J. Mountain Res. P-ISSN: 0974-3030, E-ISSN: 2582-5011 DOI: https://doi.org/10.51220/jmr.v21-S2.4
Vol. 21(S2), (2026) 23-36

Text Generation and Sentiment Analysis Using NLP

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Received: 24.02.2025; Revised: 26.12.2025; Accepted: 8.1.2026

Abstract: Recently deep learning has greatly improved automatic text generation making machine-produced language sound much more human and enabling applications in social media, scripts, and poetry while sentiment analysis has become common in education, business, and online platforms but still struggles with noisy, informal student feedback and large data volumes. To clear how NLP, machine learning, and deep learning are used in this educational context, this work presents a PRISMA-based mapping study of 90 papers published between 2015 and 2021, highlighting key contributions, trends, and gaps, and showing that although the field is growing rapidly especially with deep learning there remains a strong need for standardized methods well-designed datasets and better approaches to capturing and interpreting emotions

Keyword: Dialect Handling • Sentiment Recognition • Educational Feedback • Neural Networks.

Introduction

Natural Language Processing researchers explore text generation which creates new text by combining artificial intelligence and computational linguistics (Cocea et al 2018, Barrón-Estrada et al 2017). It involves producing artificial language that is semantically and grammatically sound (Kaewmak & Pong-Inwong 2016; Ullah 2016). This model receives input data, understands its context, and generates new text relevant to the input domain (Li et al 2018; Xie et al 2020). Because text production and evaluation are open-ended, generating and assessing grammatically and conceptually correct content is challenging (Qu et al 2020; Devlin et al 2018). Text can be generated at various levels word, phrase, or character (Gillioz et al 2020; Yu et al 2020). Similarly, persona-level text generation identifies specific elements within a manuscript rather than the entire text (Bi et al., 2019 Gu et al. 2016). Text generation techniques in deep learning models are broadly classified into three categories (Sukhbaatar et al 2015; Guan et al 2020):

1. Array-Succession Model: Uses a predefined-size vector as input with a variable result (Song et al 2021; Welleck et al.2019).

2. Sequence-Vector Model: Has variable-sized input and fixed-size output, often used for classification (Hugging Face 2022; Chen et al 2021).

3. Sequence-to-Sequence Model: The variable-length input and output and is the most widely used model for text generation especially for translation (Sitikhu et al 2019; Chen 2022).

Quality Evaluation of Generated Text

The overall quality of generated content determines model performance and is measured using quality metrics (Liu et al 2016; Dužsek et al 2020). Two main approaches are used: human-centric and machine-centric (Egonmwan & Chali 2019; Sankaranarayanan & Krishnan 2019).

 DOI: https://doi.org/10.51220/jmr.v21-S2.4

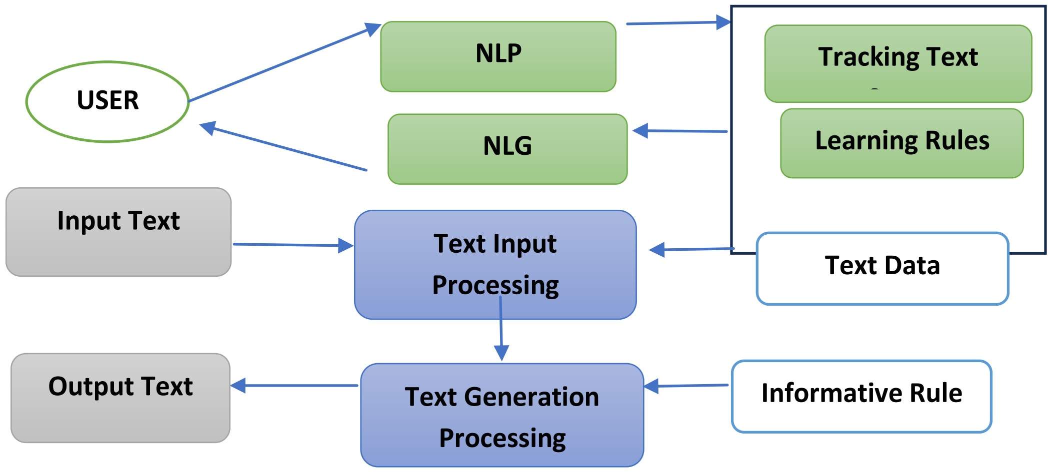

Fig 1. NLG Framework

Revealing Feelings: Sentiment Evaluation from an NLP Perspective

Sentiment analysis examines and interprets the intent and emotion expressed in a text to find the underlying viewpoint (Iqbal & Qureshi, 2020; Galassi et al., 2021). Language serves as a crucial medium for expressing human opinions and emotions (Celikyilmaz et al., 2020; Shorten & Khoshgoftaar, 2019). The sentiments conveyed through language can generally be categorized as neutral, negative, or positive.

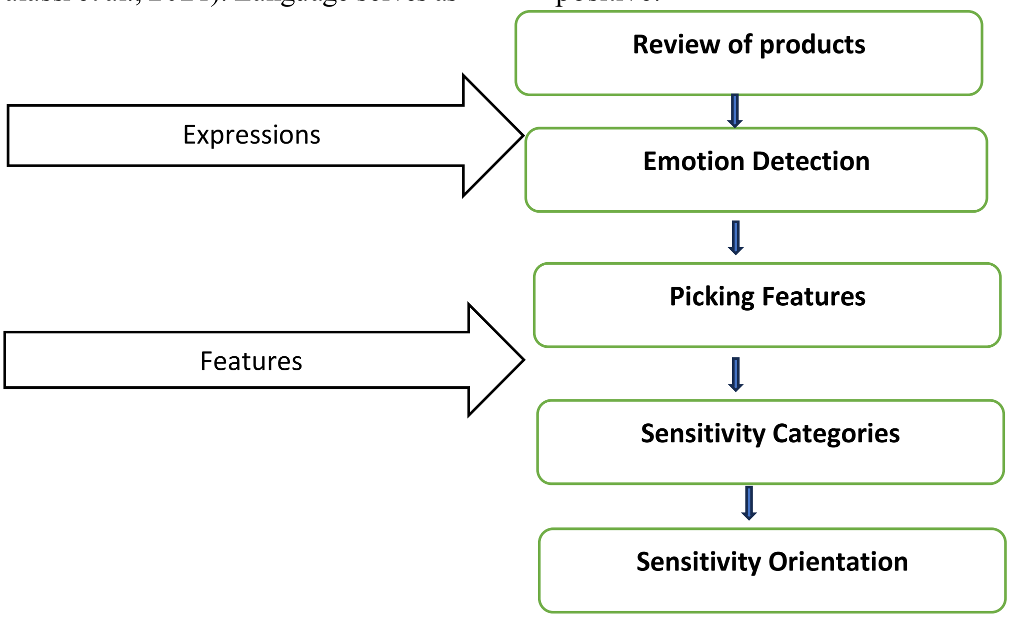

Fig 2. Flowchart of Sentiment Analysis

Levels of Sentiment Analysis

Sentiment Analysis operates at three main levels: document-level, sentence-level, and aspect-level (Abulaish & Sah 2019; Bayer et al 2021). Document-level Sentiment analysis the entire text collectively and determines whether its overall is positive or negative. Sentence-level sentiment analysis each sentence on its own first checking if it expresses an opinion or just states a fact, and then labeling the assertive sentences as positive or negative.

Methodology

This study examine previous work on text generation and sentiment analysis in NLP covering key works from 2015 to 2023 (Yu et.al 2018; Hoang et al 2018). It describes the key stages in NLP-based text generation and sentiment analysis.

Data Collection and Preparation

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The foundation of text generation is its training data, drawn from sources like books, journals, code, and social media (Moreno-Barea et al 2018; Wei & Zou 2019) .Usually creating general collections of text.

Model Selection and Training

It offers a variety of techniques for making text, each with its own strengths and disadvantages.

* **Statistical Language Models:** The probability of token sequences using term co-occurrence statistics in the training quantity (Cho et al 2019; Bose & Mukherjee 2019).

* **Recurrent Neural Networks (RNNs)** Effectively manage sequential data by retaining contextual information over extended sequences. (Berthelot et al 2019; Xie et al 2020).

* **Long Short-Term Memory** LSTM and GRU networks keep long-term context better than basic RNNs, important to more coherent text (Wiseman et al 2018; Song & Shmatikov 2019).

Evaluation and Optimization

Evaluating generated text is key to increased method performance (Du et al 2021; Lusetti et al 2018).

* **Expert Evaluation:** Experts assess fluency, coherence, grammatical accuracy, and adherence to the specified style or topic. (Narayan & Gardent 2020; Li et al 2018).

* **Automatic Metrics:** Metrics like BLEU measure similarity to reference text and ROUGE gauge precision and relevance (Xie et al 2020; Gupta & Patel 2020).

Sentiment Analysis Methodology

This was start by gathering text from sources like news articles, product reviews, social media, and customer feedback(Qu et al 2020; Devlin et al 2018). Preprocessing shelters tokenization, stop-word removal, and normalization to maintain reliability in the data. Attribute extraction captures key sentiment signals like words and phrases.

* **N-gram analysis:** Detecting recurring word sequence patterns, such as bad movie or completely unsatisfied.

* **Part-of-Speech (POS) tagging:** Recognizing grammatical roles, such as adjectives (e.g., happy) and adverbs (e.g., really) to gauge the strength of the articulated sentiment.

Classification models categorize text into sentiment labels such as positive, negative, or neutral.

1. **Rule-Based Classifiers:** Spread on rule-based methods and sentiment lexicons.

2. Machine Learning Classifiers: They learn associations among features and sentiment labels through models such as Naïve Bayes or SVMs.

3. Deep Learning Models: Employ cultured architectures like LSTMs to capture contextual dependencies enabling more nuanced and precise sentiment analysis.

Review of Literature

This section speedily reviews current text generation methods and compares deep learning-based augmentation to older methods.

Text Augmentation

In computer vision, data augmentation expands the training set by flipping, rotating, or recoloring images while preserving their original labels, providing a low-cost way to improve model robustness. A key example on the NLP side is Easy Data Augmentation for text classification, which plays a similar role for text. (Wei & Zou et al 2019) which uses simple but powerful operations to boost model performance, especially on small datasets.EDA uses simple, systematic text transformations to enlarge the training set and has demonstrated clear performance improvements, especially in low-data settings.The four main EDA techniques are:

* **Synonym Replacement (SR):** Replacing words with their synonyms.

* **Random Insertion (RI):** Inserting random words at various positions.

* **Random swap (RS):** Exchanging positions of random words.

* **Random Deletion (RD):** Removing words from sentences.

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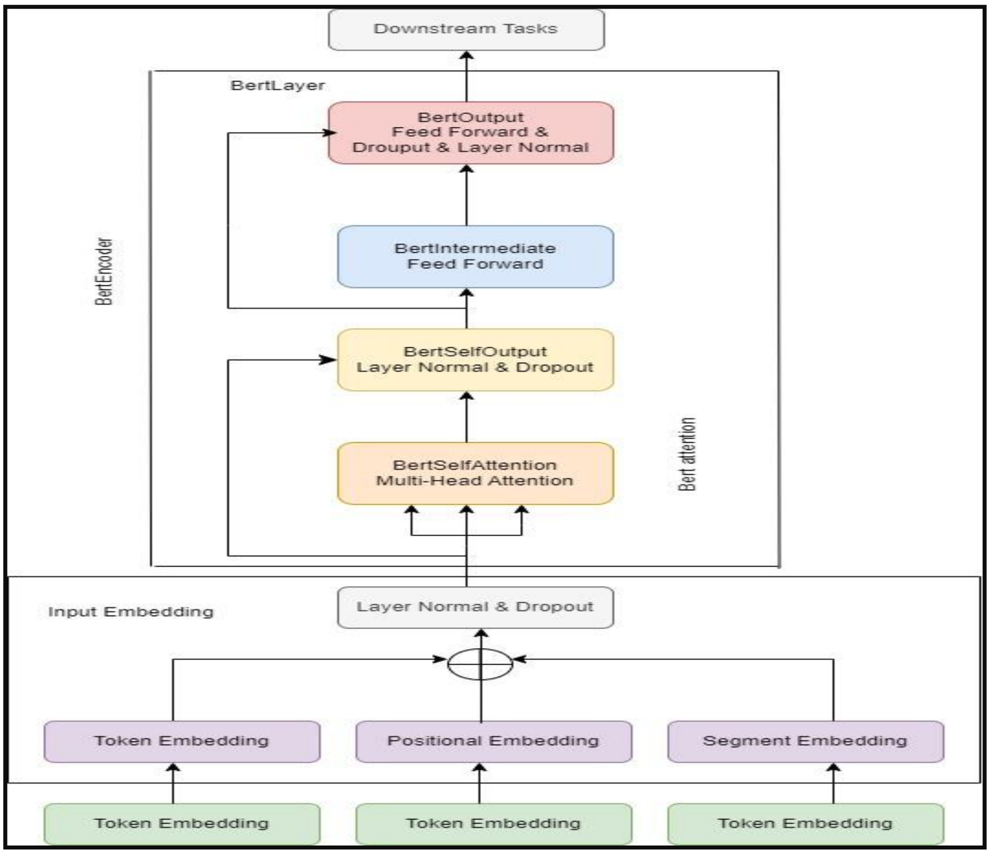

Fig 4: Bert network

Used appropriately, data augmentation can increase both the volume and variety of training data, but excessive or poorly designed transformations can degrade data quality, making a balanced strategy crucial. (Feng et al 2021; Kumar & Athavale 2022).

Text Generation

It's a core part of many NLP applications. Most modern models use an encoder–decoder design the decoder turns into a fluent output and encoder turns the input text into numbers. Recent advancements in neural networks and deep learning have greatly improved the quality and sophistication of generated text. Among these has become one of the most influential NLP models (Devlin et al 2019; Vaswani et al 2017). It pretraining objectives Masked Language Modeling and Next Sentence Prediction equip it with strong representational capabilities.

Knowledge for text generation can come from knowledge bases, graphs, keywords, topics, linguistic features, and domain datasets, and adding this structured information usually makes the output more coherent and informative. (Narayan & Gardent 2020; Li et al 2018).

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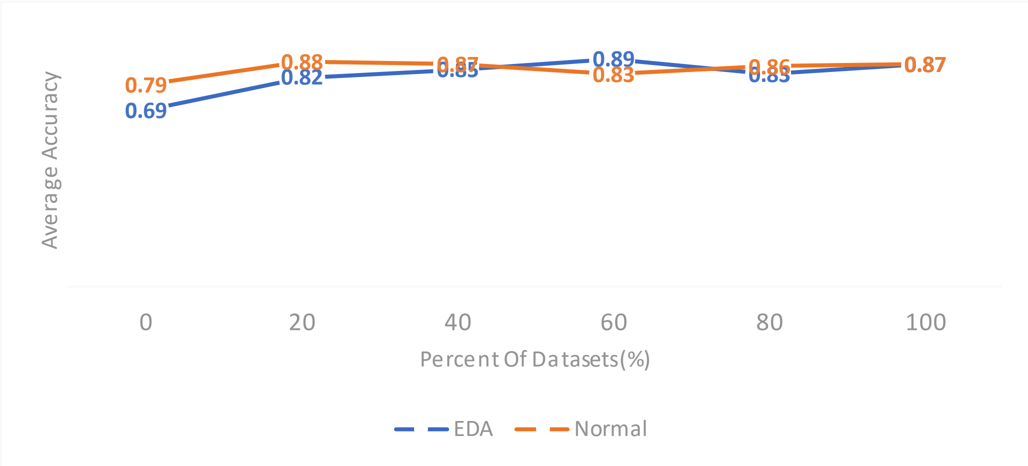

Fig 3. EDA Performance Comparison

Diagram of Opinion Examination

After reviewing previous research, it was found that studies on sentiment analysis in education primarily focus on identifying the benefits of applying SA to educational data and the methods and resources used (Raosoft 2016 Kiritchenko & Mohammad 2016). This study extends prior work by offering insights into bibliographic sources, research trends, and the latest tools available for SA.

The study presents four key information sources and tools that future researchers can use for sentiment analysis in education.

In social networks, SA helps track brand reputation and analyze public reactions during crises such as COVID-19 (Ridhwan & Hargreaves 2021). In politics SA aids candidates in understanding voter sentiment during election campaigns.

Aspect-based sentiment analysis has been used to pull out which specific factors in student feedback affect how effective a course (Walaa et al 2020). These aspects typically include course content, design, evaluation methods, and the technology used to deliver learning materials.

CORPUS ↓
Handling Paperwork → LEXICONS & LINGUISTIC RESOURCES ↓
EXAMINING PAPERWORK → LEXICONS & LINGUISTIC RESOURCES ↓
EMOTIONAL RATING FOR ELEMENTS

Fig 5: The Architecture of Sentiment Analysis

RESEARCH DESIGNS

We utilized orderly mapping as the investigate technique for the writing survey in this ponder. Utilizing the Favoured Detailing Things for Efficient Audits and Meta-Analyses rules (Shamseer et al 2015), we were able to recognize and screen the germane distributions utilizing strict criteria, as this strategy requires a built up look convention. The arranging and looking of essential investigate, think about collection, information extraction, and information amalgamation are the four fundamental components of this SLR.

RESEARCH QUESTIONS

The production of a research protocol, which involved deciding on research topics, specifying search terms, and choosing bibliographic databases to conduct the search, was the first step in the PRISMA process (Moher et al 2009). Applying the inclusion criteria was the second step; the application of the exclusion criteria was the third. Data

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extraction and subsequent evaluation constituted the final step.

RQ1. Which measures are used to assess how well text generation models perform?

RQ2. Which state-of-the-art and traditional profound learning methods are employed in the literature to produce text?

RQ3. Which application spaces make overwhelming utilize of content era?

SEARCH STRATEGY TO RETRIEVE PRIMARY STUDIES

Table 1 displayed the research retrieved from various databases. Only unique copies of each extracted primary sample were kept in EndNote. Duplicate record removal eliminated forty investigations (Shamseer et al 2015).

Table 1. Keywords

Group 1: Profound Learning Related Keywords	Profound knowledge OR natural language process OR neural network or RNN OR LSTM OR GAN OR GPT-2 OR Recursive
Group 2: Text Generation related keywords	Text generation OR language generation OR language modelling OR natural language generation OR neural language generation
Search Query	(Group 1) and (Group 2)

Looking through the five chosen bibliographic databases, the text generation search query turned up 264 papers, as Figure 6 illustrates.

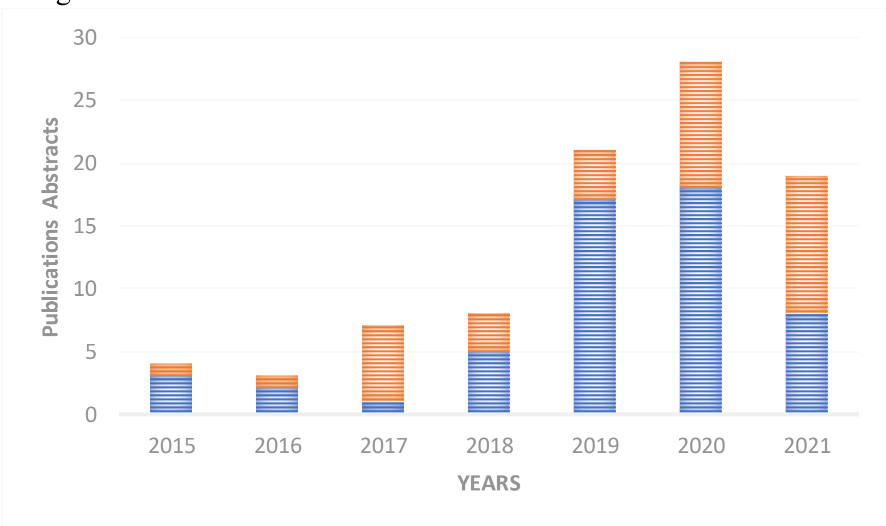

Fig 6: The quantity of meetings and publication abstracts gathered between 2015 and 2021

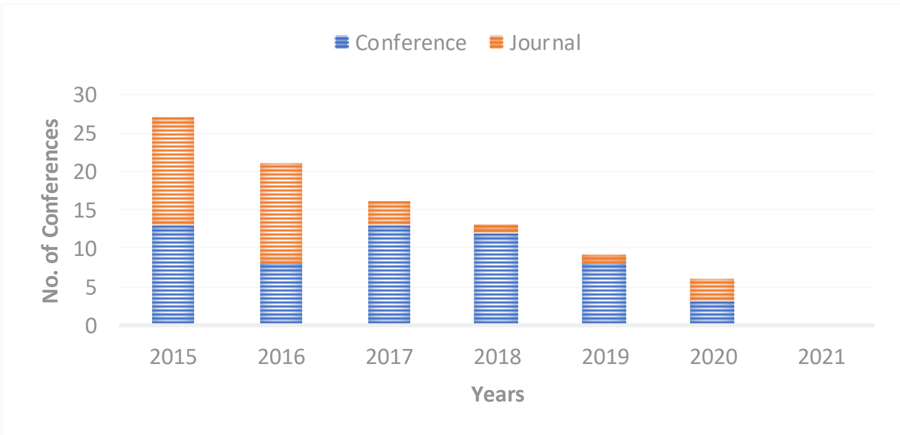

Fig 7: The quantity of conference and publication abstracts gathered between 2015 and 2020

 DOI: https://doi.org/10.51220/jmr.v21-S2.4

OUTCOMES OF THE STRUCTURED PLANNING RESEARCH

RQ1. Which measures are used to assess how well text generation models perform?

Two measures assess generated text: machine-centric and human-centric (Papineni et al., 2002; Banerjee & Lavie, 2005). Depending on evaluation techniques, studies in this SLR are divided into three categories. Table 2 shows that 64 of the 90 publications used a machine-centric methodology, three were assessed by experts, and fourteen combined both approaches.

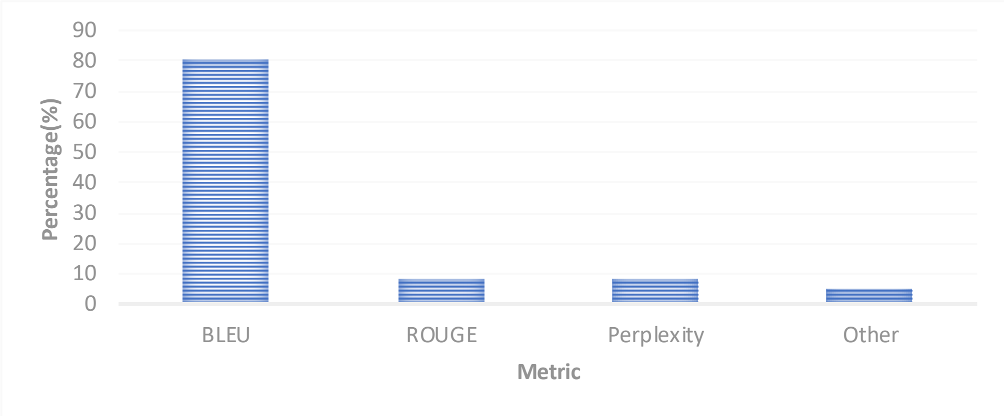

Fig 8: Evaluation metrices for text generation

RQ2. Which traditional and state-of-the-art deep learning methods are used for text generation in literature?

The two techniques used in the literature to generate text are traditional deep learning approaches and advanced deep learning approaches (ADLA). Models such as CNN, LSTM, and RNN (Hochreiter & Schmidhuber 1997) models are very strong for text generation, but the discrete nature of language still creates limitations and producing contextually accurate text often requires deep domain knowledge. and skills (Vaswani et al 2017; Radford et al 2019).

Table 2: Evaluation of Text Creation Techniques

Methods	Articles
Advanced Profound Dialects	[17],[25]-[36]
Traditional Profound Dialects	[4],[22],[35],[3],[18],[12]
Combination of both methods	[5],[17],[21]

As a result, sophisticated deep learning models such as Transformer, BERT, GPT-2, and GPT-3 were proposed to address issues in traditional methodologies. The latest models use attention-mechanism-based, content-dependent algorithms.

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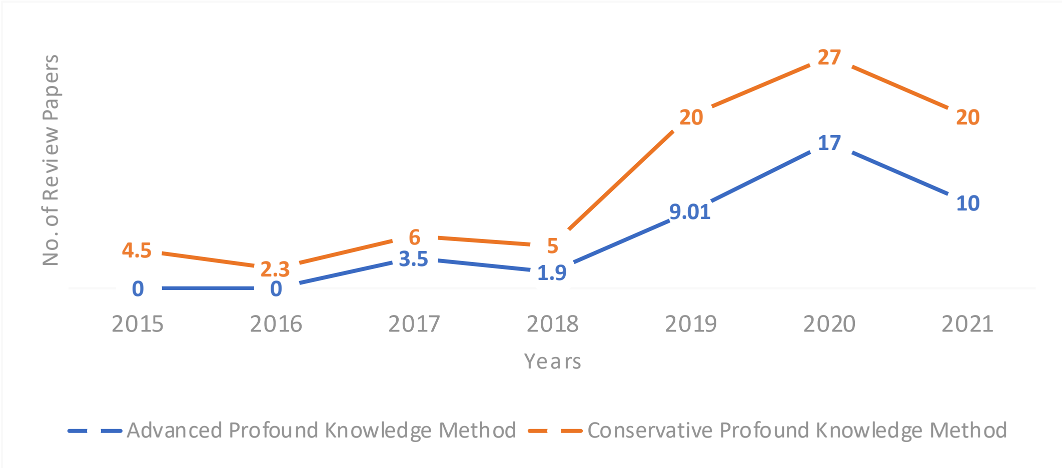

Fig 9: Text generation used approaches in the review papers

RQ3. Which application spaces make overwhelming use of content generation? As shown in Figure 10, content creation covers a wide range of applications in deep learning (Husain & Uzair, 2020) and can be divided into 18 areas. Ten of the 90 papers focus on dataset balancing, eight address data-to-text and speech-to-text, seven on script writing, and five on machine translation.

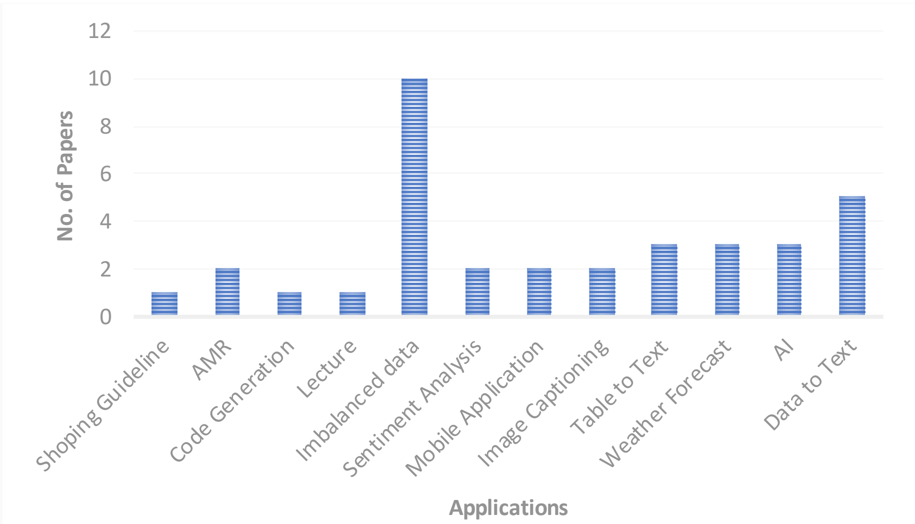

Fig 10: Applications of Text Generation

RQ4. Which sentiment analysis-related components of education have received the greatest research attention? Student feedback is a key source of information about teachers courses , institutions and analyzing it helps administrators identify where to improve. In the surveyed studies, about 81% specifically examined students opinions on these educational aspects. (Haque et al., 2018; Ghosh 2016) and attitudes toward teachers, 6% on institutions, and 13% took a broader approach examining students' views on teachers, courses, and institutions. These findings are illustrated in Fig 10.

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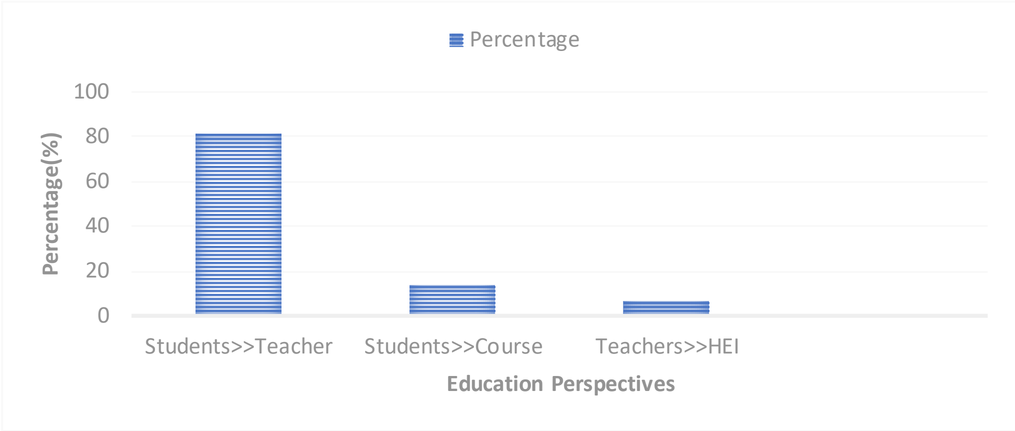

Fig 11: Aspects of feedback were examined in the publications under evaluation.

RQ5. Which assets are most often used to get feedback from students?

Several data sources were identified and divided into four categories for clarity:

1. **Discussion forums, blogs, and social networks:** Includes data from platforms such as Facebook, Twitter, and online communities.
2. **Surveys and queries:** Contains data gathered through questionnaires distributed to students and instructors (Smutny & Schreiberova, 2020).
3. **Educational and research platforms:** Includes information from sites like ResearchGate, LinkedIn, and edX.
4. **Combination of databases:** Includes research that used several datasets for their researches.

Figure 12 illustrated that 64 (69.57%) of the studies specified the sources used to obtain data, while nearly one-third provided no data at all.

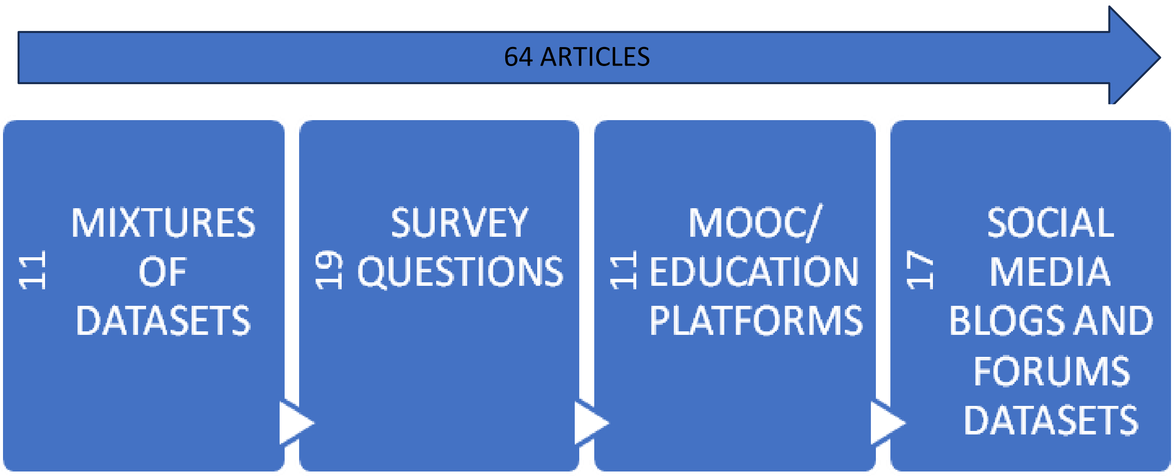

Fig 12: Categories of Sources

RQ6. Which assessment criteria are most usually practical for assessing sentiment analysis systems' efficiency?
Frameworks for sentiment examination were evaluate using data retrieval-based measures such as F1-score, recall, and accuracy. Some studies also assessed system performance using additional statistical metrics. Figure 13 compares the number of articles that performed no evaluation, omitted metrics (Kiritchenko & Mohammad, 2016), or used specific assessment measures. According to Figure 13, 68% of publications reported the F1-score—alone or with other metrics like accuracy and recall. About 27% did not specify any criteria, 3% used Kappa, and 2% used Pearson R-values.

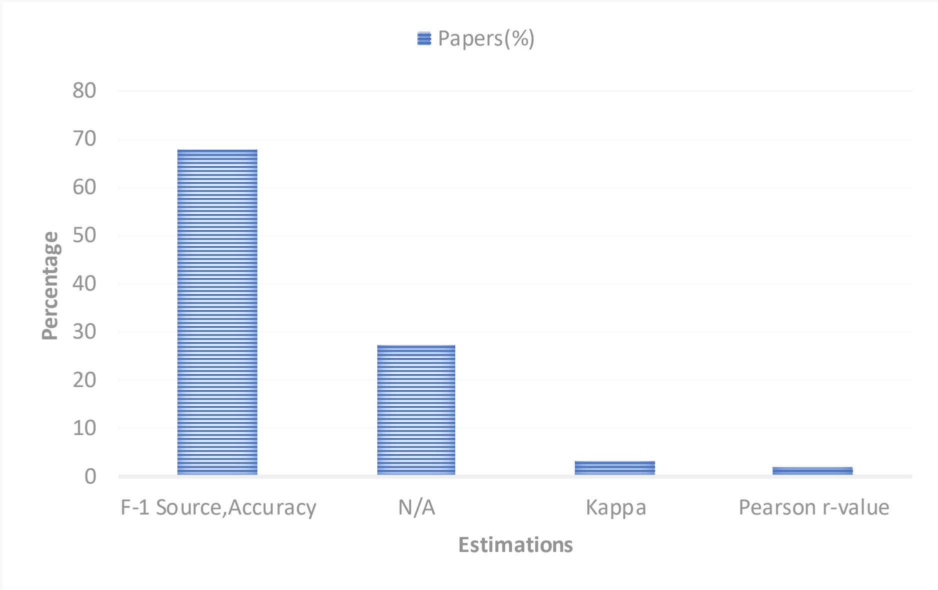

Fig 13: Evaluation metrices

Challenges and Gaps

Our mapping analysis revealed several gaps that must be addressed to better understand sentiment analysis of student comments and text generation. Major issues are listed below:

Necessity for diversification: Most text generation strategies (Feng et al 2021) suffer from repetitive and low-quality content creation.

Incorrect choice of quality indicators: Many studies chose poor evaluation metrics leading to weak assessments of text quality for instance BLEU can work for short sentences but often fails to capture true semantic meaning compared with human judgment or semantic methods like AMR.

Restricted resources: Low-resource languages such as Arabic, Bengali, Russian, and Korean lack linguistic tools like dictionaries and POS taggers. While Google Translate supports many languages.

Limited availability of datasets: Languages with limited resources often lack public datasets. For example, Bengali and Czech studies used their own datasets due to the absence of standard ones.

Unconventional dataset sources: Many datasets come from Quora, GitHub, Kaggle, and personal websites.

Extremely fine sentiment analysis: Most studies focus on general opinions rather than fine-grained components of teaching and learning.

Metaphorical language: Further research is needed to detect figurative language such as sarcasm and irony in student feedback (Abdul-Mageed et al 2020).

Generalization: Most methods are domain-specific and perform poorly across domains.

Visualization strategies: The use of contextualized and general-purpose word embedding visualization is underexplored (Mirzaee & Ghasem-Aghaee 2022).

Suggestions and Directions for further Research

This section outlines several avenues for future study to improve text generation performance.

Standardized Dataset:

There is an urgent need for shared, standard sentiment analysis datasets for low-resource languages so that systems become more accurate, consistent, and reliable. (Abdul-Mageed et al., 2020) across tools and frameworks.

Quality Metrics:

DOI: https://doi.org/10.51220/jmr.v21-S2.4

Many papers used weak or poorly chosen metrics, and about 27% did not report any evaluation at all, making it hard to judge text quality fairly. Relying only on BLEU (Papineni et al., 2002) often misrepresents how good the text really is, so clearer reporting and more consistent metrics like accuracy and F1-score are needed.

Conclusion

It represents the creative dimension of AI (Narayan & Gardent 2020; Li et al 2018). To get closer to human-like thinking, AI needs to generate text that could pass a Turing test, at least in some settings. Thanks to huge amounts of online text from social media, news, and messaging apps, powerful models for high-resource languages can now generate or predict words, characters, and full sentences in many applications.

Over the years, research has increasingly focused on advanced machine learning methods for text production, particularly since 2018 (Radford et al 2019). English remains the most represented language in text generation studies. This comprehensive review benefits researchers and educators by summarizing data sources, methodologies, trends, and techniques. In the education sector, sentiment analysis using deep learning and NLP has grown notably over the past decade. These tools help researchers understand students' behaviors, thoughts, and feelings toward instruction (Haque et al 2018).

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