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# A Constructive Content-Based Filtering Recommendation Application: Optimizing Coffee Selection Based on User Preferences

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**Abstract:** Coffee, a typical beverage consumed worldwide, offers various options, from bean origin to brewing methods. However, this abundance of choice often leads consumers to experience decision-making challenges, a phenomenon known as choice overload. Therefore, this study focuses on developing and implementing a recommendation application to help users make informed coffee choices based on their preferences. The study employs a system development life cycle (SDLC) approach and utilizes content-based filtering techniques to achieve the purpose. Data for this study was gathered from three prominent coffee shops: Zus Coffee Shop, Richiamo Coffee Shop and Gigi Coffee Shop, providing a diverse dataset for analysis. The study employs usability testing to evaluate the usefulness, perspicuity, dependability, and attractiveness of the developed recommendation application. Through rigorous testing, we assess user acceptance and overall system performance. The results indicate a significant reduction in choice overload and an enhanced user experience, validating the competence of the recommendation application. The study implies that by using a content-based filtering recommendation system, coffee drinkers can enjoy more personalized suggestions tailored to their taste preferences, such as roast level, milk type, etc. For users who may feel overwhelmed by the variety of options at a coffee shop, this system simplifies the decision process by recommending coffee types that match their stated preferences. By exploring avenues such as collaborative filtering, sentiment analysis, and incorporating additional user feedback, we aim to further enhance the accuracy and personalization of coffee recommendations, ultimately improving the overall coffee selection experience for consumers.

**Keywords:** *Coffee selection, content-based filtering, recommendation system, user preferences*

## 1. Introduction

When Hainanese Chinese opened kopitiams during the colonial era in Malaysia, the country's coffee culture was born (Ali & Ramanathan, 2021). Then, the international coffee shop chains such as Starbucks and Coffee Bean and Tea Leaf were introduced in Malaysia in the late 1990s (Minh, 2022). As more local and international coffee companies and coffee shops open their doors in Malaysia these days, the country's coffee market is expanding (Ong, 2021). As more coffee shops are being opened, consumers are frequently confronted with decision-making challenges, particularly in domains with extensive coffee product offerings. However, too many options can cause choice overload, where the ability to make a choice is reduced when customers have too many options, and they tend to be less satisfied with their final decision (Chernev et al., 2015).

The psychological implications of choice overload are well-documented (Iyengar & DeVoe, 2003). It leads to decision fatigue, decreased satisfaction with the chosen option, and, in some cases, decision avoidance altogether. Recognizing the gravity of this issue in the context of coffee selection, this study endeavors to introduce an innovative approach to alleviate choice overload and enhance the user experience. One of the ways to mitigate the choice overload issue is by using recommender systems (Haubl & Trifts, 2000). According to Roy and Dutta (2022), a recommender system is a system that, from an extended selection of alternatives, can either guide the user in a personalized manner to useful objects or it can deliver tailored recommendations as output. The recommender system's objective is to provide each other with a personalized recommendation based on user input (Burke et al., 2011).

Drawing inspiration from the field of recommender systems, we implemented a content-based filtering recommendation system tailored specifically for assisting consumers in their coffee choices. This system leverages user references, preferences, and past selections to generate personalized recommendations, ultimately empowering consumers with a more streamlined and gratifying decision-making process. To ensure the robustness and applicability of our recommendation system, we conducted data collection efforts at three

distinct coffee establishments: Zus Coffee Shop, Richiamo Coffee Shop and Gigi Coffee Shop. This multi-source data set provides a comprehensive foundation for analysis and model development, encompassing a diverse range of coffee offerings and consumers' preferences.

In this paper, we present the methodology behind the content-based filtering technique employed in our recommendation system and detail the process of data acquisition and preprocessing. Subsequently, we outlined the framework for usability testing that we employed to assess how well our solution relieves choice overload. Finally, we discuss the results of our study and offer forward-looking recommendations for the refinement and expansion of the coffee recommendations system. By addressing the pervasive issue of choice overload in coffee selection, this research not only contributes to the fields of consumer psychology and recommender systems but also offers practical implications for enhancing the overall coffee consumption experience.

## 2. Literature Review

### Popular Malaysian Coffee Chains by Price and Accessibility

Khaw (2025) from Valcan Post stated that the five most popular Malaysian coffee shops based on affordability and accessibility are Zus, Gigi, San Francisco, Bask Bear and Richiamo. These chains have been recognized for their balance of price and accessibility within Malaysia's coffee scene. Four of these chains provide a loyalty program through their app; only Richiamo is not currently offering a loyalty program. Due to time constraints in collecting data for these five coffee shops, only three were used in this study: Zus, Gigi and Richiamo.

### Recommendation System for Coffee Selection

The problem of choice overload, which is characterized by the drawbacks of having too many options, researchers from a wide range of disciplines, including psychology, marketing and economics, have given it a lot of attention. To mitigate choice overload, recommender systems have emerged as a viable solution. Specifically, this paper focuses on the development of a recommendation system tailored for coffee selection. The system relies on user preferences to generate personalised suggestions, thereby guiding consumers toward options that align with their preferences. This method is the foundation of content-based filtering, which uses an item's properties and characteristics to provide recommendations (Ricci et al., 2022). The utilization of user preferences in conjunction with content-based filtering represents a novel and promising avenue for enhancing the coffee selection experience. While the utilization of recommendation systems in coffee selection is a relatively nascent area of research, there have been notable strides in related domains. Studies focusing on recommender systems in gastronomy and beverage selection have demonstrated their efficacy in enhancing user experience (Lin, 2018). Additionally, research on choice overload in various consumer contexts provides a foundational understanding of the challenges that necessitate innovative solutions (Adriatico, 2022).

### Types of Filtering Techniques

In the domain of recommendation systems, several filtering techniques are available. Content-based filtering examines item attributes and matches them to the user's preferences to produce recommendations for features or characteristics that are similar. A popular method that makes recommendations based on patterns found in user-item interactions is called collaborative filtering (Ricci, 2015). It examines user behaviour, recommending items preferred by users with similar behaviour. The benefits of both content-based and collaborative filtering are combined in hybrid filtering, which has shown promise in mitigating the limitations of individual techniques (Roy & Dutta, 2022). Table 1 provides a detailed comparison of these three techniques.

**Table 1: Features Comparison between Filtering Techniques**

| Features | Content-Based | Collaborative | Hybrid |
|---|---|---|---|
| Accuracy | High | Variable | High |
| Handling Many Inputs | Yes | Yes | Yes |
| Simplicity | Moderate | Moderate | Moderate |
| Pros | Utilizes user preferences and item attributes. No | Leverages user-item interactions for | Combining the strengths of content-based and |

| | | | |
|---|---|---|---|
| | need for explicit user-item interactions | recommendation. Effective in capturing user preferences | collaborative learning. Address sparsity issues |
| Cons | Limited diversity in recommendations. Reliance on accurate item attributes | Sparsity of data can impact accuracy. | Increased complexity in system design. Require integration of multiple algorithms. |

In conclusion, because content-based filtering offers simple programmability and accuracy qualities, it has been chosen. This technique is known for its high accuracy. It relies on the analysis of item attributes and user preferences to make recommendations, resulting in precise suggestions that align with users' tastes and preferences. Content-based filtering can efficiently process many inputs in a single run. This makes it well-suited for scenarios with extensive item catalogues or where a substantial amount of data needs to be processed at once. The simplicity of content-based filtering can also lead to easier implementation and maintenance.

## 3. Methodology

Understanding workflow is a crucial process to achieve the objectives of this study. The developed application used the System Development Life Cycle (SDLC) methodology. The simplicity of this model is one of the reasons why it was chosen as the methodology of this study. This section divides the research methods into four subsections: Data gathering, design, mobile platform implementation, and testing.

### Data Gathering

For this study, we needed to compile a comprehensive list of coffee beverages available in Malaysia. To accomplish this, we collected data on 152 distinct coffee drinks offered by three distinct coffee shops: Zus Coffee, Richiamo Coffee and Gigi Coffee. This information was sourced directly from the respective websites of these establishments. Subsequently, the data underwent a thorough cleaning process using Microsoft Excel in preparation for its integration into the recommendation model. Figure 1 shows a snippet of the dataset used in this study.

**Figure 1: Snippet of the Dataset**

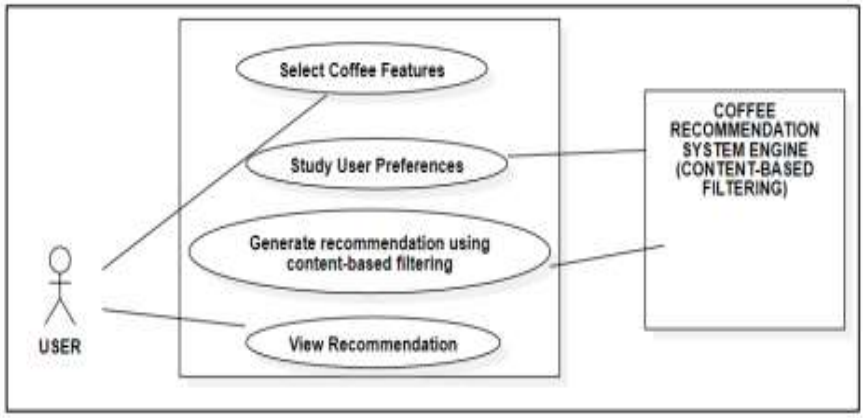
| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | id | Coffee_Name | Coffee_Type | Description | Coffee_Shop | Flavour | Milk_Type | Tempera | Roast_Type | Origin |
| 2 | 1 | Espresso | Espresso | "A standard Italian | Zus Coffee | | | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 3 | 2 | Hot Flat White | Flat White | seeking the | Zus Coffee | | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 4 | 3 | Hot Americano | Americano | Espresso gently | Zus Coffee | | | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 5 | 4 | Iced Americano | Americano | Espresso gently | Zus Coffee | | | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 6 | 5 | Hot Salted Caramel Latte | Latte | like their coffee | Zus Coffee | Caramel | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 7 | 6 | Iced Salted Caramel Latte | Latte | like their coffee | Zus Coffee | Caramel | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 8 | 7 | Hot Roasted Hazelnut Latte | Latte | like their coffee | Zus Coffee | Hazelnut | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 9 | 8 | Iced Roasted Hazelnut Latte | Latte | like their coffee | Zus Coffee | Hazelnut | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 10 | 9 | Hot French Vanilla Latte | Latte | like their coffee | Zus Coffee | Vanilla | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 11 | 10 | Iced French Vanilla Latte | Latte | like their coffee | Zus Coffee | Vanilla | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 12 | 11 | Hot Café Latte | Latte | enjoy their coffee | Zus Coffee | | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 13 | 12 | Iced Café Latte | Latte | enjoy their coffee | Zus Coffee | | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 14 | 13 | Hot Cappuccino | Cappuccino | delicious coffee | Zus Coffee | | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 15 | 14 | Iced Cappuccino | Cappuccino | delicious coffee | Zus Coffee | | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 16 | 15 | Hot Caramel Macchiato | Macchiato | Salted Caramel | Zus Coffee | Caramel | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 17 | 16 | Iced Caramel Macchiato | Macchiato | Salted Caramel | Zus Coffee | Caramel | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 18 | 17 | Hot Pandan Coconut Latte | Latte | wondered what | Zus Coffee | Pandan, Coconut | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 19 | 18 | Iced Pandan Coconut Latte | Latte | wondered what | Zus Coffee | Pandan, Coconut | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 20 | 19 | Hot ZUS Cocoa Mocha | Mocha | Mocha, with | Zus Coffee | Chocolate | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 21 | 20 | Iced ZUS Cocoa Mocha | Mocha | Mocha, with | Zus Coffee | Chocolate | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 22 | 21 | Hot Café Mocha | Mocha | chocolate & | Zus Coffee | Chocolate | Dairy Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 23 | 22 | Iced Café Mocha | Mocha | chocolate & | Zus Coffee | Chocolate | Dairy Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 24 | 23 | Hot OATLY ZUS Cocoa Mocha | Mocha | Mocha The | Zus Coffee | Chocolate | Oat Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 25 | 24 | Iced OATLY ZUS Cocoa Mocha | Mocha | Mocha The | Zus Coffee | Chocolate | Oat Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 26 | 25 | Hot OATLY Café Mocha | Mocha | The OATLY | Zus Coffee | Chocolate | Oat Milk | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 27 | 26 | Iced OATLY Café Mocha | Mocha | The OATLY | Zus Coffee | Chocolate | Oat Milk | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 28 | 27 | Hot OATLY Spanish Latté | Latte | The OATLY | Zus Coffee | | Oat Milk, Cor | Hot | Medium Dark | Brazil, Papua New Guinea, Indonesia |
| 29 | 28 | Iced OATLY Spanish Latté | | The OATLY | Zus Coffee | | Oat Milk, Cor | Iced | Medium Dark | Brazil, Papua New Guinea, Indonesia |

### Design

Three main activities were involved in this phase to fulfil the objectives of this study: System Use Case, System Flowchart and Content-Based Filtering Algorithm Design.

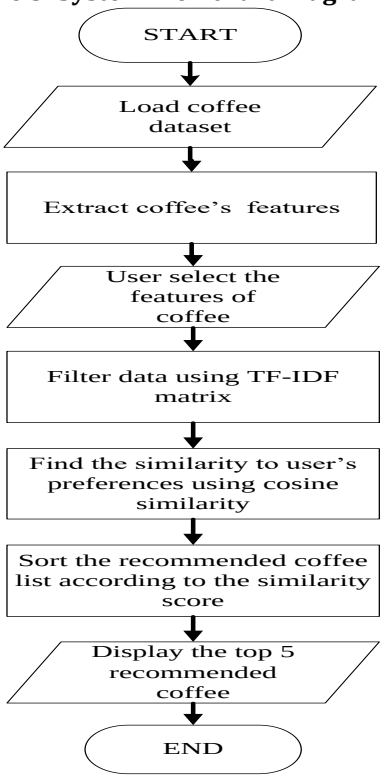
**System Use Case**: In this study, a use case model was employed to analyse and describe the system's functionality. This model outlines the interactions between a user and the system, specifying tasks that need to be addressed before system development. It serves as a tool to ensure that the system's requirements align with the objectives set forth for this study.

**Figure 2: System Use Case Diagram**



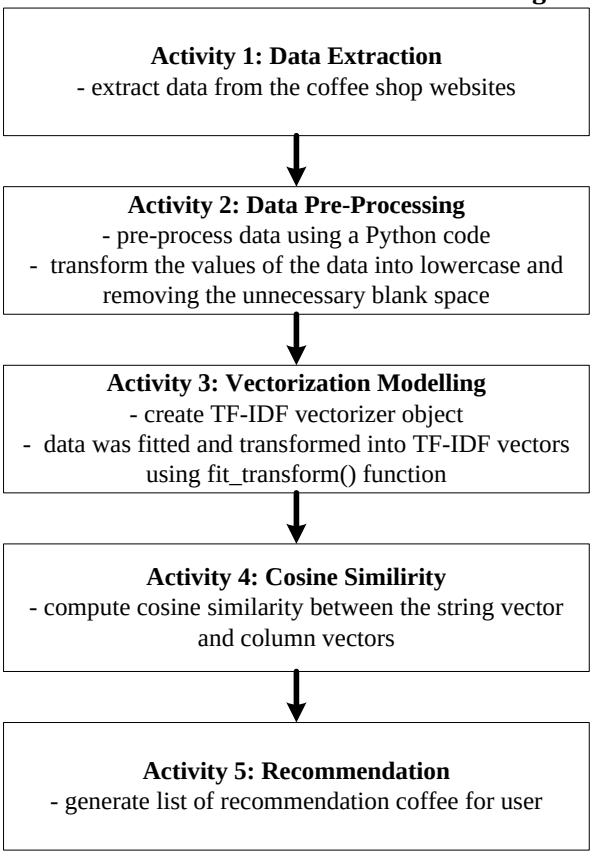

**System Flowchart**: Figure 3 provides an overview of the coffee recommender system's operation. Initially, the system loads a comma-separated value (CSV) file containing the coffee dataset. From this dataset, coffee features including coffee name, type, shop, flavour, milk type, roast level and origin are extracted. Upon user interaction with the application, they are prompted to select one or more preferred coffee features. Subsequently, the provided data undergoes filtering using the term frequency-inverse document frequency (TF-IDF) matrix. Next, the system measures the similarity between user-input values and the TF-IDF matrix using cosine similarity. This similarity score is then sorted to compile a list of recommended coffees. Finally, the resulting list is presented within the application interface for user consideration.

**Figure 3: System Flowchart Diagram**



**Content-Based Filtering Algorithm Design**: This study employs content-based filtering algorithms for providing coffee recommendations to the user. Within this framework, techniques such as TF-IDF and cosine similarity were applied, which are well-established methods in content-based recommendation systems. Figure 4 illustrates the specific five-step activity involved in this approach.

**Figure 4: Activities involved in Content-Based Algorithm Design**




**Mobile Platform Implementation**

The Android application was chosen as the platform for the user to access the recommendation system. The application was built in Android Studio using Java for the functions and XML for the layout. Two XML layout files were created for the main activity layout and the recommender activity layout. The main activity layout is the user interface that enables the user to select the features of the coffee, meanwhile, the recommender activity layout is the one responsible for displaying the coffee recommendation from the JavaScript Object Notation (JSON) file. In the main activity, the Java code is used to make the dropdown menu for the coffee features functional. The dropdown menu is called Spinner. The coffee features that are selected will be sent to the recommendation activity to display the recommendation. The recommendation activity will retrieve the JSON file from the system and process the file using the Retrofit Client. The top 5 recommended coffees will then be displayed in the recommendation activity layout.

**Testing**

Functionality and usability tests were the two types conducted in this study. Functionality evaluation is the process of determining whether each use case module can produce the intended result. Getting actual users to interact with an application and observe their behavior and responses is the goal of usability evaluation. Finding usability issues as soon as feasible before the design is accepted is the goal of usability testing. Therefore, the evaluation is using the quantitative survey known as the User Experience Questionnaire (UEQ), proposed by Laugwitz (2008). Four dimensions of UEQ were chosen that related to the study, as shown in Table 2.

**Table 2: UEQ Dimension and Question for Usability Test**

| Dimension | Item | Question |
|---|---|---|
| Usefulness | U1 | Is the application useful? |
| | U2 | Is this application helpful? |
| | U3 | Is this application beneficial? |
| | U4 | Is this application rewarding? |
| Attractiveness | A1 | Is this application enjoyable? |
| | A2 | Is this application good? |
| | A3 | Is this application pleasant to use? |
| | A4 | Is this application user-friendly? |
| Perspicuity | P1 | Is this application easy to understand? |
| | P2 | Is this application easy to learn? |
| | P3 | Is this application easy to use? |
| Dependability | D1 | Is the reaction of the application to your input and command predictable? |
| | D2 | Does the reaction of the application to your input and command meet expectations? |

## 4. Results and Discussion

By giving 35 respondents access to the application for them to test it further and provide feedback. To find out if the goals have been reached, functionality and usability testing were conducted. Functionality testing is conducted to verify whether each feature and function within the application operates as intended. Usability testing with the target audience could produce quantitative data on usability issues or difficulties and device performance (whether the application is user-friendly, whether a new user can quickly grasp how to use the application, the device's ease of use, and the degree of the user's control over the application).

### Functionality Testing

The application's functionality was accessed based on the provided coffee features. Figure 5 indicates the application snapshot, where the user is selecting the coffee features. Then, the application shows the top five recommended coffees based on the user's selection, as in Figure 6. This comprehensive evaluation was conducted to confirm that the function aligns with the specified requirements and operates accurately for the user. By conducting testing for 15 distinct attempts, the pass results of these functionality tests are summarized in Table 3.

**Figure 5: Snapshot of the Coffee Features Being Selected**

**Figure 6: Snapshot of the Recommendation Result**

**Table 3: Functionality Test Result**

| Test case | Remark ([✓] Successful / [X] Failed) | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| Select coffee features | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| View recommendation for user | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Usability Testing**

Usability testing was done to see if the objectives have been met. Quantitative information on usability issues or difficulties and device performance (such as usefulness, attractiveness, perspicuity, and dependability) was obtained through usability testing with the targeted respondents. 35 volunteers, both male and female, received a survey in the form of a Google form to help with the application's usability test. Table 4 displays the UEQ's overall average value along with the mean and average mean results in detail.

**Table 4: Means and Confidence Intervals UEQ for the Application**

| Dimension | Item | Mean | Average Mean |
|---|---|---|---|
| Usefulness | U1 | 4.514 | **4.471** |
| | U2 | 4.486 | |
| | U3 | 4.457 | |
| | U4 | 4.429 | |
| Attractiveness | A1 | 4.343 | **4.371** |
| | A2 | 4.371 | |
| | A3 | 4.4 | |
| | A4 | 4.371 | |
| Perspicuity | P1 | 4.743 | **4.648** |
| | P2 | 4.600 | |
| | P3 | 4.600 | |
| Dependability | D1 | 4.771 | **4.729** |
| | D2 | 4.686 | |
| **Average Total Mean Score** | | | **4.555** |
| **Average Percentage** | | | **91.1%** |

**Usefulness:** Feedback indicates that the application's mean score on four questionnaires measuring its usefulness, helpfulness, benefits and reward was 4.471. A notable 89% of participants acknowledged the application's usefulness in aiding their coffee selection process. Users highlighted the relevance of the recommendations to their stated preferences and noted that it introduced them to new and enjoyable coffee options.

**Attractiveness:** The attractiveness dimension asked whether the application is enjoyable, good, pleasant to use and user-friendly. With an average of 4.371, item A3 has the highest rating out of all the other items, indicating that using the application is enjoyable. Participants demonstrated high levels of positive impression with the recommendation application, with 87% expressing contentment with suggestions provided. Users particularly liked this application for simplifying their decision-making process in coffee selection.

**Perspicuity:** The third dimension is perspicuity, which evaluates whether the user can trust the product and if it enables straightforward access. Feedback shows the average mean value of 4.648 for the three questions that have been asked. The application's interface was generally well-received for its clarity and intuitiveness. 93% of participants found the navigation straightforward, emphasizing the ease with which they could input their preferences and view the recommendations.

**Dependability:** Dimension four is dependability, when asked about how the program responds to user input and whether it is predictable and satisfies expectations, feedback indicates that respondents thought the application had the highest average mean of 4.729. This recommendation application exhibited a high level of dependability, with 95% of participants reporting consistent and reliable suggestions across multiple interactions. This reliability instilled confidence in users' ability to rely on the application for accurate recommendations.

The usability analysis indicates that the content-based filtering recommendation application has a high level of acceptance for its usability, in improving the usefulness, attractiveness, perspicuity and dependability of the coffee selection process. In summary, the overall average of the mean score for this recommendation application is 91.1%. The results affirm that the coffee recommendation system successfully optimizes coffee selection. The positive feedback and high levels of user acceptance highlight the system's potential to mitigate choice overload and improve the overall coffee consumption experience. The suggested refinements, such as advanced customization features and user feedback mechanisms, provide valuable insights for future iterations of the recommendation system.

## 5. Conclusion and Recommendations

The study was aimed at developing a recommendation mobile application using content-based filtering techniques, and the development was successful. This study contributes to the fields of consumer psychology and recommender systems by offering a tailored solution to the challenge of choice overload in coffee selection. The result of the functionality test, which evaluated the use case function, demonstrates that the application's functions are operational. The results of the usability test utilizing the four UEQ dimensions a good and show potential, proving the acceptance of this recommendation application. By providing consumers with personalized recommendations based on their preferences and references, we aim to streamline the decision-making process and ultimately improve the overall coffee consumption experience. We hope this study serves as a foundation for continued research in enhancing consumer experiences in domains characterized by an abundance of choices. The study also implies how machine learning and recommendation systems can be effectively applied in the food and beverages industry, particularly in niche areas like specialty coffee. The system developed in this study can potentially be adapted to other types of food or beverage selection systems, as a valuable implication for broader Food and Beverage (F&B) personalization. For the next improvement, exploring avenues such as collaborative filtering, sentiment analysis, and incorporating additional user feedback can further enhance the accuracy and personalization of coffee recommendations, ultimately improving the overall coffee selection experience for consumers.

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