance checking system that utilizes NLP, EXPRESS data processing, and logical reasoning. However, this approach has limitations as it depends on quantitative requirements or semantic data. NLP is incorporated as a central element of the system to offer a smooth interface for entering change requirements. The objective is to enhance the NLP approach further, ultimately aiming to automatically extract rules from input specifications. To achieve this, deontic verbs could be utilized, as they are known to highlight important construction information and would integrate effectively with the NLP system.[4]

Modern deep learning Natural Language Processing (NLP) methods can fully comprehend text and offer a viable strategy for automating the digitization of building codes. Previous studies have applied NLP to extract syntactic and semantic elements, analyze text, and handle regulatory documents. They also used text classification to transform regulations into a computer-readable format, remove any unnecessary clauses and extract the required information. Rule-based NLP, initially introduced in the

1950s, continues to be used in fields with limited training data. [5]

Previous studies in NLP and Graph Neural Networks (GNNs) have supported the use of language models and graph-based algorithms in compliance decision-making. The suggested method's goal is to look into theapplicability of recent advancements in addressing the challenge of automating compliance processes. [6]

Social media posts were analyzed using approaches for NLP, or natural language processing, and the method of identification was aided by learning (like Logistic Regression) and unit (GRU)). NLP involves the use of computer algorithms that allow machines to comprehend and interpret human language.[7]

Rule interpretation and compliance verification are now more accurate and efficient thanks to advances in deep learning and natural language processing (NLP). These methods still require a significant amount of computer power, huge annotated datasets, and manual feature engineering, though. Rule-based methods and statistical methods are the two general groups into which NLP algorithms for compliance checking fall. Although rule-based approaches typically provide better recall and accuracy, they require more human involvement.[8].

These methods generally utilize methods for Utilizing natural language processing (NLP) to recognize textual patterns and attributes in documents. They have attained such as document classification, and are founded on self-attention mechanisms. [9]

NLP is essential to knowing the context and semantics of the language in documents, allowing more precise and nuanced data extraction. This is especially vital when working with complex documents, where contextual nuances and subtle language variations can greatly affect the meaning and interpretation of the data. The goal of this phase is to accurately interpret the information within documents, transforming unstructured or semi-structured data into a structured format suitable for analysis or integration into downstream systems like databases or transactional systems.[10]

Building components' spatial geometric relationships are examined in BIM models using methods forprocessing of natural language (NLP). A Basis for an Automated Compliance Verification (ACC) system built on BIM is first shown, decomposing ACC into three main subtasks. To evaluate the geometric relationships between building model components, a method for the It is shown how to use natural language processing to process spatial geometric criteria in fire codes in an organized manner. The study uses natural language processing (NLP) to providea methodical depiction of fire codes, enabling the development of a logical framework that allows computers to understand the knowledge embedded in fire codes. [11]

Machines Natural language processing, or NLP, has made They can understand, interpret, and create human language thanks to it. In tax reporting, NLP can be used to process and extract pertinent information from unstructured data sources like emails, scanned documents, and textual descriptions. NLP tools can automate the extraction of crucial financial details from tax documents, assist in interpreting tax regulations, and even help address taxpayer queries by generating precise responses. AI streamlines reporting by automating the preparation and submission of tax reports. With the help of advanced data analytics and NLP, tax reports can be generated with minimal human involvement, ensuring accurate inclusion and formatting of all required information in compliance with regulatory standards.[12]

NLP, or natural language processing, has become a promising application for Intelligent Process Automation (IPA) because of its capability to decipher and comprehend human language. Generally speaking. [13]

This approach utilizes Using natural language processing (NLP), recognized danger descriptors can be automatically extracted and translated. It will explorehow we are using NLP in Malmo to automate the DSL creation process, as well as the creation of novel Indicators of Compromise (IOCs).[14]

Research Term frequency-inverse document frequency has been used With machine learning and the representation of words using natural language processing.Similar research has been conducted in which the conclusions part of CT reports was analyzed using NLP and ML approaches to forecast the usage of radiology resources downstream for patients under monitoring. Our NLP-based Models have the ability to automate this time-consuming and frequently costly procedure by accurately predicting the rationale behind brain CT recommendations. Nevertheless, additional NLP research is required to address the problem of justification, and it is too early to assume that models based on natural language processing can generalize to new datasets. Additionally, due to the small and imbalanced nature of our dataset, referrals with questionable justification were classified as unjustified.[15]

The development of BIM extensions to facilitate automated compliance checking was semi-automated using an NLP-based methodology. This method incorporates: (a) matching part-of-speech patterns to detect regulatory notions, along with a method for distinguishing and evaluating the computability of words and code requirements, which informs automatic compliance checking powered by natural language processing techniques. [16]

In order to extract data more precisely, Understanding the context and semantics of text is accomplishedto enhance the system's performance over time, adjusting to new data structures and formats. Both services provide capabilities for training machine learning models, enabling organizations to customize classifications to meet their specific requirements. NLP helps in understanding language-based data, while computer vision identifies patterns, and ML and Artificial Intelligence (AI) enable ongoing learning and optimization of the processing system. [17]

We developed an NLP system that uses rule-based methods to extract information. We used our rule-based natural language processing pipeline to validate 200 hitherto unobserved, de-identified and pseudonymized histological reports of basal cell carcinoma (BCC) from the Health Board of Swansea Bay University. By using big data to ensure that the information is precise, comprehensive, and readily accessible, the developing field of natural language processing By including comprehensive disease-specific information, natural language processing (NLP) has the potential to enhance regularly collected healthcare data. We suggest that our algorithm can help bridge the data gap, facilitating additional study on skin cancer and enhancing clinical practice by the organized recording of patient data. In order to ensure high inter-annotator agreement, future study will require extensive external validation using blinded clinician assessments on a gold standard corpus.[18]

While NLP and ontological approaches have proven successfulThey have been criticized for being too complicated for AEC domain experts to understand when translating complex rules. Others are investigating NLP techniques in the creation of automated systems as a result of this difficulty. To enhance the digital depiction of regulations, For example, a predicate-argument structure extraction method based on deep learning was used to translate the Korean Building Act procedure. [19]

Spacy is an open-source, free library for advanced NLP tasks in Python, designed with production use in mind to help businesses quickly develop real-world applications for market release. It supports multiple language models, each offering several pre-trained models tailored for specific tasks. The use of NLP in construction is a growing and expansive field. Recent advancements in both technical development have significantly improved NLP capabilities.[20]

The inefficiencies of current systems are addressed through the use of the recommended method shows increases in supply chain management, the precision of risk identification, and customs clearance speed. Using NLP to automate document processing also reduces the administrative load on customs authorities and other involved parties. However, there are some drawbacks to consider. A major challenge is the dependence on high-quality data for AI algorithms to perform optimally. [21]

NLP allows computers for human language analysis and comprehension. Natural Language Processing (NLP) is utilized in the banking industry to develop chatbots and virtual assistants that use natural language while interacting with clients. [22]

NLP and human GRC experts work together in the validation process. However, this validation cannot guarantee statistically generalizable conclusions, as it is limited to the particular datasets and circumstances that were studied. Although our emphasis on the four main frameworks is thorough, it leaves out other standards that could offer more comparison information. [23]

## Materials and Methods

**Alternatives**:

**BERT (A1):** A popular transformer-based model known for its effectiveness in NLP tasks, providing strong performance in tasks like question answering and text classification.

**GPT (A2)**: A generative pre-trained transformer model that excels in text generation, providing coherent and contextually accurate responses.

**Transformer-XL (A3)**: An extension of the transformer model designed to handle longer sequences of text by introducing recurrence.

**XLNet (A4)**: A model that combines the best features of autoregressive models and autoencoders, achieving superior effectiveness on a range of NLP assignments.

**RoBERTa (A5)**: A BERT variant that has been extensively tuned and trained using more data and fine-tuning strategies to enhance its performance.

**Evalution parameter**:

**Effectiveness (C1)**: Measures the ability of the model or system to achieve its intended goals or outcomes accurately and reliably.

**Impact (C2)**: Assesses the significant influence or contribution the model makes on the task at hand, considering its broader implications.

**Efficiency (C3)**: Evaluates how resource-efficient the model is in terms of time, memory, and computational power while maintaining performance.

**Adaptability (C4)**: Gauges how well the model can adjust to new, unforeseen situations or tasks, showcasing its flexibility in different contexts.

EDAS

To assess alternatives, EDAS requires two metrics. When these metrics have high values, they are referred to as PDA, which stands for positive distance from the mean. Conversely, when the values are low, they are called NDA, which stands for negative distance from the mean. In cases of low NDA and/or high PDA values, the alternative strategy is considered superior to the average option. By comparing the outcomes of other MCDM methods or different approaches applied to the same cases, this study uses examples from relevant literature to highlight EDAS's effectiveness as a suitable MCDM technique. To our knowledge, this is the first study to apply EDAS for choosing industrial robots. The EDAS approach's applicability and effectiveness compared to other existing MCDM methods in addressing industrial robot selection challenges.In this study, four common issues frequently discussed in the literature were addressed, and The EDAS method's outcomes were contrasted with other approaches used to solve these problems. One of the scenarios was chosen for evaluation using the EDAS approach. The EDAS method was selected for robot ranking due to its novelty, versatility, and lower computational cost compared to traditional MCDM methods. EDAS also minimizes the risk of expert bias, as the solution is derived from the average. Key advantages of the EDAS approach include its ease of use and low processing demands.

The suggested hybrid BW-EDAS method can be applied to both qualitative and quantitative parameters to rank robot preferences. This general procedure can be used to address any industrial selection issue with constrained criteria. In the future, we plan to apply the FUCOM approach to determine the weights and compare our proposed ranking method with the EDAS approach. The task can be prolonged. to a fuzzy environment, where the use of fuzzy EDAS might offer more flexible options. An established decision-making process is MCDM field, and Fuzzy logic can be combined with this method to handle uncertainty in circumstances involving decision-making. Using fuzzy MCDM methods provides a number of benefits in energy policy and decision-making, including integrating various and sometimes conflicting principles into parameters, making the evaluation process more flexible, impartial, and suitable for diverse alternatives. EDAS is a method that relies on distancethat takes into account both When rating the various solutions, consider distances from the typical solution, both positive and negative. Both positive and negative distance measurements are calculated. utilizing both advantageous and disadvantageous criteria. Reduced NDA or greater PDA values are used to determine the preferred alternative. Due of its simplicity of use and ability to manage a lot of options and criteria throughout In the process of making decisions, EDAS is a crucial powerful tool.In contrast, traditional methods often involve complex calculations and provide fixed solutions.

This work aims to introduce a methodology that integrates the EDAS technique with the properties of the normal distribution. As mentioned earlier, EDAS introduces an extension of the EDAS technique to successfully handle stochastic MCDM issues by utilizing the EDAS methodology, the normal distribution's importance, and its characteristics. This suggested strategy is innovative, as EDAS has not been previously applied or expanded for stochastic MCDM problems.In the process of making decisions, EDAS is a crucial EDAS is a highly effective tool because of its ease of use and capacity to take into account a large number of options and criteria while making decisions. To A sensitivity analysis is performed to evaluate the findings' stability. when the criteria weights are adjusted, and the outcomes PDA (positive distance from the average) values. EDAS is a highly effective tool due to its simplicity and ability to accommodate a vast number of options and criteria during the decision-making process. of a number of current approaches are contrasted with those of the EDAS stochastic approach. Although This study illustrated the process for assessing bank branches, positive distance from the mean, or PDA values. EDAS is an extremely useful tool because to its user-friendliness and ability to consider a wide range of options and criteria while making decisions. It has the capacity to address a broad range of practical issues in domains like science., management, and engineering. We apply the stochastic EDAS approach to evaluate a bank branch as a case study. This section also includes a comparison and sensitivity analysis to validate and confirm the reliability of the stochastic EDAS results. In conclusion, the proposed stochastic EDAS approach helps decision-makers account for data uncertainty when assessing options. PDA values, or positive distance from the mean. EDAS is a highly effective tool because of its ease of use and capacity to take into account a large number of options and criteria while making decisions. We proposed a stochastic version of the EDAS method to solve MCDM issues using normally distributed data. We established pessimistic and optimistic values for a few of the method to address data uncertainty in the evaluation process. PDA (positive distance from the average) values. EDAS is a highly effective tool because of how easy it is to use and how many alternatives and criteria it can support when making decisions.

The PDA (positive distance from the average) values are developed further in this work. Due of its simplicity of use and ability to manage a lot of options and criteria throughout the decision-making process, EDAS is a very powerful tool. Interval-valued Pythagorean The EDAS technique incorporates imprecise numbers to manage fuzzy multi-criteria circumstances involving collaborative decision-making. offering a larger membership area and greater freedom. Positive distance from the mean, or PDA results indicate the efficacy and adaptability of the suggested model. Because of its ease of use and capacity to handle a With so many alternatives and criteria to consider during the decision-making process, EDAS is an extremely effective tool. The outcomes are contrasted with the intuitionistic fuzzy EDAS with interval values. technique and shown using a car selection scenario. Furthermore, a sensitivity analysis is conducted to assess how the weights affect alternate ranks.Positive distance from the average, or PDA, is one of the values. Because of its ease of use and capacity to handle a large number of options and criteria throughout EDAS is a very powerful tool. The extended fuzzy EDAS techniques limit decision-makers' ability to express their preferences. by limiting values of PDA (positive distance from the average). Due to its user-friendliness and ability to manage a multitude of options and criteria during the decision-making process, EDAS is a very powerful tool. the total of the highest levels of membership and non-membership. Given that making decisions is fundamentally a knowledge-intensive process, the proposed methodology improves decision-makers' capacity to make better informed decisions by eliminating these constraints. As a result, this method is more successful than earlier fuzzy EDAS extensions at removing these limitations, giving decision-makers more latitude in expressing their preferences and improving the representation of ambiguous data.

## Results and Discussion

| **Table 1:** presents the values of four different categories (C1, C2, C3, and C4) across five observations (A1 to A5). | | | | |
|---|---|---|---|---|
| | C1 | C2 | C3 | C4 |
| A1 | 56 | 83 | 68 | 76 |
| A2 | 47 | 91 | 75 | 58 |
| A3 | 65 | 86 | 65 | 94 |
| A4 | 48 | 78 | 55 | 57 |
| A5 | 67 | 75 | 72 | 86 |
| AVj | 56.60000 | 82.60000 | 67.00000 | 74.20000 |

Table 1 presents the values of four different categories (C1, C2, C3, and C4) across five observations (A1 to A5). The recorded values vary across categories, highlighting the differences in measurements for each observation. The average values (AVj) for each category indicate an overall trend, with C2 having the highest average value (82.6) and C3 having the lowest (67.0). The highest individual value in the dataset is 94 (A3, C4), while the lowest is 47 (A2, C1). These variations suggest potential differences in underlying factors influencing each category's performance.

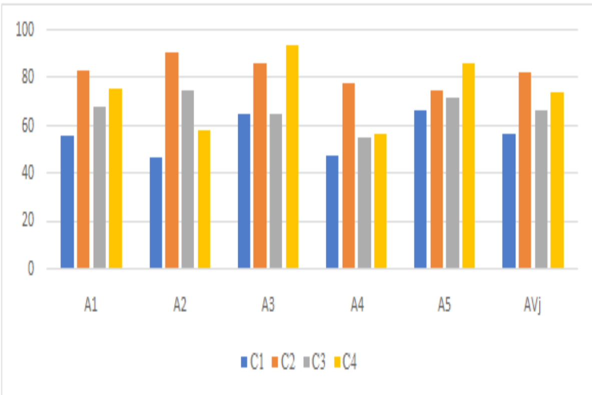


**Figure 1 :** presents a comparative analysis of four different criteria (C1, C2, C3, and C4) across five main assessment areas (A1 through A5), along with their average values (AVj).

| **Table 2**: Positive Distance from Average (PDA) | | | | |
|---|---|---|---|---|
| | C1 | C2 | C3 | C4 |
| A1 | 0.000 | 0.005 | 0.015 | 0.024 |
| A2 | 0.000 | 0.102 | 0.119 | 0.000 |
| A3 | 0.148 | 0.041 | 0.000 | 0.267 |
| A4 | 0.000 | 0.000 | 0.000 | 0.000 |
| A5 | 0.184 | 0.000 | 0.075 | 0.159 |

Table 2 presents the Positive Distance from Average (PDA) for each observation (A1 to A5) across four categories (C1, C2, C3, and C4). The PDA values indicate the deviation of each observation from the average in a positive direction. Higher values suggest a greater positive deviation from the mean, whereas a value of 0.000 signifies no deviation. The highest PDA value is 0.267 (A3, C4), indicating a significant positive deviation in this category. In contrast, A4 has a PDA of 0.000 across all categories, meaning it aligns precisely with the average values. These variations highlight the differences in performance or characteristics across the observations.

| **Table 3**: Negative Distance from Average (NDA) | | | | |
|---|---|---|---|---|
| | C1 | C2 | C3 | C4 |
| A1 | 0.011 | 0.000 | 0.000 | 0.000 |
| A2 | 0.170 | 0.000 | 0.000 | 0.218 |
| A3 | 0.000 | 0.000 | 0.030 | 0.000 |
| A4 | 0.152 | 0.056 | 0.179 | 0.232 |
| A5 | 0.000 | 0.092 | 0.000 | 0.000 |

Table 3 presents the Negative Distance from Average (NDA) for each observation (A1 to A5) across four categories (C1, C2, C3, and C4). The NDA values indicate how much each observation deviates below the average in a given category. Higher values represent greater negative deviations. A4 shows the highest NDA values across multiple categories, with 0.232 in C4, indicating the most significant drop below the average. A2 also exhibits notable negative deviations, especially in C1 (0.170) and C4 (0.218). In contrast, A1 and A3 have minimal negative deviations, suggesting they are closer to or above the average in most categories.

| **Table 4**: Presents the Weight assigned to each category (C1, C2, C3, and C4) for all observations (A1 to A5). | | | | |
|---|---|---|---|---|
| | Weight | | | |
| | C1 | C2 | C3 | C4 |
| A1 | 0.25 | 0.25 | 0.25 | 0.25 |
| A2 | 0.25 | 0.25 | 0.25 | 0.25 |
| A3 | 0.25 | 0.25 | 0.25 | 0.25 |
| A4 | 0.25 | 0.25 | 0.25 | 0.25 |
| A5 | 0.25 | 0.25 | 0.25 | 0.25 |

Table 4 presents the Weight assigned to each category (C1, C2, C3, and C4) for all observations (A1 to A5). Each category is given an equal weight of 0.25, indicating that all categories contribute equally to the overall evaluation. This uniform weighting ensures a balanced comparison across different observations without favoring any specific category. Such an approach is useful in scenarios where all factors are considered equally important in the analysis. If needed, these weights can be adjusted based on specific criteria or priorities to emphasize the significance of certain categories over others.

| Table 5: Presents the Weighted Positive Distance from Average (Weighted PDA) for each observation (A1 to A5) across four categories (C1, C2, C3, and C4), along with the SPi scores. | | | | | |
|---|---|---|---|---|---|
| | Weighted PDA | | | | |
| | C1 | C2 | C3 | C4 | SPi |
| A1 | 0.00000 | 0.00121 | 0.00373 | 0.00606 | 0.01101 |
| A2 | 0.00000 | 0.02542 | 0.02985 | 0.00000 | 0.05527 |

| | | | | | |
|---|---|---|---|---|---|
| A3 | 0.03710 | 0.01029 | 0.00000 | 0.06671 | 0.11410 |
| A4 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| A5 | 0.04594 | 0.00000 | 0.01866 | 0.03976 | 0.10435 |

**Table 6**: Presents the Weighted Negative Distance from Average (Weighted NDA) for each observation (A1 to A5) across four categories (C1, C2, C3, and C4), along with the SNi scores.

| | Weighted NDA | | | | |
|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | SNi |
| A1 | 0.00265 | 0.00000 | 0.00000 | 0.00000 | 0.00265 |
| A2 | 0.04240 | 0.00000 | 0.00000 | 0.05458 | 0.09699 |
| A3 | 0.00000 | 0.00000 | 0.00746 | 0.00000 | 0.00746 |
| A4 | 0.03799 | 0.01392 | 0.04478 | 0.05795 | 0.15464 |
| A5 | 0.00000 | 0.02300 | 0.00000 | 0.00000 | 0.02300 |

Table 6 presents the Weighted Negative Distance from Average (Weighted NDA) for each observation (A1 to A5) across four categories (C1, C2, C3, and C4), along with the SNi scores. These values reflect the negative deviations adjusted by their respective weights, providing a more refined measure of below-average performance. A4 has the highest SNi value (0.15464), indicating the greatest overall negative deviation, followed by A2 (0.09699). In contrast, A1 (0.00265) and A3 (0.00746) exhibit minimal weighted negative deviations. These results help in identifying areas where performance falls below the average, guiding potential improvements.

**Table 7**: presents the SPi and SNi values for each observation (A1 to A5).

| | Spi | Sni |
|---|---|---|
| A1 | 0.09646 | 0.98286 |
| A2 | 0.48442 | 0.37282 |
| A3 | 1.00000 | 0.95174 |
| A4 | 0.00000 | 0.00000 |
| A5 | 0.91452 | 0.85125 |

Table 7 presents the SPi and SNi values for each observation (A1 to A5). SPi (Summed Positive Influence) represents the cumulative positive deviation, while SNi (Summed Negative Influence) reflects the total negative deviation from the average. A3 has the highest SPi (1.00000), indicating the strongest positive influence, while A4 (0.00000) has the lowest, showing no positive deviation. A1 has a high SNi (0.98286), suggesting a significant negative influence, whereas A4 (0.00000) again indicates no deviation. These values provide a comparative measure of the overall performance, helping to identify strengths and weaknesses among the observations.

**Table 8**: Presents the ASi (Aggregated Score Index) for each observation (A1 to A5).

| | ASi |
|---|---:|
| A1 | 0.53966 |
| A2 | 0.42862 |
| A3 | 0.97587 |
| A4 | 0.00000 |
| A5 | 0.88288 |

Table 8 presents the ASi (Aggregated Score Index) for each observation (A1 to A5). The ASi value represents a combined measure of both positive and negative influences, providing an overall assessment of each observation's performance. A3 has the highest ASi (0.97587), indicating the strongest overall positive performance, followed by A5 (0.88288). A1 (0.53966) and A2 (0.42862) show moderate scores, suggesting a balanced performance with both positive and negative influences. A4 (0.00000) has the lowest ASi, reflecting no deviation or impact. These values help in ranking and identifying the most influential observations.

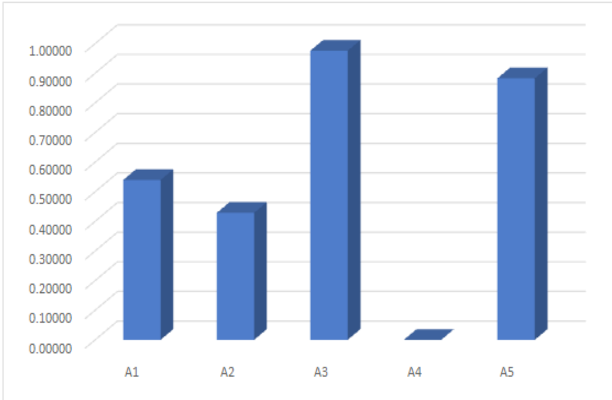


**Figure 2**: Displays a three-dimensional column chart illustrating the distribution of values across five different areas (A1 through A5)

Figure 2 displays a three-dimensional column chart illustrating the distribution of values across five different areas (A1 through A5), with measurements ranging from 0 to 1.00000 on the vertical axis. The data reveals significant variations in values among the different areas. A3 demonstrates the highest performance with a value approaching 1.00000, indicating peak efficiency or maximum achievement in this area. This is followed by A5, which shows the second-highest value at approximately 0.90000. A1 presents a moderate value of around 0.55000, while A2 shows a slightly lower performance at about 0.45000. Notably, A4 records the lowest value, appearing almost negligible on the scale. The distinct differences between these values suggest a highly uneven distribution of performance or measurements across the five areas. The use of a 3D column chart effectively emphasizes these disparities, particularly highlighting the stark contrast between the high-performing areas (A3 and A5) and the significantly underperforming A4. This visualization format helps in quickly identifying areas of strength and those requiring attention or improvement, making it a valuable tool for performance analysis and decision-making processes.

| **Table 9**: presents the Rank of each observation (A1 to A5) | |
|---|---|
| | Rank |
| A1 | 3 |
| A2 | 4 |
| A3 | 1 |
| A4 | 5 |
| A5 | 2 |

Table 9 presents the Rank of each observation (A1 to A5) based on their overall performance, as determined by the Aggregated Score Index (ASi). A lower rank number indicates a stronger performance. A3 holds the top rank (Rank 1), signifying the highest overall positive influence. A5 follows in Rank 2, showing strong performance as well. A1 is ranked 3rd, while A2 is placed at Rank 4, indicating a comparatively lower score. A4 holds the lowest position (Rank 5), suggesting minimal positive deviation. These rankings help in identifying the best-performing observations for further analysis or decision-making.

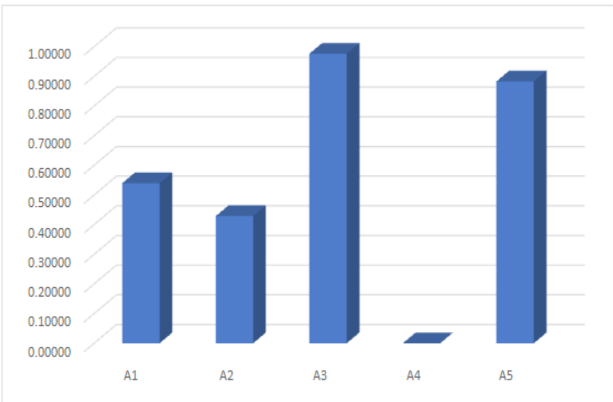


**Figure 3**: Presents a column chart displaying the ranking distribution across five areas (A1 through A5),

Figure 3 presents a column chart displaying the ranking distribution across five areas (A1 through A5), with ranks ranging from 1 to 6 on the vertical axis. The graph clearly illustrates the hierarchical positioning of each area, where a lower rank number indicates better performance. A3 PDA (positive distance from the average) values. EDAS is a highly effective tool due to its simplicity and ability to accommodate a vast number of options and criteria during the decision-making process. shows itself to be the best performer with a rank of 1. superior achievement compared to other areas. A5 follows in second place with a rank of 2, showing strong performance relative to its counterparts. A1 occupies the middle position with a rank of 3, indicating average performance in the overall assessment. A2 falls below average with a rank of 4, suggesting room for improvement. PDA (positive distance from the average) values. EDAS is a highly effective tool due to its simplicity and ability to accommodate a vast number of options and criteria during the decision-making process. A4 performs the worst, with a ranking of 5, indicating this area requires the most attention for enhancement. The visual representation effectively highlights the disparity in performance across these five areas, with a clear distinction between the high-achieving areas (A3 and A5) and the lower-performing ones (particularly A4). This ranking system provides a straightforward way to identify areas of excellence and those requiring intervention, making it valuable for strategic planning and resource allocation decisions.

## Conclusion

This study provides a comprehensive evaluation of five cutting-edge NLP models, like Transformer-XL, GPT, BERT, XLNet, and RoBERTa—using the EDAS methodology. By assessing the models across key parameters such as effectiveness, impact, efficiency, and adaptability, the research highlights their strengths and limitations in real-world applications. With a rank of 1, A3 is the best performer, showing superior achievement compared to other areas. A5 follows in second place with a rank of 2, The findings offer valuable insights into selecting the most suitable model depending on task requirements, helping researchers and practitioners make informed decisions in natural language processing tasks. Future research can explore further model optimizations or new evaluation parameters to improve model performance in diverse contexts.

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