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The Rise of Intelligent Cinema: Systematic Mapping of Natural Language Processing Techniques in Film Analysis, Translation, and Recommendation

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ABSTRACT

This study presents a PRISMA-guided systematic literature review of 171 peer-reviewed journal articles published between 2021 and 2025, examining the application of Natural Language Processing (NLP) in the film industry. The objective is to map methodological trends, identify research gaps, and propose a unified analytical framework across five major domains: sentiment and emotion analysis, content generation, multilingual translation, recommendation systems, and knowledge extraction. The research contribution is the development of an integrated "cinematic intelligence" framework that synthesizes previously fragmented NLP applications within a single domain-specific mapping study. Studies were selected from the Scopus database based on predefined inclusion criteria (English-language, peer-reviewed journals, film-related NLP focus), ensuring methodological transparency and reproducibility. The findings indicate a clear transition toward transformer-based, multimodal, and explainable AI architectures. Transformer models such as BERT, GPT, and LLaMA dominate emotion analysis, automated script generation, and cross-lingual subtitle processing. However, persistent challenges include limited long-context narrative modeling, cross-cultural generalization constraints, cold-start bias in recommendation systems, and the absence of standardized evaluation metrics for AI-generated creative content. Overall, the review demonstrates that NLP in cinema is evolving toward integrated, scalable, and context-aware systems, while highlighting critical research opportunities and practical implications for both academic and industry stakeholders.

1. Introduction

Advances in Natural Language Processing (NLP) technology have contributed significantly to the progress of the entertainment industry, particularly in the field of filmmaking [1]-[4]. NLP enables computational systems to understand, interpret, and generate human language automatically [5], [6], allowing large-scale analysis of audience opinions, narrative structures, and emotional responses in cinematic content [7]-[10]. Recent developments in deep learning architectures such as BERT, BiLSTM, convolutional neural networks (CNN), and attention mechanisms have demonstrated strong performance in sentiment and emotion classification tasks using large datasets such as IMDb and SemEval interpret narrative meaning, and even create film content independently [11]. In the last decade, combinations of deep learning models such as BERT [11]-[18].

However, applying conventional NLP techniques directly to cinematic contexts presents several challenges. Film narratives contain complex dialogue structures, character interactions, emotional dynamics, and cultural references that differ significantly from traditional textual domains such as news articles or social media posts. In addition, cinematic content often involves multimodal information, including visual scenes, audio signals, and narrative context that cannot be fully captured through text-based analysis alone. These characteristics indicate that NLP applications in cinema require domain-specific adaptation to effectively model narrative meaning, character emotions, and audience perception.

Recent developments increasingly conceptualize these capabilities within a broader framework referred to as Intelligent Cinema, which integrates multiple NLP-driven functions such as sentiment analysis, recommendation systems, automated script generation, translation, and knowledge extraction into a unified digital ecosystem for film production and audience engagement. Unlike traditional research domains that treat these applications separately, Intelligent Cinema emphasizes the interconnected role of language technologies across the cinematic value chain. This perspective positions NLP not only as a text analysis tool but also as a core component in the development of intelligent and adaptive film production environments.

Despite these advances, existing research remains fragmented across individual applications. Many studies focus on isolated tasks such as review sentiment analysis or recommendation algorithms without examining how different NLP techniques can be integrated within the broader cinematic ecosystem. Furthermore, several limitations persist, including the dominance of English-language datasets, limited multilingual resources, and insufficient integration of multimodal information in film analysis. These challenges highlight the need for a systematic review that maps current research trends and identifies emerging opportunities for integrating NLP technologies in the film industry.

Based on these motivations, this study aims to systematically examine the application of NLP techniques in the film industry and identify research gaps that may guide future developments in intelligent cinematic systems. Specifically, this study addresses the following research questions:

- RQ1. How is NLP applied in various aspects of the film industry to understand language, emotions, and cinematic narratives?
- RQ2. What are the gaps and opportunities for integration between NLP application fields in film that can shape a smart and adaptive film production ecosystem?
- RQ3. How can the application of NLP in content generation enhance creativity and cultural value in K-Dramas from epistemological, ontological, and axiological perspectives?

The research contribution is threefold. First, this study provides a systematic mapping of NLP applications across key domains in the film industry, including sentiment analysis, recommendation systems, content generation, translation and subtitling, and knowledge extraction. Second, it identifies current research gaps related to multilingual processing, multimodal integration, and explainable AI in cinematic contexts. Third, it proposes the conceptual perspective of Intelligent Cinema as an integrated ecosystem that connects NLP technologies with creative and cultural processes in film production.

2. Related Work

Various studies highlight how NLP is used to analyze movie reviews and audience behavior [19]-[22]. The BERT–LSTM model, for example, achieved an accuracy rate of 94% in text classification tasks, demonstrating that the integration of contextual embedding with sequential architecture improves the system's performance in capturing emotional nuances [23]-[26]. Similarly, Paneru et al. [27] showed that combining RoBERTa embeddings with recurrent convolutional neural networks can achieve high classification accuracy on the IMDb dataset, demonstrating the effectiveness of transformer-based language representations in film-related sentiment analysis.

In addition to sentiment analysis, NLP is also used to build more personalized recommendation systems [28]-[30]. Nandhini et al. [3] introduced the CineInsight NaïveFlix algorithm, which combines user reviews from YIFY, YouTube, and IMDb to generate contextual movie recommendations [6], [31]. This system shows improved accuracy compared to Naïve Bayes and Linear SVC, although it still faces limitations in handling new movies or biased reviews. Graph-based approaches such as SeVGAER (Semantic-Enhanced Variational Graph Autoencoder) also show high effectiveness in linking semantic features and audience preferences to improve recommendation personalization [4], [32]-[36]. These studies indicate a shift toward hybrid recommendation systems that combine collaborative filtering, semantic representation learning, and contextual information.

The field of content generation is showing rapid development towards creative automation. Dharaniya et al. [37] developed the EMCG (Ensemble Movie Script Generation) model, which combines BiLSTM, GPT-3, and GPT Neo X, enabling it to generate movie scripts with cohesive dialogue and plot structures [30], [38] This system shows great potential in helping screenwriters create consistent and expressive narratives. A study [39] even shows that AI-generated scripts have a level of creativity that is almost comparable to human work in several linguistic and structural indicators [40], [41]. However, existing generative models still face challenges in maintaining long narrative coherence and cultural authenticity in storytelling, highlighting the need for improved narrative understanding and long-context modeling in cinematic text generation.

In addition, the application of NLP in the field of translation & subtitling strengthens cross-language and cross-cultural access [38], [42]. A study by J. Zhang et al. [43] introduced the PhraseBT model, which combines a phrase-level data augmentation approach with Llama3-8B-Instruct, improving the quality of Japanese Chinese subtitle translations. The Cultural-Aware Machine Translation (CAMT) approach has also been developed to preserve cultural context and emotion in film dialogue translation [44], [45]. These studies highlight the importance of incorporating cultural context and linguistic diversity in machine translation systems for cinematic content.

Other studies highlight the aspect of knowledge extraction in understanding the semantic structure of films [4]. Fourati et al. [46] use the Structured Topic Model (STM) and LSCOM Ontology approaches to link narrative topics with the conceptual knowledges of films, while Ligabue et al. [47] developed CtxKG (Contextual Knowledge Graph), which combines relationships between entities based on narrative context. This approach supports recommendation systems, automatic script generation, and semantic-based genre classification [48]-[50].

Research trends point toward multimodal, multilingual, and explainable AI (XAI) models that integrate text data [51]-[53], [5], [54], [55], audiovisual [56], [57] and social context to generate a more complete understanding of films and their audiences [58], [59]. However, several challenges remain, including cold-start problems in recommendation systems, dependence on English-language datasets, and the need for culturally adaptive models that preserve local storytelling traditions in automated film production processes.

This research gap opens new opportunities for the application of NLP in content generation for Korean dramas (K-Dramas), which are known for their emotional depth, moral values, and strong cultural narratives. Through the application of models such as GPT-4 or Llama 3 trained on a corpus of Korean drama scripts, AI can help create storylines that reflect the values of han (existential sadness), jeong (emotional bonds), and heung (collective joy). This approach not only supports creative storytelling but also contributes to preserving cultural authenticity while expanding the global reach of the K-content industry.

3. Methodology

This study employs a Systematic Literature Review (SLR) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, reproducibility, and methodological rigor in the literature selection process [60]. The review process consists of four PRISMA stages, namely Identification, Screening, Eligibility, and Inclusion, followed by data synthesis and thematic analysis to identify research trends and emerging domains of NLP applications in the film industry. Fig. 1 presents a research methodology flowchart illustrating the study selection procedure and the analytical framework used to synthesize the selected literature.

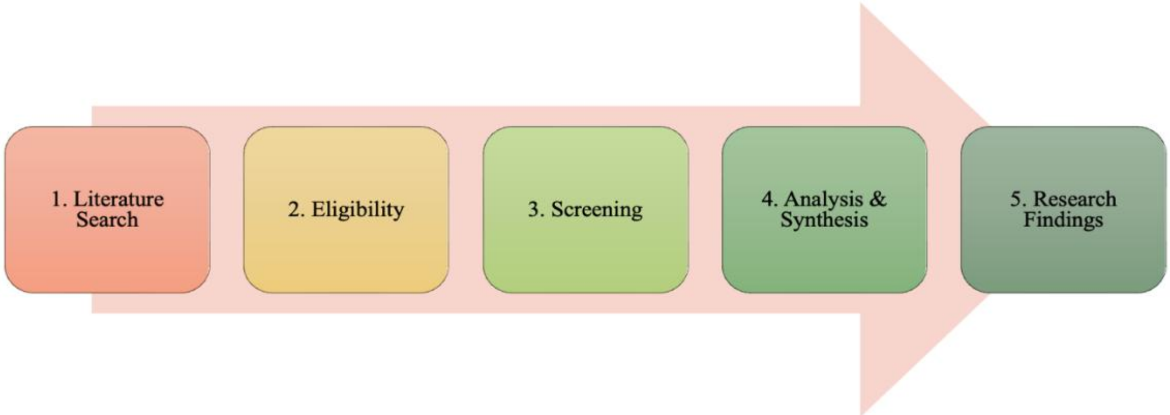

Fig. 1. SLR process

3.1. Search Strategy (Identification)

A comprehensive literature search was conducted in the Scopus database on September 15, 2025. Scopus was selected because it provides extensive multidisciplinary coverage and indexes peer-reviewed journals across engineering, artificial intelligence, and computational linguistics, making it suitable for capturing NLP-related research within the film domain. Nevertheless, reliance on a single database may introduce potential coverage bias; therefore, this limitation is acknowledged and discussed as part of the methodological considerations of the study.

The search strategy was designed using Boolean operators based on keywords derived from the research questions and domain terminology. The query combines film-related keywords such as *movie*, *drama*, and *theater* with artificial intelligence and NLP-related terms including *deep learning*, *NLP*, and *natural language processing*. Parentheses were introduced to improve clarity and logical grouping of the search expressions, ensuring that the query structure reflects the intended conceptual relationship between film-related and NLP-related keywords. The search string used in this study is presented in Table 1.

Table 1. Search string keyword

Search String
(TITLE-ABS-KEY (movie) OR TITLE-ABS-KEY (drama) OR TITLE-ABS-KEY (theater) AND TITLE-ABS-KEY (deep learning) OR TITLE-ABS-KEY (NLP) OR TITLE-ABS-KEY (natural language processing)) AND (LIMIT-TO (LANGUAGE,"English")) AND PUBYEAR > 2021 AND PUBYEAR < 2025

The publication year range of 2021–2025 was selected to capture recent developments in deep learning models and large language models that have significantly influenced NLP applications in cinematic contexts. Through this search process, a total of 1,919 records were initially identified, representing the preliminary dataset for further screening and evaluation. In order to maintain methodological consistency and ensure the academic reliability of the analyzed literature, grey literature such as industry whitepapers, technical reports, and non-peer-reviewed preprints was not included in this review.

3.2. Eligibility Criteria and Quality Assessment

To ensure relevance and methodological rigor, explicit inclusion and exclusion criteria were defined. Studies were included if they were published between 2021 and 2025, appeared in peer-reviewed journals (Q1–Q4), were written in English, and explicitly addressed NLP applications in film-related contexts, including sentiment analysis, script generation, recommendation systems, translation, or cinematic knowledge extraction [61]-[64]. Studies were excluded if they were unrelated to NLP applications in film, lacked accessible full-text versions, provided insufficient methodological information, or did not report empirical evaluation results.

A quality assessment checklist was subsequently applied to ensure methodological robustness. Each study was evaluated based on methodological transparency, dataset specification, reproducibility of the proposed approach, appropriateness of evaluation metrics, and consistency between results and conclusions. Studies lacking empirical validation or presenting methodological ambiguity were excluded from the final dataset. The screening process also involved manual verification of titles, abstracts, and full texts by the research team, with any disagreements resolved through discussion and consensus to maintain objectivity.

3.3. Screening and Study Selection

The study selection procedure followed the PRISMA workflow to systematically refine the identified literature. From the initial 1,919 records, title and abstract screening was conducted to remove irrelevant publications and non-journal documents, resulting in 734 potentially relevant articles. Subsequently, 199 studies underwent full-text assessment during the eligibility stage, where the predefined inclusion, exclusion, and quality assessment criteria were applied. After this evaluation process, 171 studies met all methodological and thematic requirements and were included in the final dataset for analysis. The overall study selection process following the PRISMA framework is illustrated in Fig. 2.

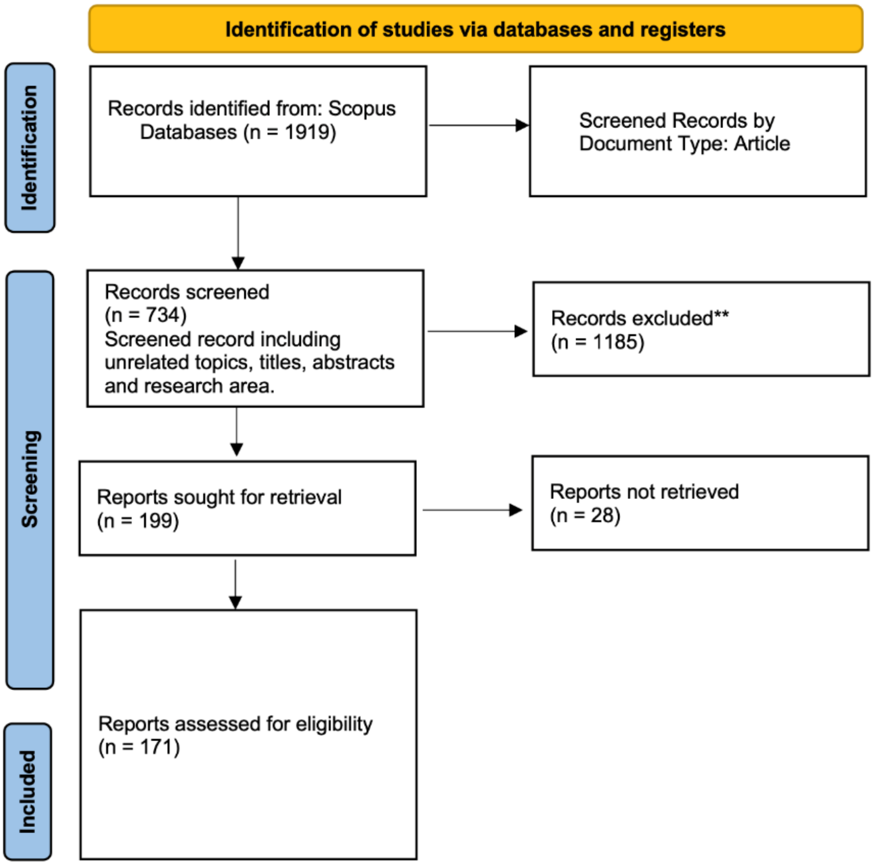

Fig. 2. PRISMA flowchart

3.4 Data Analysis and Domain Classification

After the final dataset had been established, the selected studies were analyzed using comparative analysis and thematic synthesis techniques to identify research patterns and methodological trends within the field of NLP applications in the film industry. Through an iterative review of research objectives, datasets, and technological approaches reported in the selected literature, the studies were grouped into several major application domains.

The analysis revealed five major domains of NLP applications in the film industry, namely sentiment and emotion analysis, recommendation systems, content generation, translation and subtitling, and cinematic knowledge extraction. These domains were not predefined prior to the analysis but emerged through thematic clustering of the retrieved studies, allowing the classification to reflect actual research trends within the dataset.

Furthermore, comparative analysis was conducted to examine methodological approaches, datasets, evaluation metrics, and reported performance across the selected studies. This process enabled the identification of technological developments, methodological patterns, and existing research gaps in the application of NLP technologies within cinematic contexts. The synthesis results were then used to formulate the intelligent cinema framework, which conceptualizes the integration of NLP technologies across multiple stages of film production, audience analysis, and cross-cultural content dissemination, thereby illustrating how language technologies contribute to the development of intelligent cinematic ecosystems.

4. Results and Discussion

The following table (as shown in Table 2) presents the evolution of NLP research in the film industry from 2021 to 2025, showing a shift from conventional *deep learning-based* approaches toward the integration of hybrid, multimodal, and *explainable AI* models. Each period reflects an increase in complexity, context, and technological maturity in sentiment analysis, translation, and film recommendation systems.

(i) Main findings of the present study

The synthesis of 171 PRISMA-selected studies reveals that NLP research in the film industry can be organized into five interrelated domains: sentiment and emotion analysis, content generation, subtitle and multilingual translation, recommendation systems, and knowledge extraction for film understanding. These domains collectively form a technological ecosystem that enables automated interpretation, creation, and distribution of cinematic content. The analysis further indicates that transformer-based architectures such as BERT [87], [168], GPT [112], and Llama models, often combined with sequential networks such as BiLSTM, CNN, or GRU, have become the dominant methodological paradigm for processing cinematic language data [17], [23], [27]. Compared with earlier deep learning pipelines, these architectures provide stronger contextual representation and improved performance in tasks such as emotion recognition, multilingual translation, and narrative modeling.

(ii) Implications and explanation of findings

The results indicate that NLP technologies now play a dual role within the film industry as both analytical infrastructure and creative augmentation tools. In analytical contexts, sentiment and emotion analysis models enable filmmakers and streaming platforms to interpret audience perception and feedback, thereby supporting marketing strategies and audience engagement analysis. In creative workflows, generative models such as GPT-based architectures assist in script development, character dialogue generation, and narrative design. Furthermore, multilingual translation systems facilitate cross-cultural dissemination of film content, allowing cinematic narratives to reach broader global audiences. Recommendation systems powered by graph learning and contextual embeddings enhance user experience by providing personalized content discovery. When integrated with knowledge extraction techniques, these technologies contribute to a unified cinematic intelligence system capable of connecting language, narrative structure, emotional dynamics, and audience behavior.

(iii) Strengths and limitations

A key strength of this study lies in its systematic synthesis of 171 peer-reviewed publications, enabling a comprehensive mapping of NLP research trends within the film industry. The classification of five research domains provides a structured perspective on how various NLP technologies interact within a cinematic ecosystem. However, several limitations should be acknowledged. First, the reviewed studies employ heterogeneous datasets, tasks, and evaluation metrics, which restricts the possibility of conducting a quantitative meta-analysis. Second, many transformer-based models require substantial computational resources, which may limit their practical deployment in smaller production environments. Third, the predominance of English-language datasets suggests the need for more culturally diverse and multilingual corpora to better represent global cinematic contexts.

Table 2. Development and direction of NLP evolution in the film industry (2021–2025)

Year	Author	Evolution
2021	[8], [10], [16], [64]-[76]	Emphasizing hybrid deep learning-based models (CNN-LSTM, attention, XLM-R) for sentiment analysis, text classification, and movie recommendations. Research focus on multilingual transfer learning, knowledge graphs, and fake review detection marks a shift toward contextual, adaptive, and interactive models in natural language processing.
2022	[4], [25], [38], [45], [52], [54], [77]-[86]	Highlighting deep learning-based hybrid models (BERT, BiLSTM, CNN, CapsuleNet) with combined embeddings for sentiment analysis, text classification, and movie recommendations. The focus on multilingual context, emotion detection, and multimodal integration such as posters and subtitles mark the direction toward contextual and semantically aware models in the film industry.
2023	[2], [30], [37], [42], [46], [55], [61] [87]-[106]	Focusing on deep learning-based hybrid models (BERT, GRU, CNN, fuzzy logic) for cross-language sentiment analysis, automated script generation, and chatbot-based movie recommendations and reinforcement learning. The research also highlights multimodal translation and analysis linking text, audio, and emotions, marking a shift toward more adaptive, multimodal, and contextual NLP systems in the film industry.
2024	[1], [3], [9], [11], [13], [23], [24], [26], [28], [32], [33], [47], [56], [63], [91], [107]-[151]	Highlighting hybrid models (BERT/XLNet + BiLSTM/GRU/CNN, graph/autoencoder) for three domains: sentiment/aspect (low-resource, code-mixed, domain adaptation, ABSA, XAI), recommendation (conversational, knowledge graph + topic modeling, multimodal plot-audio-visual, cold-start/sparsity), and content understanding (multimodal genre/tag, semantic search). Cross-domain, focus on robustness (adversarial/backdoor detection), more mature augmentation/embedding, and MLLM+speech integration towards a reliable and culturally-linguistically sensitive end-to-end pipeline.
2025	[6], [12], [15], [17]-[19], [22], [27], [34], [35], [39], [41], [43], [44], [48], [58], [59], [152]-[182]	emphasizes hybrid models that combine deep learning (BERT, RoBERTa, BiGRU, CNN) with traditional techniques to improve accuracy and interpretability in three main areas: sentiment and emotion analysis, movie recommendation systems, and content understanding and translation. New approaches focus on multimodal integration, evolutionary optimization, XAI, and data augmentation to address adversarial challenges and preserve cultural and emotional context across languages. Research directions indicate a shift toward real-time, explainable, and applicable NLP systems in the film industry.

Fig. 3 illustrates the conceptual relationship between the five major NLP domains identified in this study. The figure highlights how sentiment analysis informs audience perception modeling, which may subsequently influence content generation systems to produce narratives aligned with audience preferences. Multilingual translation expands cultural accessibility, while recommendation systems distribute relevant content to appropriate audiences. Knowledge extraction provides semantic structure by modeling relationships among film entities such as characters, themes, and narrative events. Together, these components form an integrated technological framework for intelligent cinematic systems.

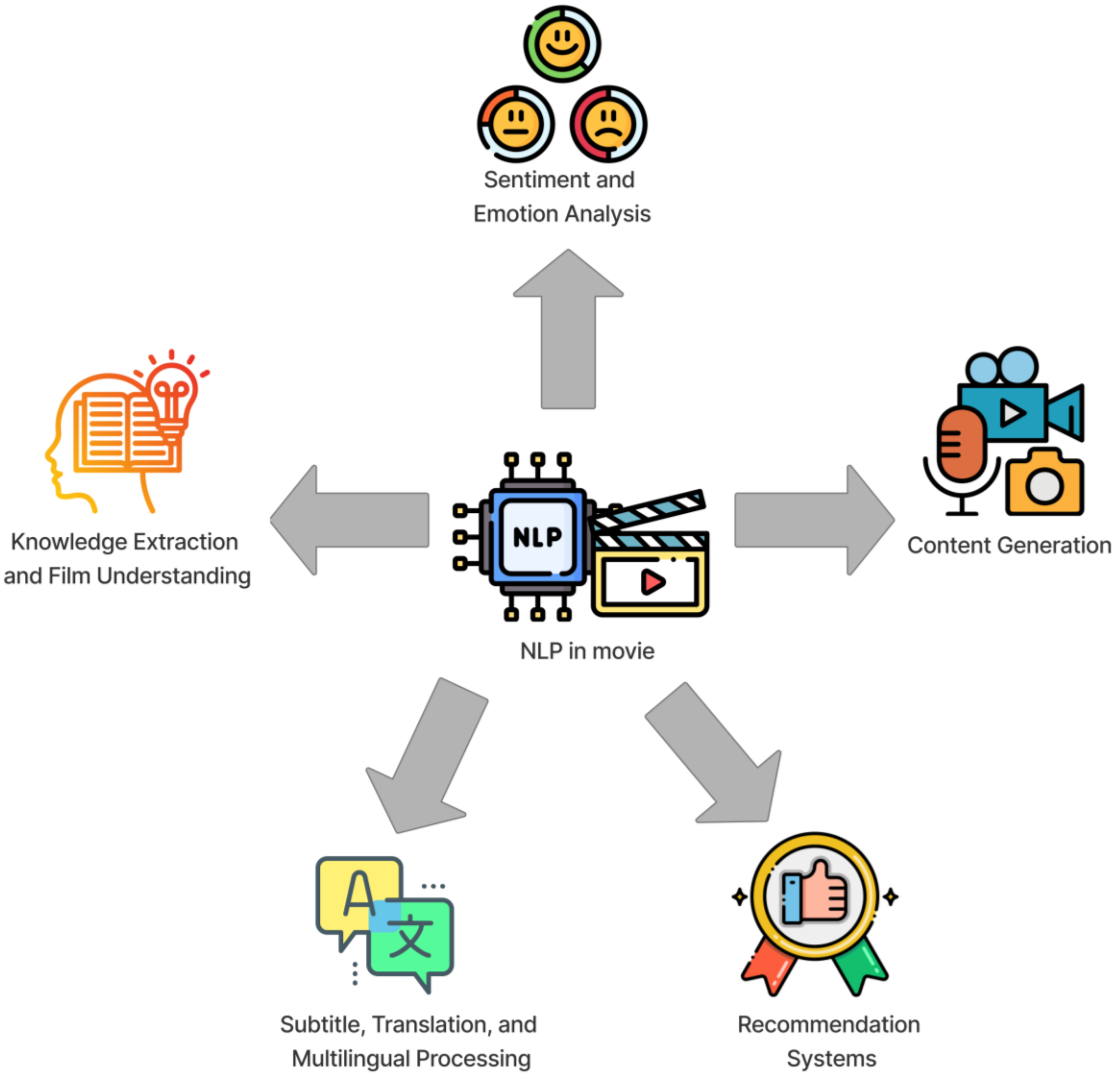

Fig. 3. NLP in movies

4.1. Sentiment and Emotion Analysis

Research in sentiment and emotion analysis (Table 3) shows a clear transition from conventional machine learning to hybrid deep learning and transformer-integrated architectures [14], [22], [73], [86], [124], [183]. Efficiency-oriented models such as Multinomial Naïve Bayes [109] and SVM [154] remain practical for large-scale datasets but struggle with sarcasm and contextual nuance. Hybrid and contextual systems including NPSC [17], CNN and LSTM-based models [104], [141], and transformer-enhanced approaches [107], [166] and transformer-enhanced approaches [18] optimize convergence and stability. However, performance gains are consistently accompanied by increased computational cost and limited cross-domain generalization.

Cross-lingual extensions such as SenTAS [182] and MSA-GCN [21], [61], [79], [118] expand sentiment modeling to multilingual contexts but introduce greater architectural complexity and data demands. Owing to heterogeneity in datasets (e.g., IMDB, SemEval, multilingual corpora) and evaluation metrics (e.g., Accuracy, F1-score, BLEU), formal quantitative meta-analysis was not feasible; thus, findings are synthesized comparatively rather than statistically aggregated. Overall, the literature reveals three dominant trajectories: the shift to transformer-based contextual modeling, expansion toward multilingual sentiment analysis, and the persistent trade-off between contextual depth and computational efficiency.

Table 3. Overview of sentiment & emotion analysis

Dataset	Core Method	Advantages	Limitations	Research Gap
IMDB	BERT + BiLSTM + CNN + Attention (NPSC) [17], [18], [84], [166], [168]	Improving accuracy and recall through deep context understanding	Requires high computing power	Optimizing transformer model efficiency for large datasets
IMDB, SemEval-2016	LWGBM & H2O ML [18]	High accuracy (95.39%) and more efficient than XLNet	Limited to the film domain	Cross-domain adaptation and complex emotions
IMDB (50K)	SVM [154]	High accuracy for main emotion extraction (joy, fear)	Does not detect sarcasm	Requires a combination of linguistic models for subtle emotions
IMDB, 20News	Fuzzy Deep Belief Network + ELM [156]	Effective for semi-labeled data	Difficult to handle very large data	Integration with modern unsupervised learning
IMDB	Multinomial Naïve Bayes + TF-IDF [109]	Simple, fast, 87.6% accuracy	Less robust for long contexts	Combination with contextual embeddings (e.g., BERT)
Twitter Movie Reviews	SenTAS Model [182]	Strong for code-mixed language	Difficult to adapt to other languages	Generalization for minor local languages
Multilingual Corpus	MSA-GCN [21], [61], [79]	Overcoming semantic differences between languages	High complexity	Optimization of lightweight multilingual models

4.2. Content Generation

The field of content generation in the film industry has undergone a substantial transformation during the review period, shifting from structured sequence models toward Large Language Model (LLM)-driven creative systems [28], [39], [129] as seen in Table 4. Earlier approaches, such as Attentive Seq2Seq trained on the Cornell Movie Dialog Corpus [23] and Variational Hierarchical Conversation RNN with Attention (VHCRA) [74], primarily focused on dialogue coherence and multi-turn contextual modeling. While these models improved conversational structure, their ability to sustain long-range narrative consistency and nuanced emotional dynamics remained limited. The development of Ensemble-based Movie Script Generation (EMCG) [37], integrating Bi-LSTM with GPT-3 and GPT Neo X, represents a transitional phase in which transformer-based architectures began to dominate generative pipelines. However, such ensemble systems require substantial computational resources and may exhibit stylistic overfitting, indicating scalability constraints compared to fully LLM-centered frameworks.

Within this evolution, transformer-based LLMs have increasingly redefined research priorities in content generation by enabling scalable, context-aware, and stylistically adaptive narrative production [28], [39], [129], as further illustrated in Table 4. In contrast, traditional Generative Adversarial Networks (GANs), once explored for multimodal or script-related generation, appear to have diminished relevance in textual film content generation due to instability issues and weaker coherence compared to autoregressive transformer models. Cross-study synthesis further reveals that while AI-generated drama scripts are beginning to rival human-authored works in structural and linguistic creativity [39], persistent challenges remain in emotional controllability, cross-scene narrative alignment, and the absence of standardized metrics for evaluating artistic creativity. Collectively, the literature indicates a clear transition from rule-based and RNN-driven systems toward LLM-centered creative architectures, suggesting that future research should prioritize controllable storytelling, emotion-grounded generation, and computational efficiency to enhance both theoretical robustness and practical applicability within the film industry.

Table 4. Overview of content generation

Dataset	Core Method	Advantages	Limitations	Research Gap
Movie Script Data	Ensemble Movie Script Generation (Bi-LSTM, GPT-3, GPT Neo X) [37]	Generates adaptive and realistic movie scripts	Requires many parameters and GPUs	Computational efficiency for large-scale creative production
Cornell Movie Dialog Corpus	Attentive Seq2Seq + Hyperparameter Optimization [23]	High accuracy for movie dialogues	Performance decreases in emotional dialogues	Integration of emotional context in script generation
Cornell Movie Dialog	VHCRA (Hierarchical RNN + Attention) [74]	Natural contextual responses	Limited to the conversation domain	Requires multi-genre generalization
Chatbot Logs	Emotional Chatbot for Recommendation [33]	Improving *user engagement*	Limitations of realistic conversation datasets	Film dialogue dataset covering emotional variations
AI vs Human Play	NLP-based Creativity Assessment [39]	Assessing AI creativity compared to humans	Difficulty in objectively measuring creativity	Cognitive evaluation standards for AI content

4.3. Recommendation Systems

As summarized in Table 5, recommendation systems play a crucial role in improving user experience on digital movie platforms. Early approaches focused on classical machine learning techniques for review classification and recommendation generation. For instance, the CineInsight NaïveFlix algorithm combines Naïve Bayes and Linear SVC to classify reviews and generate recommendations, but its performance decreases when handling new items due to the cold-start problem [3]. Subsequent studies attempted to address this limitation through richer contextual modeling. Graph-based approaches such as SeVGAER leverage contrastive learning and graph representations to capture relationships between films and users, improving recommendation accuracy, although at the cost of higher computational complexity that may hinder large-scale deployment [32].

Table 5. Overview of recommendation systems

Dataset	Core Method	Advantages	Limitations	Research Gap
IMDB, YIFY, YouTube	CineInsight NaïveFlix (NB + SVC) [3]	Superior performance on online platforms	Sensitive to new films	*Cold start* handling in movies is not yet popular
MovieLens100k	SeVGAER (Graph Autoencoder + Contrastive Learning) [32]	Accurate personalized recommendations	High computational cost	Multimodal integration (plot, poster, audio)
MovieLens 100k–10M	HFLBC-DCSNN-MRS [157]	Improved *precision* and *recall*	High model complexity	*Explainability of* recommendation results
IRM, MovieLens	C-NGE (Collaborative Neural Generative Embedding) [35]	Adaptive to *cold-start* and multimodal data	Low interpretability	Integration of *contextual emotion signals*
MovieLens	HybridFlicks (Matrix + Content-based TF-IDF) [161]	High accuracy and simplicity	Not dynamic	Real-time adaptation based on user behavior

Across the literature, a clear trend emerges toward integrating multiple data sources and advanced neural architectures to enhance recommendation quality. Models such as HFLBC-DCSNN-MRS [157] and Collaborative Neural Generative Embedding (C-NGE) [35] combine collaborative filtering with deep neural networks, while C-NGE further incorporates multimodal signals—including textual features, genre information, and user behavior—to mitigate the cold-start problem. Similarly, HybridFlicks integrates matrix factorization with TF-IDF-based content features for efficient recommendations [161] whereas KERL introduces knowledge graphs within conversational recommender systems to capture semantic relationships among movie entities [144]. Collectively, these studies indicate a broader shift from traditional recommendation models toward hybrid, multimodal, and knowledge-enhanced systems. However, key challenges remain, particularly in computational efficiency, interpretability of recommendations, and the ability to adapt dynamically to evolving user preferences in real-time streaming environments.

4.4. Subtitles, Translation, and Multilingual Processing

The field of subtitling and multilingual translation plays a critical role in enabling cross-cultural dissemination of film content [21]. Recent studies have focused on improving translation accuracy for multilingual and code-mixed subtitles. For example, transliteration approaches for Marathi–English mixed text have been proposed to enhance automatic translation in local film contexts, although phonetic inconsistencies and character-mapping errors remain key limitations [132]. Meanwhile, large-scale subtitle corpora such as the WCC-JC 2.0 dataset, containing 1.4 million Japanese–Chinese sentence pairs extracted from movie subtitles, provide valuable resources for training translation models and have demonstrated improvements in BLEU-based translation performance [97]. Complementary advances include phrase-level back translation methods supported by large language models such as Llama3-8B-Instruct, which improve translation quality for creative dialogue and lyric-like expressions, although these approaches may still face overfitting risks when training data is limited [43].

Across these studies, a broader trend emerges toward integrating contextual, multimodal, and culturally aware translation strategies. For instance, multimodal approaches combining neural voice activity detection (VAD) and audio classifiers have been used to synchronize subtitles with dialogue, showing that text–audio integration can significantly enhance subtitle alignment despite higher annotation and computational requirements [45]. Similarly, research on machine translation for low-resource languages demonstrates that translation into high-resource pivot languages (e.g., Slovak English) can facilitate textual analysis, although challenges remain in translating humor, idiomatic expressions, and culturally sensitive dialogue [44]. Collectively, these findings indicate that the field is evolving from purely text-based subtitle translation toward context-aware and cross-modal subtitling systems capable of handling linguistic diversity, cultural nuance, and multimodal information, as summarized in Table 6.

4.5. Knowledge Extraction and Film Understanding

Research on knowledge extraction and film understanding highlights the growing role of NLP in semantic narrative analysis and film entity representation, as summarized in Table 7, [184]-[187]. Several studies have explored transformer-based and knowledge-driven approaches to extract narrative structures, emotional dynamics, and entity relationships from film-related data. For example, BERT-based models have been applied to analyze character emotional intensity in films such as *Forever Young*, enabling detailed emotional mapping within narrative structures [13]. Meanwhile, knowledge-based approaches integrating Knowledge Graphs (KG) with topic modeling techniques such as Latent Dirichlet Allocation (LDA) improve semantic connections among entities—including actors, directors, and themes—in film datasets such as MovieLens [110]. Similarly, contextual graph models such as Contextual Knowledge Graph (CtxKG) further enhance entity identification accuracy, although challenges remain in managing redundant or excessive contextual relationships [47].

Across these studies, a clear trend emerges toward combining deep language models, knowledge graphs, and semantic extraction techniques to support richer film narrative understanding. Methods such as EmbedRank and KeyGames improve keyword extraction and thematic identification from film synopses, demonstrating the potential of automated content understanding despite limitations in processing long or structurally complex texts [170]. Other works extend NLP applications toward cultural and analytical interpretation of film narratives, including gender-based analysis of themes such as death in cinema [174] and emotional metaphor analysis in artistic domains such as Chinese opera using NRC and LIWC lexicons [22]. Furthermore, multi-label classification frameworks based on models such as BERT and LLaMA2 have been used to automate film review categorization and production-related documentation in animation contexts [159]. Collectively, these studies suggest a broader transition from isolated text-processing methods toward integrated knowledge-driven systems capable of supporting narrative analysis, cultural interpretation, and intelligent film information management.

Table 6. Overview of subtitling, translation, and multilingual processing

Dataset	Core Method	Advantages	Limitations	Research Gap
Marathi-English Mixed Text	Transliteration-based Machine Translation [132]	Handles mixed texts well	Prone to phonetic errors	Cross-language semantic adaptation
WCC-JC 2.0 (Japanese Chinese subtitles)	Parallel Subtitle Corpus + BLEU Evaluation [97]	High accuracy for bilingual subtitles	Focus on two languages only	Expansion to multi-script subtitles
WCC-JCL + Llama3	Phrase-level Back Translation + LLM [43]	Improved quality of lyric translations	Overfitting on small corpora	Cross-domain evaluation (films, music, advertisements)
DEC Corpora	Neural VAD + Audio Classifier [45]	Automatic synchronization of subtitles and dialogue	Requires manual audio labeling	Multi-speaker and multi-noise generalization
Slovak Movie Texts	Machine Translation + Sentiment Analysis [44]	Effective for *low-resource* languages	Humor nuances are not accurate	Translation of cultural and expressive nuances

Table 7. Overview of knowledge extraction and film understanding

Dataset	Core Method	Advantages	Limitations	Research Gap
"Forever Young" Film Sample	BERT-based Fine-Grained Emotion Analysis [13]	Focus on one film	Cross-genre and cross-cultural generalization	Generalization across genres and cultures
MovieLens Dataset	Knowledge Graph + LDA Topic [110]	Capturing semantic relationships between entities	Prone to entity redundancy	Temporal storyline integration
Wikipedia Corpus	CtxKG + Domain Graph [47]	Accurate identification of key entities	Still contains irrelevant relationships	Reduction of *context-dependent bridges*
Movie Synopses	EmbedRank + KeyGames [170]	Efficient and high F-score results	Difficult to handle long synopses	Integration with multimodal keyword extraction
Cinemorgue Wiki	NLP Gender-based Classifier [174]	Text-based sociocultural analysis	Limited dataset	Expansion to non-verbal emotion representation
Animation Review Notes	Multi-label Text Classification (BERT, LLaMA2) [159]	Accurate for multi-label annotation	Limited to animation data	Application to film post-production processes
150 Chinese Opera Scenes	Syntax Parsing + NRC/LIWC [22]	Detecting metaphors and emotions	Highly specialized language	Adaptation to modern genres and cross-cultural contexts

4.6. Future Research Directions for NLP in the Film Industry

Overall, the synthesis of the five domains indicates a clear shift toward an integrated, transformer-driven, and multimodal NLP ecosystem in the film industry. As summarized in Table 8, research across sentiment analysis [17], [18], [88], [188], [189], content generation [23], [37], [100], [190], multilingual translation [43], [97], recommendation systems [32], [144], and knowledge extraction [13], [110], [170] increasingly emphasizes contextual depth, explainability, cross-domain integration, and cultural adaptability. This synthesis is derived from a qualitative analysis of the reviewed studies, focusing on methodological approaches, datasets, and technological developments reported in the selected literature. Despite these advances, several challenges persist, including computational scalability, limitations in detecting implicit emotions, preservation of cultural nuances in multilingual contexts, and the need for greater model transparency and interpretability.

Table 8. Future directions of NLP in film

Field	Key Research Gaps	AI/Technological Solutions	Social & Cultural Solutions	Economic/Industrial Solutions	Education & Research Solutions
Sentiment & Emotion Analysis	Model efficiency & implicit emotion detection.	Development of multimodal emotion transformers and cross-lingual sentiment transfer.	Adjustment of emotion dictionaries based on local culture and social context.	Implementation of real-time sentiment dashboards for the film and social media industries.	Interdisciplinary research in psychology-AI for modeling human emotions.
Content Generation	Balancing machine creativity and human control.	Integration of reinforcement learning and human feedback loops in script generation.	Creator-AI collaboration with narrative ethics to preserve cultural values.	The use of AI as a writing assistant for pre-production cost efficiency.	An interdisciplinary curriculum combining film studies, linguistics, and data science.
Subtitles & Multilingual Translation	Expressive translation & idiomatic nuances.	Use of context-aware NMT with LLM-based semantic alignment.	Involvement of language experts and native speakers in AI post-editing.	The streaming industry is investing in automated localization systems.	Development of multilingual datasets and cross-cultural linguistics studies.
Recommendation Systems	Explainability and user data bias.	Explainable Graph Recommender with federated learning.	Recommendation transparency code of ethics for user fairness.	Model optimization to suit local consumer behavior.	User behavior studies and ethical perceptions of AI in entertainment.
Knowledge Extraction & Film Understanding	Semantic context consolidation & narrative interpretation.	Integration of knowledge reasoning, LLM-based graph construction, and auto-summarization.	Enriching datasets with cultural interpretation and social context.	Automated film analytics system for market research and content production.	Interdisciplinary studies in computational narratology and digital humanities.

From an industry perspective, NLP now functions both as analytical infrastructure and creative augmentation. Sentiment analysis enhances audience analytics, generative models accelerate script development, multilingual systems expand global distribution, recommendation systems optimize user engagement, and knowledge extraction supports structured film intelligence. However, the implementation of these technologies still faces practical barriers, including high computational costs, limited multilingual datasets, and ethical concerns related to cultural representation and algorithmic bias. Addressing these challenges requires stronger collaboration between academia, industry practitioners, and cultural experts to ensure responsible and culturally aware AI integration in film production and distribution.

As a domain-specific illustration, the K-Drama industry represents a high-impact application context due to its narrative complexity and global reach. AI-assisted script generation using GPT-based and attention-driven architectures [23], [37] can enhance production efficiency while preserving cultural authenticity. Nevertheless, the adoption of such systems must consider cultural specificity, narrative authenticity, and ethical supervision to avoid oversimplification of culturally embedded storytelling elements. Therefore, rather than replacing human creativity, AI-based systems should function as collaborative tools that complement screenwriters and production teams within culturally informed cinematic workflows.

In summary, future research in NLP for the film industry should focus on developing lightweight and efficient transformer models, multimodal reasoning frameworks that integrate text, audio, and visual signals, culturally diverse multilingual datasets, and explainable AI systems that enhance transparency and trust. These directions highlight the importance of building an integrated intelligent cinema ecosystem that combines technological innovation with cultural sensitivity and ethical AI deployment.

5. Conclusion

This systematic review demonstrates that Natural Language Processing (NLP) has become a key technological foundation in the transformation of the modern film industry. Across the reviewed literature, NLP applications can be broadly categorized into five interconnected domains: sentiment and emotion analysis, content generation, recommendation systems, subtitling and multilingual translation, and knowledge extraction for film understanding. Recent studies increasingly rely on deep learning and transformer-based architectures such as BERT, GPT, RoBERTa, and LLaMA, which significantly improve the ability of computational systems to analyze audience emotions, generate narrative content, enhance personalized recommendations, and facilitate cross-cultural translation of film dialogue. These findings highlight the emergence of an integrated digital ecosystem in which language technologies support both film production and audience engagement. Overall, the review confirms that NLP has moved beyond traditional linguistic analysis toward context-aware systems capable of supporting multiple stages of the cinematic workflow.

From a theoretical perspective, this study contributes to the understanding of film narratives as structured semantic systems that can be computationally modeled through language representations, contextual embeddings, and knowledge graphs. The synthesis of the reviewed studies indicates a shift toward data-driven and context-aware approaches, although most existing work still relies primarily on text-based analysis rather than multimodal film data. This limitation highlights the need for more integrated analytical frameworks that combine linguistic, visual, and auditory information to better capture cinematic meaning and narrative complexity.

Several research opportunities emerge from the literature. First, there is a lack of long-context understanding for narrative structures, particularly in script analysis and cross-scene dialogue modeling. Second, bias and popularity imbalance in movie recommendation systems remain significant challenges, especially when addressing cold-start problems or representing less popular films. Third, multilingual subtitling systems still struggle with culturally specific expressions, humor, and idiomatic dialogue, indicating the need for culturally adaptive translation models. Fourth, current research rarely integrates multimodal signals such as text, audio, and visual features, which are essential for deeper understanding of cinematic narratives and emotional dynamics. Finally, the lack of standardized evaluation metrics for creative AI outputs, such as AI-generated scripts or dialogue, remains an open research problem in computational storytelling.

This study also has several limitations. The literature search focused primarily on the Scopus database within a defined time range, which may exclude relevant studies from other academic databases, industry reports, or preprint repositories. Many reviewed studies also rely on English-centered datasets such as IMDb, MovieLens, and the Cornell Movie Dialog Corpus, which may introduce linguistic and cultural bias. Furthermore, variations in datasets and evaluation metrics across studies limit direct comparison of model performance. Additionally, most models remain experimental and have not yet been widely validated in real-world film production environments.

Future research should address these limitations by developing multimodal NLP systems, expanding multilingual and culturally diverse datasets, and designing explainable and ethically responsible AI models for cinematic applications. Integrating large language models with knowledge graphs, audiovisual signals, and human-centered evaluation frameworks represents a promising direction for advancing intelligent cinema systems. Such developments may enable more accurate narrative understanding, more inclusive cultural representation, and more interactive cinematic experiences supported by artificial intelligence.

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