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Unlocking knowledge-sharing live streaming e-commerce: An LLM-empowered analytics framework for book sales prediction

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A B S T R A C T

Streamers' discourse plays a key role in shaping purchasing decisions in live streaming e-commerce, especially in knowledge-sharing formats where product promotion is combined with information delivery. Previous studies have shown that streamers' discourse can influence product sales, with few studies systematically extracting semantic features across different dimensions and quantifying their impact on sales prediction performance. The main contribution of our research is the design of a predictive framework for sales in knowledge-sharing live streaming. The framework integrates social support theory with fine-tuned large language models (LLMs) to systematically extract multi-dimensional semantic cues from streamers' discourse for sales prediction. We collected data from 80 live streams across 35 Douyin rooms over two months for our experiments. In the social support classification experiment, the fine-tuned Ernie-SFT model outperformed the best baseline LLM, with improvements of 11.12% in accuracy, 11.87% in weighted F1-score, and 7.83% in macro F1-score. In the sales prediction experiments, we validated the proposed framework using four mainstream classifiers and observed consistent performance gains. The best-performing classifier achieved improvements of 12.53% in accuracy, 10.83% in weighted F1-score, and 4.24% in macro F1-score. These findings highlight the strong predictive value of social support features embedded in streamers' discourse, offering actionable insights for streamers and enabling data-driven optimization strategies for platforms.

1. Introduction

Live streaming e-commerce has been increasingly adopted by enterprises and individuals as an important emerging sales channel (Huang & Morozov, 2025). Existing research has shown that the multifaceted characteristics of live streaming rooms, streamers, and promoted products significantly influence e-commerce outcomes (Pan et al., 2022). As consumers become more familiar with generic live streaming e-commerce, distinctive or vertical-specific live streaming practices (e.g., tourism, agriculture) have attracted growing attention (Xie et al., 2022). A representative example is Dong Yuhui,[1] a highly influential streamer in China, whose team combines product promotions with substantive knowledge-sharing.[2] This integrated approach has generated strong viewer engagement and achieved outstanding sales conversion rates. However, whether streamers' discourse in knowledge-sharing live streaming contains

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[1] https://global.chinadaily.com.cn/a/202206/15/WS62a91b55a310fd2b29e62bc3.html
[2] https://www.chinadaily.com.cn/a/202207/07/WS62c639d0a310fd2b29e6ae62.html

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0306-4573/

predictive signals for the sales of associated products, and specifically which content dimensions have measurable predictive value, remains underexplored in both theoretical and empirical research. Although previous studies have shown that streamers' discourse can influence sales, its textual representations often lack interpretability (Liu et al., 2023). Social support theory provides a theoretical foundation for content categorization, and previous studies have found that different categories of social support can influence consumer decision-making (Hajli, 2014). Nevertheless, its application to live streaming e-commerce remains nascent (Wang et al., 2020). In knowledge-sharing live streaming, streamers' discourse exhibits rich and complex patterns. Social support theory offers a systematic framework for decoding such unstructured discourse into interpretable semantic dimensions (De Choudhury & Kiciman, 2017), facilitating the identification of sales-predictive features. However, these transcripts typically contain significant lexical redundancy and colloquial expressions, and promotional messages are often intertwined with informational content, creating hybrid text features that pose substantial computational challenges for semantic understanding and multi-dimensional content categorization.

Large language models (LLMs) have demonstrated state-of-the-art performance in text classification and semantic comprehension tasks (Siano, 2025). However, their application to live streaming transcript analysis within management studies remains underexplored. Given that most LLMs are pretrained on extensive book corpora (Brown et al., 2020), and book promotion live streaming represents one of the most typical and quantitatively dominant forms of knowledge-sharing e-commerce, our investigation strategically focuses on this specific domain. Specifically, our study develops a novel framework combining social support theory with fine-tuned LLMs to achieve interpretable content categorization of live streaming transcripts. The framework enables the identification of both holistic descriptions for each book and the multifaceted supportive cues (emotional, informational, instrumental) embedded within comprehensive textual collections. To better understand the influence of textual content on sales prediction performance, we further integrate multi-source heterogeneous data and develop a product sales prediction model designed for book live streaming scenarios. Guided by this overall objective, our research addresses the following two questions: RQ1: How can streamers' discourse be categorized into interpretable dimensions? RQ2: How do these different dimensions of discourse affect the performance of sales prediction models, and how do their effects differ? To address these research questions, we develop a novel analytical framework combining social support theory with fine-tuned LLMs and conduct comprehensive experiments on real-world live streaming data.

The primary contributions of this study are threefold. First, we design a sales prediction framework for knowledge-sharing live streaming e-commerce. Second, we develop a fine-tuned LLM-powered analytics method to extract entities and content from live streaming transcripts. Third, we advance the use of social support theory and theory-driven LLMs for understanding and predicting outcomes in knowledge-sharing live streaming e-commerce. We conduct extensive experiments on a real-world dataset. The results demonstrate that emotional, informational, and instrumental cues derived from discourse transcripts in knowledge-sharing live streaming e-commerce significantly enhance sales prediction performance. To our knowledge, this study is among the first to validate the predictive role of social support mechanisms in live streaming. The managerial implications of this study are as follows. For merchants and streamers, this study offers actionable insights into designing more effective discourse strategies that improve sales forecasting and optimize product presentation. For live streaming platforms, the proposed framework provides a basis for data-driven traffic allocation, thereby supporting more efficient platform operations.

The rest of this paper is organized as follows. Section 2 reviews related work in live streaming e-commerce, text understanding, and social support theory. The details of the proposed prediction model are presented in Section 3. Section 4 contains a discussion of our experiments and the experimental results. The last section presents a summary and directions for future research. The data and code are available on our GitHub page.[3]

2. Related work

2.1. Live streaming E-commerce

Live streaming e-commerce is gaining worldwide popularity owing to its real-time interactivity and seamless integration of entertainment with shopping (Zhang et al., 2024). Extensive research has examined how key consumer purchase determinants (e.g., streamer sales skills, popularity, and flow experience) affect viewer engagement and sales performance (Pan et al., 2022; Ye & Ching, 2023; Zhang et al., 2023). Manufacturers benefit from live streaming channels through higher profits when pricing is consistent with consumer behavior across channels (Du et al., 2023; Wang et al., 2024). Numerous elements influence purchase decisions, including seller credibility, brand reputation, discounts, advertising frequency, and product quality (Cheng et al., 2020; Kulkarni et al., 2012; Li et al., 2023, 2021; Winterich et al., 2018). Furthermore, user-generated content such as reviews and ratings often builds greater trust than seller-provided information (Liu & Teng, 2019). Live streaming content also helps reduce consumer uncertainty and risk perception (Fan et al., 2017), with real-time interactions shaping buying intentions (Park et al., 2018).

To support business decision-making, scholars have extensively developed sales prediction frameworks (Liu et al., 2022) that improve predictive accuracy by incorporating product and live streaming features. Increasingly, multimodal data such as text, images, and audio are used to enhance predictive models (Xu et al., 2024). Methodologically, both traditional machine learning (Wu et al., 2023) and hybrid deep learning models (Chen et al., 2023) have proven effective.

Recent studies have documented that live streaming e-commerce has expanded not only into vertical-specific markets (Xie et al., 2022) but also into innovative sales modalities. A key example is knowledge-sharing live streaming, which goes beyond selling

[3] https://github.com/uibe-jrx/knowledge-sharing/tree/main

products by offering educational content (Gu et al., 2025). These live streaming sessions attract viewers by providing useful information, building trust, and creating emotional connections, which in turn encourage purchases (Diao et al., 2023). Streamers' discourse influences product sales and contains information that can be leveraged for sales prediction (Yang & Wang, 2022). However, few studies have explored interpretable methods for extracting semantic cues or quantified the impact of semantic features across different dimensions on sales prediction performance.

2.2. Text understanding

Early approaches to text understanding relied on handcrafted rules and lexical databases (Loughran & McDonald, 2011). However, with the explosion of data, these methods showed limited conceptual coverage (Frankel et al., 2021) and struggled to perform fine-grained semantic analysis (Maibaum et al., 2024). To address these limitations, researchers have leveraged large-scale datasets to refine conceptual frameworks and build hierarchical structures (Wu et al., 2012). They have also applied machine learning to improve knowledge graphs (He et al., 2023), thereby enabling more fine-grained concept classification.

As language complexity increased, deep learning became dominant. Neural networks can automatically extract features and capture contextual and semantic patterns from large datasets (Krizhevsky et al., 2017). Scholars developed new frameworks for semantic analysis, including denoising methods for bag-of-words models and hierarchical clustering for concept labeling, improving the accuracy of semantic representations (Jiang et al., 2020). Others integrated deep learning with traditional models to refine sentiment lexicons and analyze consumer emotions in online reviews (Yu et al., 2023). Topic modeling was also improved using term clustering to reduce data sparsity (Yang & Subramanyam, 2022).

A significant breakthrough came with the advent of Transformer-based pretrained models, such as BERT and GPT, which have revolutionized text understanding (Devlin et al., 2019). To overcome the limitations of traditional knowledge graph methods in handling multi-hop reasoning, researchers developed a new framework that incorporated multi-hop reasoning modules with BERT, significantly improving knowledge inference (Wang et al., 2023). Advanced systems like XLORE3 combine pretrained models with knowledge completion to convert unstructured text into structured knowledge (Zeng et al., 2024). The KICE framework merges pretrained models with symbolic knowledge to expand coverage and improve understanding with limited annotations (Lu et al., 2023).

Large language models (LLMs) generally outperform traditional methods in various NLP tasks, including classification, sentiment analysis, and semantic parsing (Arora et al., 2024; Liu et al., 2024). In the realm of knowledge representation, LLMs enhance the construction and validation of knowledge graphs by improving key aspects such as data quality, relation extraction, and semantic consistency (Colombo et al., 2025; Gajo & Barrón-Cedeño, 2025; Zou et al., 2025). Moreover, researchers have leveraged the deep text understanding capabilities of LLMs to augment existing research frameworks, such as those for tourism demand forecasting (Wu et al., 2025) and academic evaluation (Huang et al., 2025), resulting in more accurate and interpretable outcomes.

Streamers in knowledge-sharing live streaming generate extensive discourse content, blending informational and emotional elements (Xu et al., 2020). Extracting useful insights from these complex transcripts remains a challenging task (Lee et al., 2024). However, existing studies have rarely developed theory-driven LLM methods for interpretable content categorization, and the potential of fine-tuned LLMs to capture insights from complex live streaming discourse remains largely unexplored. To address these gaps, this study proposes a theory-driven LLM framework for interpretable content categorization and investigates how domain-adapted LLMs can extract actionable insights from complex live streaming discourse.

2.3. Social support theory

Social support comprises three key dimensions: emotional support, instrumental support, and informational support (House, 1981). Perceived emotional care and assistance during group interactions enhance individuals' subjective well-being and satisfy their psychological needs, thereby influencing their behavioral decisions (Liang et al., 2011).

In live streaming e-commerce, informational support affects user cognition through decision-relevant data and expert advice, thereby reducing uncertainty and driving purchase decisions (Qin et al., 2022). Emotional support, shaped by real-time interactions, establishes affective connections and significantly boosts customers' participation intentions (Qiang et al., 2023; Sun et al., 2019). Instrumental support directly impacts user behavior and decisions by providing tangible assistance or resources and plays a significant role in generating positive affect (Granziera et al., 2022).

In knowledge-sharing live streaming e-commerce, three dimensions of social support are particularly salient: informational, emotional, and instrumental. Streamers provide informational support by sharing extensive background information and in-depth product knowledge, thereby facilitating deeper understanding and reducing perceived uncertainty in the purchase process. They also create an atmosphere of emotional support by responding to comments and demonstrating empathy, fostering a sense of being understood and accepted, which enhances viewers' trust in both the streamer and the platform (Chen et al., 2020). In addition, instrumental support is provided through tangible measures, such as discounts and purchase links, which lower transactional barriers and directly influence purchase behavior.

Based on existing literature, we classify live streaming content into four categories: informational support (e.g., product introductions, background information); emotional support (e.g., emotional exchange, encouraging words); instrumental support (e.g., pricing, discounts); and a residual category labeled as nonsense (irrelevant or noncontributory discourse). Although live streaming research has grown exponentially, the systematic distinction of social support categories in streamers' discourse remains underexplored. This distinction is crucial for revealing the predictive value of various content dimensions on product sales and quantifying their individual contributions. By addressing this gap, our study advances the understanding of social interaction dynamics in live streaming and contributes to both social support theory and e-commerce literature.

2.4. Main differences between our work and previous studies

Our study differs from existing research in three key aspects. First, previous sales prediction models have primarily focused on the general scenario of live streaming e-commerce. We focus on knowledge-sharing live streaming by using book live streaming as an example, and construct a sales prediction model for this particular scenario. Second, existing methods struggle to extract explanatory information from the long transcripts of live streaming e-commerce that are highly colloquial and redundant. To address this, we adopt a fine-tuned LLM-based classification framework that improves key information extraction in semantically complex contexts and links transcript content to sales more effectively. Third, although social support theory is increasingly applied in online contexts, its application in knowledge-sharing live streaming remains underexplored. We validate its applicability in book live streaming and demonstrate that support-based text representations significantly enhance sales prediction performance, offering new insights for future research.

3. The proposed framework

This section presents the LLM-based sales prediction framework for knowledge-sharing live streaming (Fig. 1). First, data collection and preprocessing were conducted on both structured data and video data. At the segment level, an LLM extracted product names from the streamers' discourse. This extraction step is essential for addressing RQ1, as subsequent social support classification requires product identification. At the sentence level, a fine-tuned LLM based on social support theory classified the discourse into distinct support categories, which form the interpretable dimensions used to address RQ1. The outputs of these two tasks were mapped back to the live streaming transcripts, establishing one-to-many links between each identified product name and all associated support categories. BERT was subsequently employed to generate text representations, which were combined with the social support features and structured data. Classifiers were applied to evaluate the impact of different social support features on sales prediction, thereby addressing RQ2.

3.1. Data collection and preprocessing

The data for this study were collected from Douyin, China's leading live streaming platform. Given its active user base and frequent commercial interactions, Douyin is a key data source for real-time live streaming marketing research (Yang et al., 2023). Structured data (see Table 1) were obtained from Feigua Data[4], a third-party analytics platform. In addition, since Douyin does not allow replay for most live sessions, live broadcasts were recorded in real-time using built-in screen recording software according to the pre-announced schedule.

3.1.1. Structured data preprocessing

Duplicate entries were removed from the raw dataset. Missing values were imputed using the mean of temporally adjacent sessions for the same streamer, sorted by broadcast time. Categorical variables were converted via one-hot encoding (Sun et al., 2019). Sales entries marked as "-" (indicating missing or unavailable data) were removed. In the original dataset, each product had a specific sales volume as well as a corresponding sales category. Approximately 62 % of products had sales of fewer than 50 units. The sales of products exceeding this threshold exhibited a pattern consistent with a long-tail distribution. To mitigate the imbalance in the data and enhance interpretability, we used the dataset's existing classification labels for our experiments: zero (0 units), low (1–50 units), and high (>50 units). Consequently, our task was formulated as a multiclass prediction based on sales categories. Finally, the structured features were normalized using min-max scaling to remove scale differences.

3.1.2. Text data preprocessing

Live streaming videos were converted to transcripts in batches using Tongyi Tingwu,[5] an automatic speech recognition platform. To reduce noise, stop words were removed from the transcripts. The live streaming transcripts were then processed at two levels. First, segment-level processing was performed using a recursive character splitter that prioritized Chinese punctuation marks. Transcripts were divided into units of up to 1000 characters with no overlap. Second, sentence-level processing involved extracting sentences via regular expressions based on sentence-final punctuation. Further filtering was applied to remove sentences in which over 80 % of characters were identical or consecutively repeated, or sentences containing fewer than five meaningful characters. Sentences with >50 % non-Chinese symbols or predefined meaningless tokens (e.g., fillers, emojis) were also excluded. The segment units were used for product name extraction, while the filtered sentences served as input for social support classification. This two-level processing and filtering approach ensured that input transcripts were semantically appropriate and of sufficient quality for their respective tasks.

[4] https://www.feigua.cn/

[5] https://tingwu.aliyun.com/home

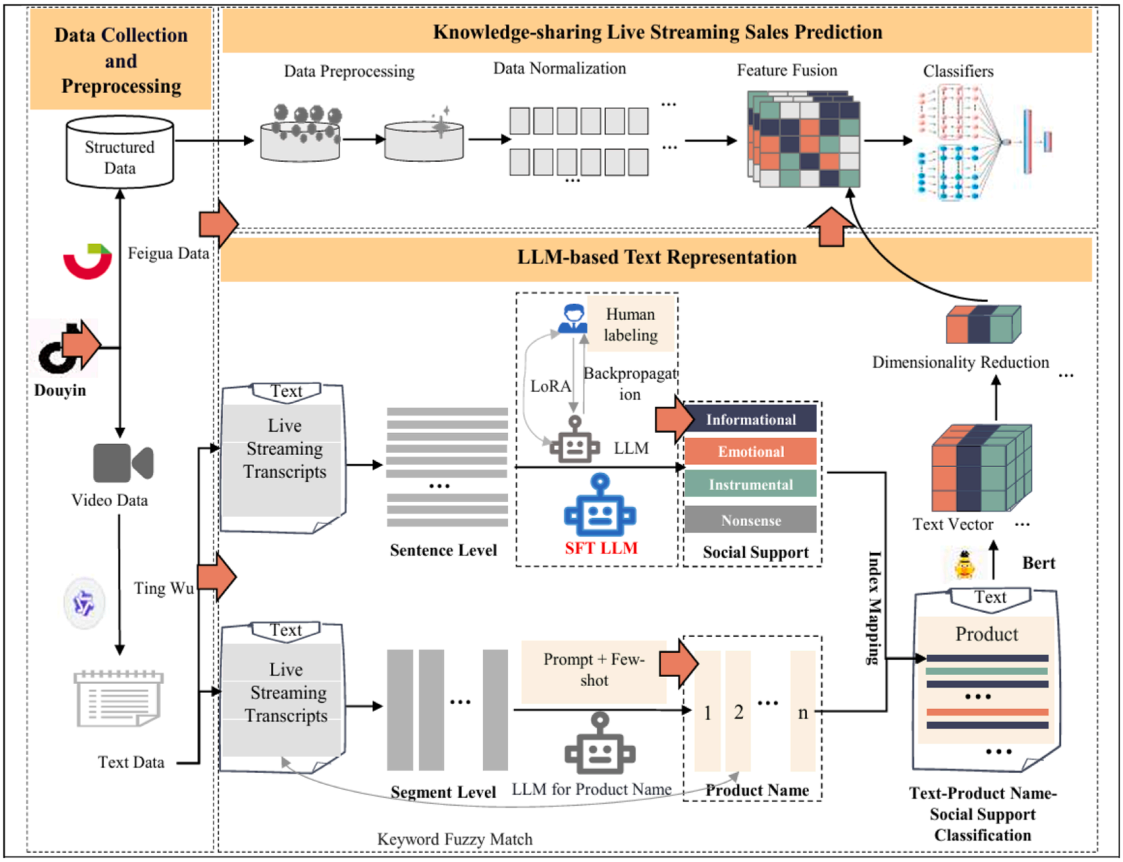

Fig. 1. Knowledge-sharing live streaming sales prediction framework based on LLMs.

Table 1
Structured data.

Component	Description
Streamer Information	Streamer Name, Number of Followers, Reputation Evaluation, Number of New Followers Added During the Live Streaming
Live Streaming Information	Live Streaming Room Name, Live Streaming Duration, Number of Viewers, Average Number of Online Viewers, Peak Number of Online Viewers, Total Number of Bullet Comments
Product Information	Product Name, Price, Sales Volume, Time on the Shelf

3.2. LLM-based text representation

Section 3.1.2 details the conversion of live streaming recordings into transcripts. This section introduces the method for efficiently identifying product names and social support categories in streamers' discourse. Knowledge-sharing live streaming exhibits a multi-layered structure, in which streamers intersperse product-related explanations with emotional interactions, occasional nonsense, and promotional information. To decode this complex structure, we employed a hierarchical identification strategy. First, transcripts were divided into coherent segments within which product names were identified using an LLM with carefully designed prompts. Second, guided by social support theory, each sentence was classified into a social support category using a fine-tuned LLM. A structured mapping was then created to link each product to its corresponding categories within the original transcript structure. Finally, BERT embeddings were extracted from the classified transcripts and combined with structured features as input for downstream classifiers.

3.2.1. LLM-based product name extraction

Streamers typically begin by explicitly mentioning the product name, after which their discourse often transitions into knowledge-sharing content and broader thematic discussions. In much of the subsequent discourse, the product is referenced only indirectly through related content, without explicit repetition of its name. This indirect referencing poses challenges for accurately extracting product names.

To address this, we developed an LLM-powered system for extracting product names from Chinese live streaming transcripts. First, the segmented transcript units were processed sequentially by the LLM via API calls. Second, carefully crafted prompt templates that incorporate role-based instructions, few-shot exemplars, and structured output constraints guided the extraction process. Third, additional prompts instructed the LLM to correct potential misspellings or typographical errors in its outputs. Finally, fuzzy string matching based on Levenshtein distance was used to map the LLM-extracted names (e.g., "Journey to the West") to the corresponding product names in the source transcripts (e.g., "Journey to the West: Deluxe Edition"), with similarity quantified as the normalized Levenshtein distance:

$$score = \left(1 - \frac{Levenshtein\ distance}{\max(len(query), len(choice))}\right) \times 100 \tag{1}$$

3.2.2. Supervised fine-tuned LLM for social support classification

The identification of social support categories in streamers' discourse enables a comprehensive analysis of different linguistic dimensions and quantifies their impact on sales prediction. However, the fragmented discourse and the complexity of social support categories pose significant challenges for classification. Moreover, the limited availability of data annotated for social support reduces the effectiveness of conventional classification models. To address these challenges, we developed a supervised fine-tuning framework that integrates instruction tuning with manually labeled data (see Fig. 2).

The fine-tuning process began by inputting sentence-level transcripts into the base LLM to generate social support categories. During this process, the base model's parameters were kept frozen, and Low-Rank Adaptation (LoRA) modules were applied for efficient fine-tuning. Next, the cross-entropy loss between the predicted social support categories and the ground-truth labels was computed to guide parameter updates in the LoRA modules. The cross-entropy loss is defined as follows:

$$CE_{(p,q)} = -\sum_{i=1}^{c} p_i \log(q_i) \tag{2}$$

where c is the number of support classes, p_i is the one-hot encoded ground truth label, and q_i is the predicted probability for class i.

This loss was then backpropagated through the network to compute gradients with respect to the LoRA parameters, which were subsequently updated using an optimizer. Specifically, for a LoRA-augmented weight matrix W decomposed as:

$$W_{LoRA} = W + \Delta W = W + AB \tag{3}$$

where A and B are low-rank matrices. During iterative training, the model progressively converged toward the ground-truth label distribution while keeping the base model weights frozen. Finally, we evaluated the performance of the fine-tuned model on the validation set.

3.2.3. Text feature representation

To capture deep semantic representations from live-streaming transcripts, we developed a context-aware feature extraction framework based on BERT. The cleaned text was tokenized with the BERT-base-Chinese embeddings,[6] and input sequences were constructed with [CLS] and [SEP] tokens and truncated to a maximum of 128 tokens when necessary. Each sentence was fed into the pretrained BERT model, and the hidden state of the [CLS] token was extracted as a 768-dimensional sentence-level embedding. For each category, we obtain a category-level vector by averaging the [CLS] embeddings of its sentences:

$$V_c = \frac{\sum_{i=1}^{N} BERT_{(s_i)}}{N} \tag{4}$$

where V_c is the aggregated vector for category c, s_i denotes the i-th sentence in this category, and N is the number of sentences. To further reduce dimensionality and preserve category-specific information, a separate autoencoder was trained for each category. The encoder compresses each 768-dimensional vector into a 16-dimensional bottleneck representation, optimized with the Adam algorithm to minimize reconstruction error. This process yields compact and informative semantic features for sales prediction tasks.

3.3. Classifier selection for sales prediction

To evaluate the contribution of various semantic signals, we incrementally incorporated different categories of text features into the prediction model, while structured data were consistently included as the foundational features. These included unclassified text (i.e., streamers' discourse not categorized by social support theory), emotional support, informational support, instrumental support, and the combined embeddings of all three support categories. Sequentially adding these feature sets allowed us to quantitatively compare their effects on multiclass sales prediction. We evaluated a range of machine learning and deep learning models and observed that ensemble models achieved the best results. This performance may have been attributed to their capacity to handle heterogeneous feature types, resist class imbalance, and perform reliably on small- to medium-sized datasets. We therefore selected four mainstream ensemble models to compare the performance of different feature sets: Random Forest, XGBoost, LightGBM, and CatBoost.

[6] https://huggingface.co/google-bert/bert-base-chinese

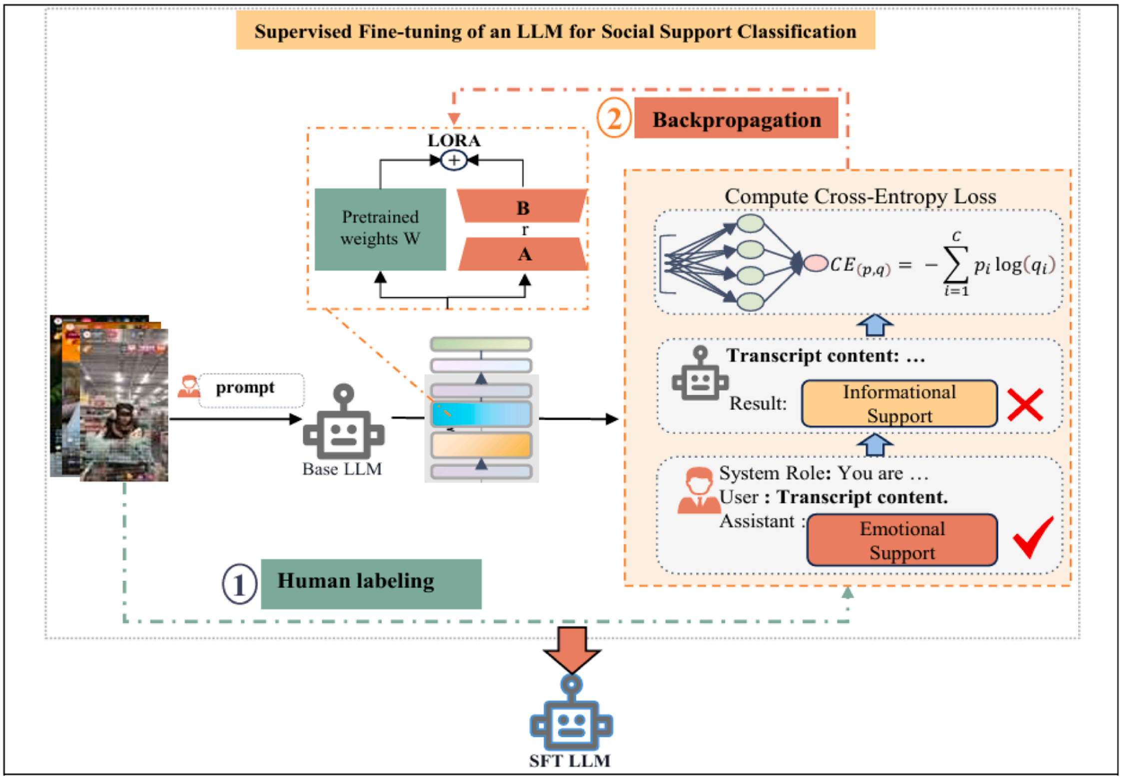

Fig. 2. Supervised fine-tuning of LLM for social support classification.

4. Empirical analysis

4.1. Data description

Our study used two datasets. The first dataset was used to evaluate top-performing models for extracting product names and social support categories from streamers' discourse. To this end, we carefully selected four authentic and complete Douyin book live streaming sessions. After preprocessing (see Section 3.1.2), the dataset contains 167 segments and 3099 sentences. Three sessions served as training data, and one serves as the validation set. Annotations of product names and social support categories were independently conducted by three coders. Inter-rater agreement among the three coders was evaluated using Fleiss' kappa, yielding a value of 0.72, which indicates good agreement. Based on these annotations, the final dataset was created by integrating the three sets of labels using a majority-vote scheme to ensure both reliability and consistency. Although modest in size, the dataset provided adequate evidence of our approach's effectiveness and substantially reduced annotation cost.

The second dataset was designed to quantify how different dimensions of linguistic cues in streamers' discourse influence sales prediction performance. It included 1014 product records from 80 Douyin book live streaming sessions conducted between July 13 and September 13, 2024. These sessions comprised 2082 segments and 78,984 sentences. Alongside the transcript data, the dataset contained all corresponding structured features as detailed in Table 1, supporting comprehensive sales prediction modeling.

4.2. Evaluation metrics

Given the multiclass nature of the tasks, weighted F1-score (WF1) and accuracy (Acc) were used as primary metrics to evaluate overall performance. Weighted metrics such as WF1 account for the actual class distribution and reflect overall model performance. For class-level evaluation, we computed precision, recall, and F1-score for each individual class, based on the confusion matrix consisting of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). To provide a more comprehensive evaluation, we also reported macro F1-score (MF1), weighted precision (WP), weighted recall (WR), macro precision (MP), and macro recall (MR) as supplementary metrics.

4.3. Experimental settings

All data processing and experiments were conducted using Python, and LLM fine-tuning was performed on the Baidu Qianfan cloud computing platform.[7]

For the social support classification and product name extraction tasks, we evaluated a wide range of state-of-the-art (SOTA) LLMs. These included Qwen-Plus,[8] GLM-4-Air,[9] Ernie-4.0-Turbo-8K ,[10] Doubao-pro-32K ,[11] GPT-4o,[12] DeepSeek-R1,[13] DeepSeek-V3,[14] Llama-3–8B-Chinese,[15] and Baichuan4-Air.[16] In addition to LLMs, we also implemented a comprehensive set of non-LLM baseline methods commonly used in text classification. These included both text representation techniques (e.g., TF-IDF, Chinese Word Vectors (CWV) ,[17] and BERT-base-Chinese embeddings) and traditional machine learning classifiers, such as Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayes (NB), Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN). All baseline models were evaluated on the same dataset with identical settings to ensure fairness and reproducibility.

We selected LLMs that performed well in the social support classification and product name extraction tasks as candidate models for the sales prediction task. Additionally, for the social support classification, the best-performing base LLM was further fine-tuned in a supervised manner using the training set. The fine-tuned model was evaluated with consistent inference parameters, including a temperature of 0.65, a top-p of 0.8, and a repetition penalty of 1.

4.4. Experimental results

4.4.1. Experimental results of product name extraction

The product name extraction experiment constituted a necessary first step toward addressing RQ1. In our dataset, many segments mentioned multiple products, and LLMs could return several product names per segment. In knowledge-sharing live streaming, streamers often interleave discussion of several products within one segment. Accordingly, we adopted a strict exact-match criterion, counting a prediction as correct only if all product names in a segment were identified. To capture the realistic and complex nature of live streaming, we framed the task as multiclass classification and evaluated performance using accuracy and WF1.

As shown in Table 2, the dictionary-based baseline constructed from a fixed list of product names showed relatively poor performance. This may be because streamers in knowledge-sharing live streaming often mention products indirectly, which makes dictionary-based methods unable to cover all product names. On our dataset, Doubao-pro-32 K slightly outperformed all other models in accuracy and WF1, and was thus selected as the product name extractor for the sales prediction task.

4.4.2. Experimental results of social support classification

To address RQ1, we conducted a social support classification experiment, categorizing streamers' discourse into distinct interpretable classes to identify the multi-dimensional semantic information conveyed in knowledge-sharing live streaming. We conducted a comparative analysis of LLMs and traditional non-LLM approaches for classifying sentences into social support categories. As shown in Table 3, traditional machine learning models achieved reasonable performance, likely due to their interpretability and effective use of structured and lexical-level features. In our Chinese dataset, GPT-4o showed relatively lower performance, possibly due to its pretraining being largely based on English data. Ernie-4.0-Turbo-8 K achieved the best overall performance and was therefore chosen as the base model for supervised fine-tuning.

The fine-tuned model (Ernie-SFT) showed significant improvements across most key metrics (Table 3), with only a slight decrease in MR. This slight decline was likely due to the model adopting a more conservative strategy toward ambiguous or vaguely phrased sentences. In particular, the model favored core social support categories over the less frequent nonsense class when handling sentences that are difficult to classify. The consistent improvements across all other metrics demonstrated a clear overall performance enhancement, while also reflecting that the model prioritizes core social support cues in its predictions.

4.4.3. Ablation study of features in sales prediction

To address RQ2, we conducted experiments to quantitatively examine the impact of different social support categories on sales prediction performance. The baseline included only structured data. We then incrementally added unclassified text features, followed by category-specific social support features, including emotional, informational, and instrumental support. Unclassified text refers to

[7] https://cloud.baidu.com/product-s/qianfan_home
[8] https://www.aliyun.com/product/bailian
[9] https://bigmodel.cn/
[10] https://cloud.baidu.com/product-s/qianfan_home
[11] https://www.volcengine.com/
[12] https://openai.com/api/
[13] https://platform.deepseek.com/
[14] https://platform.deepseek.com/
[15] https://huggingface.co/FlagAlpha/Llama3-Chinese-8B-Instruct
[16] https://platform.baichuan-ai.com/
[17] https://github.com/Embedding/Chinese-Word-Vectors

Table 2
Comparison results of different methods for product name extraction.

Method	Acc (%)	WP (%)	WR (%)	WF1 (%)
Dictionary-based	27.62	61.42	27.62	35.20
Qwen-Plus	57.72	64.74	57.72	59.83
GLM-4-Air	65.04	67.48	65.04	66.24
Ernie-4.0-Turbo-8K	66.53	79.64	66.53	69.73
GPT-4o	64.02	77.51	64.02	64.04
DeepSeek-R1	52.72	70.91	52.72	58.07
Llama–3–8B-Chinese	46.86	67.82	46.86	52.27
DeepSeek-V3	70.29	81.71	70.29	71.62
Baichuan4-Air	69.11	77.30	69.11	68.04
Doubao-pro-32K	**70.73**	76.45	**70.73**	**71.79**

Table 3
Comparison of different methods for social support classification.

Method	Acc (%)	WP (%)	MP (%)	WR (%)	MR (%)	WF1 (%)	MF1 (%)
TF-IDF + MLP	50.71	51.83	51.39	50.71	49.19	51.10	49.90
TF-IDF + SVM	48.58	49.00	52.61	48.58	40.76	47.08	43.11
CWV + CNN	52.84	55.18	56.78	52.84	51.17	52.38	51.88
Embedding + LSTM	46.81	50.40	50.49	46.81	46.29	47.65	46.64
TF-IDF + NB	51.65	58.41	70.43	51.65	41.67	49.03	42.62
TF-IDF + LR	51.42	52.58	56.91	51.42	42.05	49.16	43.83
Baichuan4-Air	21.04	88.28	74.20	21.04	37.69	20.32	25.99
GPT-4o	25.53	39.60	31.24	25.53	22.86	29.77	23.45
DeepSeek-R1	48.82	67.17	55.57	48.82	52.07	44.80	44.02
Llama–3–8B-Chinese	50.95	52.09	47.38	50.95	45.59	51.32	46.00
GLM-4-Air	51.30	70.49	62.76	51.30	64.62	43.87	49.53
DeepSeek-V3	52.25	73.17	69.07	52.25	55.35	42.65	44.90
Doubao-pro-32K	54.14	73.33	68.20	54.14	61.79	46.83	51.31
Qwen-Plus	64.89	72.14	67.69	64.89	70.88	62.79	64.83
BERT-base-Chinese	64.78	65.17	67.23	64.78	60.35	64.46	62.94
Ernie-4.0-Turbo-8K	70.09	73.17	69.26	70.09	78.39	69.31	71.16
Ernie-SFT	**81.21**	81.38	**80.50**	**81.21**	77.76	**81.18**	**78.99**

Table 4
Feature ablation results.

Model Name	Description	Acc (%)	WP (%)	MP (%)	WR (%)	MR (%)	WF1 (%)	MF1 (%)
CatBoost	Baseline	56.60	66.66	54.81	56.60	65.33	57.43	55.53
	Baseline + Unclassified Text	64.40	**68.02**	58.76	64.40	64.65	65.24	**60.53**
	Baseline + Emotional	60.75	65.25	55.73	60.75	62.73	61.57	57.50
	Baseline + Instrumental	63.51	67.63	58.03	63.51	64.70	64.45	59.96
	Baseline + Informational	63.22	67.72	58.06	63.22	**65.37**	64.06	59.99
	Baseline + All Social Support	**65.19**	67.71	**59.00**	**65.19**	63.96	**65.77**	60.49
Random Forest	Baseline	57.69	66.02	54.99	57.69	64.89	58.58	56.34
	Baseline + Unclassified Text	63.61	66.76	57.81	63.61	64.25	64.30	59.80
	Baseline + Emotional	62.42	66.11	56.83	62.42	63.87	63.16	58.77
	Baseline + Instrumental	64.30	67.34	58.47	64.30	64.92	64.96	60.45
	Baseline + Informational	65.09	**67.96**	59.29	65.09	**65.47**	65.66	**61.20**
	Baseline + All Social Support	**66.08**	67.54	**59.61**	**66.08**	63.26	**66.36**	60.68
XGBoost	Baseline	56.11	65.52	54.17	56.11	**64.48**	56.85	55.03
	Baseline + Unclassified Text	63.41	63.81	55.79	63.41	56.99	63.48	56.16
	Baseline + Emotional	63.80	64.54	56.32	63.80	57.69	63.94	56.65
	Baseline + Instrumental	64.60	65.14	57.54	64.60	58.95	64.70	57.98
	Baseline + Informational	64.99	65.79	58.09	64.99	59.90	65.13	**58.64**
	Baseline + All Social Support	**66.67**	**66.06**	**59.25**	**66.67**	58.65	**66.12**	58.58
LightGBM	Baseline	56.01	66.02	54.41	56.01	**64.91**	56.77	55.11
	Baseline + Unclassified Text	62.72	62.43	54.75	62.72	54.34	62.51	54.44
	Baseline + Emotional	64.00	64.27	56.20	64.00	56.56	63.93	56.06
	Baseline + Instrumental	64.99	65.50	57.86	64.99	59.36	65.06	58.31
	Baseline + Informational	65.29	65.53	58.16	65.29	58.91	65.30	58.39
	Baseline + All Social Support	**68.54**	**67.62**	**61.70**	**68.54**	58.32	**67.60**	**59.35**

transcripts unlabeled for social support categories. Following the method in Section 3.2.3, these transcripts were represented as vectors. The unclassified text vector, the vectors for the three social support categories, and the combined vector were reduced to the same dimensionality to ensure fair comparison. To assess the generalizability of findings across classifiers, we evaluated each feature configuration independently on four commonly used models: Random Forest, XGBoost, LightGBM, and CatBoost. Due to the class imbalance in the dataset, each classifier was evaluated using Stratified 5-Fold Cross-Validation.

Experimental results (Table 4) show that the unclassified text can also improve predictive performance to some extent. Categorizing these transcripts into different social support categories can separate semantically meaningful signals from noise. Emotional, informational, and instrumental features each independently enhance predictive performance. The combination of all social support features (Baseline + All Social Support) consistently achieves the highest accuracy and WF1, which are our primary evaluation metrics. Although some individual features occasionally outperform the combined set in certain secondary metrics, integrating all social support features provides the best overall predictive performance.

We selected the best-performing LightGBM model to examine the predictive performance of different feature sets within each sales category. As shown in Fig. 3, overall performance is higher in the low- and high-sales categories than in the zero-sales category. Social support features enhance predictions for low- and high-sales categories but slightly reduce performance for zero-sales cases. This suggests that social support features may introduce noise and reduce prediction performance when no purchase occurs. However, they effectively capture predictive signals from streamers' discourse when purchases occur, improving overall model performance.

4.4.4. SHAP value analysis of feature contributions

To address RQ2, we analyzed feature contributions using mean absolute SHAP values derived from the top-performing LightGBM model that combines baseline features with all three social support categories. As shown in Fig. 4A, individual social support features make smaller contributions to the model's output compared to structured numerical features. However, the combined effect of the three social support categories exceeds that of structured features. The mean absolute SHAP values across the three categories are comparable, with emotional slightly higher than instrumental, which is marginally higher than informational.

The feature ablation results (Table 4) show that while informational features exhibit the strongest predictive power when used individually, the combination of all three social support categories achieves the highest overall performance. Complementing this, the analysis of mean absolute SHAP values (Fig. 4A) reveals that emotional features exert a stronger influence within the complete feature set, underscoring their heightened role in interactive contexts. These results are not contradictory but complementary: informational support exhibits strong predictive power on its own, whereas emotional support exerts greater influence when combined with other support features.

As shown in Fig. 4B, we quantified the relative strength of pairwise interaction effects among the three social support feature

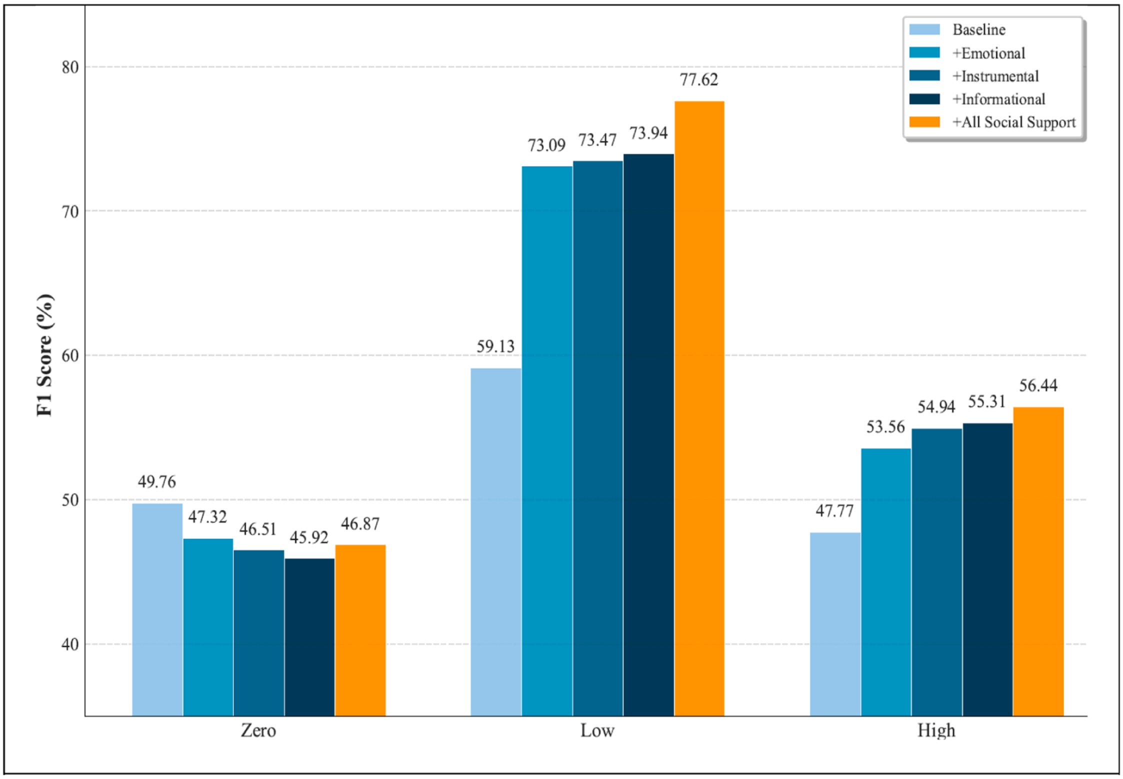

Fig. 3. Feature ablation of LightGBM across different sales categories.

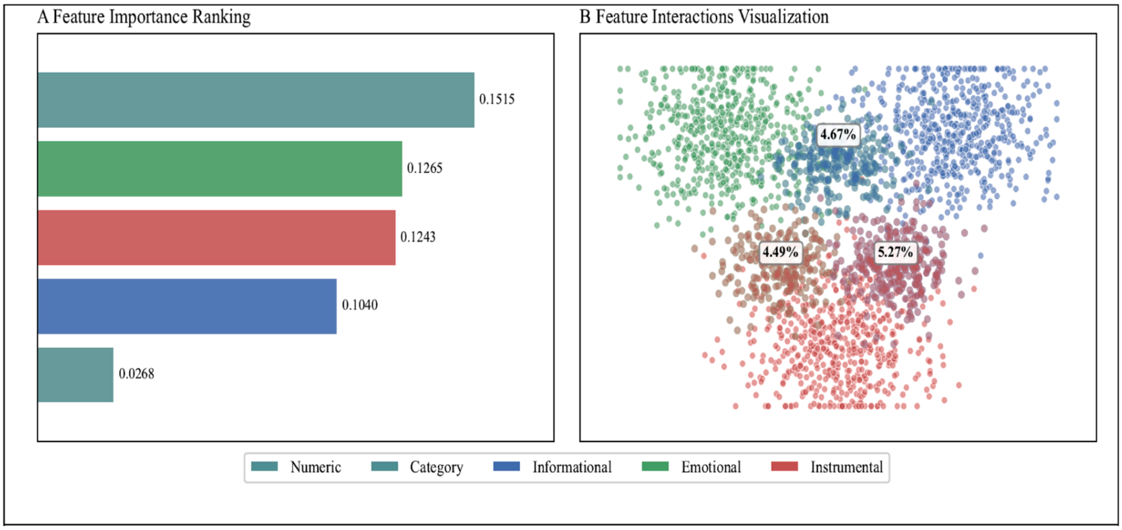

Fig. 4. A feature importance ranking; b feature interactions visualization.

categories compared to their individual contributions. The results reveal generally weak interaction effects, suggesting that the complementarity observed in the ablation experiments arises mainly from the distinct individual predictive contributions of each feature type rather than from substantial nonlinear synergies. In other words, the three categories provide additive complementary signals, as they capture different dimensions of the streaming context. Specifically, in knowledge-sharing live streaming, informational support delivers product-related and expert knowledge, instrumental support conveys price incentives such as discounts, and emotional support fosters trust through streamer–viewer interactions. Each category thus contributes unique predictive signals that, when combined, improve the overall accuracy of sales prediction.

4.4.5. *Concrete examples of social support cues*

This section demonstrates the application of the proposed framework for extracting and analyzing the proportions of social support categories in streamers' discourse. Three books were selected from the same live streaming session, and Table 6 shows representative excerpts of streamers' discourse for each book. Product 1 belongs to the zero-sales category, with 39 % of its transcripts classified as nonsense. Products 2 and 3 belong to the low- and high-sales categories, respectively, and both show a higher density of social support and less nonsense in their transcripts than Product 1.

Table 6
Examples of live streaming transcripts.

Number	Name	Sample Text	Social Support Proportion
1	*Will Enter the Wine (Jiang Jin Jiu)*	"… I've got a book I really want to recommend to my dear family! **(Emotional)** Here's *Will Enter the Wine (Jiang Jin Jiu)*, only 9.9 in the live streaming session. **(Instrumental)** Guess what I just ate? I just finished my meal and I'm pretty stuffed. **(Nonsense)** *Will Enter the Wine* is all about power struggles, telling the story of the protagonist and the antagonist battling with wits and strategy. **(Informational)** After eating I just feel so sleepy—once the stream is over, I really want to take a nap **(Nonsense)**…"	Informational ≈ 28 % Emotional ≈ 16 % Instrumental ≈ 17 % Nonsense ≈ 39 %
2	*To Live*	"…By scanning the QR code, you can not only listen to the audiobook but also verify whether it is an authentic copy, and we guarantee triple compensation for any counterfeit. **(Instrumental)** The protagonist experiences many hardships throughout his life; his family members gradually leave him, and in the end, only an old ox remains as his companion. **(Informational)** Yu Hua's novel has also been adapted into a movie. **(Informational)** I highly recommend everyone to read this book; after finishing it, you will be filled with mixed emotions. **(Emotional)** I'm thirsty, let me take a sip of water first. **(Nonsense)** We should be humble and resilient like wild grass, because only by persevering can we have hope and avoid letting ourselves down. **(Emotional)**…"	Informational ≈ 30 % Emotional ≈ 35 % Instrumental ≈ 28 % Nonsense ≈ 7 %
3	*The Conquest of Happiness*	"… Huh? I didn't see the comment you just sent. **(Nonsense)** This book has given me so much strength, especially when I face setbacks—it gives me the courage to confront them. **(Emotional)** Right now, it's only 29.9, and shipping is free! **(Instrumental)** It has also made me much more optimistic, because so much of life's sorrow depends on how you choose to face it. **(Emotional)** The author even won a Nobel Prize **(Informational)**…"	Informational ≈ 10 % Emotional ≈ 61 % Instrumental ≈ 15 % Nonsense ≈ 14 %

4.5. Robustness analysis

4.5.1. Robustness validation of the proposed social support classification model

While LLMs can exhibit output variability due to their probabilistic nature, our social support classification model (Ernie-SFT) shows notably improved stability. To rigorously validate Ernie-SFT's robustness, we conducted five independent runs with identical prompts and parameters, then calculated the standard deviation (SD) and relative standard deviation (RSD) for each category. As shown in Table 5, all RSD values remain below 5 % for precision, recall, and F1-score, suggesting that Ernie-SFT achieves highly consistent performance despite the inherent variability of its base LLM.

4.5.2. Comparison of different product types

In the original dataset, products were classified into three types: educational and practical books, social sciences and history books, and literature and fiction. Fig. 5 shows that compared with the baseline, incorporating social support features improves prediction accuracy across all three product types.

For educational and practical books, relying solely on informational support cues such as detailed product descriptions and knowledge dissemination yields the highest prediction accuracy. This may suggest that readers of these books place greater emphasis on knowledge-related information and practical guidance when making purchasing decisions. In contrast, for social sciences and history books as well as literature and fiction books, the best prediction results are achieved by combining all three categories of social support features. These more narrative or content-oriented book types depend more on detailed explanations, emotional resonance, and interactive atmospheres created by streamers, which provide the model with richer predictive signals. It is likely that consumers of practical books place greater emphasis on direct and functional elements, whereas readers of content-oriented books may be more influenced by the emotional and informational support conveyed in streamers' discourse. Therefore, adapting feature construction to specific book types can enhance sales prediction accuracy and increase the real-world relevance of the results.

4.5.3. Comparison of different account types

In the original dataset, streamer accounts were classified into four types: bookstore, publisher, individual, and others. Fig. 6 shows that compared with the baseline, incorporating social support features improves prediction accuracy across all four account types.

For bookstore and individual accounts, prediction accuracy is highest when only informational support is used. This may be because bookstore accounts typically maintain extensive inventories and provide systematic explanations of a wide range of books, whereas individual accounts may emphasize knowledge-sharing and in-depth personal interpretations of book content. In both cases, informational support emerges as the most effective predictive signal. For publishers, prediction accuracy is highest when instrumental support is incorporated, and this is likely because they often launch new books and run promotional campaigns. Therefore, practical incentives and concrete offers may provide richer predictive information. For other accounts, prediction accuracy shows little variation across feature combinations but reaches a relatively higher level when all social support categories are included. This may reflect the multi-sourced and heterogeneous nature of these accounts, whose discourse is semantically rich and complex, thereby making the full set of social support features more effective in capturing predictive signals. Overall, these findings suggest that tailoring feature design to account types can enhance predictive performance and enable more targeted operational strategies.

4.6. Discussion and implications

Our findings provide both theoretical and practical implications for the study of knowledge-sharing live streaming.

4.6.1. Theoretical implications

This study extends social support theory into the domain of knowledge-sharing live streaming e-commerce through a novel LLM-powered prediction framework. First, we developed a theory-driven framework based on social support theory and fine-tuned LLMs to categorize streamers' discourse into interpretable categories: informational, instrumental, and emotional support. This approach extracts interpretable dimensions from the discourse and directly addresses RQ1. Subsequently, our ablation experiments (Table 4) and the analysis of mean absolute SHAP values (Fig. 4) quantify the differential effects of these support categories on sales prediction, thereby addressing RQ2 and extending prior findings. This study offers a novel perspective on applying social support theory with LLMs in knowledge-sharing e-commerce contexts.

4.6.2. Practical implications

The findings provide actionable guidance for streamers, merchants, and platforms. Streamers and merchants can adjust their communication to emphasize specific social support categories according to product or account characteristics, as shown in Figs. 4 and 5, thereby improving prediction performance and optimizing product presentation in live streaming. Platforms can apply the proposed framework to allocate traffic in a data-driven manner, enhancing overall platform performance.

Beyond categorization, feature ablation experiments and the analysis of mean absolute SHAP values confirm the predictive value of social support features and show that the three support types complement each other in enhancing predictive performance. Overall, the interpretable discourse taxonomy from RQ1, together with empirical evidence from RQ2, provides a solid basis for understanding how different social support categories influence sales prediction. These findings support evidence-based improvements to live streaming strategies.

Table 5
SD and RSD of each category for Ernie-SFT.

Social Support	Precision (SD)	Precision (RSD)	Recall (SD)	Recall (RSD)	F1-score (SD)	F1-score (RSD)
Informational Support	0.0155	**1.85 %**	0.0241	**3.01 %**	0.0197	**2.41 %**
Emotional Support	0.0121	**1.50 %**	0.0064	**0.73 %**	0.0089	**1.06 %**
Instrumental Support	0.0208	**2.31 %**	0.0250	**3.07 %**	0.0192	**2.24 %**
Nonsense	0.0156	**2.30 %**	0.0127	**2.05 %**	0.0112	**1.73 %**

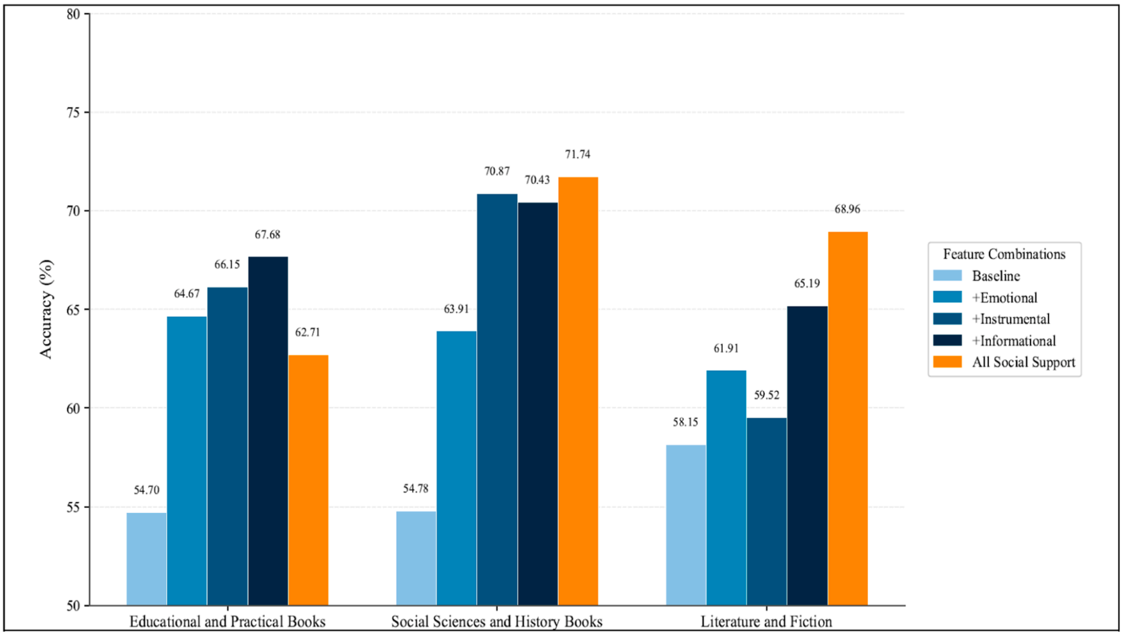

Fig. 5. Comparison of different product types.

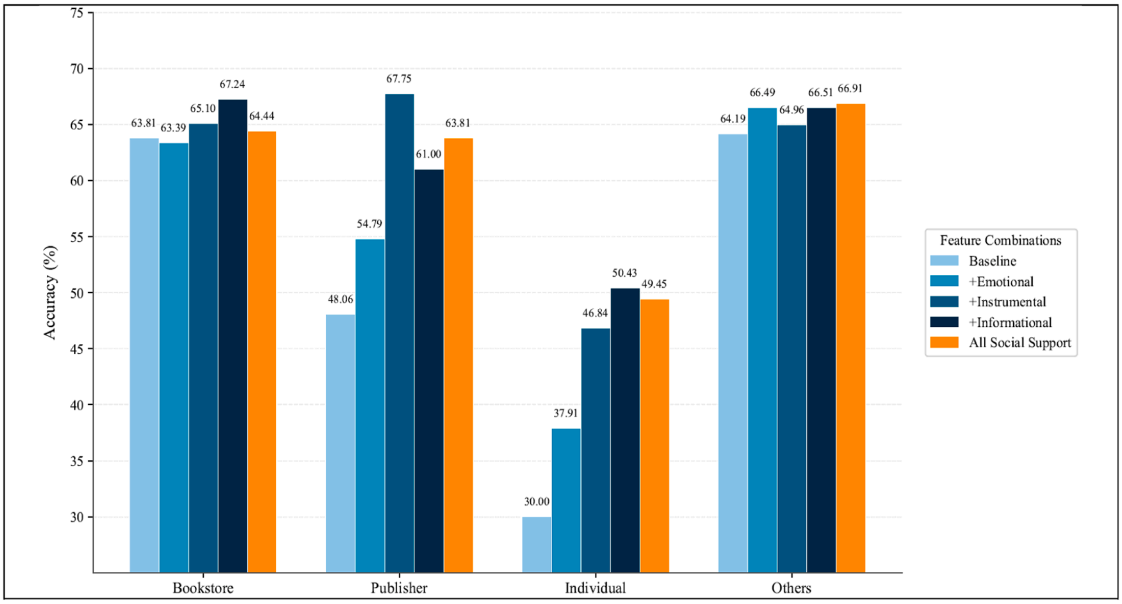

Fig. 6. Comparison of different account types.

5. Conclusions and future work

Our study demonstrates an LLM-powered framework for sales prediction in knowledge-sharing live streaming. Using real-world Douyin data, we show that fine-tuned LLMs can effectively extract interpretable social support cues from streamers' discourse to address RQ1. In addition, we find that discourse-level semantic signals based on social support theory improve sales prediction and reveal the differential effects of various features, thereby addressing RQ2. By leveraging state-of-the-art LLMs to extract interpretable linguistic categories, our approach connects theoretical constructs with practical applications in a scalable manner.

This study has several limitations. Although our framework is effective for social support analysis, it does not fully capture nuanced linguistic phenomena such as humor, metaphor, and implicature. Future research could explore more advanced natural language understanding (NLU) models or contextual embeddings to better handle these subtleties and improve interpretability. In addition, our focus on real-time data limits the inclusion of pre-stream promotions and post-stream feedback, both of which are important for comprehensive omnichannel sales attribution. Future work should consider building end-to-end data pipelines that incorporate both upstream and downstream factors to achieve a more holistic understanding of the sales process. A third limitation is that while our framework can quantify the contributions of different social support categories to sales prediction performance, it does not reveal how these categories drive actual purchase behavior or influence consumers' cognitive processes. Future work could empirically investigate the effects of different social support categories on users' purchase-related cognition and decision-making to better understand the underlying mechanisms.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with translation and to improve the clarity and readability of the language. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

CRediT authorship contribution statement

Runyu Chen: Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Junru Xiao:** Writing – original draft, Software, Methodology, Data curation. **Luqi Chen:** Writing – original draft, Data curation. **Xiaohe Sun:** Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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