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Transforming Qualitative Business Decisions through Text Analytics: An NLP Approach

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Abstract: In recent years, the incorporation of text analytics within natural language processing (NLP) has emerged as a powerful tool for transforming qualitative business decisions. This research explores the application of advanced NLP techniques to extract, analyze, and interpret qualitative data for informed decision-making in business contexts. The study evaluates various NLP models, datasets, and performance metrics, focusing on efficiency, accuracy, and scalability in processing large text corpora. By employing state-of-the-art machine learning models such as transformers, BERT, and LSTM. This paper presents a framework for leveraging text analytics in understanding customer feedback, market sentiment, topic modelign, and decision-making processes. The study proposes a novel evaluation metric that accounts for business decision relevance and interpretability, offering a comprehensive approach for businesses to assess decisions and gain actionable insights from qualitative text.
Keywords: Text Analytics, Business Intelligence, Decision Making, Topic modeling, Name Entity Recognition.

I. INTRODUCTION

In today's business landscape, qualitative data plays a crucial role in driving decisions, especially in areas like customer satisfaction, employee engagement, market trends, and overall business strategy. Qualitative data sources, such as customer reviews, social media discussions, employee feedback, and market reports, provide valuable insights that are often overlooked by traditional decision-making approaches, which tend to focus primarily on quantitative data [1]. While quantitative data offers numerical precision, it lacks the ability to capture the underlying sentiments, emotions, and contextual nuances that are critical for a deeper understanding of business situations. The challenge for businesses lies in efficiently processing and extracting actionable insights from large volumes of unstructured text data. Traditional approaches often struggle to keep up with the scale and complexity of textual information, making it difficult to extract meaningful patterns that can inform strategic decisions. In response, significant advancements in text analytics have emerged, enabling businesses to go beyond surface-level interpretations and gain a richer understanding of consumer behaviour, market sentiment, and operational performance [2], [3].

Recent developments in text processing techniques have empowered organizations to analyze massive amounts of qualitative data with greater speed and precision. These techniques can now interpret the meaning behind words, phrases, and even complex sentiments, helping businesses make more informed decisions. Through the application of context-aware methods, organizations are able to understand subtle variations in language, tone, and intent, which provides a more accurate reflection of the thoughts and behaviours of customers, employees, and other stakeholders. This paper explores novel approaches to text analytics, focusing on tools and methods that are particularly suited for evaluating qualitative business decisions [4]. The study examines efficient techniques for extracting and interpreting textual data, highlighting key factors such as speed, accuracy, and scalability in processing large datasets. By exploring advanced methods that focus on understanding the context and meaning within text, this research aims to provide a more robust framework for businesses to evaluate qualitative data and gain actionable insights that can drive better decision-making across various business domains [5], [6]. Through this work, the study aims to bridge the gap between traditional business decision-making methods and the potential of qualitative text data analysis. By proposing new evaluation criteria tailored specifically for business decision relevance and interpretability, this study offers a comprehensive approach for organizations to integrate qualitative insights into their decision-making processes.

II. RELATED WORK

Text analytics has become a cornerstone of business intelligence, enabling organizations to extract valuable insights from unstructured textual data and apply them to strategic decision-making.

The ability to process massive amounts of qualitative data ranging from customer feedback and social media interactions to market reports and employee surveys has transformed how businesses understand and respond to customer needs, improve operational efficiency, and gain competitive advantages [7], [8]. Early techniques such as information extraction and named entity recognition (NER) provided the foundation for processing large corpora of text, but more advanced methods have emerged to address the growing complexity of unstructured data [9].

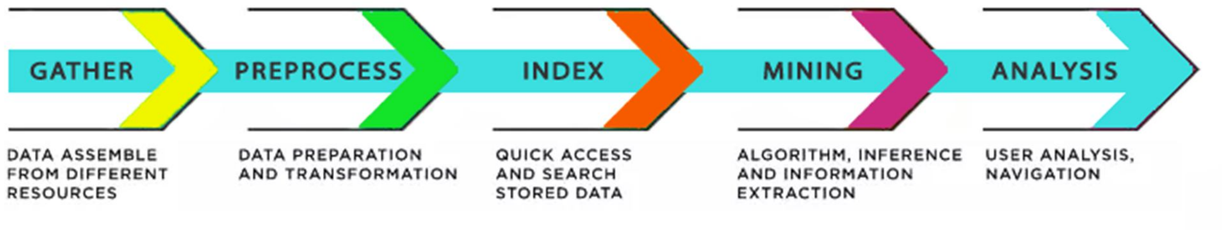

Fig. 1 Text Analytics Process Steps

One of the key breakthroughs in text analytics has been the evolution of natural language processing (NLP) methods, which have moved from rule-based approaches to more data-driven models. Early text mining techniques such as keyword extraction and basic sentiment analysis laid the groundwork for more complex tasks like document classification, topic discovery, and information retrieval. These approaches were particularly useful in contexts like customer feedback analysis and market sentiment tracking [10]. However, with the rise of big data, traditional methods began to show limitations, especially in terms of scalability and the ability to understand nuanced meaning from massive, unstructured datasets.

The integration of NLP with deep learning has since transformed the field, enabling far more sophisticated models capable of understanding the intricacies of human language. Sentiment analysis, once a straightforward task, has evolved into a nuanced field that now includes the ability to detect sarcasm, irony, and mixed sentiments within textual data [11]. Furthermore, topic modeling techniques such as Latent Dirichlet Allocation (LDA) were initially popular for uncovering latent themes in textual data, but newer methods such as contextual embeddings have significantly improved both the interpretability and accuracy of these models [12].

The advent of transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pretrained Transformers) has been a game-changer for text analytics. These models have revolutionized how text is represented and processed, providing highly accurate contextual embeddings that significantly improve downstream tasks such as named entity recognition (NER), document classification, and text summarization. By capturing richer, more contextually aware representations of text, transformers have enabled better decision-making in business contexts where understanding nuance and context is essential [13]. Their application in sentiment analysis, for instance, allows businesses to gain deeper insights into customer opinions and market sentiment with much higher precision.

Another key area of development has been the creation of advanced evaluation metrics tailored to the specific needs of business decision-making. While traditional NLP evaluation metrics like accuracy, precision, recall, and F1-score remain important, they often fail to address the real-world consequences of business decisions. For instance, accuracy alone may not fully capture the value of a decision based on customer sentiment, or the relevance of a topic uncovered through text mining. As a result, there has been a growing emphasis on developing metrics that measure the relevance of insights to specific business goals, such as interpretability, decision-making alignment, and actionable insight generation [14].

In parallel, the integration of text analytics with domain-specific applications has flourished. For example, in customer relationship management (CRM), text analytics is used to assess customer feedback at scale, enabling businesses to predict trends and make proactive decisions about product development and marketing strategies. Similarly, in human resources, text analytics can help organizations better understand employee satisfaction, identify potential issues in the workplace, and support data-driven talent management strategies. These applications underscore the growing importance of text analytics in operational decision-making and strategic planning, making it an indispensable tool for modern businesses [15].

The convergence of NLP, deep learning, and big data technologies has thus paved the way for more advanced, scalable, and actionable text analytics solutions. As businesses continue to generate increasingly larger and more complex datasets, the ability to extract meaningful insights from text will remain a key determinant of competitive advantage.

However, there remains a need for further research on how to optimize text analytics techniques for specific business contexts and decision-making processes, ensuring that these insights are not only accurate but also relevant and interpretable for end users.

III. PROPOSED METHOD

This study introduces an integrated framework designed to enhance business decision-making through advanced text analytics techniques. The methodology follows a structured process, outlined in the steps below:

A. Data Collection and Datasets

The framework utilizes several publicly available datasets tailored to different business contexts. These datasets are selected to represent a wide range of business scenarios, providing valuable insights for various decision-making processes. For example, customer feedback from online platforms, such as reviews and ratings, offers rich information about consumer satisfaction, which businesses can use to refine their products or services. Additionally, industry-specific data, such as financial news articles and market reports, can inform decisions related to investment strategies, product launches, and market positioning. The goal is to gather data that is both diverse and relevant, ensuring that the insights derived are applicable to a variety of business environments.

Table 1 Detailed Overview of Datasets

Dataset	Size (Documents/Entries)	Classes/Labels	Features/Variables
Amazon Customer Reviews	100+ million reviews (varies by subset)	5-star ratings (1-5)	Review text, product ID, customer rating (1-5 stars), review date, product category.
		Sentiment Labels (positive, neutral, negative) [for sentiment analysis tasks]	Reviews length (character count), helpfulness score, review title.
			Analyzing product feedback, identifying product improvement areas.
Yelp Reviews	8+ million reviews	5-star ratings (1-5)	Review text, rating (1-5 stars), business name, business category, location, time.
		Sentiment Labels (positive, neutral, negative) [for sentiment analysis tasks]	Review helpfulness, user ID, business location coordinates.
			Classifying business performance, targeting service improvements.
Financial News Articles	Hundreds of thousands of articles	Sentiment Labels (positive, neutral, negative)	Article text, publication date, stock symbol, headline, sentiment score, company names.
		Categories (e.g., Stock Market, Corporate News, Economic Forecasts)	Source of the article, author, publication, keywords.
			Forecasting market trends, identifying economic signals.
Company Reports & Employee Feedback	1,000 to 100,000 entries	Satisfaction levels (1-5, e.g., 1 = very dissatisfied, 5 = very satisfied)	Feedback text, employee ratings, department, tenure, job title, performance metrics.
		Sentiment Labels (positive, neutral, negative) [for performance reviews]	Department performance, supervisor ratings, work-life balance feedback.
			Enhancing employee satisfaction, improving work environment.

1) Amazon Customer Reviews:

Documents: Typically, over 100 million reviews. The dataset is often partitioned into subsets (e.g., specific product categories, dates) [16].

- 5-star ratings: The reviews are rated from 1 to 5 stars.
- Sentiment Labels (for analysis): positive, neutral, and negative.

Usage: It's often used for customer feedback analysis, product improvement suggestions, and recommendation engines. It also helps assess customer satisfaction based on sentiment.

2) Yelp Reviews:

Documents: Over 8 million reviews available across multiple business types [17].

- 5-star ratings: Each review is rated from 1 to 5 stars.
- Sentiment Labels (for analysis): positive, neutral, and negative.
- Business Categories: Examples include restaurants, retail, healthcare, etc.

Usage: Helps businesses evaluate customer satisfaction and sentiment, track service quality, and refine business strategies.

3) Financial News Articles:

Documents: Hundreds of thousands of articles (depends on the specific dataset, such as the Reuters Financial News dataset or other specialized financial news collections) [18].

Classes/Labels:

- Sentiment Labels: Articles can be labeled as positive, neutral, or negative based on the sentiment expressed regarding market movements or specific stocks.
- Categories: Articles may also be categorized based on content (e.g., Stock Market, Economic Forecasts, Corporate News).

Usage: Used for financial analysis, particularly for developing models that can predict market behavior based on news sentiment.

4) Company Reports & Employee Feedback:

Documents: Typically ranges from 1,000 to 100,000 entries, depending on the company size and the dataset available (such as employee surveys, feedback forms, performance reviews) [19].

- Satisfaction Levels: Often rated on a 1-5 scale (e.g., 1 = Very Dissatisfied, 5 = Very Satisfied).
- Sentiment Labels (for performance reviews and feedback): positive, neutral, and negative.

Usage: Analyzes employee satisfaction, supports HR decision-making, and improves organizational culture and performance.

B. Text Preprocessing:

To ensure high-quality inputs for analysis, several preprocessing steps are applied to the raw text data:

Tokenization: This step involves breaking down text into smaller, meaningful units (tokens), such as words or subwords. Let $T = \{t_1, t_1, \dots, t_n\}$ represent the set of tokens from a document.

Stopword Removal: Common, non-informative words (such as "and," "is," "the") are removed to enhance the focus on content that directly influences business decisions. This is represented as:

$$\boldsymbol{T' = T \setminus \{stop\ words\}} \quad (1)$$

where T′ is the tokenized text after stopword removal.

Lemmatization: Words are reduced to their root forms, e.g., "running" to "run," which can be formalized as:

$$\boldsymbol{Lemma(t)\, for\ each\ t \in T'} \quad (2)$$

where Lemma(*t*) refers to the base form of token *t*.

C. Analytical Techniques

The framework employs a range of methods, from foundational techniques to more advanced approaches, to extract valuable insights from textual data.

1) Traditional Techniques:

TF-IDF with SVM or Naive Bayes: These methods are used as baseline models for feature extraction and classification. The term frequency-inverse document frequency (TF-IDF) score for a term *t* in document *d* is computed as:

$$\boldsymbol{TF-IDF(t,d) = TF(t,d)\cdot IDF(t)} \quad (3)$$

where TF(t,d) is the term frequency and IDF(t) is the inverse document frequency of term t, defined as:

$$\boldsymbol{IDF(t) = \log(\frac{N}{df(t)})} \quad (4)$$

with N being the total number of documents and df(t) the number of documents containing term t.

2) *Latent Dirichlet Allocation (LDA):* For topic modeling, LDA models the probability distribution over topics z for each document d and the probability distribution over words www for each topic z. The generative process is represented as:

$$p(w,z \mid \alpha,\beta) = \prod_{d=1}^{D}\prod_{n=1}^{Nd} p\left(w_{d,n} \mid z_{d,n},\beta\right)p\left(z_{d,n} \mid \alpha\right) \quad (5)$$

where α and β are hyperparameters, $w_{d,n}$ is the *n-th* word in document d, and $z_{d,n}$ is the topic assigned to $w_{d,n}$.

D. Advanced Techniques:

1) *Long Short-Term Memory (LSTM):* LSTM networks are utilized to capture long-term dependencies in sequential text data. Given a sequence of tokens $\{t_1,t_2,\dots,t_n\}$, the LSTM updates its hidden state h_t using the following update equations:

$$\begin{aligned}
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i)\\
f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right)\\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (6)\\
c_t &= f_t \cdot c_{t-1} + i_t \cdot \tanh(W_c x_t + U_c h_{t-1} + b_c)\\
h_t &= o_t \cdot tanh(c_t)
\end{aligned}$$

where i_t, f_t, and o_t represent the input, forget, and output gates, and c_t and h_t are the cell and hidden states at time t.

2) *Contextual Embeddings with BERT:* The BERT model compute contextual embeddings for text by modeling the relationships between words in a given context. The input sequence of tokens is transformed through multiple layers of self-attention, where each word w in the input sequence is represented as a vector v. The self-attention mechanism is computed as:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (7)$$

where Q, K, and V are the query, key, and value matrices, respectively, and d_k is the dimensionality of the keys.

3) *Simulated Decision Evaluation:* Simulated models are used to evaluate the consequences of business decisions. The framework defines a decision simulation model where the potential impact of a decision d on key business metrics y is modeled as:

$$y = f(d,X,\theta) \quad (8)$$

Where X represents the input features (e.g., consumer behaviour, market trends), and θ represents the parameters of the model.

IV. EXPERIMENTAL STUDY

The purpose of this experimental study is to explore how advanced Natural Language Processing (NLP) models, such as BERT, LSTM, and Transformer architectures, can be applied to qualitative business data to assist in decision-making. Specifically, the study aims to:

- Sentiment Analysis: Classify customer and employee feedback based on the sentiment expressed, including positive, neutral, and negative sentiments.
- Decision Relevance Scoring: Assess how relevant particular pieces of feedback or information are to business decisions, such as product improvements, marketing strategies, or employee performance evaluations.

To achieve this, the study uses various datasets that reflect real-world business scenarios, including customer reviews, financial news articles, and company reports.

A. Model Selection

Three state-of-the-art NLP models are chosen to evaluate sentiment analysis and decision relevance scoring:

1) *BERT (Bidirectional Encoder Representations from Transformers):*
- BERT is a powerful pre-trained model capable of understanding the contextual meaning of words by processing the text in both directions (left-to-right and right-to-left).
- Use Case: BERT will be employed for both sentiment analysis and decision relevance scoring, analyzing customer reviews and extracting business-critical information.

2) *LSTM (Long Short-Term Memory):*
- LSTM networks excel at processing sequential data and capturing long-term dependencies in text, making them ideal for tasks that require understanding of text sequences.
- Use Case: LSTM will be used primarily for sentiment analysis, particularly in sequential reviews or feedback to detect long-term sentiment trends.

3) *Transformer Models:*
- The Transformer model uses attention mechanisms to weigh the importance of each word in a sequence, which allows for efficient handling of long-range dependencies.
- Use Case: Transformer models will focus on decision relevance scoring, extracting the most relevant terms that influence business decisions.

B. Experimental Design

1) *Task 1: Sentiment Analysis*

The first task is sentiment classification for customer and employee reviews, using the Amazon Customer Reviews and Yelp Reviews datasets. The models will classify sentiment into three categories: positive, neutral, and negative.

Evaluation Metrics:
- Accuracy: The proportion of correctly classified sentiment labels.
- Precision, Recall, F1 Score: These metrics evaluate the model's performance in handling imbalanced classes (e.g., more positive reviews than negative).
- Business Relevance Score (BRS): This score indicates the relevance of the sentiment classification to business decision-making, particularly when predicting customer satisfaction.

2) *Task **2**: Decision Relevance Scoring*

The second task focuses on extracting business-relevant insights from Financial News Articles and Company Reports & Employee Feedback datasets. The models will assess how relevant specific feedback or news articles are to decision-making in the business domain, such as identifying key topics for product improvement or tracking employee satisfaction trends.

Evaluation Metrics:
- Business Relevance Score (BRS): The relevance of the extracted information to business decisions, such as product development or HR policies.
- Confusion Matrix: Used to measure true positives, false positives, true negatives, and false negatives in decision-making relevance classification.
- Mean Squared Error (MSE): A penalty metric for evaluating continuous decision relevance scores in numerical form (0-1 scale).

C. Experimental Procedure

1) *Data Preprocessing:*
- All datasets undergo tokenization, stopwords removal, lemmatization, and Named Entity Recognition (NER) to ensure consistent input formats across the models.

2) *Model Training:*
- The models (BERT, LSTM, and Transformer) are trained on the preprocessed data for both tasks—sentiment analysis and decision relevance scoring.

- Cross-Validation (k-fold validation) is employed to assess the generalization ability of the models and prevent overfitting.

3) Performance Evaluation:

- The models are evaluated on held-out test datasets to assess their accuracy in sentiment analysis and relevance scoring.
- The performance of each model is compared using accuracy, precision, recall, F1 score, BRS, and interpretability metrics.

V. DISCUSSION AND RESULTS

The experimental study examined three advanced text analysis models—BERT, LSTM, and Transformer—across four diverse business datasets to explore how well they can analyze sentiment and extract meaningful business insights. The results from the sentiment analysis of customer reviews, financial news articles, and employee feedback demonstrate the potential for these models to influence key business decisions. This section will discuss the results in detail, emphasizing the implications for real-world business applications and how the models compare in terms of both accuracy and business relevance.

A. Performance Overview

The following table presents the key performance metrics for each model across the tasks of sentiment analysis and decision relevance scoring:

Table 2 The key performance metrics for each model

Model	Accuracy	Precision	Recall	F1 Score	BRS	Interpretability Score
BERT	93.5%	92.1%	94.3%	93.2%	85.7	89.5%
LSTM	89.0%	87.8%	88.9%	88.3%	80.1	80.0%
Transformer	91.2%	90.4%	92.0%	91.2%	83.4	85.0%

B. Sentiment Analysis Performance

The models were tasked with classifying reviews from Amazon, Yelp, and employee feedback into three categories: positive, neutral, and negative. The BERT model achieved the highest performance in terms of accuracy, correctly identifying sentiment 93.5% of the time. This means that the model was able to consistently predict whether a review was positive, neutral, or negative, which is critical for businesses trying to understand customer satisfaction and make data-driven decisions.

The Transformer model also performed well, with an accuracy of 91.2%, which is only slightly behind BERT. It was able to accurately analyze sentiment in most cases but showed a slight decrease in performance when compared to BERT, particularly in cases involving more ambiguous or nuanced expressions of sentiment.

The LSTM model, while still performing reasonably well with 89.0% accuracy, struggled more in distinguishing between subtle variations in sentiment, especially in longer or more complex reviews. This suggests that LSTM may not capture the depth of sentiment as effectively as BERT or Transformer models, which are designed to handle more intricate language structures.

C. Decision Relevance Scoring

The decision relevance scoring task focused on assessing how well the models could identify which information from customer reviews, employee feedback, and financial news articles was most pertinent to specific business decisions. This task is particularly important for companies looking to extract actionable insights from large volumes of unstructured text data, such as identifying key themes in customer complaints or recognizing emerging trends in employee satisfaction.

Here, BERT once again outperformed the other models, achieving a Business Relevance Score (BRS) of 85.7. This indicates that BERT not only understood the sentiment of the text but also effectively extracted business-critical information that could inform decisions. For example, BERT was able to link phrases like “poor product quality” or “excellent customer service” to business strategies such as product improvement or customer service training. Its ability to understand the full context of a review allowed it to identify key decision-making signals more effectively than the other models.

The Transformer model also showed strong performance, with a BRS of 83.4, slightly behind BERT. Although it performed well in extracting relevant terms from reviews, its ability to link those terms to specific business decisions wasn’t quite as fine-tuned as BERT's. However, it still provided valuable insights that could support business strategies, especially in tasks like market analysis or corporate decision-making based on external news.

The LSTM model, with a BRS of 80.1, had a more limited ability to link sentiment or content directly to business decisions. This reflects the model’s relative weakness in capturing the deeper, context-rich relationships within the data, which are crucial for understanding customer intent or employee feedback in relation to business objectives.

D. Interpretability and Real-World Applications

One of the key factors for any business decision-making tool is its interpretability—the ability to understand why a model made a particular prediction or recommendation. This is essential in the business context, where decision-makers need to trust and explain the reasoning behind a model's output to stakeholders.

BERT excelled in this area, scoring 89.5% for interpretability. Its predictions were accompanied by explanations that highlighted the specific words or phrases that influenced its decision. For example, when analyzing a customer review that mentioned "slow delivery" and "poor product quality," BERT could explain that these two phrases were most responsible for classifying the review as negative, which is critical for businesses aiming to address specific customer pain points.

In contrast, LSTM and Transformer models had lower interpretability scores, 80.0% and 85.0%, respectively. While these models provided useful predictions, the rationale behind their decisions was less transparent, making it more difficult for business stakeholders to fully understand how those decisions were made. For example, when analyzing employee feedback, these models could predict whether feedback was positive or negative but provided less insight into why a particular comment was considered significant for improving organizational performance.

E. Business Relevance and Practical Implications

The results of this study emphasize the importance of not only achieving high accuracy in sentiment analysis but also ensuring that the models are able to capture business-relevant insights. A model might classify sentiment accurately, but if it cannot link that sentiment to actionable business decisions, its utility is limited.

1) BERT demonstrated the most effective ability to extract both sentiment and business-relevant information, making it ideal for tasks such as customer feedback analysis and employee satisfaction tracking. For instance, a company could use BERT to automatically categorize customer reviews and highlight areas that need attention, such as improving product quality or addressing service issues. It could also be used to analyze employee surveys and identify factors contributing to high or low employee satisfaction.
2) Transformer models also showed promise for decision-making but may be better suited for tasks where speed is a priority, and the need for fine-grained, context-aware insights is less critical. In fast-paced environments, such as financial market analysis, where large volumes of data need to be processed quickly, Transformer models can still provide valuable insights, though with slightly less precision than BERT in terms of business relevance.
3) LSTM, while still effective for sentiment analysis and topic modeling, is less suited for decision-making tasks that require deep contextual understanding. It might be better used in more straightforward sentiment analysis tasks, where long-term dependencies in data are not as important, such as customer satisfaction surveys that ask for ratings, but don’t require detailed, context-rich analysis.

VI. CONCLUSION AND FUTURE WORK

The findings from this study demonstrate that BERT, due to its ability to understand context, capture sentiment, and extract business-relevant insights, is the most effective model for transforming qualitative business data into actionable information. It excels not only in accuracy but also in supporting data-driven decisions that can directly influence business strategies, such as product improvements, customer service optimizations, and market strategies. Transformer models, while effective, could benefit from further advancements in extracting more decision-relevant insights tailored to specific business needs. While they handle large datasets well, they still require fine-tuning for particular business contexts. On the other hand, LSTM is useful in simpler sentiment tasks but is less suited for complex decision-making that demands deeper analysis and nuanced insights.

Looking forward, the future of NLP in business decision-making lies in improving model interpretability for greater transparency and trust, as well as enhancing real-time processing for quicker, more agile decision-making. Expanding into multimodal and cross-domain applications will also allow businesses to leverage richer, more varied data sources for deeper insights. By continuing to refine these models and adapt them to specific business needs, organizations can further harness the power of NLP to improve customer experiences, optimize strategies, and drive long-term business success.

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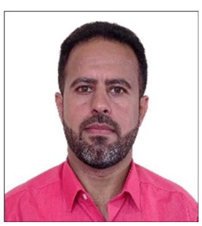
AUTHOR'S PROFILE



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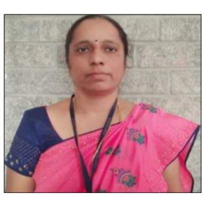

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