

## I. Introduction

The current advancements in technology enable users to search for skincare products online. However, a drawback of online product searches is that users may feel uncertain and cannot determine which products are suitable for their skin condition or needs [1], [2]. Therefore, it is necessary to develop a system that can provide product recommendations personally and according to the user's skin needs. Conversational recommender system (CRS) is one of the solutions that can be used to overcome these problems. Unlike the usual recommender system, CRS allows users and the system to interact dynamically through natural language [3]. CRS also allows users to search for items iteratively with the help of conversational agents commonly called chatbots [4].

Many studies have developed CRS using natural language processing (NLP). Christakopoulou et al. [5] developed CRS using NLP to understand user preferences regarding the type of cuisine, location, and also price in a restaurant selection. Meanwhile, Radziwill et al. [6] use conversational agent-based CRS and utilize NLP to understand user preferences regarding destinations, accommodations, and activities. Based on previous research, there have been many significant advances in the development of CRS in various domains, such as restaurants, travel planning, etc. However, there are still some drawbacks such as limitations in handling long and complex conversations and integration of information from multiple sources that are often not consistent or accurate. One effective method to address this drawback is the use of pretrained language models, such as transformers [7] to enhance the understanding of conversational context and generate more relevant responses.

Devlin et al. [8] showed that transformer models such as bidirectional encoder representations from transformers (BERT) can achieve excellent performance in various NLP tasks, by using pre-training and fine-tuning approaches. Sun et al. [9] also used BERT to improve recommendation accuracy by understanding the sequence of user interactions. However, BERT has major drawbacks in terms of large model sizes and high computational requirements.

Based on these issues, we propose the use of DistilBERT in developing a recommender system. Sanh et al. [10] used DistilBERT which is a distilled version of BERT on CRS and found various advantages, especially in the context of real-time recommendation. The main advantage of DistilBERT lies in its ability to process unstructured text and capture complex context with higher speed and lower resource requirements than BERT. However, the use of DistilBERT as the main method in text processing in the context of conversational recommendation is still rarely explored. As in the research by Manzoor et al. [11] who only used DistilBERT to calculate the similarity between candidate responses in conversational recommendation.

To improve user experience, Mahmood et al. [12] proposed the use of critiquing methods in CRS by utilizing adaptive conversations to improve recommendation results. Murti and Baizal [13] used compound critiquing on CRS. Meanwhile, Jin et al. [14] revealed that both UC and SC are viewed at the same level by users. However, users tend to require a lot of effort to find recommendation results using SC. Therefore, UC is considered more effective in terms of more efficient usage. In this study, we propose the development of a chatbot-based CRS to recommend skincare products that are more personalized and tailored to the user's needs. We use the DistilBERT language model along with a critiquing-based approach with UC type, allowing users to provide direct and specific feedback if they are not satisfied with the recommendations. This is expected to enhance the relevance and personalization of skincare product recommendations. The NLP used in this study is based on the Indonesian language to process and understand user input within the conversational recommendation system.

The remaining sections of this paper are organized as follows. In Section 2, we discuss the research methodology, including the workflow of the system, the dataset used, and the application of the DistilBERT model. Next, Section 3 covers the results and discussion, such as the performance of the DistilBERT model, the implementation results of the model in the CRS, and the recommendation accuracy results. Section 4 presents the conclusion of the overall provides suggestions for future research.