I. Introduction

The beauty products industry has become one of the sectors influenced by technological advancements and changes in consumer behavior. The demand for beauty products continues to rise with shifts in consumer preferences and their shopping methods [1]. However, several challenges are faced in this industry, such as product complexity, changing trends, and consumer confusion when selecting products, especially when purchasing online [2]. In this context, technology is vital in helping consumers find products that align with their needs and preferences. One proposed solution is recommender systems, which aim to provide relevant and personalized suggestions based on individual needs and preferences. These recommender systems are beneficial in reducing information overload, making it easier for users to find the products they are interested in [3][4].

In this era, many studies have developed recommender systems for beauty products. Nakajima et al. [5] utilized an ingredient frequency-inverse product frequency method to create a beauty product recommender system based on the composition and reviews of a product using Natural Language Processing. Other studies have also developed recommender systems using Convolutional Neural Networks (CNN) [6] and deep learning [7] to recommend cosmetic products. However, these systems are still limited to consumer skin types, making the recommendations too general and not personalized.

Conventional recommender systems have limitations in understanding users' complex and dynamic needs and preferences. One factor is that the system only tracks user behaviour and provides recommendations based on previous interactions, such as when users log into the service [8]. LLM can understand natural language and complex user preferences, while CRS can build more dynamic interactions with users to understand their preferences better [9]. Liu et al. [10] found that the collaboration between LLM methods and CRS has already shown promising results in providing recommendations. However, the performance improvement from this collaboration remains marginal compared to the pure performance of LLM or CRS. This is due to the e-commerce domain, which involves many products and highly diverse user preferences.

Previous studies have applied various methods to recommender systems for beauty products. Still, these systems often struggle to understand complex and dynamic user preferences and have yet to provide sufficiently personalized recommendations. To address this issue, we propose developing a system that adopts the collaboration between LLM and CRS for beauty products. The main contribution of this research is developing an approach that integrates the language understanding capabilities of LLM with the dynamic interaction of CRS specifically for the beauty product domain, which has not been done before, which we have named Belle. Belle is a recommender system built using the GPT-4o model that has been fine-tuned to produce more accurate and personalized recommendations. By leveraging LLM within CRS, Belle can understand individual preferences, skin types, and beauty goals, allowing each recommendation to be tailored to the user's unique needs.

The next sections of this paper are organized as follows. Section 2 will discuss previous research on using LLM in CRS. Section 3 will outline the proposed system in this study, including the workflow process, dataset preparation for fine-tuning, GPT fine-tuning techniques, prompt engineering, and implementation. Section 4 will present and analyze the experimental results in depth, comparing the performance of the fine-tuned GPT model with that of the non-fine-tuned version. Finally, Section 5 will conclude with the key findings of this study and provide suggestions for further development in the field of LLM CRS in the future.