

**DEVELOPMENT OF BODY-AWARE FASHION
RECOMMENDATION CHATBOT USING
OPENAI API FOR E-COMMERCE**



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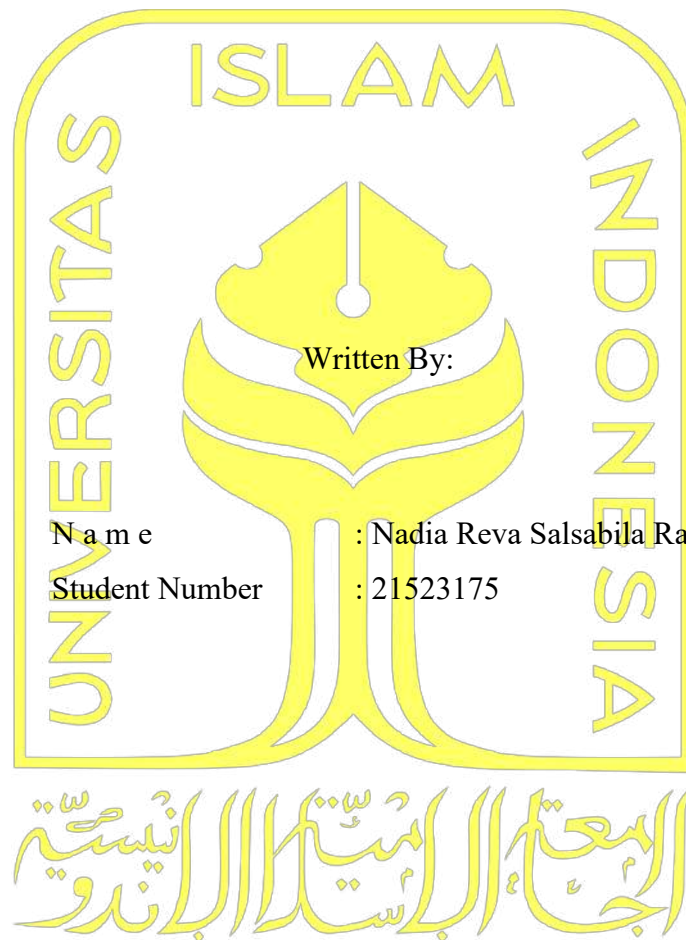
**DEPARTMENT OF INFORMATICS – UNDERGRADUATE PROGRAM
FACULTY OF TECHNOLOGY INDUSTRY
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2025

SUPERVISOR ENDORSEMENT PAGE

**DEVELOPMENT OF BODY-AWARE FASHION
RECOMMENDATION CHATBOT USING
OPENAI API FOR E-COMMERCE**

UNDERGRADUATE THESIS



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Yogyakarta, July 23, 2025

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EXAMINER ENDORSEMENT PAGE

**DEVELOPMENT OF BODY-AWARE FASHION
RECOMMENDATION CHATBOT USING
OPENAI API FOR E-COMMERCE**

UNDERGRADUATE THESIS

Has been defended before the examination board as one of the requirements for obtaining the degree of bachelor's degree from the Informatics Undergraduate Program at the Faculty of Industrial Technology, Islamic University of Indonesia.

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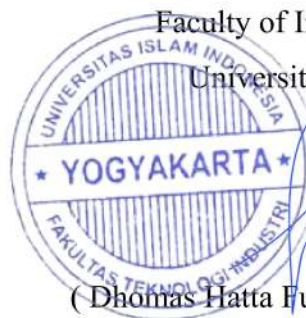


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I hereby declare that all components and content of this undergraduate thesis are entirely my own work. If, at any time in the future, it is proven that any part of this work is not my own, I am prepared to have this thesis withdrawn and to accept any risks and consequences that may arise.

This declaration is made sincerely and is intended to be used as appropriate.

Yogyakarta, July 23, 2025



A handwritten signature in black ink, appearing to read 'Nadia' followed by a stylized surname.

(Nadia Reva Salsabila Ramadhani)

DEDICATION PAGE

Alhamdulillahirabbil'alamiin.

I extend my deepest gratitude and praise to Allah SWT, whose grace, mercy, and guidance have enabled me to complete this undergraduate thesis successfully. This work is wholeheartedly dedicated to my parents, whose unwavering support has been invaluable throughout this journey. Last but not least, I would like to express appreciation for myself for not giving up in the face of challenges, for continuing to believe in my ability, and for showing resilience until the very end.

MOTTO

“Allah does not burden a soul beyond that it can bear”

(Q.S Al-Baqarah 286)

“So verily, with the hardship, there is relief, Verily, with the hardship, there is relief”

(Q.S Al-Inshirah 5-6)

“In chaos, there is order; hidden patterns shaping every uncertain path”

—Chaos Theory

PREFACE

Alhamdulillahirabbil'alamin. All praise be to Allah SWT for His abundant mercy, guidance, and enlightenment, through which the writing of this undergraduate thesis, entitled “Development of Body-Aware Fashion Recommendation Chatbot Using OpenAI API for E-Commerce”, has been made possible. This thesis is submitted as one of the requirements for graduation from the Informatics Department, Faculty of Industrial Technology, Universitas Islam Indonesia. The journey of completing this thesis was not without its challenges. However, with the support of many individuals, along with hard work and dedication, the author was able to complete it successfully. On this occasion, the author would like to express sincere gratitude to the following parties:

1. Allah SWT, the Almighty God, for His endless grace and guidance throughout this journey.
2. My beloved family, for their constant prayers, moral support, and material assistance during the process of writing this thesis.
3. Mr. Mukhammad Andri Setiawan, S.T., M.Sc., Ph.D., as my supervisor, for his valuable guidance, insights, and motivation throughout the research and writing process.
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5. The Sehat Selalu Orang Oring and Sobat Labrizz groups, dear friends who have accompanied and supported the author through this process: Yasmin, Jihan, Zahwa, Diva, Nuges, Helga, and Siraj.

The author realizes that this thesis is still far from perfect and contains several shortcomings. Constructive feedback and suggestions for improvement are genuinely welcomed. Hopefully, this undergraduate thesis can contribute meaningfully to the development and implementation of fashion recommendation systems.

Yogyakarta, July 23, 2025



(Nadia Reva Salsabila Ramadhani)

ABSTRACT

The rapid growth of e-commerce has transformed the fashion retail landscape, offering convenience and variety but also introducing new challenges related to personalization and fit accuracy, and user confidence, especially in the absence of physical try-on experiences. Clothing choices are often influenced not only by style but also by psychological and body image factors, including body shape, height, weight, and skin tone. These complex variables are often overlooked in current fashion recommender systems, which tend to rely heavily on historical data or generalized filters, resulting in recommendations that lack relevance and inclusiveness.

This research presents the development of a body-aware fashion recommendation chatbot utilizing the OpenAI API by implementing the GPT-3.5 Turbo model to provide personalized clothing suggestions through natural language conversations. The chatbot system integrates multiple components, including a fashion-focused prompt engineering strategy that enables the language model to consider physical attributes and user preferences during recommendation generation. The product catalogue data was gathered via web scraping from local e-commerce platforms using Selenium and BeautifulSoup, while the web-based chatbot interface was implemented using a combination of PHP, Python, HTML/CSS, and JavaScript.

To manage multi-turn dialogues and maintain context, a linked keyword system structure was designed, enabling the system to track user preferences throughout the conversation. The recommendations are refined through SQL queries that filter products based on real-time inventory availability, user preferences, and inferred body-related parameters. The chatbot's performance was evaluated through User Acceptance Testing (UAT) using the ResQue framework, covering eight indicators: recommendation quality, interaction adequacy, interface adequacy, interface sufficiency, ease of use, perceived usefulness, transparency, user attitude, and behavioral intent.

The findings demonstrate that incorporating body-aware personalization into a conversational AI framework significantly enhances the relevance, usability, and trustworthiness of a fashion recommendation. Users expressed satisfaction with the chatbot's ability to understand their needs, provide appropriate suggestions, and improve their confidence during the online shopping experience.

Keywords: fashion recommendation, body-aware chatbot, conversational AI. OpenAI API, prompt engineering, web scraping, e-commerce personalization

GLOSSARY

Artificial Intelligence	a field of computer science that focuses on creating systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, decision-making, and natural language understanding.
Back-End	the server-side logic of a web application, responsible for database interactions, business logic, and API communication.
Body-Aware	a term used to describe a system or technologies that incorporate users' physical attributes, such as height, weight, body shape, and skin tone, into personalization processes.
Chatbot	a conversational agent designed to simulate human dialogue through text or voice.
Entity Relationship Diagram (ERD)	a visual representation of the data model used in a system, showing the relationships between entities in a database.
E-Commerce	a digital platform or website that facilitates the buying and selling of goods or services over the internet.
Front-End	the part of web application that user interacts with directly, including the visual interface and client-side functionality
Keyword Extraction	a process in natural language processing that identifies significant terms or phrases from user's input, which are then used to generate relevant responses or queries.
Likert Scale	a psychometric scale commonly used in surveys to measure attitudes or opinions
Linked List	a linear data structure in which elements (called nodes) are connected using pointers. Each node contains data and reference (or link) to the next node in the sequence.
Prompt Engineering	the practice of crafting effectively prompts to guide large language models in generating accurate and relevant outputs. This includes specifying tasks, context, and desired formats.
Recommendation System	an algorithmic system that provides personalized suggestions based on user preferences, behaviors, or contextual data.
User Acceptance Testing (UAT)	a testing method where real users evaluate the system to determine whether it meets their needs and expectations, often conducted before deployment.
Waterfall	software development methodology.

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CHAPTER I

INTRODUCTION

1.1 Background

Clothing is one of the main necessities for humans, alongside food and shelter. However, its significance extends far beyond covering oneself. Studies have shown that clothing choices can significantly impact an individual's psychological well-being and self-expression.

Research conducted in Canada reveals that clothing can serve as a coping mechanism, boosting self-esteem, mood, and self-comfort (Wenderski et al., 2023). A study in South Korea found that people tend to dress to satisfy themselves rather than to satisfy others (Lee et al., 2020). Furthermore, research by Cham et al. (2018) in Malaysia indicated that Generation Y values uniqueness in clothing, seeking to differentiate themselves from society. A recent study by Suganya et al. (2024a) demonstrated a correlation between clothing choice, self-confidence, and mental health, suggesting that certain clothing choices can positively impact mood, performance, and confidence, potentially leading to better mental health.

However, clothing choice can also be influenced by body image concerns. Women in particular, have a tendency to appear thin, shown by a study conducted by Fernández-Bustos et al. (2019) in Spain, which found that they often have higher levels of body dissatisfaction compared to their male counterparts. This dissatisfaction can lead to the use of clothing to conceal perceived flaws, affecting self-esteem and confidence (Frith & Gleeson, 2008). Men are not exempt from these concerns; Sung & Yan (2020) discuss the relationship between self-esteem, body dissatisfaction, and clothing-related behaviors in Generation Y men. They found that concerns about muscle, height, and weight influence clothing behaviors, with weight being the most influential factor regarding clothing image avoidance. When men feel dissatisfied with their body image, they choose clothing that can conceal the body part they are dissatisfied with (Sung & Yan, 2020).

Given the psychological importance of clothing choices, it is crucial to consider how people shop for clothes in the modern era. This brings us to the realm of e-commerce, which has revolutionized the way people purchase clothing and other goods.

E-commerce refers to websites that provide tools for online transactions. E-commerce also refers to a way to shop or sell products online, where websites offer 'get and deliver' services (Sudaryono et al., 2020). E-commerce emerged in the 1960s with the implementation

of Electronic Data Interchange (EDI) for business-to-business transactions (Taher, 2021). Since then, it has grown exponentially, transforming shopping habits worldwide.

As of 2023, there are approximately 2.64 billion e-commerce users globally, accounting for about 33% of the world's population. In Indonesia, the e-commerce market has shown remarkable growth. With about 58.6 million users in 2023, this number is projected to reach 93.3 million by 2028. Indonesia has emerged as the largest e-commerce market in Southeast Asia, valued at approximately 62 billion dollars (Nurhayati-Wolff, 2023). Among the various categories of products sold online, clothing and footwear stand out as one of the most popular in Indonesia (Nurhayati-Wolff, 2023). This aligns with the fundamental importance of clothing in people's lives. However, online clothing shopping presents unique challenges.

Despite the convenience and variety offered by e-commerce, customer dissatisfaction in online clothing retail remains a significant issue. Many consumers face difficulties when shopping for clothes online, primarily due to the inability to physically try on items before purchase. A study by Bozzi et al. (2022) found that the main reasons customers return products they mentioned are mostly size and fit. Incomplete product descriptions, lacking information regarding sizes, materials, and quality are also an issue that consumers might encounter during online purchasing, which can lead to misunderstandings and dissatisfaction (Deshmukh, 2020). Poor customer service is also another challenge that e-commerce consumers often experience.

To address these challenges, e-commerce platforms have begun leveraging Artificial Intelligence (AI) to enhance the online shopping experience. AI, a technology consisting of systems and algorithms that allow machines to act and think like humans (Kanade, 2022), has found various applications in e-commerce. One such application is the use of chatbots for customer service. A recent study shows that chatbots can increase customer satisfaction and efficiency, reducing the need for human involvement in conversation by 87% which means only 13% of conversations require human intervention (Ngai et al., 2021).

Despite the growth of e-commerce and the popularity of online shopping for clothing, finding the right fashion items remains challenging due to the lack of personalized assistance. This issue is exacerbated by the rise of fast fashion, leading to anxiety and lowered self-esteem among consumers. Additionally, clothing choices are closely tied to self-esteem and mental health, with both men and women facing pressures related to body image. While AI and chatbots have enhanced customer service in e-commerce, their potential for providing personalized fashion recommendations is underutilized. Therefore, there is a need for an AI-

driven chatbot that helps users find clothing suited to their body type and preferences, improving their online shopping experience, and boosting their confidence.

Based on these problems, the author aims to develop a body-aware fashion recommendation chatbot on a website platform to help users find fashion items that suit their body type. The chatbot will need input/keywords to determine suitable fashion items for the user. It will then recommend fashion items based on the user's input.

1.2 Problem Formulation

The key questions of the problems in this study are as follows:

- a. How can we develop a chatbot that understands and interprets user fashion preferences, including style, size, color, and body-type considerations, to provide personalized clothing recommendations?
- b. How can body-type considerations (height, weight, body shape, and skin tone) be systematically incorporated into AI-driven fashion recommendation algorithms using prompt engineering?
- c. How effective is a conversational AI chatbot system in providing satisfactory fashion recommendations that the user finds useful and trustworthy?

1.3 Scope

The scopes for this research are:

- a. This research uses open-source e-commerce code as the development base.
- b. The chatbot can only recognize text as an input.
- c. The clothing items that will be recommended are only limited to the catalogue for the e-commerce website.

1.4 Objectives and Contribution of Research

The objectives of this research are:

- a. To create a chatbot that understands and interprets user fashion preferences, including style, color, size, and physical characteristics.
- b. To incorporate body-type considerations such as height, weight, body shape, and skin tone into the recommendation process through prompt engineering.
- c. To evaluate the chatbot's effectiveness in providing relevant, trustworthy, and user-friendly recommendations.

The expected contributions of this research are:

- a. Demonstrate a comprehensive approach to fashion preference interpretation - showing how conversational AI can effectively capture and process multiple user preference dimensions, style, size, color, body-type, through natural language dialogue to deliver personalized recommendations.
- b. Establish a systematic method for body-aware fashion recommendations - proving that prompt engineering can successfully integrate physical attributes, such as height, weight, body shape, skin tone into AI recommendation algorithms, addressing the poor fit accuracy problems in online fashion retail.
- c. Validate user acceptance and trust in conversational fashion AI - confirming that users find AI-driven fashion recommendations useful, satisfactory, and trustworthy enough to influence their actual purchasing decisions.

1.5 General Research Methodology

This research will use the following methodologies:

1.5.1 Literature Review

During the literature review process, the author will gather information regarding the problem, references, and theories that will be used. Literature review is done for the purpose of reviewing journals, articles, and books that have similar topics, and exploring the sources cited by the text being read with similar discussions.

1.5.2 Requirement Analysis

After the literature review process is done, the in-depth requirement analysis process regarding the solution will begin. The requirement analysis includes understanding the user needs, deciding which literature that will be adopted, the technologies that will be used, as well as tools that will be used.

1.5.3 Data Collection

The data for catalogue will be taken from various sources on the internet such as existing e-commerce websites. The data that will be collected will be the image of the clothing item, the description of the clothing item, the color of the clothing item, the size chart of the clothing item, as well as the price of the clothing item.

1.5.4 Implementation

The data for this research is collected through a systematic literature review to establish theoretical foundations about fashion e-commerce challenges and conversational AI

opportunities, supplemented by empirical user testing to validate system effectiveness using the ResQue framework. For the product catalogue, data will be collected from various e-commerce websites through web scraping techniques, including clothing item images, descriptions, colors, size charts, and prices.

1.5.5 Testing

The testing process employs User Acceptance Testing (UAT) methodology to evaluate the chatbot's performance from the user perspective. The testing involves structured evaluation with actual users using the ResQue framework, which measures eight key indicators including recommendation quality, interaction adequacy, ease of use, usefulness, control/transparency, user attitudes, and behavioral intentions through a 5-point Likert scale questionnaire to assess the system's effectiveness in providing satisfactory fashion recommendations.

1.5.6 Analysis

The analysis phase will start after doing the testing process. In this process the author will observe the result of the chatbot.

1.6 Writing Systematics

In the writing systematics, the text is divided into five chapters in sequence to facilitate discussion and make it easier for readers to understand the text. The following is the writing systematics of the research results conducted:

a. CHAPTER I INTRODUCTION

This chapter contains a basic explanation of why this research was conducted. This chapter consists of several sections such as background, problem formulation, research objectives, research benefits, problem limitations, proposed solutions, research methods, and writing systematics.

b. CHAPTER II LITERATURE REVIEW

This chapter contains the basic theories used as a reference for fundamental knowledge in designing and conceptualizing the research, ensuring that this research is scientific.

c. CHAPTER III RESEARCH METHODOLOGY

This chapter contains the steps taken in conducting the research. This chapter includes explanations about the type of data used, the criteria for the success of the research, and the research methodology.

d. CHAPTER IV RESULT AND DISCUSSION

This chapter contains the results of the research conducted, the challenges encountered during the research, and the analysis of the results obtained.

e. CHAPTER V CONCLUSION

This chapter contains the conclusions drawn from the results of the previous chapter's research. It also includes recommendations aimed at similar research to improve future endeavors.

CHAPTER II

LITERATURE REVIEW

2.1 Literature Review

2.1.1 Origin of Clothing

Roach-Higgins & Eicher (1992) define clothing as a bodily enclosure with minimal physical alteration, a concept that has remained integral to human civilization since the Stone Age, approximately 300,000 years ago. Archaeologists at the Schöningen site in Germany discovered markings on bear bones that show how ancient hominins actively used bear skin to protect themselves against cold weather (Verheijen et al., 2023). Genetic researchers in 2010 revealed that modern humans, *Homo sapiens*, incorporated clothing into their daily lives around 170,000 years ago, basing their findings on the genetic analysis of divergence between clothing lice and head lice during this period (Toups et al., 2011).

As societies evolved, clothing transcended its purely functional role to reflect cultural, political, and economic conditions (Hsiao & Grauman, 2021). Wardaya et al. (2024) demonstrate how clothing serves as a marker of social status and individual identity throughout history. Changes in fashion often marked significant societal transitions; for example, during World War I (1914-1918), women abandoned restrictive corsets in favor of more practical, boyish flapper dresses and shorter hairstyles (A. Sharma, 2024). Economists also recognized clothing's role as an economic indicator. The hemline index from the 1920s revealed how skirt lengths functioned as an unexpected economic barometer: longer hemlines corresponded with economic downturns, while shorter styles emerged during periods of prosperity.

This phenomenon demonstrates how clothing functions not merely as a functional necessity but as a complex social and economic indicator. Throughout history, clothing has evolved from a basic survival need to become a powerful medium of personal and societal expression, setting the stage for its profound psychological impact in modern society. Building upon clothing's evolution from purely functional to socially significant, modern society has witnessed a further transformation in how individuals interact with and are affected by their clothing choices. In modern society, clothing transcends its basic function of covering the body. Individuals use it as a means of self-expression to achieve spiritual and psychological balance (Efremov et al., 2021). Additionally, people employ clothing as a form of disguise to transform their appearance and persona (Efremov et al., 2021).

Researchers have extensively documented how clothing influences human behavior and well-being. Wenderski et al. (2023) demonstrated through Canadian research that people use clothing as a coping mechanism to enhance self-esteem, mood, and self-comfort. Lee et al. (2020) discovered in their South Korean study that people primarily dress to satisfy themselves rather than others. In Malaysia, Cham et al. (2018) found that Generation Y particularly values uniqueness in clothing, actively seeking to differentiate themselves from society. Suganya et al. (2024) confirmed that clothing choices directly enhance mood, performance, and confidence.

Body image profoundly shapes women's clothing choices. Fernández-Bustos et al. (2019) discovered in their Spanish research that women report higher levels of body dissatisfaction compared to men. Social media exposure significantly influences this phenomenon: women aged 25-35 who spend more than two hours daily on social media demonstrate stronger pursuit of thinness, while those aged 14-24 who follow visual-centric social media accounts report higher levels of body dissatisfaction (Vall-Roqué et al., 2021). Women often use clothing to conceal perceived flaws and highlight desirable body features, which affects their self-esteem and confidence (Frith & Gleeson, 2008 as cited in Li et al., 2024)

Men also experience complex psychological effects related to clothing and body image. Media representations of the ideal male form, characterized by muscularity and low body fat, create significant pressure regarding body image. This pressure generates body dissatisfaction, reduces self-esteem, and inhibits open discussions about body image issues (Kaushik, 2024). Sung & Yan (2020) examined the relationship between self-esteem, body dissatisfaction, and clothing-related behaviors in Generation Y men. Their research revealed that concerns about muscle, height, and weight profoundly influence clothing choices, with weight emerging as the primary factor in clothing image avoidance. When experiencing body dissatisfaction, men strategically select clothing that conceals areas of bodily concern, managing their perceived physical inadequacies through sartorial strategies (Sung & Yan, 2020).

The psychological impact of clothing and its influence on body image perceptions significantly shape consumer behavior in clothing selection. As demonstrated above, individuals' clothing choices intertwine deeply with their psychological well-being, self-perception, and confidence levels. These psychological factors create an important foundation for understanding the practical criteria that consumers consider when making clothing purchase decisions.

2.1.2 Criteria to Choose Clothing Items

Consumers evaluate multiple physical attributes of clothing items when making purchase decisions, with different demographic groups prioritizing various characteristics differently (North et al., 2003). Research across different demographics has revealed distinct patterns in attribute prioritization.

KPMG (2019), a global organization of independent firms providing Audit, Tax and Advisory services, conducted a comprehensive survey that provides deeper insights into consumer preferences across multiple cities. Approximately 1,000 respondents from each city were surveyed on their key considerations when shopping for clothing items. Table 2.1 presents these findings, revealing that Price/Value, Size/Fit, Quality, Style, and Convenience of Purchasing emerge as the most important factors globally.

Table 2.1 Survey Questionnaire Results

	All	Hongkong	London	New York	Shanghai	Tokyo
Price/Value	67%	74%	78%	71%	37%	74%
Size/Fit	55%	56%	69%	60%	35%	58%
Quality	54%	55%	60%	58%	49%	44%
Style	41%	38%	49%	48%	39%	33%
Convenience of purchasing	32%	38%	33%	33%	31%	25%
Materials	31%	37%	31%	23%	27%	35%
Brand	24%	21%	17%	25%	32%	24%
Ability to or the ease of return/refund	20%	18%	24%	24%	25%	12%
Shopping experience	14%	21%	12%	17%	16%	4%
Safety	12%	17%	3%	8%	20%	12%
Personalization	9%	12%	4%	5%	20%	3%
Country of origin	9%	14%	5%	8%	10%	7%
Environmental friendliness concept/message of the brand	8%	6%	9%	6%	16%	3%
Pretty packaging	6%	6%	1%	3%	17%	1%
Transparency of manufacturing practice	5%	4%	3%	5%	10%	2%
Promotion by celebrity/KOL	5%	4%	2%	4%	11%	1%
Other	1%	0%	2%	2%	-	1%

Source: <https://assets.kpmg.com/content/dam/kpmg/cn/pdf/en/2019/01/sustainable-fashion.pdf>

These findings highlight that while specific attribute rankings vary by city, there is strong global consistency in valuing price, fit, quality, and style as primary considerations in clothing

purchases. Beyond global statistics, regional studies provide additional insights into how cultural and demographic factors influence clothing choices.

A. Sharma & Jain (2017) demonstrate through their Indian study how age significantly influences clothing attribute priorities. Their research shows that people between 21-25 years old prioritize price above all other factors. Those aged 26-30 years old place highest value on style and sex-appropriateness, reflecting their heightened awareness of social perception. Meanwhile, individuals aged 31-35 years old prioritize comfort in their clothing selections.

Wutichai Namjaiprasert (2015), focusing on male shopping behavior in Thailand, discovered that men primarily value style and quality when selecting clothing items. Similarly, research in China Ning (2012) revealed that consumers place high importance on both clothing style and material quality.

Arubayi & Awowede (2024) conducted research on frameworks for understanding factors that influence clothing choices. They identified social and psychological factors as key elements that people consider when selecting clothing items. These social and psychological factors encompass several components: culture, as different cultures hold varying perceptions about appropriate attire; gender, which plays a significant role in clothing selection through cultural, religious, and biological influences, while different clothes are often designed specifically for different genders, some garments may appear similar across genders depending on cultural contexts; occupation, since a person's job significantly impacts their clothing decision; trends, as desire to follow popular styles represents an important psychological motivator; occasion, where specific events determine appropriate clothing selection; and body structure (figure), defined as a person's height and body proportions, which plays a crucial role in clothing choices.

In Indonesia specifically there are also a certain pattern that people consider when they want to purchase a clothing item. Research by Setiani (2016) stated that the most important factors for people when buying a clothing item are material quality, the design of the clothing, the fashion model of the clothing, the price of the clothing, the comfort of the clothing, size variation, and color variation respectively.

Purwaningtyas & Rahadi (2021) stated that clothing attributes that affect people's online clothing purchase decisions are price, product design/style, product quality, and product variety. Adrianti et al. (2021) identified brands, design, color, price, and quality as key decision factors. Although this research specifically focused on batik clothing, these attributes are

widely discussed in broader fashion literature and align with general consumer behavior in fashion retail.

According to KPMG global survey, the top five universal factors are: Price/Value (67% of respondents globally), Size/Fit (55%), Quality (54%), Style (41%), and Convenience of Purchasing (32%). These findings align with other research showing that consumers across different cultures consistently prioritize style, quality, and price in their clothing decisions.

Notably, while younger consumers (21-25 years) tend to prioritize price above all else, those in their late twenties focus more on style and appropriateness, and individuals in their thirties emphasize comfort. These universal criteria maintain their importance even as the retail landscape transforms dramatically, shifting from traditional brick-and-mortar stores to digital marketplaces that offer new ways of purchasing clothing.

Analysis of these various studies reveals consistent patterns in clothing purchase decisions across global, regional, and Indonesian studies, which are price, style/design, quality, fit/size, and comfort. Although the order of priority may vary depending on age group, gender, or cultural background, these attributes remain central to consumer decision-making. Younger consumers tend to focus more on price, those in their late twenties prioritize style and appropriateness, while consumers in their thirties emphasize comfort. These universal criteria maintain their relevance as shopping shifts from physical store to digital platforms.

2.1.3 E-Commerce

The rise of e-commerce has fundamentally transformed retail channels, reshaping how consumers interact with fashion brands and making purchase decisions. Sudaryono et al. (2020) define e-commerce as websites providing tools for online transactions, facilitating shopping or selling products through "get and deliver" services. This digital shift began with the introduction of Electronic Data Interchange (EDI) for business-to-business transactions in the 1960s (Taher, 2021), and since then, e-commerce has grown exponentially, revolutionizing shopping habits worldwide.

This widespread adoption and transformation of shopping habits is largely due to the numerous advantages e-commerce offers consumers, significantly enhancing their purchase experience. Taher (2021) highlights how e-commerce provides flexibility and convenience, enabling consumers to order items from anywhere at any time. Furthermore, Ahmad et al. (2020) note that competitive pricing and discounts across retail stores on e-commerce platforms often motivate customers to choose online purchases over offline shopping.

Current data demonstrates the remarkable scale of e-commerce adoption globally, with approximately 2.64 billion users worldwide, representing about 33% of the world's population. Indonesia exemplifies this remarkable growth trajectory in the e-commerce sector, boasting about 58.6 million users in 2023, with projections reaching 93.3 million by 2028. Nurhayati-Wolff (2023) reports that Indonesia leads Southeast Asia's e-commerce market, valued at approximately 62 billion dollars, establishing the country as a significant player in the regional digital economy.

Research reveals distinct gender-based patterns in Indonesia e-commerce usage, with women demonstrating significantly higher engagement levels. Rahmawati (2024) in their research found that 57% of women respondents conduct 3 to 5 transactions per month, while only 47% of men respondents complete fewer than 3 transactions monthly. This gender disparity extends to annual purchasing behavior, as Rania et al. (2024) documented that women purchase an average of 45 products per year compared to 42 products for men, indicating that e-commerce platforms have become particularly integral to women's shopping behaviors and preferences.

Within this booming Indonesian e-commerce landscape, clothing and footwear dominate online sales (Nurhayati-Wolff, 2023). This reflects both the popularity of fashion products, and the convenience online shopping provides for apparel discovery and purchase. This dominance of fashion categories in e-commerce underscores the significant role digital platforms play in modern fashion retail, creating both opportunities and challenges for consumers and businesses in this space.

2.1.4 Challenges in Fashion E-Commerce

Despite the numerous advantages and rapid growth of e-commerce, online fashion shopping presents significant challenges that continue to impact customer satisfaction and business sustainability. These challenges stem primarily from a fundamental limitation: consumers' inability to physically try on items before purchase (Ibrahim et al., 2024), which creates a cascade of problems affecting the entire online fashion shopping experience.

The most prominent issue in online fashion retail is sizing and fit, which research consistently identifies as the leading cause of product returns. (Bozzi et al., 2022) found that size and fit mismatches are the primary reasons customers return clothing purchases, with apparel becoming the most frequently returned item category in online retail. The scale of this problem is substantial, with return rates in Southeast Asia reaching up to 20% due to sizing and style mismatches (Arora et al., 2022; Bozzi et al., 2022).

Further illustrating the severity of this challenge, research by Wojciechowski et al. (2023) reveals that over 64% of customers who returned items described sizing mismatch as their primary reason. Another 19% resorted to buying multiple versions of the same product to find the right fit. This behavior indicates not only customer frustration but also significant inefficiencies in online fashion retail systems that fail to provide adequate sizing guidance and fit prediction capabilities.

These sizing challenges are often intensified by incomplete product descriptions that lack essential details, leading to consumer frustration and misunderstanding (Deshmukh, 2020). Such insufficient product information frequently causes customers to abandon their intended purchases altogether (Amsl et al., 2023). The absence of comprehensive product details, including material quality, fit guidance, styling suggestions, and contextual usage information, creates uncertainty that prevents confident purchase decisions.

This issue of incomplete product descriptions contributes to a broader information gap that becomes particularly problematic in fashion e-commerce. Consumers require a detailed understanding of how products will look, feel, and fit before making purchase commitments. Unlike other product categories where specifications can be objectively evaluated, fashion items require subjective assessment that traditional product descriptions often fail to support adequately.

Furthermore, the lack of personalization in online platforms makes it difficult for users to find products aligned with their preferences, resulting in disengagement and lower customer satisfaction (Tarmizi & Lidiana, 2024). Current e-commerce platforms often rely on generic filtering mechanisms that fail to capture the nuanced and multifaceted nature of fashion preferences, including individual body types, lifestyle requirements, cultural considerations, and personal style evolution.

This personalization deficit is particularly challenging in fashion contexts, where individual preferences vary significantly based on body characteristics, cultural background, lifestyle demands, and personal aesthetic preferences. Traditional filtering systems cannot effectively accommodate the complex interplay of factors that influence fashion suitability and appeal, leading to recommendations that feel irrelevant or inappropriate to users.

These challenges have persisted despite significant technological advances and increased investment in e-commerce platform development. The fundamental issues of fit accuracy, information adequacy, and personalization continue to create barriers between consumer needs and system capabilities, suggesting that current approaches may be addressing symptoms rather

than underlying causes of customer dissatisfaction in online fashion retail. The persistence of these problems across different markets, platforms, and technological implementations indicates that systemic changes in approach may be necessary to address the core challenges preventing online fashion shopping from achieving the satisfaction levels consumers experience in physical retail environments.

2.1.5 Recommendation Systems

Recommendation systems have become fundamental components of modern e-commerce platforms, designed to help users discover products that match their preferences and needs. These systems analyze user behavior, product characteristics, and interaction patterns to generate personalized suggestions that enhance the shopping experience and improve business outcomes. In fashion e-commerce, however, recommendation systems face unique challenges due to the highly subjective nature of style preferences and the critical importance of physical fit considerations.

Most fashion recommender systems rely on Collaborative Filtering (CF) approaches, which utilize historical user behavior data to generate product suggestions (Abdul Hussien et al., 2021). These systems operate on the principle that users with similar past behaviors will have similar future preferences, analyzing patterns in purchase history, browse behavior, and rating data to identify products that similar users have found appealing.

However, these systems face the "cold start" problem, making it challenging to generate suitable recommendations for new users or recently added items that lack sufficient historical data (Widayanti et al., 2023). This limitation proves particularly problematic in fashion e-commerce, where new users represent a significant portion of platform traffic and require immediate value demonstration to encourage continued engagement. The cold start problem creates a challenging cycle where both new users and new products suffer from inadequate recommendation quality, potentially leading to reduced user satisfaction and lower product discoverability.

More importantly, when addressing fit issues, these systems do not take into account the user's body type (Kaur et al., 2021). This represents a fundamental gap in current fashion recommendation approaches, as physical characteristics such as height, weight, body shape, and proportions significantly influence how clothing items will fit and appear on individual users. The absence of body-type considerations means that recommendation systems cannot effectively address the primary source of customer dissatisfaction in online fashion shopping, which is sizing and fit accuracy.

This limitation becomes particularly significant given the documented high return rates and customer frustration associated with poor fit in online fashion purchases. Without incorporating physical attributes into recommendation algorithms, systems cannot provide the personalized guidance that would help users select items more likely to fit appropriately and meet their individual needs.

Recent advancements in Hybrid Systems and Deep Learning have shown improvements, but these models are often data-intensive and still struggle to handle conversational nuances and the diversity of real-world body types (Almahmood & Tekerek, 2022; Kaur et al., 2021; Tran et al., 2020). While these sophisticated approaches offer enhanced capabilities compared to traditional collaborative filtering methods, they introduce new challenges related to computational requirements and data dependency.

The data-intensive nature of these advanced models creates barriers for implementation, particularly for platforms with limited computational resources or insufficient historical data. More critically, these systems continue to struggle with the complexity of human communication about fashion preferences and the wide diversity of body types that characterize real-world users, indicating that technological sophistication alone may not address the fundamental challenges in fashion recommendation.

Despite these documented limitations in current recommendation systems, the underlying infrastructure of e-commerce platforms continues to expand, generating increasingly complex data environments that both enable and constrain recommendation system development. The high volume of fashion retailers and massive user base in e-commerce generates vast amounts of data through online platforms (Fernando & Fernandes Andry, 2020). Shweta & Hemlata (2024) note that e-commerce platforms collect diverse data types, including transaction records, business activity logs, click-stream data, video data, and voice data. These platforms generate both opportunities and challenges through their vast data repositories, continuously producing valuable information about consumer behavior, market trends, and product performance.

However, organizations require specialized tools and techniques to collect and analyze this complex, high-volume data effectively to support recommendation system functionality. The dependency on large datasets creates additional barriers for developing effective recommendation systems, particularly for platforms seeking to implement sophisticated algorithms that can address the personalization and fit accuracy challenges inherent in fashion e-commerce. As businesses seek to harness these valuable insights for recommendation

systems, they have developed various data extraction and processing techniques to support their algorithmic approaches.

2.1.6 Web Scraping

Computer software extracts information from websites such as e-commerce platforms through web scraping or web crawling. These programs mimic human internet navigation by either simulating full web browsers like Mozilla Firefox or Internet Explorer or by directly engaging with websites through low-level Hypertext Transfer Protocol (HTTP) requests (Khder, 2021). (Sirisuriya, 2015) defines web scraping as a technique that transforms unstructured website data into structured database information for storage and analysis.

Various sectors employ web scraping to facilitate data extraction and analysis from the web. N. Sharma & Agnihotri (2024) demonstrate how e-commerce companies use web scraping as a tool for price monitoring on platforms like Amazon. Beyond price tracking, organizations utilize web scraping to gather comprehensive product information, including descriptions, specifications, and reviews. Shreekumar et al. (2022) highlight how web scraping helps analyze user behavior by tracking browsing patterns, purchase history, and product preferences.

Developers rely on specialized tools and libraries to implement web scraping effectively. Beautiful Soup has emerged as one of the most widely adopted technologies in this field. Zheng et al. (2015) describe Beautiful Soup as a Python library built on an HTML/XML parsing engine that retrieves, processes, and modifies data within the Document Object Model (DOM) tree of webpages. This library excels at locating specific document components, enabling element extraction based on tags, classes, identifiers, attributes, or text content. Farias et al. (2024) note how this functionality streamlines selective data extraction, improving efficiency.

Despite Beautiful Soup's user-friendly nature, developers face certain challenges. Thivaharan et al. (2020) identify longer processing times compared to alternative technologies like RegEx as a significant drawback. Chen (2024) notes that while Beautiful Soup handles static websites effectively, it sometimes struggles with more dynamic or complex web pages.

While Beautiful Soup specializes in static web scraping, Selenium expands possibilities through browser automation. Originally developed for web application testing, Selenium controls browser operations through its WebDriver package, simulating human-like interactions (Fatima et al., 2021). Sai Lakshmi et al. (2024) emphasize Selenium's effectiveness in managing dynamic content through techniques such as waits and delays, ensuring elements load properly before interaction. Through its robust programming interface, Selenium enables

automated website navigation and interaction, allowing diverse actions such as button clicking, form completion, and data extraction.

K. Sharma & Borkar (2024) advocate combining BeautifulSoup and Selenium to create more robust web scraping solutions, particularly for websites with dynamic content, automated navigation, and pagination requirements. The data collected through these web scraping tools plays a vital role in building comprehensive datasets for AI training, establishing the foundation for developing and training AI models.

2.1.7 Artificial Intelligence

Kanade (2022) defines AI as a technology comprising systems and algorithms that enable machines to think and act like humans. Du-Harpur et al. (2020) expand this definition, describing AI as machines' ability to converse, reason, and function independently in both known and unknown situations, mimicking human behavior. Organizations that implement AI ethically can enhance human life quality, boost productivity, and simplify daily living (Ali et al., 2023).

The broad capability of AI results in its multiple uses in various fields. Medical professionals use AI to predict cardiovascular disease risk (Briganti & Le Moine, 2020). Educational institutions implement AI to create personalized and interactive learning experiences, develop adaptive learning systems, and automate essay grading (Baidoo-Anu & Owusu Ansah, 2023). E-commerce companies employ AI to improve Customer Relationship Management (CRM), enhance customer service, and achieve sales targets (Soni, 2020).

Generative AI represents one of AI's most significant breakthroughs, enabling systems to generate diverse content types, including text, images, and music, by learning from existing data without replicating it (Yehia, 2024). This advancement creates new challenges in effective human-AI communication, leading to the emergence of prompt engineering as a crucial field in AI development.

2.1.8 Prompt Engineering

Prompt engineering has emerged as a crucial field in Generative AI. Prompt engineering in generative AI involves writing, refining, and optimizing prompts to enhance interaction quality (Park & Choo, 2024). Several key elements determine prompt effectiveness, requiring careful consideration and implementation.

Effective prompting begins with fundamental elements that shape LLM responses. Clear and specific content eliminates ambiguity, helping LLMs generate concise and insightful responses. Context enhances prompt effectiveness by directing LLMs to produce more specific

and appropriate responses aligned with particular fields. Tabatabaian (2024) emphasizes the importance of avoiding leading or biased language to maintain objectivity and generate unbiased results.

Deldjoo (2023) identifies three essential components in prompt construction. Task description provides detailed instructions to enhance model accuracy. Feature description delivers more specific task guidance. Domain knowledge integration helps improve model understanding and precision by incorporating specific expertise.

Dai et al. (2023) outlines four critical input components for prompt design. The question component represents the problem the model aims to address. The thought component encompasses conceptual and computational reasoning for the task. The action component identifies the AI's chosen approach for addressing the current task. Action input serves as the model's input argument.

These input components generate three outcome components. Observation represents the model's output that influences subsequent decision-making steps. Thought displays findings from the AI's analysis of the Observation. The final answer emerges from the outcome evaluation. When AI determines that current results address the initial question adequately, it provides the final answer; otherwise, it continues analysis and invokes additional functions.

This structured approach to prompt engineering and response generation has transformed how humans interact with AI systems. Cid et al. (2024) demonstrate that well-constructed prompts significantly enhance AI system performance. Park et al. (2023) quantified this improvement through their study of conversational AI technology, comparing four query methods and revealing an average 11.46% performance improvement over unmodified queries. These advancements have proven crucial in developing more sophisticated and context-aware AI applications, with chatbots emerging as one of the most successful implementations. As Dai et al. (2023) demonstrate, this systematic approach to input components and outcome generation has fundamentally shaped how modern chatbots process queries and generate responses, leading to improved understanding of user intent and more relevant information delivery.

2.1.9 Chatbot

Building upon this principle of AI and prompt engineering, chatbots are a practical implementation of these technologies in real-world applications. Developers design chatbots to interact as smart entities during conversations through either text or voice (Khanna et al., 2015). Researchers trace the origins of chatbots to ELIZA, which Weizenbaum developed in

1966 using pattern machine algorithm (Weizenbaum, 1996 as cited in Adamopoulou & Moussiades, 2020).

Adamopoulou & Moussiades (2020) identify six types of chatbot classification in their paper:

- a. "Knowledge" - categorizes chatbots based on their access to or the amount of training data.
- b. "Service Provided" - classifies chatbots based on the user interaction levels and task requirements.
- c. "Goals" - categorizes chatbots according to their primary objectives.
- d. "The Input Processing and Response Generation Method" - classifies chatbots based on their technical approach to process inputs and generate responses.
- e. "Human-Aid" - identifies chatbots that incorporate human computations in at least one element.
- f. "The Build Method" - categorizes chatbots based on their development platform whether open-source or closed platforms.

Various industries have widely adopted chatbots to enhance communication, efficiency, and customer engagement. E-commerce platforms particularly benefit from chatbot integration; these AI-powered systems deliver real-time customer support, generate personalized recommendations, and manage orders efficiently (Thatavarthi, 2023). Supporting this claim, Khansa & Sutabri (2024) found that implementing AI in e-commerce can increase customer satisfaction by 20% and reduce response time by 15%.

However, despite the documented potential benefits of chatbot implementation in e-commerce, current chatbot implementations in fashion retail often demonstrate limited conversational depth, typically providing generic responses rather than engaging in meaningful dialogue (Aslam, 2023). This limitation suggests that while chatbot technology has proven effective in general e-commerce applications, the specific requirements of fashion consultation, which often involve subjective aesthetic judgments, personal style preferences, and body-type considerations, present unique challenges that current implementations have not yet adequately addressed.

To address these limitations, this research adopts a two-phase dialogue structure, in which the system first focuses on style recommendation before moving to product recommendations. This staged approach is grounded in Cognitive Load Theory (Sweller, 1988), which states that presenting too much information at once can overwhelm users and

reduce decision-making quality. By starting with style preferences, the system reduces initial complexity, ensuring that users can focus on defining their fashion taste before showing specific items.

From consumer behavior perspective, this approach mirrors the offline shopping behavior where users can get tailored advice and recommendations based on individual customer needs and preferences, which can enhance the overall shopping experience (Pandey & Rao, 2024). Research in digital retail decision-making shows that breaking down the process reduces choices overload (Chernev et al., 2012), a common issue in online marketplace that can lead to decision fatigue (Peng et al., 2021)

Furthermore, this design follows the Progressive Disclosure principle in user interface design (Springer & Whittaker, 2018), where information is revealed incrementally to avoid overwhelming users while allowing them to access more detailed information as needed. In the context of fashion recommendations, this means aligning on general aesthetic direction before introducing detailed product recommendations. Prior research in recommender systems (Knijnenburg et al., 2012) has shown that having preference elicitation process has a substantive impact on user experience and recommendation accuracy. By integrating these principles, the chatbot not only improves logical flow of interaction but also enhances the overall user experience in making fashion decisions.

2.2 Similar Research

Recent studies in fashion recommendation systems show a gradual shift from basic approaches to more advanced solutions. Early research mainly used collaborative filtering and simple rule-based chatbots, but these methods had some notable challenges - they needed lots of user data to work well and struggled with new users who hadn't made many purchases yet. More recent work has started exploring ways to combine different technologies, such as image recognition and conversational AI, to help overcome these limitations. Table 2.2 shows several studies that illustrate this development, demonstrating how researchers are experimenting with newer approaches like deep learning models and AI chatbots to create recommendation systems that might better understand what users are looking for and provide more helpful suggestions, even when there isn't much user history available.

Table 2.2 Studies on Fashion Recommender System and Chatbot Technology

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
1.	Fashion Recommendation System	Vinitha et al. (2024)	Collaborative Filtering, Matrix Factorization	Traditional collaborative filtering approach for fashion recommendations	Enhanced user engagement and satisfaction in e-commerce through collaborative filtering; however, the system requires extensive historical user-item interaction data and struggles with the cold start problem for new users without purchase history
2.	Improving Recommender Systems using Hybrid Techniques of Collaborative Filtering and Content-Based Filtering	Widayanti (2023)	Collaborative Filtering, Content-Based Filtering, Hybrid Approach	Traditional Recommendation system addressing cold start limitations	Traditional collaborative filtering suffers from the cold start problem, where the system does not have any form of data on new users and new items. Collaborative

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
					filtering requires extensive user-interaction data to make accurate recommendation
3.	Understanding the usability of retail fashion chatbot: Evidence from customer expectations and experiences	Aslam (2023)	Rule-based chatbots, Declarative responses, FAQ systems	Traditional chatbot implementation in fashion retail	The existing literature suggests that chatbots tend to provide automated and generic responses that may not fully address complex customer inquiries. Rule-based chatbots provide pre-programmed responses and lack conversational depth and personalization capabilities
4.	Fashion Recommendation System	K et al. (2022)	CNNs, Deep Learning, Matching Clothes		The model achieved an accuracy of

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
			Recommender Algorithm		around 86% for clothing labelling, the system classifies clothing types and identifies colors from images, a wardrobe feature allows users to store images of their clothes. The system recommends clothes based on user wardrobe images, it utilizes machine learning and deep learning for clothing classification, the aim is to ease decision-making for users with little fashion sense
5.	A Literature Survey of Recent Advances in Chatbots	Caldarini et al. (2022)	Rule-based vs Basic AI chatbots comparison, Traditional NLP	Comprehensive analysis of chatbot limitations	Chatbots are less able to understand conversational

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
					context and emotional linguistic cues compared to humans. Traditional rule-based approaches show significant limitations in handling complex, context-aware conversations particularly in personalized domains
6.	Generative AI-based Style Recommendation Using Fashion Item Detection and Classification	Kalinin et al. (2024)	YOLOv8 CNN, GPT-4.0 Vision, OpenAI API	Two-Component Style Recommendation System: (1) Uses YOLOv8 CNN for clothing item detection and cropping from input images (selfies/studios photos), (2) Employs GPT-4.0 Vision model via	GPT-4.0 Vision and Gemini 1.5 Pro achieved average score of 2.8 vs Claude 3-Opus at 2.3; YOLOv8 achieved 70% precision, 74.5% recall, 76% mAP50; System successfully generated comprehensive fashion advice

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
				OpenAI API to generate comprehensive fashion advice including current style analysis and personalized recommendations	including current style analysis and personalized recommendations
7.	From traditional recommender systems to GPT-Based chatbots: a survey of recent developments and future directions.	Al-Hasan et al. (2024)	Comparison between GPT-based conversational systems and traditional recommendation approach	Comparative analysis of GPT-based vs traditional recommendation approaches	GPT-based chatbots offer recommendations that are more contextually relevant and engaging than traditional approaches. They can better understand user intentions and deliver personalized suggestions. Potential to address cold-start problems through conversational data collection

No	Title	Author and Year	Recommendation Method/Techniques	Approach	Key Finding
8.	Chatbots as Conversational Recommender Systems in Urban Contexts	Kucherbayev et al. (2017)	Conversational AI framework, Online user feedback integration	Interactive recommendation system with real time learning capabilities	Framework can make effective use of online user feedback, improving personalized recommendations over static model by 25% after asking only 2 questions. Demonstrates superiority of conversational approaches over traditional static systems

The analysis of existing studies reveals a clear evolution in fashion recommendation technologies, progressing from traditional collaborative filtering approaches to more sophisticated AI-driven systems. Vinitha et al. (2024) and Widayanti et al. (2023) demonstrated the foundational role of collaborative filtering and hybrid techniques in fashion e-commerce, establishing the baseline for personalized recommendations while highlighting the inherent data dependency challenges. Aslam (2023), K et al. (2022), and Caldarini et al. (2022) illustrate the significant limitations of conversational approaches, particularly in chatbot implementations where rule-based systems provide automated, generic responses lacking conversational depth and personalization capabilities, with traditional NLP methods struggling to understand contextual and emotional linguistic cues. The research landscape shows a pivotal shift toward more advanced methodologies, with Kalinin et al. (2024), Al-Hasan et al. (2024) representing the emerging paradigm of generative AI and GPT-based systems that demonstrate better contextual understanding compared to traditional approaches, and showing enhanced user engagement capabilities.

Collectively, these studies establish a comprehensive foundation for understanding current fashion recommendation and conversational AI technologies, spanning from matrix factorization and content-based filtering to advanced neural networks, YOLOv8 CNNs, and large language models. The progression reveals increasing sophistication in addressing user personalization needs, with newer conversational approaches showing measurable improvements up to 25% in recommendation quality after minimal user interaction, demonstrating the advantages of dynamic systems over static models. While traditional methods have proved effective in established e-commerce environments with sufficient user data, the literature indicates growing recognition of the need for more adaptive, conversational systems capable of handling complex customer inquiries and providing comprehensive style analysis. However, despite these technological advancements, significant gaps remain in integrating body-aware personalization with conversational AI systems, particularly in addressing cultural sensitivity and physical attribute considerations that are crucial for fashion recommendations. This body of research provides essential context for understanding both the achievements and limitations of current fashion recommendation methodologies, highlighting the need for systems that can effectively conversational capabilities with comprehensive body-type considerations to address the persistent challenges of poor fit accuracy in online fashion retails.

2.3 Research Gap Analysis

The comprehensive review of existing literature reveals several critical research gaps that this study aims to address. No existing research explicitly combines advanced conversational AI capabilities with comprehensive body-aware personalization that includes height, weight, body shape, and skin tone considerations for fashion recommendations. While Kalinin et al. (2024) achieved success with GPT 4.0 Vision and Al-Hasan et al. (2024) demonstrated GPT-based chatbot potential, their approaches focus primarily on general style advice without a structural approach to incorporating physical characteristics. Additionally, no research has implemented structured two-phase dialogue systems that replicate in-store personal stylist consultations in digital environments. Current chatbot implementations identified by Aslam (2023) provide generic responses lacking conversational depth, while existing conversational systems like those by Kucherbaev et al. (2017) do not address fashion-specific consultation patterns.

Furthermore, while traditional collaborative filtering studies by Vinitha et al. (2024) and Widayanti et al. (2023) acknowledge the cold start problem, no research provides validating solutions for overcoming this limitation in fashion domains without requiring historical data. Al-Hasan et al. (2024) suggests theoretical potential for conversational data collection but lacks practical implementation. The literature also reveals that no existing research demonstrates the complete pipeline from conversational AI input to actual product retrieval from real inventory systems. While studies show either conversation quality improvements or recommendation accuracy separately, none validate the practical translation of natural language preferences into specific product suggestions from commercial databases. Finally, no research provides practical solutions for incorporating cultural considerations into AI-driven fashion recommendation systems, despite documented importance of cultural diversity in fashion preferences, with existing systems operating on standardized parameters that fail to account for regional fashion concepts and cultural interpretations.

This research fills these significant gaps by implementing OpenAI's large language model with structured prompt engineering that incorporates comprehensive body-type considerations into personalized fashion recommendations through natural language dialogue, developing and validating a two-phase dialogue approach that mimics professional stylist consultation processes, demonstrating how conversational AI can effectively generate personalized fashion recommendations for new users without dependency on purchase history, implementing and testing a complete system that connects conversational insights with actual product inventory through keyword extraction mechanisms and category-based scoring algorithms, and developing a culturally sensitive recommendation system specifically tailored for the Indonesian fashion market that incorporates local fashion preferences and cultural considerations into the AI prompt engineering framework.

CHAPTER III

RESEARCH METHODOLOGY

This chapter outlines the methodology employed in this research, providing a comprehensive framework for the development of the body-aware fashion recommendation chatbot. Building directly on the identified problems of poor fit accuracy, lack of personalization, and cold-start problems in fashion e-commerce, this methodology establishes a systemic approach for developing a body-aware conversational AI solution.

The research follows the waterfall methodology for software development, where each process is completed sequentially before proceeding to the next stage, avoiding process overlap (DEMİRAG et al., 2023). The waterfall methodology was selected for this research because it provides a systematic approach essential for developing AI-driven systems which includes this step: (1) Requirement Analysis, (2) Design, (3) Implementation, and (4) Testing. This approach is particularly suitable for academic research, as it supports clear documentation, stable requirements, and measurable deliverables that align with thesis milestones. It also reduces the likelihood of mid-project scope changes, ensuring the project remains focused on predefined objectives and is completed within the timeframe available. Figure 3.1 illustrates the process flow of the waterfall methodology used in this research.

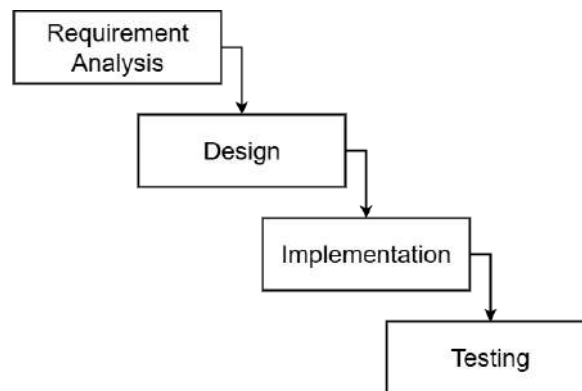


Figure 3.1 Waterfall Methodology

3.1 Requirement Analysis

The requirements analysis is conducted through a comprehensive literature review to establish the theoretical foundation for developing a body-aware conversational AI chatbot. This phase directly addresses the identified research gaps, particularly the need for fashion recommendation systems that can function effectively without extensive purchase history data while incorporating physical attributes into the recommendation process.

This phase aims to understand the challenges consumers face during online shopping, identify user needs for a body-aware fashion recommendation chatbot, and recognize research gaps that the proposed system will address. The requirement analysis process involves determining the key indicators and variables for measuring system effectiveness, as well as establishing data collection methodology that will be used for this research.

3.1.1 Determination of Research Indicators and Variables

Building on the comprehensive literature review and directly addressing the three main research objectives, this research seeks to:

- a. Create a chatbot that understands and interprets user fashion preferences, including style, color, size, and physical characteristics.
- b. Incorporate body-type considerations such as height, weight, body shape, and skin tone into the recommendation process through prompt engineering.
- c. Evaluate the chatbot's effectiveness in providing relevant, trustworthy, and user-friendly recommendations.

To systematically evaluate the achievement of these objectives, this study adopts the ResQue framework (Pu et al., 2011) specifically designed for evaluating conversational recommendation systems. This framework was selected because it comprehensively addresses the key challenges identified in fashion e-commerce: recommendation relevance, user interaction quality, and system transparency, all critical factors in addressing the cold start problem and body-aware personalization objectives established in Chapter 1.

Unlike traditional e-commerce evaluation methods that focus on click-through rates and purchase completion, ResQue evaluates the conversational interaction quality, recommendation explanation effectiveness, and user control, all critical factors for addressing the body-aware personalization objectives and cold start problems in fashion recommendation systems. Based on these research objectives and the selected evaluation framework, the following indicators and variables have been identified to guide the evaluation process:

a. Research Indicators

The research indicators represent the key performance dimensions that will be measured to assess the system's effectiveness in addressing the specific challenges in fashion e-commerce:

1. **Quality of Recommended Items:** Demonstrates how effectively the system provides fashion recommendations that match user interests, attractiveness, and personal context requirements. This directly addresses the challenges of personalization where

existing systems fail to provide relevant suggestions without an extensive purchase history.

2. **Interaction Adequacy:** Measures the extent to which the system facilitates adequate communication for users to express and revise their fashion preferences. This indicator evaluates the system's ability to overcome the cold start problem through natural language dialogue rather than requiring historical purchase data.
3. **Interface Adequacy:** Measures how sufficiently the system interface provides necessary information for users to make informed decisions about fashion recommendations. This addresses the incomplete product descriptions challenge in online fashion retail.
4. **Perceived Ease of Use:** Demonstrates how easily users can learn, navigate, and interact with the recommendation system. This indicator evaluates whether the conversational approach reduces the complexity barriers associated with traditional filtering systems.
5. **Perceived Usefulness:** Measures how effectively the system helps users find ideal fashion products that meet their needs. This evaluates the practical value of the conversational AI approach in supporting fashion discovery and selection processes.
6. **Control/Transparency:** Measures the extent to which users feel in control of the recommendation process and understand the reasoning behind product suggestions.
7. **User Attitudes:** Demonstrates the level of user satisfaction, confidence, and overall sentiment toward the recommendation system. This indicator assesses whether the body-aware approach successfully builds user trust and confidence.
8. **Behavioral Intent:** Measures users' willingness and intention to use the recommendation system in the future and make purchases again based on its suggestions. This evaluates the commercial viability of the proposed solution.

b. **Research Variables**

The research variables operationalize the indicators into measurable constructs that can be assessed through user evaluation, with each variable directly addressing specific problems in fashion e-commerce:

1. **Recommendation relevance to user interests:** This variable directly addresses the personalization challenge where existing systems fail to provide relevant suggestions without extensive purchase history. It measures the degree to which recommended items align with user fashion preferences and personal style, evaluating the system's

ability to overcome the cold start problem through conversational AI rather than collaborative filtering approaches.

2. Adequacy of preference expression mechanisms: This variable evaluates the system's capacity to collect user preferences through natural language dialogue, addressing the challenge of requiring extensive historical data for effective recommendations. It assesses the extent to which the system provides sufficient ways to communicate fashion preferences and body-type information through conversational interaction.
3. Sufficiency of interface information: This variable directly addresses the incomplete product descriptions challenge in online fashion retail. It measures how clearly and comprehensively the system presents product information and recommendations to support user decision-making in the fashion selection process.
4. System usability perception: This variable assesses how easily users can interact with the conversational AI system to express preferences and receive personalized fashion recommendations, evaluating whether the proposed approach reduces interaction complexity compared to traditional filtering systems.
5. Effectiveness in finding ideal products: These variable measures how successful the system is in helping users discover fashion items that match their style preferences and body-type considerations, directly addressing the research objective of incorporating physical attributes into recommendations.
6. User control and understanding: This variable evaluates the extent to which users feel they have control over the recommendation process and comprehends how their physical attributes influence product suggestions, addressing the transparency concerns highlighted in the literature review.
7. Overall user satisfaction: These variable measures users' general satisfaction with the recommendation system and their confidence in the suggested fashion items, evaluating the overall effectiveness of the body-aware conversational AI approach.
8. Intention for continued usage: This variable assesses users' willingness to use the body-aware conversational AI system again and their likelihood to make purchases based on its recommendations, evaluating the commercial viability and long-term sustainability of the proposed solution.

3.1.2 Data Collection

Following the establishment of the measurement framework, the data collection process is designed to gather comprehensive information about user needs and system requirements.

The data for this research is collected through a systematic literature review of similar research presented in Chapter II, supplemented by empirical user testing to validate theoretical foundations.

The literature review methodology involves systematically examining relevant publications and extracting key information about current challenges in fashion e-commerce, limitations of existing recommendation systems, and opportunities for conversational AI integration. This systematic approach ensures that subsequent development phases are supported by evidence-based user needs and established research findings, directly addressing the research gaps in fashion recommendation systems.

3.2 Design

The design phase follows the identification of user needs and requirements, translating the theoretical foundation established in the requirement analysis into practical system architecture. During this phase, the complete system design is developed, encompassing system architecture, database schema, interface design, and interaction flow. To clarify the structure and flow of the system, several diagrams are created, including use case diagrams, activity diagrams, system architecture diagram, and database schema.

3.2.1 Use Case Diagrams

Use Case diagrams represent what will be processed by a system and its components (Setiyani, 2021). A Use Case diagram visualizes the interaction between an actor and the system (Ramdany et al., 2024). A use case diagram consists of two primary elements: Actor and use case. An actor represents anything that interacts with the system, whether it's a person, described by their role and not their name, or another computer system. An actor is visualized using a stick figure with their role underneath. A use case is denoted by an ellipse with an active verb inside which represents the activity from the actor's perspective (Ramdany et al., 2024).

3.2.2 Activity Diagram Flow

Activity diagrams represent visual representations of the activities that happen in a system and the sequence in which they occur. In detail, activity diagrams define where a workflow started, where it stopped, what activities happened during a workflow, and how the sequence occurred (Ramdany et al., 2024).

An activity diagram uses several notations to illustrate different aspects of the workflow. The diagram begins with an initial node that marks the starting point and ends with a final node that indicates completion. Individual actions are represented by activity boxes, which appear as rectangles with rounded corners, each showing a single step in the process. The flow between

these activities is shown using arrows that create control flow lines, illustrating the path that execution follows from one action to the next.

Decision boxes are used to represent branching points where different paths can be taken based on specific conditions, represented using diamond-shaped boxes. To organize related activities, swim lanes group actions that are performed by the same object or actor, creating clear activity partitions that show responsibility and ownership.

For situations where multiple activities can happen simultaneously, the diagram uses synchronization bars along with fork and join nodes. A fork node splits the flow by having one incoming edge that branches into multiple outgoing edges, allowing parallel execution. Conversely, a join node brings parallel flows back together by accepting multiple incoming edges and merging them into a single outgoing edge, synchronizing the concurrent activities before proceeding to the next step (Kulkarni & Srinivasa, 2021).

3.2.3 Entity Relationship Diagram

To support the robust data requirements of the body-aware fashion recommendation chatbot, a well-structured database design is essential. The Entity Relationship Diagram (ERD) is a structural diagram used to design a database (Larassati et al., 2019).

An entity relationship diagram consists of three fundamental components that work together to model database structure. The first component is entities, which represent the objects or concepts that require data storage within the database. These entities are visually depicted as rectangles and are named to reflect the specific objects they represent.

The second component involves attributes, which serve as the descriptive characteristics of each entity. Every entity contains one or more attributes that function as descriptors, providing specific details about that entity, and these attributes are typically written within the entity rectangle.

The final component is relationships, which illustrate the connections that exist between two or more entities. These relationships are shown through lines that connect the related entities and are named according to the specific type of relationship they represent, helping to clarify how different entities interact with one another within the database model (Palinggi et al., 2024).

3.3 Implementation

The implementation phase involves turning the system design into a working software application, directly addressing the technical challenges in fashion e-commerce. Following the waterfall methodology, this phase started after the design phase was completed. The

development used various technologies including HTML, CSS, JavaScript, PHP, and Python to create a web-based body-aware fashion recommendation chatbot application.

To create a realistic data source for the application, a web scraping system was created using Python with the help of Selenium and BeautifulSoup libraries to collect clothing items for the database. Selenium was used to handle websites with interactive elements and dynamic content, while BeautifulSoup was used to extract specific HTML elements to extract product information. This automated system gathered product descriptions, prices, and images, providing the application with real and up-to-date fashion items for recommendations.

Following the data collection process, the back-end system was developed using PHP for server-side operations and Python for natural language processing tasks. This development aims to address the research objectives established during the requirement analysis phase, particularly the need to design a conversational AI that can infer user fashion preferences and incorporate body-type considerations into the recommendations.

To generate personalized fashion suggestions, the system connected to the OpenAI API by implementing the GPT-3.5 Turbo to generate personalized clothing recommendations based on user information. Prompt engineering methods were applied to improve the AI-generated fashion advice through carefully written system prompts that guided the AI to act as a fashion consultant and provide properly formatted responses. This approach directly addresses the cold start problem by enabling personalized recommendations without requiring extensive historical purchase data.

To improve how the chatbot keeps track of the conversation, a conversational context management system is developed. This system uses a linked keywords structure to track user inputs throughout the dialogue, allowing the AI to remember clothing items, preferences, and specific attributes such as colors, sleeve lengths, or clothing lengths. Built using a linked-list based architecture, each node contains key attributes related to fashion item and updates dynamically as the conversation progress. This enables the system to maintain continuity in multi-turn dialogues and ensures that user preferences are accurately retained and referenced later in response.

After generating the style recommendation and identifying the user's preferences, the system uses a custom SQL-based product filtering query to retrieve relevant fashion items from the product database. The query works by joining product data with variant and photo tables, aggregating available sizes, colors, and calculating the minimum price for each product. It filters out out-of-stock items and can dynamically apply additional constraints based on the

user's gender category (e.g., male or female) and budget range. Only products with available stock and matching the specified attributes are returned. This query ensures that the final recommendations are grounded in real, available inventory, each item being complete with price, available sizes/colors, and product images, ready to be shown on the front-end interface

Once the back-end system was ready, the user interface was developed as a web-based application designed for ease of use. HTML5 formed the basic structure, CSS3 handled the visual appearance, and JavaScript added interactive features throughout the interface. The development prioritized simple navigation and user-friendly design, enabling users to easily enter their personal details like height, weight, skin color, and style preferences to receive clothing recommendations. The front-end development included responsive design features to ensure the application worked well on different devices and screen sizes, supporting the research indicators related to interface adequacy and perceived ease of use identified in the requirement analysis.

3.4 Testing

User Acceptance Testing (UAT) was employed as the primary testing methodology for evaluating the recommendation system chatbot. UAT refers to the application testing process conducted with actual users to ensure the system meets the requirements and expectations of the end users. This phase involves evaluating the application from the user's perspective to verify that it functions correctly and satisfies the final user needs before the system is deployed or released (Wulandari et al., 2023).

To systematically evaluate the chatbot's performance in addressing the challenges in fashion e-commerce, the ResQue framework was implemented to measure the overall usability of the chatbot application from the user perspective. This framework aligns with the research indicators and variables established during the requirement analysis phase, providing a comprehensive assessment tool for conversational recommendation systems.

The ResQue framework was specifically chosen because it addresses the unique challenges of conversational recommendation systems in fashion e-commerce. Unlike traditional e-commerce evaluation methods that focus on click-through rates and purchase completion, ResQue evaluates the conversational interaction quality, recommendation explanation effectiveness, and user control, all critical factors for addressing the body-aware personalization objectives and cold start problems in fashion recommendation systems.

The evaluation utilized a 5-point Likert Scale to score user responses, where participants could express their level of agreement with each statement ranging from Strongly Disagree (1) to Strongly Agree (5), as shown in table 3.1

Table 3.1 Likert-Scale for Evaluation

Answer	Point
Strongly Disagree (SD)	1
Disagree (D)	2
Neutral (N)	3
Agree (A)	4
Strongly Agree (SA)	5

The testing process involved a structured questionnaire that addressed eight key indicators, each designed to evaluate specific aspects of the system's performance and user experience. The comprehensive set of questions used during the evaluation were carefully designed to assess the system's strengths and identify areas for improvement across all critical dimensions of user interaction with the recommendation system. The detailed questions for each indicator are shown in table 3.2

Table 3.2 List of Testing Questions

No.	Indicator	Questions
1.	A1. Quality of Recommended Items	The items recommended to me match my interest
2.		The items recommended to me are attractive
3.		Some of the recommended items are familiar to me
4.		The items recommended to me took my personal context requirements into consideration.
5.		I enjoyed the items recommended to me
6.	A2. Interaction Adequacy	The recommender provides an adequate way for me to express my preferences
7.		The recommender provides an adequate way for me to revise my preferences
8.		The recommender explains why the products are recommended to me
9.	A3. Interface Adequacy	The recommender's interface provides sufficient information

No.	Indicator	Questions
10.		The information provided for the recommended items is sufficient for me
11.	A4. Perceived Ease of Use	I became familiar with the recommender system very quickly
12.		I found it easy to tell the system about my preferences
13.		I found it easy to make the system recommend different things to me
14.		Finding an item to buy with the help of the recommender is easy
15.	A5. Perceived Usefulness	The recommended items effectively helped me find the ideal product
16.		I feel supported to find what I like with the help of the recommender
17.	A6. Control/Transparency	I feel in control of telling the recommender what I want
18.		The system helps me understand why the items were recommended to me
19.		I understood why the items were recommended to me
20.	A7. Attitudes	I am convinced of the products recommended to me
21.		I am confident I will like the items recommended to me
22.		Overall, I am satisfied with the recommender
23.	A8. Behavioral Intentions	If a recommender such as this exists, I will use it to find products to buy
24.		I will use this recommender again
25.		I would buy the items recommended, given the opportunity

The quantitative results obtained from the UAT were analyzed using descriptive statistics. Mean scores were calculated for each evaluation indicator to understand the central tendency in user responses. To interpret the composite score of the testing result, class interval was created for each indicator, based on the method proposed by Alkharusi (2022). Where:

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n}$$

The maximum score was obtained by multiplying the number of questions by the highest value in the Likert scale, while the minimum score was obtained by multiplying the number of questions by the lowest value. And then it was divided by the number of scale categories.

Since each evaluation indicator contains a different number of questions, the total scores were converted into percentages to ensure fair comparison across all indicators. The percentage was calculated using the following formula:

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

This analysis approach allows for an objective evaluation of user feedback while focusing on practical usability insights. It ensures the system's performance is aligned with the research goals and provides a clear benchmark for assessing the effectiveness of conversational fashion recommendation systems.

CHAPTER IV

RESULT AND DISCUSSION

4.1 Requirement Analysis Result

This section presents the results of the requirements analysis based on the comprehensive literature review and user needs identification described in Chapter III. This analysis aims to understand the key challenges in online fashion shopping, particularly those related to body fit accuracy, lack of personalization, and the cold-start problem in recommendation systems.

Based on the literature and problem context, the following user needs were identified:

- a. Users require personalized clothing recommendations that consider their body type attributes, such as height, weight, body shape, and skin tone
- b. Users need an assistant that can operate without relying on prior purchase history
- c. Users value transparency, ease of interaction, and explanation of recommendations in conversational systems.
- d. The system should support natural language inputs, allowing users to freely describe their needs in a human-like manner.

Based on these user needs, the system is required to have these following functionalities:

- a. Accept user inputs in the form of text-based chat.
- b. Extract key fashion preferences and physical attributes from user input
- c. Generate style-based recommendations using Conversational AI
- d. Retrieve multi-turn conversations to refine and clarify preferences

The outcome of this requirement analysis forms the basis for the system design and is described in the design section, where user needs and system specifications are translated into architectural, functional, and interface components.

4.2 Design Result

This section presents the result of the system design phase, which was developed based on the requirements identified in the requirement analysis stage. The design phase focuses on translating user needs and functional specifications into structured system architecture. This includes the design of key components such as the use case diagram, activity diagram, system architecture, and database structure. Each element is created to support the development of body-aware conversational AI chatbot that can effectively interpret user preferences, process fashion-related input, and deliver personalized recommendations. The design serves as a

blueprint for the implementation phase, ensuring that all features are aligned with the project's objective and user expectations.

4.2.1 Use Case Diagram

The Use Case diagram is used to visualize the interaction between the actors with the chatbot recommendations system. Figure 4.1 illustrates the Use Case diagram for the body-aware fashion recommendation chatbot for e-commerce platform, which defines the interaction within the system.

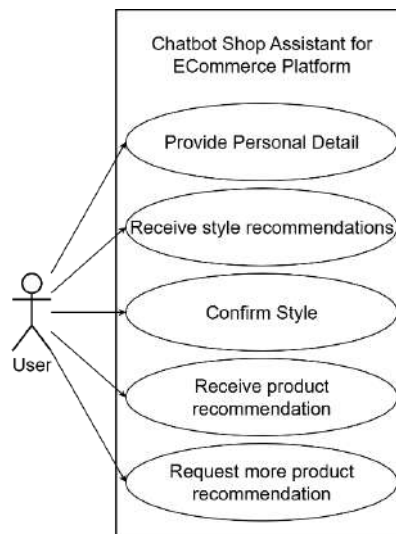


Figure 4.1 Use Case Diagram of Body-Aware Fashion Recommendation Chatbot

The primary actor in this system is the User, represented by the stick figure on the left side of the diagram. The User represents any individual who interacts with the body-aware fashion recommendation chatbot to receive personalized fashion recommendations. This actor encompasses potential customers, existing customers, or anyone seeking fashion advice through the conversational AI interface.

The system provides five main use cases that define the core functionality available to the User:

- a. **Provide Personal Detail:** This use case allows the User to input their personal information including height, weight, body shape, skin tone, cultural background, and style preferences. This information forms the foundation for generating body-aware and culturally sensitive fashion recommendations.
- b. **Receive Style Recommendations:** Through this use case, the User obtains personalized style advice from the AI system based on their provided personal details. The system

processes the user's physical attributes and preferences to generate appropriate fashion guidance and styling suggestions.

- c. **Confirm Style:** This use case enables the User to approve or modify the received style recommendations before proceeding to specific product suggestions. This confirmation mechanism ensures user satisfaction with the styling direction and implements the two-phase dialogue approach designed in the system architecture.
- d. **Received Product Recommendation:** In this use case, the User receives specific product suggestions from the inventory database that match their confirmed style preferences and physical attributes. The system presents curated fashion items with relevant details such as sizing recommendations, pricing, and availability.
- e. **Request More Product Recommendation:** This use case allows the User to request additional product suggestions beyond the initial recommendations. Users can ask for more options within the same category or explore different clothing types while maintaining their established style preferences and personal context.

The use case diagram demonstrates a sequential interaction pattern where the User progresses through the system's two-phase dialogue approach. The interaction begins with personal detail provision, flows through style consultation and confirmation, and concludes with product recommendation and optional additional suggestions. This systematic flow ensures comprehensive preference capture and personalized recommendation delivery while maintaining user control throughout the process.

The use case diagram effectively captures the essential functionalities required to address the research objectives of developing a conversational AI system that can understand user fashion preferences and provide body-aware recommendations through natural language dialogue.

4.2.2 Activity Diagram

Building upon the functional requirements identified in the use case diagram, the activity diagram provides a detailed view of the sequential processes and decision flows that occur within the system during user interactions. Activity diagrams represent visual representations of the activities that happen in a system and the sequence in which they occur. In detail, activity diagrams define where a workflow started, where it stopped, what activities happened during a workflow, and how the sequence occurred (Ramdany et al., 2024).

As illustrated in Figure 4.2, the activity diagram demonstrates the comprehensive workflow of the body-aware fashion recommendation chatbot, encompassing both user

interactions and system processing activities. The process flows are organized into distinct phases that reflect the two-phase dialogue approach designed for this research.

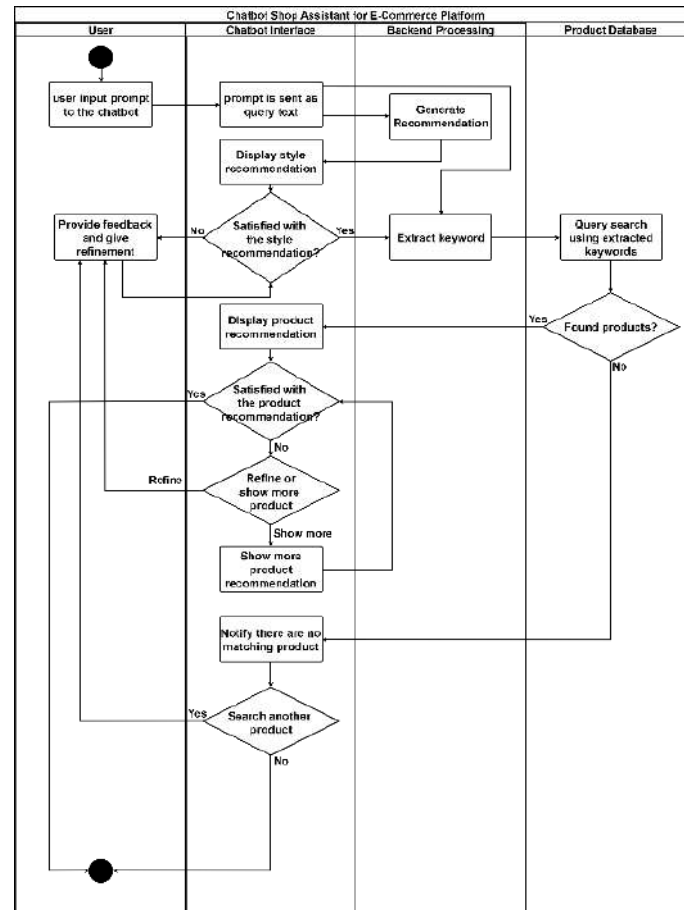


Figure 4.2 Activity Diagram of Fashion Recommendation Chatbot

The interaction flow of the chatbot begins when the user submits a prompt describing their fashion preferences or product needs. Once the input is received, the system immediately performs keyword extraction to identify key terms, using Natural Language Processing (NLP) and Regular Expression (RegEx) that can later be used for product matching. At the same time, the full prompt is also sent to the OpenAI model to generate a personalized style recommendation based on the user's request.

After the style recommendation is generated, it is displayed to the user through the chatbot interface. The user is then asked whether they are satisfied with the suggested style. If they are not satisfied, they have the option to provide feedback or refine their input to receive a better recommendation. However, if the user accepts the suggested style, the system proceeds to extract additional keywords from the AI-generated response. These new keywords are

combined with the earlier extracted terms to enrich the query used to search for relevant products in the database.

If the product database returns matching results, the chatbot presents the product recommendations to the user. The user is once again asked whether the results meet their expectations. If satisfied, the process concludes. However, if the user wants to see more options or make further refinements, the chatbot can display additional products accordingly. In cases where no matching products are found, the chatbot will notify the user and offer the option to initiate a new search with a different input.

4.2.3 Entity Relationships Diagram

To support the robust data requirements of the body-aware fashion recommendation chatbot, a well-structured database design is essential. The Entity Relationship Diagram (ERD) is a structural diagram used to design a database (Larassati et al., 2019). Figure 4.3 shows the entities and their relationship for the recommendation process.

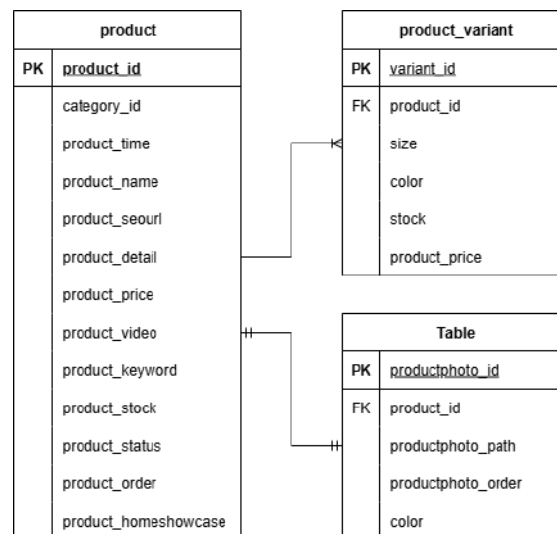


Figure 4.3 ERD of Fashion Recommendation Chatbot

The ERD system uses a structured database consisting of three main entities to support the recommendations process, which are: **Product**, **Product_Variant**, and **Product_Photo**. Each entity plays a distinct role in storing and retrieving information relevant to the recommendations results. The following tables explain the structure of each entity and its function in the system.

Table 4.1 Product Table for Fashion Recommendation Chatbot

Attributes	Data Type	Description
product_id (PK)	int(11)	Primary Key, unique identifier for each product
category_id	int(11)	Referring to the category this product belongs to
product_time	timestamp	Timestamp of when the product was added
product_name	varchar(250)	Name of the product displayed to the users
product_seourl	varchar(250)	SEO-friendly URL used for linking and navigation
product_detail	text	Full description of the product
product_price	float(9,2)	Price of the product
product_video	varchar(50)	Optional product video file name, path, or URL
product_keyword	varchar(250)	Keywords associated with the product for search and filtering
product_stock	int(11)	Total available stock for this product
product_status	enum('0', '1')	Indicates if the product is active (1) or inactive (0) in the store
product_order	int(2)	Determine the display order of the product in listings
product_homeshowcase	enum('0', '1')	Flag to showcase whether the product appears on the homepage showcase
product_gender	varchar(50)	The gender category of the clothes

Table 4.1 serves as the main storage for all product-related information in the system. It not only includes essential attributes such as product name, description, price, and stock, but also metadata that supports user experience and product visibility, such as SEO links, homepage display statues, and gender category of the product. During the product recommendation process, this table is queried using extracted keywords to retrieve items that match the user's needs and preferences.

Table 4.2 product_variant table

Attribute	Data Type	Description
productvariant_id (PK)	int(11)	Primary Key, Unique identifier for each product variant
product_id (FK)	int(11)	Reference the main product
size	varchar(50)	Size option available for this variant
color	varchar(50)	Color option available for this variant
stock	int(11)	Total available stock for this product
product_price	float(9,2)	Price of the product

Table 4.2 stores information about each available variant of a product, including size and color options. The system presents the available sizes and colors to the user as part of the product details. This supports user decision-making by allowing them to see which options are available for each recommended item.

Table 4.3 product_photo table

Attribute	Data Type	Description
productphoto_id (PK)	int(11)	Primary Key, Unique identifier for each product image
product_id (FK)	int(11)	References for the related product
productphoto_path	varchar(255)	File path or URL to the product image
productphoto_order	int(3)	Determine the display order of the product photo
color	varchar(50)	Color of the specific product

Table 4.3 stores visual assets of each product, supporting the chatbot interface by displaying product images alongside textual recommendations, enhancing the overall user experience.

4.3 Implementation Result

The results discussed in this section demonstrate the successful implementation of the design phase specifications. Following the waterfall methodology established in Chapter 3, the implementation systematically converted the designed system architecture into a working software application. The focus of this section is to show how this implementation process

achieves the research objectives and addresses the problems identified during the requirement analysis phase.

4.3.1 Data Collection and Web Scrapping Implementation

To build a realistic and comprehensive data source for the application, a sophisticated web scraping system was implemented using Python with Selenium and BeautifulSoup libraries to collect clothing items for the database. This automated data collection approach addresses the requirement for current, diverse fashion inventory that supports meaningful body-aware recommendations without relying on static or limited product datasets.

The web scraping process was conducted between 22 December until 24 December 2024, ensuring that all collected product information and HTML structures reflect the state of the target websites at that time. Recording the scraping date is crucial part of the data documentation, because modern e-commerce platforms use dynamic web pages that frequently change content, layout, and availability in real-time, meaning future site versions may differ from those captured during scraping (K. Sharma & Borkar, 2024).

Selenium was strategically employed to handle websites with interactive elements and dynamic content, enabling the system to navigate complex e-commerce platforms that utilize JavaScript-heavy interfaces and lazy-loading mechanisms. BeautifulSoup complemented this approach by providing robust HTML parsing capabilities to extract structured product information from the retrieved web pages. This dual-library implementation ensures comprehensive data extraction while maintaining reliability across different website architectures. The web scraping implementation follows a systematic three-phase approach designed to ensure comprehensive data collection while maintaining data quality and uniqueness.

a. Product Link Collection

The scraping process initiates with systematic collection of product links from target e-commerce platforms. The implementation uses Selenium WebDriver to navigate category pages and handle dynamic content loading.

```

top = webdriver.Chrome()
url = "https://executive.co.id/collections/women-tops?itm_source=mega-menu&itm_campaign=top"
top.get(url)
WebDriverWait(top, 20).until(EC.presence_of_element_located((By.CSS_SELECTOR, 'a.product-link'))))
scroll_pause_time = 5
last_height = top.execute_script("return document.body.scrollHeight")
while True:
    top.execute_script("window.scrollTo(0, document.body.scrollHeight);")
    time.sleep(scroll_pause_time)
    new_height = top.execute_script("return document.body.scrollHeight")
    if new_height == last_height:
        time.sleep(5)
        if new_height == top.execute_script("return document.body.scrollHeight"):
            break
    last_height = new_height
soup = BeautifulSoup(top.page_source, "html.parser")
links = soup.find_all("a", attrs={"class": 'product-link'})

```

Figure 4.4 Product Link Collection Code

This approach implements intelligent infinite scroll handling to ensure complete page content loading, addressing the challenge of dynamically loaded product listings common in modern e-commerce platforms.

b. Link Processing and Duplicate Removal

Following link collection, the system processes and validates all discovered product URLs to ensure data quality and prevent duplicate entries. Figure 4.5 shows the code used for this process.

```

unique_links = set()
product_links = []
for link in links:
    href = link.get('href')
    if href:
        full_url = "https://executive.co.id" + href
        if full_url not in unique_links:
            product_links.append(full_url)
            unique_links.add(full_url)

```

Figure 4. 5 Link Processing and Removing Duplication Code

This duplicate removal mechanism ensures database integrity while optimizing scraping efficiency by preventing redundant data collection operations.

c. Product Detail Extraction

The final phase involves detailed product information extraction using sophisticated parsing techniques that capture multiple product attributes essential for body-aware recommendations. Figure 4.6 shows the code used for the product detail extraction.

```

def scrape_product_details(product_url):
    product_data = {}
    try:
        top.get(product_url)
        WebDriverWait(top,
30).until(EC.presence_of_element_located((By.CSS_SELECTOR, "h3.title")))
        title = top.find_element(By.CSS_SELECTOR, "h3.title").text.strip()
        price = top.find_element(By.CSS_SELECTOR, "span.current-
price").text.strip()
        full_description = top.find_element(By.CSS_SELECTOR, "div.cc-
accordion-item_panel").text.strip()
        if full_description.lower().startswith("material:"):
            clean_desc = re.split(r",\s*Material:", full_description,
maxsplit=1)[1].strip()
        else:
            clean_desc = re.split(r",\s*Material:", full_description,
maxsplit=1)[0].strip()
            color_match = re.search(r'Color:\s*([^\,]+)', full_description,
re.IGNORECASE)
            material_match = re.search(r'Material:\s*([^\,]+)', full_description,
re.IGNORECASE)
            fit_match = re.search(r'Fit:\s*([^\,]+)', full_description,
re.IGNORECASE)
            color = color_match.group(1) if color_match else None
            material = material_match.group(1) if material_match else None
            fit = fit_match.group(1) if fit_match else None
        try:
            main_image_element = top.find_element(By.CSS_SELECTOR, "div.main-
image a.show-gallery")
            image_url = main_image_element.get_attribute("href")
            if not image_url.startswith("http"):
                image_url = "https:" + image_url
        except Exception as e:
            image_url = None
        size_data = scrape_size_chart(top)
    except Exception as e:
        print(f"Error scraping {product_url}: {e}")
    return product_data

```

Figure 4.6 Product Detail Extraction Code

Recognizing the critical importance of sizing information for body-aware recommendations, the system implements specialized size chart extraction functionality shown in Figure 4.7. This size chart extraction addresses the research objective of incorporating body-type considerations by capturing detailed sizing information that enables accurate fit recommendations based on user physical attributes.

```

def scrape_size_chart(driver):
    try:
        size_chart_container = WebDriverWait(driver, 10).until(
            EC.presence_of_element_located((By.CLASS_NAME, "size-chart-
container")))
        size_chart_link = size_chart_container.find_element(By.CLASS_NAME,
"size-chart-link")
        size_chart_link.click()

        WebDriverWait(driver, 10).until(
            EC.visibility_of_element_located((By.CLASS_NAME,
"customization_popup")))

        size_chart_table_button = WebDriverWait(driver, 10).until(
            EC.element_to_be_clickable((By.ID, "sizePakaian")))
        size_chart_table_button.click()

        WebDriverWait(driver, 10).until(
            EC.presence_of_element_located((By.ID, "tablePakaian")))

        soup = BeautifulSoup(driver.page_source, "html.parser")
        size_table = soup.find("table", {"id": "tablePakaian"})

        if not size_table:
            print("Size chart table is not found.")
            return None

        headers = [th.text.strip() for th in
size_table.find("thead").find_all("th")]
        rows = []
        for tr in size_table.find("tbody").find_all("tr"):
            row_data = [td.text.strip() for td in tr.find_all("td")]
            rows.append(row_data)

        size_data = [dict(zip(headers, row)) for row in rows]
        return size_data

    except Exception as e:
        print(f"Error in scraping size chart table: {e}")
        return None

```

Figure 4.7 Size Chart Scraping Code

To enhance the resilience of the scraping scripts against minor HTML structure changes, several practical measures were incorporated into the implementation. The system uses CSS selectors and HTML attribute targeting, for example the class attributes, to identify elements, avoiding overly rigid absolute XPath that tend to break when page layouts change. Exception handling with try-except blocks is implemented in the product detail and size chart extraction functions, allowing the script to skip problematic items and continue running rather than failing entirely. Explicit waits (WebDriverWait) are used in multiple scraping steps to ensure elements are only interacted with after they are fully loaded, improving reliability when handling dynamically rendered content. While some fixed delays (time.sleep()) are still used in the

infinite scrolling process, these are complemented by explicit waits to better handle asynchronous page loading. Although significant structural changes to the target websites would still require manual updates to the selectors, these measures help reduce vulnerability to small changes and improve the stability of the scraping process.

The automated web scraping system successfully gathered comprehensive product information including titles, pricing data, detailed descriptions, color variants, material specifications, fit classifications, size charts, and high-quality product images. This diverse dataset provides the application with real and up-to-date fashion items for recommendations, ensuring that users receive suggestions for products that are actually available for purchase.

Figure 4.8 presents a sample of the product data successfully extracted through the web scraping implementation, demonstrating the comprehensive information captured for each clothing item.

title	price	description	color	material	fit	size_chart	image_url
Balloon Sleeve Tunic	Rp 83,970	Tunik lengan panjang, Round neck, Balloon sleeves, Front button opening, Drop shoulder details	Off White	Cotton	Loose	{'SIZE': 'S', 'BUST': '48', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '51', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '54', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '57', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '59', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-TNWKCA123C108_OFF_WHITE_1.jpg?v=1679886179
Tiered Long Sleeve Tunic	Rp 99,900	Tunik A-line lengan panjang, Tied high neck, Tiered details, Textured fabric	Brown	Plaid Crinkle	Regular	{'SIZE': 'S', 'BUST': '47', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '49', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '52', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '55', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '57', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-TNWFUR3238022BROWNfijab_1.jpg?v=1676888471
Basic Slim Fit Long Sleeve Shirt	Rp 179,910	Blouse lengan panjang, Kerah keremeja, Full front button opening, Rounded hemline	Navy	Cotton Nylon Spandex	Slim	{'SIZE': 'S', 'BUST': '47', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '49', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '52', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '55', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '57', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-BLWBS5C5070014_NAVY_1.webp?v=1672823521
Basic V-Neck Cotton T-Shirt	Rp 89,910	T-shirt lengan pendek, V-neck, Regular length, Stretch fabric	Bronze	Cotton Spandex	Regular	{'SIZE': 'S', 'BUST': '47', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '49', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '52', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '55', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '57', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-TSKBSC5380017_BRONZE_1_T.jpg?v=1671607077
Basic Slim Fit Long Sleeve Shirt	Rp 179,910	Blouse lengan panjang, Kerah keremeja, Full front button opening, Rounded hemline	Black	Cotton Nylon Spandex	Slim	{'SIZE': 'S', 'BUST': '47', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '49', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '52', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '55', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '57', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-BLWBS5C5010014_BLACK_1_T.jpg?v=1671607071
Basic Round Neck Cotton T-Shirt	Rp 89,910	T-shirt lengan pendek, Round neck, Regular length, Stretch fabric	Jade	Cotton Spandex	Regular	{'SIZE': 'S', 'BUST': '47', 'WAIST': '75', 'LENGTH': '56'}, {'SIZE': 'M', 'BUST': '49', 'WAIST': '80', 'LENGTH': '58'}, {'SIZE': 'L', 'BUST': '52', 'WAIST': '85', 'LENGTH': '60'}, {'SIZE': 'XL', 'BUST': '55', 'WAIST': '90', 'LENGTH': '62'}, {'SIZE': 'XXL', 'BUST': '57', 'WAIST': '95', 'LENGTH': '64'}	https://executive.co.id/cdn/shop/products/5-TSKBSC5350013_JADE_1_T.jpg?v=1671607045

Figure 4.8 Result of Scraping Process

4.3.2 Back-End Implementation

OpenAI Integration and Prompt Engineering

The system successfully connected to the OpenAI GPT-3.5-turbo model to generate personalized clothing recommendations based on user information. While the front-end provides the interface for users to interact with the system, the prompt engineering component serves as the critical bridge between user input and the fashion recommendations generated by the OpenAI GPT-3.5 Turbo model.

Following guidelines from OpenAI's documentation, the prompt was structured around four main components that work together to guide the AI's responses. The first component,

identity, establishes the AI's role as a fashion consultant and sets the tone for communication. The instructions component tells the AI what kind of recommendations to provide, how to format the response, and what parameters to consider, such as user's physical attributes. To help the AI understand what good responses look like, example responses were included, which serve as templates for the AI to follow. Finally, contextual information was provided to help the AI generate relevant recommendations, such as suggesting casual outfits when users don't specify an occasion.

The prompt was designed using a few-shot learning approach (Dang et al., 2022), where carefully chosen examples guide the AI toward giving helpful and appropriate fashion advice. This approach allows the system to provide personalized recommendations even when users provide minimal information initially.

Prompt creation followed an iterative trial-and-error process, in which earlier versions were progressively refined to improve personalization, enforce consistent formatting, and ensure style suggestions always lead up to product recommendations. Each iteration incorporated additional constraints, and clearer question prompts to gather essential user attributes before making recommendations. This process concluded in Table 4.4, which aligned chatbot outputs with the research objectives and ensures that recommendations were consistent, relevant, and tailored to user preferences. The complete prompt evolution, along with sample output from each stage, is documented in Appendix for reference.

Table 4.4 Prompt Breakdown

Prompt Component	Category	Description
"You are a fashion consultant. Your task is to provide detailed fashion recommendations for users based on their appearance and style preferences. Respond in a friendly, natural tone and avoid using structured JSON or code format. Instead, communicate recommendations in conversational sentences."	Identity	Establishes the AI's role as a fashion consultant and sets the tone for communication
"Always ask for their gender, weight and height, skin tone, their ethnical background and use this information as a base for your recommendations... When asking for style preferences, ALWAYS format them as bullet	Instructions	Tells the AI what kind of recommendations to provide, how to format the response, and what parameters to

Prompt Component	Category	Description
points with examples... Always format each clothing recommendation as a bold heading with size recommendation in parentheses... Use this exact format: [Clothing Item Name] (Disarankan Ukuran [Size]) ... Based on the user's measurements, body type, and daily activities, provide a size recommendation... Give at least 3 items recommendation... Do not mention any specific brand of clothing."		consider, such as user's physical attributes
" Kemeja Flanel Oversized (Disarankan Ukuran L) Kemeja flanel oversized memberikan tampilan santai namun tetap stylish. Cocok dipadukan dengan celana jeans atau celana panjang. Dengan aktivitas yang cukup aktif, ukuran L akan memberikan kenyamanan dan gaya yang Anda inginkan. --- Kemeja Polo Slim Fit (Disarankan Ukuran M) Kemeja polo slim fit cocok untuk aktivitas sehari-hari yang lebih formal. Potongan yang pas akan memberikan tampilan yang rapi dan profesional."	Examples	Example responses included to serve as templates for the AI to follow, showing what good responses look like
" Style Preferences: sleeve length preference (sleeveless, short sleeve, 3/4 sleeve, long sleeve), clothing length preference (crop top, regular length, tunic, longline for tops; shorts, capri, regular, long/full length for bottoms), fit preference (oversized, regular fit, fitted, slim fit, loose fit), daily activity level and lifestyle (sedentary/office work, moderately active, very active/athletic, mixed activities)... mention specific clothing items and how they would suit the user's attributes, such as gender, height, weight, skin tone, and consider their daily	Contextual Information	Contextual information provided to help the AI generate relevant recommendations, such as suggesting appropriate outfits based on user's lifestyle and activities

Prompt Component	Category	Description
activities when suggesting appropriate fits and styles."		

To ensure consistent and accurate fashion recommendations, the chatbot's temperature setting was configured to 0.5. A lower temperature helps reduce randomness in AI responses, making the chatbot more reliable in following system prompts and staying within expected stylist role. This decision aligns with findings from Sufi (2025), who noted that higher temperatures increase response variety but also raise the risk of generating less probable or less accurate outputs.

Conversational Context Management

In a fashion recommendation system, users often update, refine, or change their preferences throughout the conversation. To handle this dynamic behavior, the system needs to keep track of the user's current focus and preferences across multiple turns. This is especially important when users request very specific fashion combinations or correct their earlier inputs. To support this, the system uses a Linked List-based keyword management system called `LinkedKeywordSystem` class.

The system allows the chatbot to remember and update the context of the conversation by organizing fashion-related keywords, such as clothing items, styles, or color, into a structured chain. Each clothing item that the user mentions create a `ClothingChain`, which stores all relevant attributes using a series of `KeywordNode` objects. Each node stores information such as the keyword itself, its importance, the source (user input or AI response), category (color, sleeve), and the time it was mentioned.

To illustrate how this works, Figure 4.9 shows a basic two-turn conversation. In the first turn, the user says, "bisa carikan kemeja" (can you find me a shirt), and the system extracts "kemeja" as a clothing item. It creates a new chain in the tops category with "kemeja" as the head. On the next turn, when the user saya, "yang lengan Panjang warna hitam" (long sleeves, black color), the system extracts "lengan Panjang" and "hitam" and links the to the existing "kemeja" chain. When it is time to retrieve product results, the system processes the entire chain and builds a contextual search query using all linked keywords.

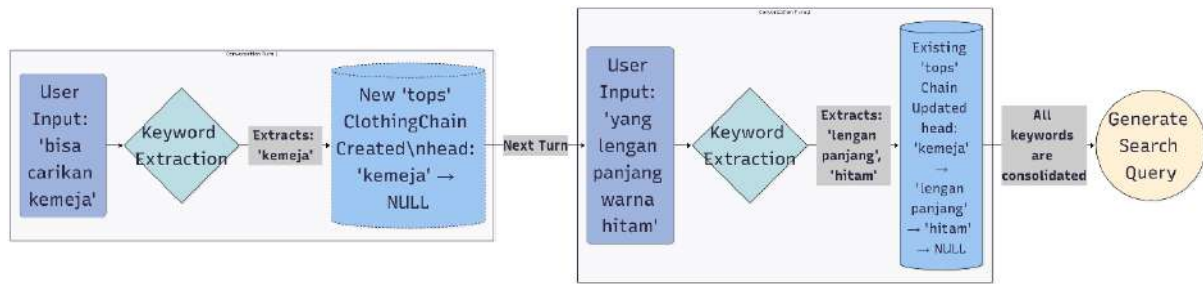


Figure 4.9 Multi-Turn Keyword Extraction and Context Retention for Enhanced Product Search

Figure 4.10 shows the core of this system, which is the KeywordNode class, which acts as a node in the linked list and stores each fashion-related keyword along with its metadata.

```

class KeywordNode:
    def __init__(self, keyword: str, weight: float, source: str, category: str):
        self.keyword = keyword
        self.weight = weight
        self.source = source
        self.category = category
        self.timestamp = datetime.now().isoformat()
        self.mention_count = 1
        self.next = None
  
```

Figure 4.10 Keyword Node Class Implementation

When a user mentions a new clothing item, the system creates a new chain using the ClothingChain class, with the clothing item as the head node, figure 4.11 shows the code for the ClothingChain class.

```

class ClothingChain:
    def __init__(self, clothing_item: str, weight: float, source: str):
        self.head = KeywordNode(clothing_item, weight, source, 'clothing_item')
        self.clothing_category = self._get_clothing_category(clothing_item)
        self.last_updated = datetime.now().isoformat()
        self.total_nodes = 1

    def _get_clothing_category(self, keyword: str):
        return fashion_categories.get_clothing_category(keyword) or 'unknown'

    def add_attribute(self, keyword: str, weight: float, source: str, category: str):
        self._clean_conflicting_attributes(keyword)

        current = self.head
        while current:
            if current.keyword.lower() == keyword.lower():
                current.weight = max(current.weight, weight)
                current.mention_count += 1
                current.timestamp = datetime.now().isoformat()
                current.source = source
                self.last_updated = datetime.now().isoformat()
                return True
            current = current.next
        new_node = KeywordNode(keyword, weight, source, category)
        current = self.head
        while current.next:
            current = current.next
        current.next = new_node
        self.total_nodes += 1
        self.last_updated = datetime.now().isoformat()
        return True

```

Figure 4.11 ClothingChain Class Implementation

After the chain is created, the user may continue to add attributes such as “putih” (white), “kantoor” (for office), or “slim fit”. These are added using the `add_attribute()` method, which also checks for and resolves conflicting values. For example, if the user initially says “lengan Panjang” (long sleeves) and later corrects it with “lengan pendek” (short sleeves), the older value will be removed to maintain logical consistency.

When the recommendation engine is triggered to fetch products, the system call `get_flatten_keywords()`, shown in figure 4.12. This method processes all chains and collects the most recent, weighted keywords into a single list, sorted by importance. These keywords are then used in the product filtering query to match the user’s intent.

```

def get_flattened_keywords(self) -> List[Tuple[str, float]]:
    all_keywords = []
    for chain in self.chains.values():
        all_keywords.extend(chain.get_all_keywords())
    all_keywords.sort(key=lambda x: x[1], reverse=True)
    return all_keywords

```

Figure 4.12 `get_flatten_keywords` Implementation

This system ensures that all relevant context, from the main clothing item to small detail-level preferences, is preserved and actively updated throughout the conversation. It also supports corrections, multi-item inputs, and decays old preferences over time. As a result, the chatbot can generate more accurate and personalized fashion recommendations without losing track of user intent.

Database Integration and Product Matching

To complete the recommendation flow, the system integrates with a real-time product database to retrieve fashion items that match the user's preferences. Once relevant keywords have been extracted through prompt engineering and conversational context management, they are passed to a product matching module that queries the product database based on filters such as gender categories and price range.

The system uses an asynchronous SQL query written in SQLAlchemy to ensure compability with the FastAPI based back-end. The `get_filtered_product()` function, shown in Figure 4.13 retrieves products by joining data from multiple related tables and applying filters based on availability and user-specified attributes. The product matching process begins by constructing a variant subquery, which aggregates variant-level data for each product.

```
variant_subquery = (
    select(
        ProductVariant.product_id,
        func.min(ProductVariant.product_price).label('min_price'),

        func.group_concat(ProductVariant.size.distinct()).label('available_sizes'),
        func.group_concat(ProductVariant.color.distinct()).label('available_colors'),
        func.sum(ProductVariant.stock).label('total_stock')
    )
    .where(ProductVariant.stock > 0)
    .group_by(ProductVariant.product_id)
    .subquery()
)
```

Figure 4.13 variant_subquery Code Implementation

This subquery collects essential product information: The price of the product (using MIN() for compatibility with grouped queries), The list of available sizes and colors, The total stock, ensuring that only available items are shown. Although all variants of a product share the same price in the current dataset, the MIN() function is used to maintain compatibility with grouped SQL queries and to allow flexibility for potential future support of price variation between product variants.

Next, the main query (base_query), shown in Figure 4.14 selects relevant product data and joins the previously created variant_subquery as well as the ProductPhoto table to retrieve image paths.

```
base_query = (
    select(
        Product.product_id,
        Product.product_name,
        Product.product_detail,
        Product.product_seourl,
        Product.product_gender,
        variant_subquery.c.min_price,
        variant_subquery.c.available_sizes,
        variant_subquery.c.available_colors,
        variant_subquery.c.total_stock,
        ProductPhoto.productphoto_path
    )
    .select_from(Product)
    .join(variant_subquery, Product.product_id == variant_subquery.c.product_id)
    .join(ProductPhoto, Product.product_id == ProductPhoto.product_id)
    .where(variant_subquery.c.total_stock > 0)
)
```

Figure 4.14 base_query Code Implementation

Once the base query is constructed, it applies optional filters based on user input, such as gender and budget range. These filters are flexible and dynamic, adjusting to whether the user has provided both, either, or none of the constraints. Finally, the query is executed asynchronously, and the results are returned as a list of matching products. Figure 4.15 shows the query for the optional filters based on the user input.

```
if gender_category:
    if gender_category.lower() in ['female', 'woman', 'perempuan', 'wanita']:
        base_query = base_query.where(Product.product_gender == 'female')
    elif gender_category.lower() in ['male', 'man', 'pria', 'laki-laki']:
        base_query = base_query.where(Product.product_gender == 'male')

if budget_range and isinstance(budget_range, (tuple, list)) and len(budget_range) == 2:
    min_price, max_price = budget_range
    if min_price and max_price:
        base_query =
base_query.where(variant_subquery.c.min_price.between(min_price, max_price))
    elif max_price:
        base_query = base_query.where(variant_subquery.c.min_price <= max_price)
    elif min_price:
        base_query = base_query.where(variant_subquery.c.min_price >= min_price)

result = await db.execute(base_query)
return result.fetchall()
```

Figure 4.15 Additional Gender and Budget Filter

This modular approach ensures that product recommendations are grounded in real-time inventory data and align with the user's stated preferences. By separating variant-level data aggregation and main product data retrieval, the system maintains efficiency while supporting flexibility in product filtering. This component bridges the gap between the AI's fashion advice and the actual product results shown to the user, completing the end-to-end recommendation process.

4.3.3 Front-End Implementation

After establishing the back-end functionality, the user interface was developed as a web-based application designed for ease of use. HTML5 formed the basic structure, CSS3 handled the visual appearance, and JavaScript added interactive features throughout the interface. The development prioritized simple navigation and user-friendly design, enabling users to easily enter their personal details like height, weight, skin color, and style preferences to receive clothing recommendations.

Conversational Interface Design

The chatbot interface was designed to provide an intuitive and accessible user experience for users with diverse linguistic backgrounds. Figure 4.16 illustrates the initial system interface, which presents users with a bilingual welcome message in both Bahasa Indonesia and English. This multilingual approach addresses the primary target demographic while ensuring broader accessibility for international users.

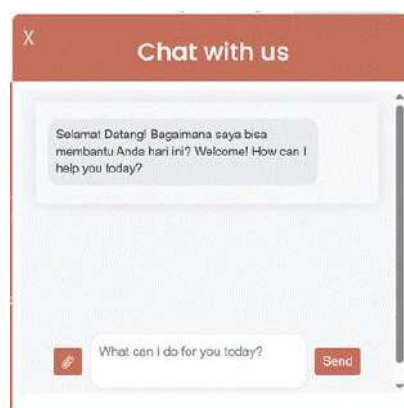


Figure 4.16 Initial Screen for the Chatbot System

Intelligent Information Gathering Implementation

The system employs an intelligent information gathering mechanism that systematically collects essential user data for personalized recommendations. When users provide insufficient detail in their initial requests, the system automatically initiates a structured inquiry process. Figure 4.17 demonstrates how the chatbot prompts users for comprehensive personal information including height, weight, cultural background, skin tone, and style preferences. This approach ensures that all subsequent recommendations are tailored to the user's specific physical attributes and cultural context.

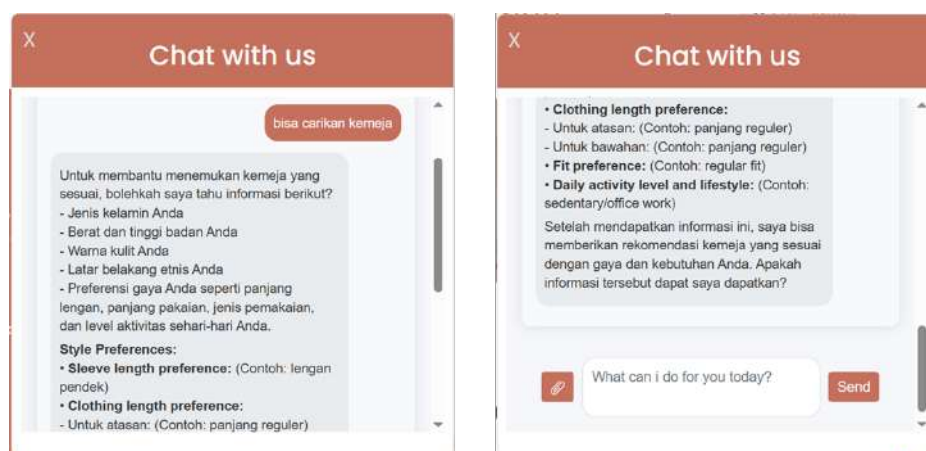


Figure 4.17 Chatbot response when given insufficient information

Two-Phase Dialogue System Implementation

The first phase focuses on generating personalized style recommendations based on the collected user information. Figure 5 demonstrates the AI's ability to synthesize user inputs into a coherent fashion advice while maintaining conversational natural tone. Following each style recommendation, the system implements a confirmation mechanism that requires explicit user approval before proceeding to product suggestions. This two-phase approach mirrors traditional in-store fashion consultation processes, ensuring user satisfaction with style directions before presenting specific products.



Figure 4.18 The style recommendation results based on the user input

Adaptive Response Capabilities

The system demonstrates adaptive capabilities by responding to user feedback and preferences in real-time. Figure 6 illustrates the system's responsiveness to user adjustment, where modifications to initial recommendations are immediately processed and reflected in updated style suggestions. This iterative refinement process ensures alignment between system recommendations and user expectations.

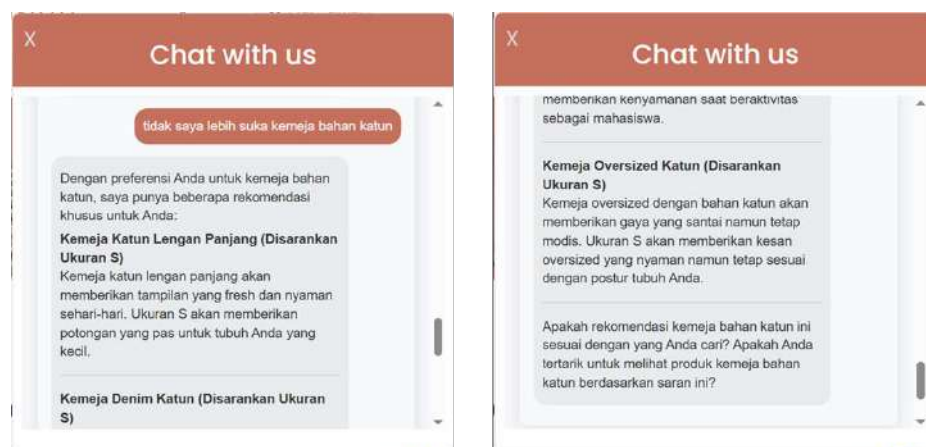


Figure 4.19 Style recommendations result after adjustment

Product Recommendation Display Implementation

Upon user confirmation of style preferences, the system transitions to second phase, which involves retrieving specific products from inventory database. Figure 7 presents the product recommendation interface, where the system displays curated fashion items that match established style preferences and user physical attributes. The implementation includes a

pagination mechanism that initially presents five products, with users able to request additional items through natural language commands. This approach prevents information overload while ensuring comprehensive product exploration.

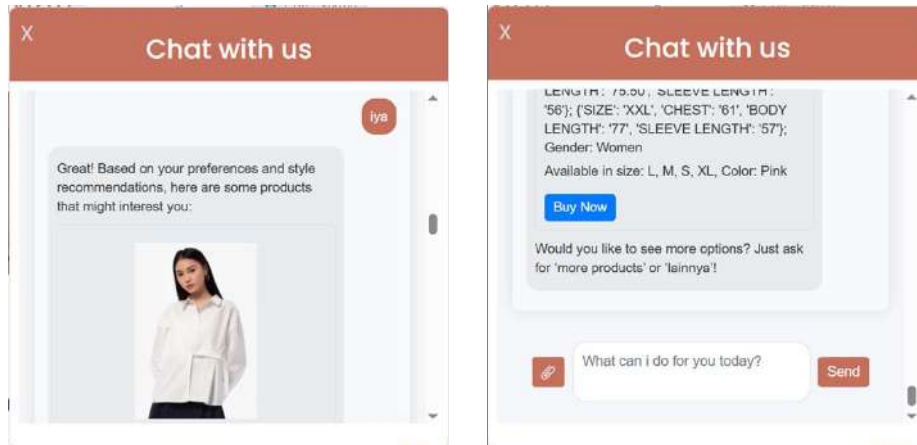


Figure 4.20 Product recommendation from the inventory of the shops

System Integration and Contextual Management

The system architecture supports continuous interaction patterns where users can seamlessly transition between different clothing categories within a single session. Figure 8 demonstrates the system's ability to maintain context while processing subsequent requests for different clothing items. The accumulated keyword mechanism preserves relevant user information across multiple requests while applying intelligent filtering to ensure new requests receive appropriate priority. This functionality enables users to build complete outfits through iterative consultation rather than requiring separate sessions for each clothing category.

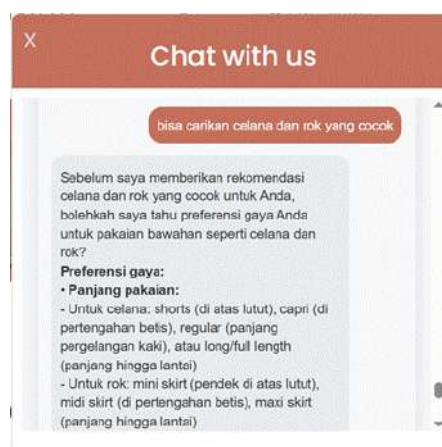


Figure 4.21 User request for another clothing item

The implementation successfully demonstrates the integration of conversational AI with body-aware personalization in a production-ready environment. The system maintains context across extended conversations, adapts to user preferences in real-time, and provides culturally sensitive recommendations appropriate for the Indonesian fashion market. The two-phase dialogue approach effectively bridges the gap between abstract consultation and concrete product recommendations, addressing the identified limitations in existing fashion recommendation systems.

4.4 Testing Result

This section presents the empirical findings from the testing of the fashion recommendation chatbot system. The assessment focused on eight indicators: A1. Quality of Recommended Items, A2. Interaction Adequacy, A3. Interface Adequacy, A4. Perceive Ease of Use, A5. Perceived Usefulness, A6. Control/Transparency, A7. Attitudes, A8. Behavioral Intentions. Testing was conducted with ten participants using a 5-point Likert scale, where 5 represents the highest/best rating and 1 represents the lowest/poorest rating. Each indicator provides critical insight into different aspects of the system's effectiveness in delivering personalized fashion recommendations. Table 4.5 shows the demographic of the testing participants.

Table 4.5 Testing Participants Demographic

	n	%
Gender		
Male	3	30
Female	7	70
Occupation		
Student	4	40%
Office Worker	2	20%
Retail Worker	2	20%
Stay at home mom	2	20%
Age Group		
18 - 28 years old	7	70%
29 - 38 years old	3	30%
> 38 years old	0	
The Frequency of e-commerce usage		
Very rare	0	
Rare	1	10%
Quite often	3	30%
Often	3	30%
Very Often	3	30%

4.4.1 Quality of Recommended Items

The Quality Recommended Items evaluate the effectiveness of the recommendation system by evaluating both the information quality and genuine usefulness of suggested products presented to the users. This evaluation framework examines five critical aspects of recommendations: interest alignment, visual attractiveness, familiarity balance, contextual relevance, and overall user enjoyment. These dimensions collectively determine whether the system successfully translates user preferences into meaningful product suggestions that support informed purchasing decisions.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $5 \times 5 = 25$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $5 \times 1 = 5$. The interval class was then

determined using the calculation below, and assessment criteria were established as presented in Table 4.6.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{25 - 5}{5} = 4$$

Table 4.6 Quality of Recommended Items Score Interval

Score Range	Percentage Range	Criteria
5 – 8	0 – 19.99%	Very Dissatisfied
9 – 12	20 – 39.99%	Dissatisfied
13 – 16	40 – 59.99%	Neutral
17 – 20	60 – 79.99%	Satisfied
21 – 25	80 – 100%	Very Satisfied

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation:

$$\text{Percentage} = \frac{\text{Total Score}}{\text{Maximum Score}} \times 100$$

The calculation of the testing result in Quality of Recommended Items indicator is shown in Table 4.7.

Table 4.7 Quality Recommended Items Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q1	2	7	1	0	0	41	82.0%
Q2	3	6	1	0	0	42	84.0%
Q3	2	7	1	0	0	41	82.0%
Q4	1	8	1	0	0	40	80.0%
Q5	2	6	2	0	0	40	80.0%
Mean						20.4	81.6%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in table 4.7, each of the five evaluations received total scores ranging from 40 to 42, with a mean score of 20.4 out of 25. Based on the scoring interval, this result falls within

the “Satisfied” category which is in the range 17 – 20, indicating that users were generally satisfied with the quality of the recommended items provided by the system.

The highest total score was observed for Q2 about the attractiveness of the recommended item with a total score of 42, suggesting that the users found the recommended products are visually appealing. Q1 and Q3 both received scores of 41, indicating that the system effectively recommended products that matched users’ tastes while balancing novelty with familiarity. Q4 and Q5 each received a score of 40, show users found the system to be effective in accounting for personal contextual information and reported positive user experiences with the recommendation process.

These results collectively demonstrate the system’s capability to deliver recommendations that are not only relevant and visually appealing but also alligned with user preferences and shopping context

4.4.2 Interaction Adequacy

The interaction Adequacy dimension evaluates the system’s capacity to facilitate meaningful user-system communication through three critical interactions mechanisms: initial preferences collection, preference revision capabilities, and recommendations explanation functionality. This evaluation framework assesses whether the users can effectively communicate their preferences to the system, modify those preferences as their needs evolve, and understand the reasoning behind the system’s recommendations. These interactions capabilities prove essential for building user trust and enabling iterative refinement of recommendation quality through ongoing user feedback and system learning.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $3 \times 5 = 15$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $3 \times 1 = 3$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.8.

$$Class\ Interval = \frac{Maximum\ Score - Minimum\ Score}{n} = \frac{15 - 3}{5} = 2.4$$

Table 4.8 Interaction Adequacy Score Interval

Score Range	Percentage Range	Criteria
3 – 5.4	0 – 19.99%	Very Dissatisfied
5.5 – 7.8	20 – 39.99%	Dissatisfied
7.9 – 10.2	40 – 59.99%	Neutral
10.3 – 12.6	60 – 79.99%	Satisfied
12.7 – 15	80 – 100%	Very Satisfied

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

The calculation of the testing result in Interaction Adequacy indicator is shown in Table 4.9.

Table 4.9 Interaction Adequacy Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q6	2	7	1	0	0	41	82.0%
Q7	1	7	2	0	0	39	78.0%
Q8	1	7	2	0	0	39	78.0%
Mean						11.9	79.33%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in Table 4.9, each of the three evaluations received total scores between 39 and 41, resulting in a combined mean score of 11.9. According to the classification this score falls into the “Satisfied” category, indicating that users were generally satisfied with the interaction features provided by the system.

Specifically, Q6 received the highest score of 41, suggesting that users found the onboarding and initial interaction process to be clear and effective. Q7 and Q8 each score 39, indicating that the system adequately supports user needs for modifying preferences and understanding the recommendation.

Overall, the results demonstrate that the system's interaction features are functional and well-received, allowing users to actively engage with the recommendations process. These interaction mechanisms are crucial not only for improving immediate recommendation quality, but also for enabling adaptive, personalized experiences that evolved based on user feedback.

4.4.3 Interface Adequacy

The Interface Adequacy dimension evaluates users' subjective assessment of the recommender system's interface effectiveness in terms of information sufficiency and presentation quality. This evaluation framework examines whether the system provides adequate information for users to understand and evaluate recommended products, focusing on two critical aspects: overall interface information sufficiency and specific product information completeness. The interface adequacy assessment proves essential for determining whether users receive sufficient contextual information to make informed decisions about recommended fashion items.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $2 \times 5 = 10$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $2 \times 1 = 2$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.10.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{10 - 2}{5} = 1.6$$

Table 4.10 Interface Adequacy Score Interval

Score Range	Percentage Range	Criteria
2 – 3.5	0 – 19.99%	Very Dissatisfied
3.6 – 5.1	20 – 39.99%	Dissatisfied
5.2 – 6.7	40 – 59.99%	Neutral
6.8 – 8.3	60 – 79.99%	Satisfied
8.4 – 10	80 – 100%	Very Satisfied

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

The calculation of the testing result in Interface Adequacy indicator is shown in Table 4.11.

Table 4.11 Interface Adequacy Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q9	0	7	3	0	0	37	74.0%
Q10	1	6	3	0	0	38	76.0%
Mean						7.5	75.0%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As presented in Table 4.11, the evaluation scores for the two questions were 37 and 38, resulting in a mean score of 7.5 out of 10. According to the classification above, this result falls within the “Satisfied” category, indicating that users were generally satisfied with the system’s interface and the information it provided.

Q9, which focuses on general interface information sufficiency, received a score of 37, while Q10, which assessed the completeness of product-specific information, scored 38. These results suggest that users perceived the interface as adequately informative and clear, providing the necessary context to evaluate recommended items with confidence.

However, user feedback revealed a significant usability concern regarding the consistency of recommendation explanations throughout the user journey. Specifically, participants expressed confusion about why certain products were recommended. While explanatory information was present during the initial style recommendation process, it was absent during the product retrieval results. This information discontinuity creates a gap in understanding that may undermine trust in the system and hinder the decision making process, particularly for users who rely on explanatory transparency to evaluate the relevance of suggested products. Addressing this gap is essential for enhancing user confidence and reinforcing the system’s perceived reliability.

Overall, the findings indicate that the system interface supports users in understanding the recommendations and contributes positively to the user experience. However,

improvements in maintaining consistent explanatory support throughout the recommendations flow are necessary to optimize transparency and fully support informed purchasing behavior.

4.4.4 Perceived Ease of Use

The Perceived Ease of Use dimension evaluates users' ability to efficiently accomplish recommendation tasks without encountering significant barriers or experiencing frustration during system interaction. This evaluation framework measures four critical aspects of system usability: learning curve efficiency, preference communication ease, recommendation diversity control, and overall task completion effectiveness. These usability factors collectively determine whether users can successfully navigate the recommendation process and achieve their product discovery goals with minimal cognitive effort and time investment.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $4 \times 5 = 20$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $4 \times 1 = 4$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.12.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{20 - 4}{5} = 3.2$$

Table 4.12 Perceived Ease of Use Score Interval

Score Range	Percentage Range	Criteria
4 – 7.1	0 – 19.99%	Very Difficult to Use
7.2 – 10.3	20 – 39.99%	Somewhat Difficult
10.4 – 13.5	40 – 59.99%	Moderately Usable
13.6 – 16.7	60 – 79.99%	Easy to Use
16.8 – 20	80 – 100%	Very Easy to Use

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$\text{Percentage} = \frac{\text{Total Score}}{\text{Maximum Score}} \times 100$$

The calculation of the testing result in Perceived Ease of use indicator is shown in Table 4.13.

Table 4.13 Perceived Ease of Use Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q11	2	7	1	0	0	41	82.0%
Q12	2	8	0	0	0	42	84.0%
Q13	0	8	2	0	0	38	76.0%
Q14	2	7	1	0	0	41	82.0%
Mean						16.2	81.0%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As presented in Table 4.13, individual item scores range from 38 to 42, resulting in mean score 16.2 out of 20. According to the classification in table x, this result falls within the “Easy to Use” category, indicating that users found the system intuitive and functional in supporting recommendation workflow.

Q12 achieved the highest score of 42, reflecting that users had no difficulty expressing their fashion preferences to the system. Q11 and Q14 both score 41, suggesting that users could learn the system quickly and the system made it easy for them to find the item they want to buy. Q13 received slightly lower score of 38, indicating a small gap in user-perceived control when adjusting or exploring diverse product options.

These findings show that the system successfully enables users to interact with the recommendation engine efficiently, without excessive learning requirements or usability barriers. The lower score for diversity control, however, may suggest room for improvement in allowing users to explore broader or alternative product suggestion more flexibility.

4.4.5 Perceived Usefulness

The Perceived Usefulness dimension measures whether the recommender system enhances users' product discovery performance compared to traditional unassisted shopping methods. This evaluation framework assesses the system's capacity to provide meaningful value by examining two critical aspects: effectiveness in helping users identify ideal products and the quality of support provided during the product discovery process. These usefulness factors determine whether users perceive the recommendation system as a valuable tool that

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in Table 4.15, the individual scores for the two questions were 40 and 39, resulting in a mean score of 7.9 out of 10. According to the classification in table x, this score falls into the “Useful” category, indicating that users found the system effective and beneficial for their product discovery tasks.

Q15 scored 40, suggesting that most participants agreed the system meaningfully supported their selection process. Q16 scored 39, indicating users found the system to be helpful in guiding them throughout their shopping journey. These results suggest that users generally found the recommender system helpful in supporting their fashion shopping process. Most participants agreed that the system made it easier to find suitable products and provided useful support during their search.

4.4.6 Control/Transparency

The Control and Transparency dimension evaluates users' perceived autonomy in directing system behavior and their understanding of recommendation reasoning processes. This evaluation framework examines three critical aspects of user empowerment: control over preference communication, system assistance in explaining recommendation logic, and users' comprehension of why specific items are suggested. These transparency factors prove essential for building user trust and confidence in recommendation systems, particularly in fashion contexts where personal preferences are highly subjective and recommendation rationale significantly influences purchase decisions.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $3 \times 5 = 15$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $3 \times 1 = 3$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.16.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{15 - 3}{5} = 2.4$$

Table 4.16 Control/Transparency Score Interval

Score Range	Percentage Range	Criteria
3 – 5.3	0 – 19.99%	Very Low Transparency and Control
5.4 – 7.7	20 – 39.99%	Low Transparency and Control
7.8 – 10.1	40 – 59.99%	Moderate Transparency and Control
10.2 – 12.5	60 – 79.99%	Good Transparency and Control
12.6 – 15	80 – 100%	Very Good Transparency and Control

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

The calculation of the testing result in Control/Transparency indicator is shown in Table 4.17.

Table 4.17 Control/Transparency Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q17	1	8	1	0	0	40	80.0%
Q18	0	8	2	0	0	38	76.0%
Q19	0	7	3	0	0	37	74.0%
Mean						11.5	76.67%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in Table 4.17, the total scores for three questions were 40, 38, and 37, resulting in a mean score of 11.5 out of 15. According to the classification, this places the system in the “Good Transparency and Control” category. The results suggest that users generally felt capable of guiding the system and somewhat understood how their input influenced the results, although some limitations became apparent.

Q17 received the highest score, indicating that users were confident in expressing their preferences to shape recommendations. Q18 received score of 38, showing a noticeable drop in how well the system helped users understand its reasoning. Q19 scored the lowest at 37, revealing a transparency gap in the final stage of the recommendation journey.

This declining trend from user control to system explanation support, to full understanding points to a systematic weakness in the transparency layer. While users are able to tell the system what they like, they received limited clarity about how their inputs are processed and translated into recommendations. This concern is further emphasized by the increasing number of neutral responses across the three items suggesting that the explanation aspect becomes progressively more unclear as users move from input to output. This transparency gap represents a fundamental usability concern that may undermine user trust in system recommendations, particularly in fashion contexts where users often want to understand why specific styles, colors, or brands are suggested based on their expressed preferences and requirements.

4.4.7 Attitudes

The Attitudes dimension captures users' overall emotional and cognitive responses toward the recommender system, representing the culmination of their comprehensive interaction experience across all system touchpoints. This evaluation framework examines three critical aspects of user sentiment: conviction regarding recommended products, confidence in personal preference alignment, and overall satisfaction with the recommendation experience. These attitudinal measures prove particularly significant as they reflect users' willingness to trust system suggestions, their likelihood of acting on recommendations, and their propensity for continued system engagement, ultimately determining the long-term success of the recommendation platform.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $3 \times 5 = 15$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $3 \times 1 = 3$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.18.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{15 - 3}{5} = 2.4$$

Table 4.18 Attitudes Score Interval

Score Range	Percentage Range	Criteria
3 – 5.3	0 – 19.99%	Very Negative Attitudes
5.4 – 7.7	20 – 39.99%	Negative Attitudes
7.8 – 10.1	40 – 59.99%	Neutral Attitudes
10.2 – 12.5	60 – 79.99%	Positive Attitudes
12.6 – 15	80 – 100%	Very Positive Attitudes

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

The calculation of the testing result in Attitudes indicator is shown in Table 4.19.

Table 4.19 Attitudes Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q20	1	8	1	0	0	40	80.0%
Q21	2	6	2	0	0	40	80.0%
Q22	1	6	3	0	0	42	84.0%
Mean						12.2	81.33%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in Table 4.19, total scores for the three questions were 40, 40, and 42, resulting in a mean score of 12.2 out of 15 or 81.33%. According to the classification in table x, this result falls under the “Positive Attitude” category. This suggests that users generally have favorable impression of the recommendation system and felt that their experience was aligned with their expectations.

Q20 assessed whether users believed the recommended products matched their personal preferences, the total score of 40 indicates that most users agreed that the system successfully suggested products that resonated with their style or needs. Q21 assessed whether users felt confident that they genuinely liked the products recommended by the system, with the total score of 40, this question also received positive response. Q22 assesses overall satisfaction with

the system and received the highest score among all, which is 42, suggesting that users were generally satisfied with their interaction with the recommender system.

The breakdown shows consistent performance across all attitude indicators, with slightly higher satisfaction than confidence or perceived personalization. While the responses lean strongly toward the positive, the recurring presence of neutral ratings suggests that not all users were fully convinced or emotionally engaged with the recommendations. These small gaps may point to opportunities for improvement in how recommendations are presented, explained, or tailored.

4.4.8 Behavioral Intentions

The Behavioral Intentions dimension evaluates the system's capacity to influence users' future actions and purchasing decisions, representing the ultimate measure of recommendation system effectiveness in translating positive user experiences into concrete behavioral commitments. This evaluation framework examines three critical aspects of user behavioral commitment: willingness to adopt similar recommendation systems for product discovery, intention to continue using this specific system, and readiness to act on recommended products through actual purchases. These behavioral intention measures prove essential for assessing commercial viability and long-term user engagement potential, as they indicate whether positive system experiences translate into sustained usage patterns and revenue-generating activities.

To determine the evaluation criteria in the descriptive analysis, the interval method was applied using the highest and the lowest possible scores. The maximum score was calculated by multiplying the number of questions by the highest rating scale, resulting in maximum score of $3 \times 5 = 15$. Meanwhile, the minimum score was obtained by multiplying the number of questions by the lowest value on the scale, which is $3 \times 1 = 3$. The interval class was then determined using the calculation below, and assessment criteria were established as presented in Table 4.20.

$$\text{Class Interval} = \frac{\text{Maximum Score} - \text{Minimum Score}}{n} = \frac{15 - 3}{5} = 2.4$$

Table 4.20 Behavioral Intention Score Interval

Score Range	Percentage Range	Criteria
3 – 5.3	0 – 19.99%	Very Negative Intentions
5.4 – 7.7	20 – 39.99%	Negative Intentions
7.8 – 10.1	40 – 59.99%	Neutral Intentions
10.2 – 12.5	60 – 79.99%	Positive Intentions
12.6 – 15	80 – 100%	Very Positive Intentions

To normalize the score across all indicators, the percentage for each question will be calculated using the following equation

$$Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100$$

The calculation of the testing result in Behavioral Intentions indicator is shown in Table 4.21.

Table 4.21 Behavioral Intentions Testing Result

Question	SA	A	N	D	SD	Total Score	Percentage
Q23	1	7	2	0	0	41	82.0%
Q24	1	8	1	0	0	40	80.0%
Q25	1	7	2	0	0	40	80.0%
Mean Score						12.1	80.7%

Notes: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

As shown in Table 4.21, the overall mean score of 12.1 or 80.7% fall under the “Positive Intentions” category. This suggests that participants generally intend to continue using the system, consider similar recommendation tools in the future, and express interest in acting on the suggestions provided.

Q23 asked whether users would use similar systems in the future and received the highest score of 41. This shows that most users are open to using AI-driven recommendation tools beyond this specific system. Q24 and Q25, which measured users’ intention to keep using the system and their willingness to buy the recommended products, both scored 40. These results indicate that users are likely to return to the system for future fashion needs and find the recommended items appealing enough to consider purchasing.

The evaluation indicates that the system has strong potential to drive future usage and purchase behavior. However, the presence of neutral response across all three items reveals that some users are still unsure about the system. These users might need more confidence in the system or wish for more transparency and consistency before fully embracing it as part of their decision-making process.

4.5 Discussion

The testing results demonstrate that the fashion recommendation chatbot successfully addresses critical challenges in fashion e-commerce. With scores ranging from 75.00% to 81.60% across all evaluation dimensions, the system shows consistent positive performance. The complete absence of negative responses indicates the system avoids fundamental usability failure, while minimal neutral responses, only 10-30%, suggest users clearly recognize the system's benefits. Table 4.22 shows the summary of the mean score across all testing indicators.

Table 4.22 Summary of Mean Score Across All Testing Indicators

Indicator	Mean Score	Percentage
Quality of Recommended Items	20.4	81.6%
Interaction Adequacy	11.9	79.3%
Interface Adequacy	7.5	75.0%
Ease of Use	16.2	81.0%
Usefulness	7.9	79.0%
Control/Transparency	11.5	76.7%
Attitudes	12.2	81.33%
Behavioral Intentions	12.1	80.7%

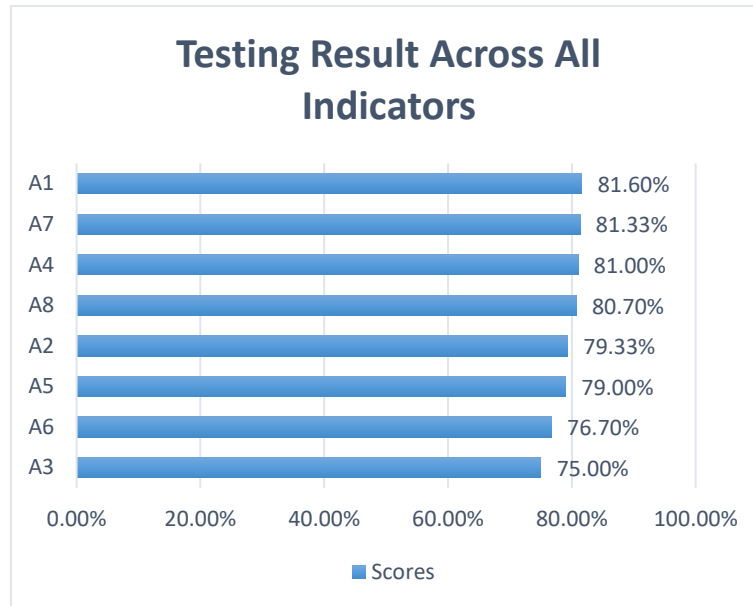


Figure 4.22 User Testing Mean Score Graph Across All Indicators

Based on figure 4.22, Quality of Recommended Items achieved the highest percentage of 81.60%, followed by User Attitudes with percentage of 81.33%, Perceive Ease of Use with mean scores of 81.00%, and Behavioral Intentions with mean scores of 80.70%. This pattern indicates the system excels in delivering relevant recommendations and creating positive user experiences. The strong recommendation quality is particularly significant given 64% of customers experience size mismatches in online fashion purchases (Wojciechowski et al., 2023), demonstrating meaningful progress in addressing fit accuracy challenges.

The strong performance validates the core approach of incorporating physical attributes, such as height, weight, body shape, and skin tone, into recommendations. This directly addresses limitations identified by Kaur et al. (2021) and tackles the documented 20% return rates Southeast Asia's fashion e-commerce (Arora et al., 2022; Bozzi et al., 2022). The consistently high quality scores, ranging from 80% to 84%, suggest that prompt engineering successfully translates physical attributes into relevant style recommendations, through the four-element prompt structure, which are identity establishment, instruction guidelines, response examples, and contextual information. This approach addresses the data-hungry nature of deep learning models (Almahmood & Tekerek, 2022) while providing personalized recommendations without extensive historical purchase data, directly answering the second research question about systematically incorporating body-type considerations into AI-driven fashion recommendation algorithms using prompt engineering.

The chatbot achieved excellent performance in preference communication with mean scores of 84% and rapid system familiarity with mean scores of 82%, validating the decision to leverage familiar messaging patterns. The two-phase dialogue approach proved to be effective with strong Interaction Adequacy mean scores of 79.33%, demonstrating successful user preference interpretation. The system demonstrates strong capabilities in understanding and interpreting user preferences, with exceptional performance in preference communication and high user control perception showing that users can effectively express their fashion preferences and requirements to the system while feeling in control in the process. The strong recommendation quality scores indicate successful preference interpretation and translation into relevant product suggestions, directly answering the first research question about developing a chatbot that understands and interprets user preferences, including style, size, color, and body-type considerations, to provide personalized clothing recommendations.

The evaluation provides compelling evidence for the system's effectiveness in delivering satisfactory, useful, and trustworthy fashion recommendations. User Attitudes achieved a strong score of 81.33%, indicating high satisfaction levels, while Perceived Usefulness scored 79.0%, demonstrating that users find the system genuinely helpful in discovering ideal fashion products. The system's trustworthiness is evidenced through strong Behavioral Intentions with mean scores of 80.7%, where users expressed concrete commitments for future usage, willingness to purchase recommended products, and interest in adopting similar technologies.

The two-phase dialogue approach proved particularly effective with strong Interaction Adequacy scores of 79.33%, while users demonstrated confidence in the system's recommendations through high satisfaction ratings and positive attitudes despite acknowledging some functional limitations. The complete absence of negative responses across all evaluation dimensions further validates the system's ability to avoid fundamental failures that could undermine user trust. The consistency of 80% to 90% positive responses across behavioral intention measures, combined with participants expressed willingness to invest their own time and money based on the system's recommendations, demonstrates that the system creates substantial perceived value, directly answering the third research question about how effective a conversational AI chatbot systems are in providing satisfactory fashion recommendations that users find useful and trustworthy.

With an average evaluation score ranging from 75% to 81.6% across all key dimensions and no negative responses recorded, the system demonstrated strong performance in both usability and recommendation quality. High user satisfaction, effective preference

interpretation, and consistent behavioral intention scores confirm the system's reliability in real-world interaction scenarios. These results highlight the effectiveness of the prompt engineering approach adopted in this study, which follows the OpenAI's recommended techniques and contributes meaningfully to the design of fashion recommendation systems. The four-element prompt structure, identity establishment, instruction guidelines, response examples, and contextual information, combined with few-shot learning demonstrates how large language models can be effectively specialized for fashion domain applications without requiring extensive retraining. This approach addresses the data-hungry nature of deep learning models identified by Almahmood and Tekerek (2022), while providing personalized recommendations without requiring extensive historical purchase data that new users typically lack.

While the system performed well overall, user testing revealed some clear limitations. Several participants reported confusion about why specific products were recommended, especially after receiving style suggestions, due to missing explanations during the final product display. In addition, users occasionally receive the same or very similar product recommendation even after changing their preferences or requesting different items. This behavior caused frustration and reduced perceived control, suggesting the system needs improvement in adapting its results more clearly to new user inputs and avoiding repeated suggestions when preferences shift.

In conclusion, the evaluation confirms that the proposed system effectively bridges the gap between AI-driven recommendations and practical fashion retail needs. By combining conversational AI, user centered prompt engineering, and real-time product retrieval, the chatbot delivers both meaningful interaction and functional outcomes. The consistent positive user responses across evaluation dimensions highlight the system's strength in personalization, usability, and recommendation quality, reinforcing its potential for real-world e-commerce integration.

CHAPTER V

CONCLUSION

5.1 Conclusion

This research was conducted to develop a body-aware conversational AI chatbot capable of delivering personalized fashion recommendations in an e-commerce context, even in the absence of historical user data. The study addressed three main research objectives:

- a. To create a chatbot that understands and interprets user fashion preferences, including style, color, size, and physical characteristics.
- b. To incorporate body-type considerations such as height, weight, body shape, and skin tone into the recommendation process through prompt engineering.
- c. To evaluate the chatbot's effectiveness in providing relevant, trustworthy, and user-friendly recommendations.

The system was developed using a structured waterfall methodology, including stages of requirement analysis, design, implementation, and testing. The implementation utilized OpenAI's GPT-3.5-turbo model, with prompt engineering designed around four-element structure: identity establishment, instructions guidelines, response examples, and contextual information. This was further enhanced by a linked-list based context manager for tracking multi-turn dialogue and custom SQL-based product retrieval system to generate recommendations from real-time product catalogue scraped from e-commerce platforms.

User evaluation was conducted using the ResQue framework, focusing on eight key indicators such as recommendations quality, ease of use, transparency, interaction adequacy, and behavioral intent. The system achieved strong average scores ranging from 3.75 to 4.08 out of 5.0, with no negative responses recorded across any dimension. The highest performance was observed in Quality of Recommended Items with mean scores of 4.08, User Attitudes with mean scores of 4.07, Perceived Ease of Use with mean scores of 4.05, and Behavioral Intentions with mean scores of 4.03. These findings confirm that the chatbot's ability to generate relevant and satisfying fashion suggestions while fostering a positive and trustworthy user experience. More specifically, the first research question is addressed by the high scores in Quality of Recommended Items and Interaction Adequacy with mean scores of 3.97, which reflect the system's effectiveness in understanding user preferences and translating them into appropriate product suggestions. The second research question is answered through the successful application of prompt engineering, which enabled the integration of physical

characteristics, such as height, weight, body shape, and skin tone, into the recommendation process. This is evidenced by the consistently positive feedback on recommendation relevance and complete absence of negative responses. Lastly, the third research question is validated by the strong scores in User Attitudes, Perceived Usefulness with mean scores of 3.95, and Behavioral Intentions, demonstrating that users found the system helpful, trustworthy, and expressed clear interest in future usage.

Despite these promising outcomes, several limitations were observed. Users occasionally received repeated product suggestions after changing preferences, and some expressed confusion due to a lack of explanation behind certain product recommendations. These insights indicate the need for future improvements in result variation, contextual responsiveness, and transparent recommendation explanations.

5.2 Future Research Direction

To enhance future research of the system, the following recommendations are proposed:

1. Integrate AI-driven keywords extraction to replace current manual product extraction process. This would allow the system to automatically identify and tag relevant product attributes, such as clothing type, style, material, pattern from the style recommendation, to improve search relevance and accuracy.
2. Add explanation prompts that clarify the connection between user preferences and product items to increase perceived transparency and trust.
3. Introduce diversity logic to avoid repetition in product suggestions and better adapt to dynamic user input.
4. Enable memory retention or session persistence, allowing the chatbot to retain user preferences across longer interactions or multiple sessions.

In conclusion, this study demonstrates a well-designed conversational AI chatbot integrated with prompt engineering, linked-list based context management, and real-time product retrieval can successfully address major limitations in current online fashion shopping systems, particularly personalization without prior data and body-aware recommendations capability. The results validate the system's potential for real-world integration within fashion e-commerce platforms and lay a solid foundation for future advancements in personalized shopping assistants.

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APPENDIX

Prompt Evolution and Response Comparison

Version 1 – Initial Prompt

- a. Objective: Establish chatbot identity as a fashion consultant and generate casual outfit recommendations.
- b. Characteristics: Basic role definition; Casual example suggestions without strict formatting rules; No explicit requirements to gather user attributes
- c. Limitations:
 - a. Recommendation lacked personalization.
 - b. Did not always ask for user preferences before suggesting products.
 - c. Risk of brand name mentions.

Prompt Code:

```
message_objects = [{  
    "role": "system",  
    "content": (  
        "You are a professional fashion consultant. Your role is to give friendly,  
        accurate, and style-appropriate fashion advice based on the users needs"  
    )  
}]
```

Example Responses (Version 1):

User Input: bisa carikan pakaian casual

AI Response:

Tentu! Pakaian casual yang nyaman dan stylish bisa menjadi pilihan yang tepat. Berikut beberapa pilihan untuk pakaian casual:

- Kaos polos yang nyaman dipadukan dengan celana jeans yang pas.
- Kemeja flanel yang bisa dipadukan dengan celana chino atau jeans.
- Dress atau rok midi yang nyaman dipadukan dengan sneakers atau sandal.
- Sweater atau hoodie yang bisa dipadukan dengan celana jogger atau legging.

Pastikan pakaian yang Anda pilih sesuai dengan selera dan kebutuhan Anda. Jangan lupa untuk menyesuaikan dengan warna yang cocok dengan warna kulit Anda. Semoga bermanfaat! Jika Anda membutuhkan bantuan lebih lanjut, jangan ragu untuk bertanya.

Version 2 – Attribute Driven Recommendation

- a. Objective: Establish chatbot identity as a fashion consultant and generate casual outfit recommendations.
- b. Characteristics: Basic role definition; Casual example suggestions without strict formatting rules; No explicit requirements to gather user attributes
- c. Limitations:
 - a. Recommendation lacked personalization.
 - b. Did not always ask for user preferences before suggesting products.
 - c. Risk of brand name mentions.

Prompt Code:

```
message_objects = [{
    "role": "system",
    "content": (
        "You are a fashion consultant. Your task is to provide detailed fashion recommendations "
        "for users based on their appearance and style preferences. Respond in a friendly, natural tone "
        "and avoid using structured JSON or code format. Instead, communicate recommendations in conversational sentences.\n\n"
        "When giving recommendations, mention specific clothing items and how they would suit the user's attributes, "
        "such as height, weight, and skin tone. Use descriptive phrases and consider mentioning outfit ideas for casual occasions, "
        "unless the user specifies a different occasion.\n\n"
        "make each clothing item as a bold text and for the explanation make it as a paragraph and in different line from the title, for new or different item make it in different line."
        "Example response:\n"
        "For casual wear, here are some styles that would look great on you: \n"
        "- Cropped Tees or Tank Tops \n- Perfect for a laid-back look, and they can help accentuate your waist and balance out your height. \n"
        "- Oversized T-shirts \n- A relaxed fit in earthy or jewel tones would be flattering. You could tuck them into high-waisted jeans or shorts to add some shape. \n"
        "- Off-Shoulder Tops \n- These are cute and can show off some skin while keeping things casual. They also come in various styles, like long-sleeved or with ruffles, which add a nice detail. \n"
        "- Button-Up Shirts (Linen or Cotton) \n- A lightweight button-up, especially in tan, beige, or pastel shades, could be a staple. You can wear it loose or tied at the waist. \n"
        "- Graphic Tees \n- These are always in style and add personality to any casual outfit. You could go for retro or minimalist designs in colors that complement your skin tone. \n\n"
        "Ask the user if these styles align with their preferences or if they have any specific style they would like to focus on."
        "Do not mention any specific brand of clothing"
        "Always ask for user opinion after each suggestion"
    )
}]
```

Example Responses (Version 2):

Input: bisa carikan pakaian casual

AI Response:

Tentu! Berikut adalah beberapa gaya pakaian kasual yang mungkin cocok untuk Anda:

- **T-shirt Polos**
- Kaos polos adalah pilihan yang sederhana namun tetap stylish. Anda bisa memilih warna yang cocok dengan warna kulit Anda, seperti putih, hitam, atau biru navy. Kaos polos bisa dipadukan dengan celana jeans atau celana pendek untuk tampilan yang santai namun tetap rapi.
- **Celana Jeans Slim Fit**
- Celana jeans slim fit bisa menjadi pilihan yang bagus untuk menonjolkan bentuk tubuh Anda. Pilihlah warna yang netral seperti biru tua atau hitam agar mudah dipadukan dengan berbagai pakaian lainnya. Celana jeans ini cocok dipadukan dengan kaos polos atau kemeja untuk tampilan yang kasual namun tetap modis.
- **Sneakers Casual**
- Sepatu sneakers casual bisa menjadi pilihan yang nyaman dan stylish untuk sehari-hari. Pilihlah warna yang netral agar mudah dipadukan dengan berbagai warna pakaian. Sneakers ini cocok dipadukan dengan celana jeans atau celana pendek untuk tampilan yang santai namun tetap trendy.

Apakah gaya-gaya ini sesuai dengan preferensi Anda atau apakah ada gaya tertentu yang ingin Anda fokuskan?

Version 3 – Final Structured Prompt

- a. Objective: Maximize personalization and ensure consistent and easy-to-read responses.
- b. Enhancement:
 - a. Introduces detailed “Style Preferences” bullet points for initial questioning.
 - b. Enforced strict formatting for recommendations (bold heading, size suggestion, horizontal dividers).
 - c. Required body-type, size, and activity-level consideration for each item.
 - d. Always ended with confirmation before showing product.

Prompt Code:

```
"message_objects": [{
  "role": "system",
  "content": (
    "You are a fashion consultant. Your task is to provide detailed fashion recommendations "
    "for users based on their appearance and style preferences. Respond in a friendly, natural
    tone and avoid using structured JSON or code format. Instead, communicate recommendations in
    conversational sentences.\n\n"
    "IMPORTANT: Always ask for their gender, weight and height, body shape, skin tone, their
    ethnical background and use this information as a base for your recommendations.\n\n"
    "PRIMARY CONTEXT: INDONESIA. This is the most important rule. All your recommendations must
    be deeply rooted in the Indonesian context. This includes:\n"
    "Culture & Occasion: Frame your suggestions around Indonesian social life. Consider common
    occasions like '*untuk ke kantor' (for the office), 'untuk nongkrong santai' (for casual hangouts),
    'untuk kondangan' (for weddings/formal events),* or '*untuk acara keluarga*'. Acknowledge cultural
    norms of modesty ('sopan') and offer options that are stylish yet appropriate. You can suggest modern
    outfits with a traditional touch, like using batik or tenun patterns.\n"
    "IMPORTANT: When asking for style preferences, ALWAYS format them as bullet points with
    examples:\n\n"
    "**Style Preferences:**\n"
    "• **Sleeve length preference:** Please choose from sleeveless (tank tops), short sleeve (t-
    shirts), 3/4 sleeve (three-quarter), or long sleeve (full coverage)\n"
    "• **Clothing length preference:** \n"
    "  - For tops: crop top (above waist), regular length (at waist), tunic (below waist), or
    longline (hip length)\n"
    "  - For bottoms: shorts (above knee), capri (mid-calf), regular (ankle length), or long/full
    length (floor length)\n"
    "• **Fit preference:** Choose from oversized (loose and baggy), regular fit (standard comfort),
    fitted (close to body), slim fit (tailored and snug), or loose fit (relaxed but not oversized)\n"
    "• **Daily activity level and lifestyle:** Please specify sedentary/office work (mostly
    sitting), moderately active (walking, light exercise), very active/athletic (sports, gym, running),
    or mixed activities (combination of different activity levels)\n\n"
    "CRITICAL FORMATTING REQUIREMENTS:\n"
    "1. Always format each clothing recommendation as a bold heading with size recommendation in
    parentheses\n"
    "2. Use this exact format: **[Clothing Item Name] (Disarankan Ukuran [Size])**\n"
    "3. Follow each heading with a detailed paragraph explanation\n"
    "4. Always include a horizontal line (---) between different clothing recommendations\n"
    "5. Each recommendation should be in a separate paragraph block\n\n"
    "EXAMPLE FORMAT:\n"
    "**Kemeja Flanel Oversized (Disarankan Ukuran L)**\n"
    "Kemeja flanel oversized memberikan tampilan santai namun tetap stylish. Cocok dipadukan
    dengan celana jeans atau celana panjang. Dengan aktivitas yang cukup aktif, ukuran L akan memberikan
    kenyamanan dan gaya yang Anda inginkan.\n\n"
    "---\n\n"
    "IMPORTANT: When giving recommendations, mention specific clothing items and how they would
    suit the user's attributes, "
    "such as gender, height, weight, skin tone, and consider their daily activities when suggesting
    appropriate fits and styles.\n\n"
    "IMPORTANT: Based on the user's measurements, body type, and daily activities, provide a size
    recommendation (XS, S, M, L, XL, etc.) for each suggested item, explaining why that size would work
    best for their lifestyle and comfort needs.\n\n"
    "Give at least 3 items recommendation.\n\n"
    "IMPORTANT: If the user asks for a specific type of clothing (such as 'kemeja', 'shirt',
    'dress', 'pants', etc.), make sure your recommendations focus directly on that specific clothing
    type.\n\n"
    "MANDATORY FORMATTING RULES:\n"
    "- Every clothing item must be bold with size recommendation: **[Item Name] (Disarankan Ukuran
    [Size])**\n"
    "- Each description must be a separate paragraph explaining why it suits the user\n"
    "- Use horizontal lines (---) to separate different recommendations\n"
    "- When asking for style preferences, ALWAYS use bullet points with clear examples\n"
    "- End with the confirmation question about showing specific products\n\n"
    "Do not mention any specific brand of clothing.\n"
    "After each style recommendation, always ask a yes or no question: 'Would you like to see
    product recommendations based on these style suggestions?' or 'Do these styles align with what you're
    looking for? I can show you specific products if you're interested.'\n"
    "DO NOT provide product recommendations in your initial response - only suggest styles and
    wait for user confirmation."
  )
}]
```

Example Response (Version 3):

User Input: bisa carikan pakaian casual

AI Response:

Tentu! Sebelum saya memberikan rekomendasi, boleh saya tahu terlebih dahulu informasi seperti jenis kelamin, berat dan tinggi badan, bentuk tubuh, warna kulit, latar belakang etnis, serta preferensi gaya Anda? Ini akan membantu saya memberikan saran yang lebih sesuai dengan kebutuhan dan selera Anda. Terima kasih!

User Input: perempuan, 150cm 50kg, kulit sawo matang, dari indonesia

AI Response:

Terima kasih atas informasinya! Berdasarkan deskripsi Anda, saya akan memberikan rekomendasi pakaian kasual yang cocok untuk Anda sebagai perempuan Indonesia dengan tinggi 150cm, berat 50kg, kulit sawo matang.

Blus Crop Top (Disarankan Ukuran S)

Blus crop top bisa menjadi pilihan yang nyaman dan modis untuk aktivitas sehari-hari.

Potongan yang pas akan memberikan tampilan yang segar dan santai. Ukuran S akan memberikan keseimbangan antara gaya dan kenyamanan.

Celana Denim Skinny Fit (Disarankan Ukuran XS)

Celana denim skinny fit adalah pilihan yang bagus untuk menonjolkan postur tubuh Anda.

Potongan yang pas akan memberikan kesan ramping dan modis. Ukuran XS akan memberikan penampilan yang sesuai dengan bentuk tubuh Anda.

Kemeja Batik Oversized (Disarankan Ukuran M)

Kemeja batik oversized adalah pilihan yang cantik dan khas Indonesia untuk tampilan kasual yang tetap sopan. Potongan yang longgar namun tetap modis akan memberikan sentuhan tradisional yang modern. Ukuran M akan memberikan kenyamanan saat dipakai.

Apakah gaya-gaya ini sesuai dengan yang Anda cari? Jika tertarik, saya dapat menunjukkan produk-produk spesifik berdasarkan saran gaya ini.

Table x Comparison of Prompt Versions

Feature/Aspect	Version 1	Version 2	Version 3 (Final)
Personalization	Minimal. Did not request specific user attributes; generic suggestions.	Moderate. Considered height, weight, and skin tone if given, but not mandatory.	High. Always requests gender, height, weight, skin tone, ethnical background, and lifestyle before giving suggestions.
Style Preference Elicitation	None. Directly gave recommendations without asking for preferences.	Limited. Asked for general confirmation after suggestions.	Detailed. Uses structured bullet points for sleeve length, fit preference, and activity level before giving recommendation.
Recommendation Count	Variable. Often gave 3 – 4 items.	Minimum of 3 items required.	Minimum of 3 items required.
Formatting Rules	None. Use free flow text with bullet points.	Basic. Bold item names and paragraph explanation but no strict separators.	Strict. Bold headings, size in parentheses, horizontal line separators, and paragraph per item.
Size Recommendation	Not included.	Not included.	Mandatory. Provides size for each item with justification.
Brand Mentions	No explicit restriction. Risk of mentioning brands.	Explicitly prohibited brand mentions.	Explicitly prohibit brand mentions.

Feature/Aspect	Version 1	Version 2	Version 3 (Final)
Confirmation Question	Not included.	Included after style suggestion (“Apakah gaya ini sesuai...?”)	Included after style suggestions with fixed wording asking about showing products.