LyFy: Enhancing Batik E-Commerce Live Streaming Through Real-Time Chat Filtering and Product Recommendation

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Abstract

Live streaming has emerged as an essential tool for e-commerce, allowing sellers to engage with potential customers in real-time. However, the massive influx of comments during these sessions often includes a mix of useful product-related queries and irrelevant or distracting messages, which can overwhelm the presenter and reduce the effectiveness of the stream. In this paper, we propose LyFy, a browser-based extension designed to filter live chat messages and provide personalized product recommendations in real-time, specifically applied in Batik e-commerce to support the preservation and promotion of this unique cultural heritage of Indonesia. Our system uses a combination of natural language processing (NLP) and machine learning models to identify relevant comments, group similar queries, and offer product suggestions based on viewers' interests. We demonstrate the effectiveness of this system through a prototype implementation and evaluate its performance with qualitative feedback from streamers and users. The evaluation results indicate high user satisfaction, with over 51% of respondents rating LyFy as highly effective and 52% as highly efficient, making it a valuable tool for enhancing e-commerce live streaming interactions.

Keywords: Live Streaming, E-commerce, Chat Filtering, Product Recommendation, Natural Language Processing

I. INTRODUCTION

E-commerce live streaming has rapidly gained popularity as a preferred method for sellers to engage directly with potential customers. According to a report by Statista, nearly 30% of internet users worldwide watched live streaming content weekly in the last quarter of 2023 [1]. The global live streaming market is expected to reach $756,5 billion by 2031, with a Compound Annual Growth Rate (CAGR) of 20.9% from 2024 to 2031 [2]. In regions like China, live shopping is projected to account for 20% of all e-commerce sales by 2026 [3]. This interactive format allows sellers to showcase products, answer questions, and provide real-time feedback, creating a personalized shopping experience.

In niche markets like Batik [4], where customers require detailed explanations about patterns, materials, and sizes, live streaming becomes invaluable. It enables sellers to not only display their products but also address customer inquiries directly, enhancing trust and providing the detailed information customers need to make informed decisions. However, while live streaming offers these benefits, managing the high volume of chat messages during popular streams poses a significant challenge. As the audience grows, so does the variety of comments, many of which may be off-topic or irrelevant.

Messages from viewers often include both product-related questions and distracting comments. For example, questions like "*Apakah ada Batik pria?*" (asking about product type) or "*Ukuran M ada?*" (asking about size) are useful for both the seller and potential buyers. However, these essential queries are frequently buried under non-useful messages such as "*Hai kak*" (greeting) or "*Duh, cantik banget kak*" (compliment to the streamer), which do not contribute to the selling process. As shown in Table 1 and Table 2, this mix of useful and non-useful messages during crowded sessions makes it challenging to maintain effective sales conversations. Without a robust mechanism to filter and prioritize chat messages, streamers must manually sift through comments, reducing their efficiency. This problem intensifies as the stream grows in popularity, with important messages increasingly buried under casual greetings or irrelevant comments, thereby hindering customer interactions and diminishing the overall customer experience.

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The Natural Language Processing (NLP) [5], [6], [7] and The Bidirectional Encoder Representations from Transformers (BERT) model [8], [9] are often used to process chat messages from a live streaming services. Previous studies have addressed various aspects of live streaming, such as real-time summarization [10], sentiment analysis [11], and semantic clustering [12]. However, these studies primarily target general platforms like Twitch [13], eSports [14], and YouTube [11]. While effective for broader live-streaming contexts, these methods often fail to meet the specific needs of e-commerce live streaming, where managing product-related queries and customer interactions is essential. This gap in research highlights the need for an approach that combines chat filtering with product recommendations, tailored specifically to the e-commerce live streaming environment.

Table 1. Examples of Useful Chat Messages in a Live Streaming Service for The Batik Marketplace

Useful Messages
Apakah ada Batik pria? *Batik lengan panjang ada nggak kak?* (Asking for type of product)
Warna kuning ada kak? (Asking for color of product)
Ukuran M ada? (Asking for size of product)
Harganya berapa kak? *Ada diskon untuk pembelian lebih dari satu?* (Asking for the price of the product)

Table 2. Examples of Non-useful Chat Messages in a Live Streaming Service for the Batik Marketplace

Non-Useful Messages
Hai kak (Greetings)
Duh, cantik banget kak *Kakak lucu banget sih!* (Appreciation to the streamer)
Jelek banget nih barangnya *Suaranya kecil banget, nggak kedengeran kak* (Complaining)
Nonton aja dulu, nggak beli hehe (Not interested in buying)

To address this growing problem, we propose LyFy, a real-time chat filtering and product recommendation system tailored for Batik e-commerce live streaming. Leveraging NLP [5], LyFy categorizes chat messages, filtering out irrelevant comments and grouping product-related inquiries. This approach allows streamers to prioritize high-value questions and engage more effectively with potential buyers. The recommendation engine in LyFy generates personalized product suggestions by analyzing the live chat for specific product inquiries. This enhances the shopping experience by aligning recommendations with customer interests, ultimately boosting conversion rates.

To sum up, key contributions of this paper are as follows:

- We implement a real-time chat filtering system that prioritizes essential messages for the streamer.
- We develop a text similarity approach to group similar queries.
- We integrate a dynamic product recommendation engine based on chat analysis.
- We evaluate LyFy through a prototype implementation and user feedback.

The rest of this paper is organized as follows: Section 2 presents the system architecture and design. This is followed by an elaboration on the methods used for chat filtering, text similarity, and product recommendation. Section 3 discusses the prototype analysis and user feedback results. Section 4 explores related works, highlighting how our proposed method differs from existing research. Finally, Section 5 concludes the paper.

II. SYSTEM MODEL

This section outlines the inner workings of LyFy. We begin by identifying the key entities involved in the system. Following that, we explain the workflow of the system, starting from the extraction of chat messages to the generation of product recommendations as the final output. The complete architecture and system model of our proposed solution are illustrated in Figure 1.

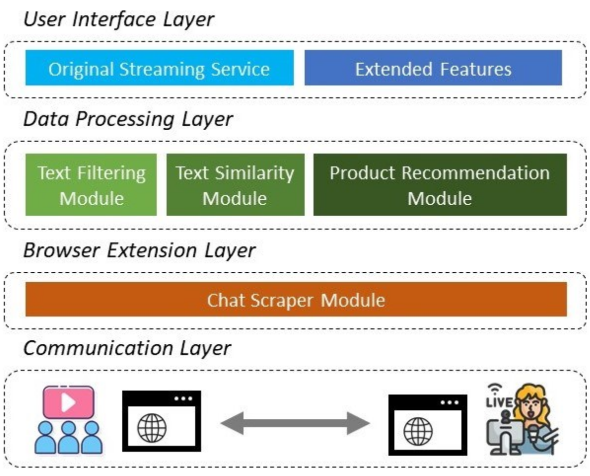

Figure 1. The architecture of Our Proposed System

A. Entities

The following are the key entities involved in our system:

- **Streamers**: Individuals who sell Batik products and host live streaming sessions to promote these items by interacting with potential customers.
- **Viewers**: Users who are interested in purchasing Batik products and participate in the live streaming sessions hosted by the streamers.
- **E-Commerce Live Streaming Service**: A third-party platform that both streamers and viewers trust to host the live streaming sessions and facilitate the Batik marketplace. Streamers and viewers are registered users of this e-commerce application.

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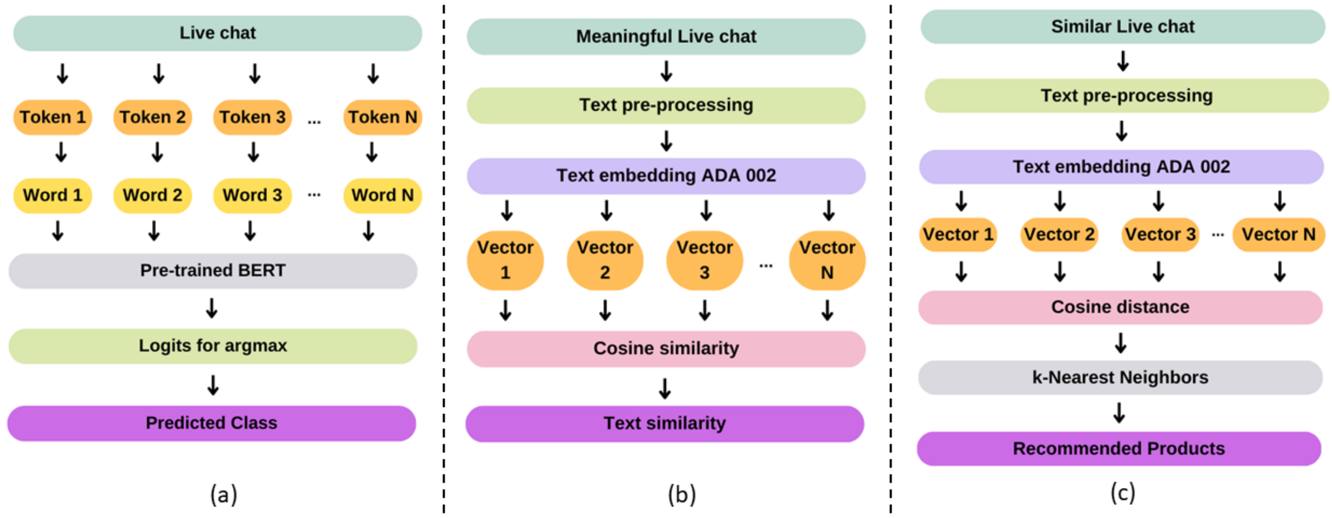

Figure 2. Processes for Analyzing Live Streaming Chat: (a) Filtering, (b) Text Similarity, and (c) Product Recommendation.

B. Starting Live Streaming Sessions

The workflow begins with streamers creating a live streaming session. Users browsing the e-commerce platform can discover this session and join the live stream. During the session, streamers promote Batik products they are selling while building engagement with viewers by reading and responding to messages sent in the chat. Viewers can interact with the streamer by typing messages in the chat box, asking questions, or making comments. This interaction takes place in what we refer to as the Communication Layer in Figure 1.

C. Obtaining Live Chat Messages

As the live streaming sessions getting more intense, viewers often send numerous messages covering a wide range of topics. These messages must be analyzed to enhance the streaming experience. However, many e-commerce platforms do not offer an application programming interface (API) to access live chat messages. To address this limitation, our system employs a scraper module designed to extract chat messages directly from the e-commerce website (as shown in the Browser Extension Layer in Figure 1). This module crawls the website's HTML structure, capturing new messages in real time for further processing.

D. Processing Chat Messages

Once the live messages are captured, the system initiates the process of analyzing and filtering the chat messages (c.f., Data Processing Layer in Figure 1). Specifically, we filter out irrelevant messages and leverage the relevant ones to create personalized product recommendations in real-time. This process NLP techniques and machine learning models. To provide a comprehensive understanding, the processing is further divided into three key stages: initial filtering of chat messages, text similarity analysis, and product recommendation generation.

0) Data Collection and Training

Before processing real-time chat messages, we collected a history of chat messages from various e-commerce services. This data then underwent a pre-processing stage, which included the removal of emojis, repeated letters, and punctuation, followed by normalization. Repeated letters were trimmed by setting a maximum limit of two consecutive identical letters to aid in normalization. All punctuation was removed except for question marks, as they help identify questions within sentences. This processed data then served as the dataset to train our classification model.

1) Filtering Process

In Figure 2(a), the filtering process is illustrated as the foundation of the chat analysis pipeline. This stage begins by tokenizing the live chat input, where each message from the chat stream is broken down into tokens, which are the smallest units of text, such as words or subwords. Tokenization ensures that the text is properly structured for analysis, that is critical in maintaining the context of each message. Since live chat messages are often informal and unstructured, this step is essential for accurate processing.

The tokenized words are then passed through a pre-trained BERT (Bidirectional Encoder Representations from Transformers) model [8]. BERT's bidirectional language understanding capabilities allow it to comprehend the context of a word by considering the words both before and after it in a sentence. This contextual analysis enables the model to generate logits, which are numerical scores representing the likelihood of each token belonging to a particular class. The system then applies argmax operations to these logits to predict the class label of each comment, categorizing messages as either useful (meaningful, relevant to the product) or non-useful (irrelevant or spam).

2) Text Similarity Process

Figure 2(b) represents the second stage, where text similarity analysis is conducted to identify relationships between viewer comments. The process begins with pre-processing the useful live chat messages, which includes cleaning the text by removing noise, correcting grammar, and normalizing slang or abbreviations commonly found in live

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chat interactions. This step ensures that the data is standardized for further analysis.

Next, the cleaned text is transformed into vector representations using the ADA 002 text embedding model [15]. Text embeddings are dense numerical representations that capture the semantic meaning of the text, enabling the system to understand contextual relationships between different words or phrases. The system then applies cosine similarity to these vectors, measuring how closely related the comments are. High similarity scores indicate that viewers are expressing a consistent interest in a particular product, which can be flagged for further recommendation.

3) Product Recommendation Process

The final stage, depicted in Figure 2(c), focuses on generating product recommendations based on the filtered and analyzed chat data. Similar to the text similarity step, the comments are pre-processed and converted into vectors using the ADA 002 model. However, instead of calculating cosine similarity, the system calculates cosine distance, a metric that identifies differences between comments to detect unique viewer interests that may not have been previously identified. The processed vectors are then passed through a k-Nearest Neighbors (k-NN) algorithm [16], which identifies the closest matching products based on the preferences expressed by viewers in the chat. The k-NN algorithm clusters comments into groups, allowing the system to pinpoint specific products that align with viewer interests. Based on these clusters, the system generates a list of recommended products that are most relevant to the ongoing live chat discussions, thereby personalizing the shopping experience and potentially increasing conversion rates for the online store.

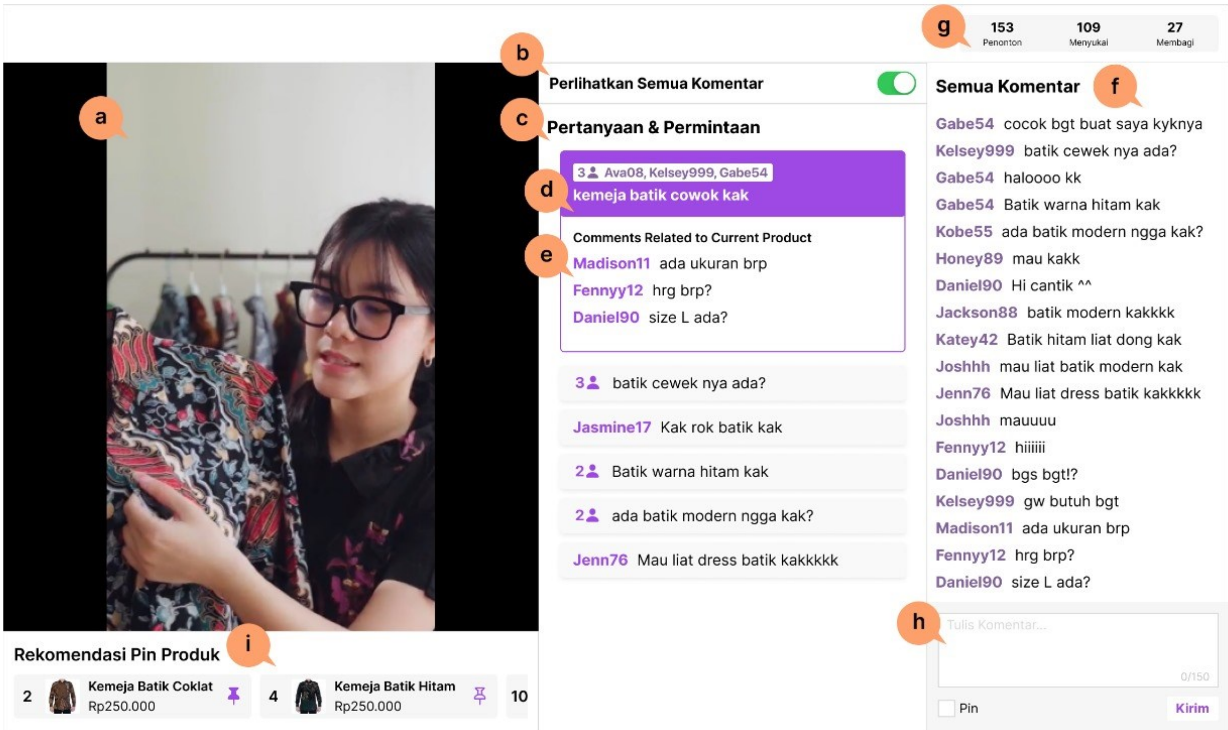

Figure 3. The Output From Our Proposed System With Nine UI Components (a) to (i) When Processing Live Chat Messages

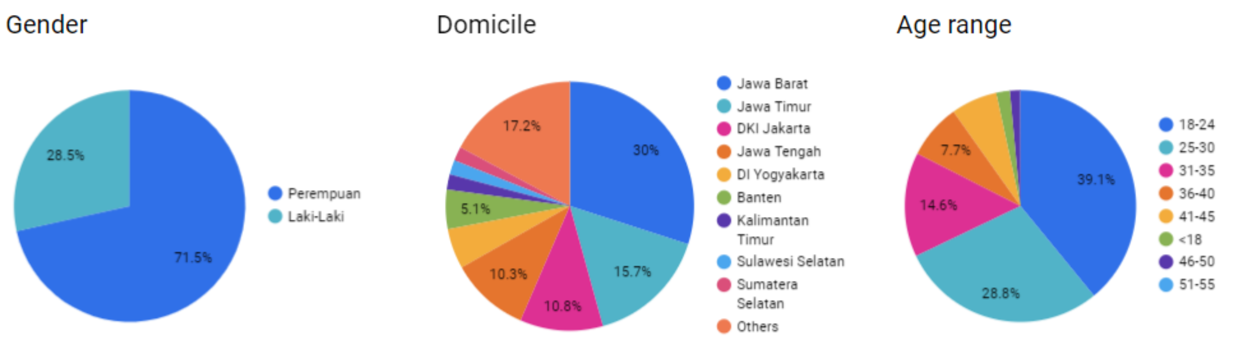

Figure 4. Respondent Information Showing Distribution of Gender, Domicile, and Age

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E. Presenting Analysis Results

The final component of the system involves presenting the chat analysis results through the User Interface (UI), enabling streamers to view the analyzed chat messages. The UI Layer, illustrated in Figure 1, displays personalized product recommendations in real time, dynamically updating as the live chat progresses. The UI provides extended features from a typical UI of a live streaming service to create a seamless user experience by offering timely and relevant suggestions that reflect the evolving interests of the audience.

III. EVALUATION

We implemented our system on a MacBook Pro with an Apple M1 chip and 16GB of RAM. The system model is developed as a Safari extension using the Javascript and Swift programming language. For processing live chat messages, we employed TensorFlow, Keras, and Python. To assess the feasibility of our prototype, we conducted two distinct evaluations.

A. Prototype Functionality and User Interface Evaluation

The first analysis aims to verify whether our prototype functions as originally designed. We conducted integration testing of the prototype and monitored the behavior of both the input—chat messages provided by viewers—and the output of the user interface (UI) used by streamers to sell their products. The results are presented in Figure 3.

The basic user interface components, typical of online shop live streaming services, are located in the leftmost and rightmost parts of the figure. The video stream from the streamer is displayed in (a). At the top right, we see live stream statistics, including the number of viewers, likes, and shares, shown in (g). Below that, the live chat messages from viewers are displayed in (f). The streamer can reply to viewers' messages or initiate communication using the provided form in (h). Additionally, a pin checkbox is available for the streamer to create and pin comments as announcements.

The remaining components represent extended features of our user interface. At the center top, there is a toggle (b) that allows the streamer to choose whether to display or hide unfiltered chat messages. Below the toggle, the filtered chat messages are shown in (c). Within (c), we display the current topics or products being discussed, indicated by (d). Messages on the same topic are grouped together in the purple box. The UI also shows the number of viewers who have sent similar messages and highlights which viewers made those comments, enabling the streamer to understand what topics are trending among viewers and engage them by name. In (e), a list of comments related to the current topic is provided to give the streamer more context. Finally, the product recommendations, relevant to the current discussion or hot topics, are shown at the bottom in (i). The streamer can pin these products, allowing viewers to easily access the promoted items.

Based on our testing, the prototype functions as expected. It successfully filters out useful and non-useful messages, groups similar texts, and provides relevant product recommendations based on the trending topics in the chat.

B. User Feedback Evaluation

In the second analysis, we want to see the usefulness and effectiveness of our application by performing user survey for streamers and viewers of shopping live streaming services.

Respondent Information

We distribute our survey form publicly online so that random people (streamers and viewers) can fill the form. In total, we obtain 200 feedbacks with respondent information summarized in Figure 4.

For starters, the majority of respondents are female, making up 71.5% of the sample, while male respondents represent 28.5%. This may show that female are more interested in shopping live streaming service than male. Moreover, the survey is dominated by younger respondents, with 39.1% falling in the 18-24 age group and 28.8% in the 25-30 group. Smaller portions of the sample are from older age brackets, such as 36-40 and 51-55, which make up 7.7% and 6.5%, respectively. This also suggest that younger generation is more interested in shopping live streaming service than older ones.

The domicile of respondents shows a wide geographic spread across Indonesia, with the largest proportion (30%) residing in Jawa Barat, followed by Jawa Timur (15.7%) and DKI Jakarta (10.8%). Other regions, such as Sulawesi Selatan, Banten, and Sumatera Selatan, also contribute to the dataset, though in smaller numbers. This regional representation indicates a diverse sample, with a higher concentration in densely populated province.

Survey Result

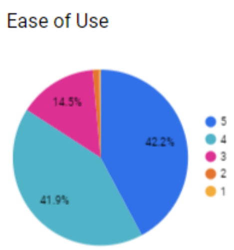

Figure 5. Distribution of Responses for Ease of Use Based on a 5-point Likert Scale.

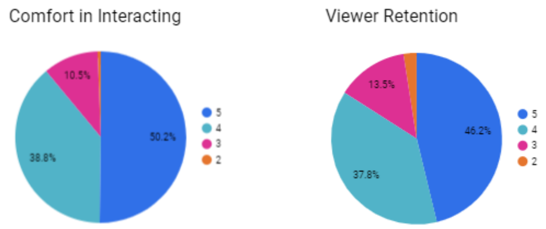

Figure 6. Distribution of Responses for Comfort in Interacting and Viewer Retention Based on a 5-point Likert Scale.

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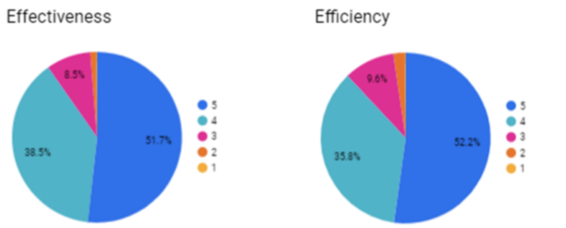

Figure 7. Distribution of Responses for Effectiveness and Efficiency Based on a 5-point Likert Scale.

We discuss the survey results into three category. First, we want to know whether users think that our UI (shown in Figure 3) has good easy of use criteria. Based on our survey results (c.f., Figure 5), about 42.2%, rated our UI with the highest Likert score of 5, and another 41.9% gave it a 4. This indicates that most users find our designed UI very easy to use, making it a tool that streamer can comfortably integrate into their workflow without complications.

Second, we want to know if LyFy can help streamers in interacting with viewers better. Based on the survey result in Figure 6, 50.2% of respondents gave a perfect Likert score of 5, while 38.8% rated it as 4 suggesting that live streamers find the platform is comfortable for real-time interactions. Regarding viewer retention, a large portion of the respondents (46.2% gave a 5, and 37.8% gave a 4) agreed that LyFy helps them effectively retain viewers during live streaming sessions, reflecting positive impact on this crucial aspect of streaming success.

Lastly, the Effectiveness and Efficiency charts, shown in Figure 7, reinforce our system's value for streamers, with over half of the respondents in both categories giving it the highest Likert rating of 5. With more than 51% and 52% of the participants rating LyFy as highly effective and efficient, respectively, it's evident that the platform is well-regarded for its ability to streamline the work process of live streamers, boosting both their productivity and overall performance.

IV. RELATED WORK

Table 3. Feature comparisons with Related Works

Paper	Method	Domain
[13]	RoBERTa model, active learning	Twitch
[14]	Long Short Term Attention (LSTA), chat-based NLP	eSports
[10]	CatchLive system, real-time summarization, NLP	General live streaming
[12]	Chitchat detection, semantic clustering ASR	Graphic design live streaming
[11]	Sentiment analysis, topic modeling, NLP	Youtube
Ours	BERT, Cosine similarity, k-NN	E-Commerce

Several recent studies have explored the use of machine learning and NLP techniques to improve live streaming experiences as summarized in Table 3. Gao et al. [13] utilized a pre-trained RoBERTa model for detecting offensive language in Twitch gaming streams, showcasing how filtering can enhance user experience by maintaining a positive chat environment. Similarly, Liaw et al. [14] applied Long-Short Term Attention (LSTA) to highlight detection in eSports streams using chat messages, helping users capture key moments of the game.

Beyond gaming, other research has focused on chat management in live streaming across various domains. Yang et al. [10] developed CatchLive, a system for summarizing live streams using both content and interaction data, while Lai et al. [12] addressed the issue of chitchat filtering in creative live streams through semantic clustering. In the context of YouTube live streaming, Liebeskind et al. [11] explored sentiment analysis and topic modeling to understand user engagement in political streams.

While all these works focus on filtering and managing chat messages, LyFy takes a different approach by focusing on e-commerce live streaming. Unlike these prior studies, LyFy not only filters messages but also clusters product-related queries and provides real-time product recommendations using techniques such as BERT, cosine similarity, and k-NN. This tailored approach enhances engagement in live shopping environments, optimizing the interaction between streamers and potential customers.

V. CONCLUSION

In this paper, we introduced LyFy, a real-time chat filtering and product recommendation system tailored to Batik e-commerce live streaming. Through a combination of NLP and machine learning techniques, LyFy addresses the challenges posed by overwhelming and unstructured live chat messages. Our system successfully categorizes messages, filters out irrelevant content, and provides personalized product recommendations, enabling streamers to focus on high-priority interactions. The system's design and architecture were tested through a prototype implementation, and the evaluation, including feedback from users, confirmed its effectiveness in improving the shopping experience for both streamers and viewers. Specifically, more than 51% of users rated LyFy as highly effective, and 52% found it highly efficient in improving their live streaming process. Future work could explore expanding LyFy's capabilities to support multiple e-commerce platforms and enhance its recommendation engine with more advanced AI-driven personalization techniques. Additionally, the system could benefit from deeper integration with e-commerce platforms to optimize user engagement and streamline operations.

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REFERENCES

[1] Statista, "Live streaming - statistics & facts," Statista, Available: https://www.statista.com/topics/8906/live-streaming/. [Accessed: Oct. 17, 2024].

[2] Meticulous Research, "Live Streaming Market by Component, Offering Model, Streaming Type, End User - Global Forecast to 2031," Meticulous Research, Available: https://www.meticulousresearch.com/product/live-streaming-market-5225. [Accessed: Oct. 17, 2024].

[3] McKinsey & Company, "It's showtime: How live commerce is transforming the shopping experience," McKinsey & Company, Available: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/its-showtime-how-live-commerce-is-transforming-the-shopping-experience. [Accessed: Oct. 17, 2024].

[4] S. Asmiatun, S. R. Cholil, and V. G. Utomo, "Pemanfaatan Marketplace Shopee Untuk Keberlangsungan UMKM Batik Kampung Tematik Durenan Indah Semarang," Abdiformatika: Jurnal Pengabdian Masyarakat Informatika, vol. 2, no. 1, pp. 13-18, 2022.

[5] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa, "Natural language processing (almost) from scratch," Journal of Machine Learning Research, vol. 12, pp. 2493-2537, 2011. Available: https://www.jmlr.org/papers/volume12/collobert11a/collobert11a.pdf.

[6] S. M. Suhaili, N. Salim, and M. N. Jambli, "Service chatbots: A systematic review," Expert Systems with Applications, vol. 184, p. 115461, 2021.

[7] M. Li and R. Wang, "Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand," Journal of Retailing and Consumer Services, vol. 71, p. 103209, 2023.

[8] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," arXiv preprint arXiv:1810.04805, 2018. Available: https://arxiv.org/pdf/1810.04805.

[9] Y. Wang, G. Chen, Y. C. Xu, and X. Lu, "Novel role-wise attention mechanism for predicting purchases made through chat-based online customer services," Decision Support Systems, vol. 169, p. 113942, 2023.

[10] S. Yang, J. Kim, J. Yim, and H. V. Shin, "CatchLive: Real-time Summarization of Live Streams with Stream Content and Interaction Data," in CHI Conference on Human Factors in Computing Systems, 2022.

[11] C. Liebeskind, S. Liebeskind, and S. Yechezkely, "An Analysis of Interaction and Engagement in YouTube Live Streaming Chat," 2021 IEEE SmartWorld Conference, pp. 272-278, 2021.

[12] V. D. Lai, A. P. B. Veyseh, F. Dernoncourt, and T. H. Nguyen, "BehanceCC: A ChitChat Detection Dataset For Livestreaming Video Transcripts," in Proceedings of the 13th Conference on Language Resources and Evaluation (LREC), pp. 7284–7290, 2022.

[13] Z. Gao, "Offensive Language Detection in Live Streaming Chats Using Active Learning," Master's Thesis, Nara Institute of Science and Technology, 2021.

[14] C.-M. Liaw and B.-R. Dai, "Live Stream Highlight Detection Using Chat Messages," 2020 IEEE International Conference on Mobile Data Management (MDM), pp. 328-334, 2020.

[15] OpenAI, "New and improved embedding model," OpenAI, 2022. Available: https://openai.com/index/new-and-improved-embedding-model/. [Accessed: Oct. 17, 2024].

[16] E. Y. Boateng, J. Otoo, and D. A. Abaye, "Basic tenets of classification algorithms: K-nearest-neighbor, support vector machine, random forest, and neural network - A review," Journal of Data Analysis and Information Processing, vol. 8, no. 4, pp. 341-357, 2020.