



# **INTELLIGENT COOKING RECIPE RECOMMENDATION SYSTEM**



## **A PROJECT REPORT**

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## **ABSTRACT**

The Intelligent Cooking Recipe Recommendation System is a computer-based system that utilizes machine learning algorithms to provide personalized recipe recommendations to users. The system analyzes various factors such as user preferences, dietary restrictions, and ingredient availability to suggest recipes that are suitable for the user's needs. The system takes into account user feedback and adapts its recommendations over time to better match the user's tastes. By providing tailored recipe recommendations, the system aims to enhance user satisfaction and simplify the process of meal planning and preparation. The Intelligent Cooking Recipe Recommendation System is designed to assist users in finding the most suitable recipes based on their individual preferences and needs. The system uses natural language processing (NLP) techniques to extract relevant information from user input, such as dietary restrictions, ingredient preferences, and cooking styles. It also considers the user's historical recipe selection data, cooking habits, and nutritional goals to personalize recipe recommendations. The system uses machine learning algorithms to analyze data from multiple sources, including recipe databases, ingredient databases, and user profiles. The algorithms use this data to generate a set of recipe recommendations for each user. The system can also learn from user feedback on recipe recommendations, adjusting future recommendations to better match user preferences. One of the key benefits of the Intelligent Cooking Recipe Recommendation System is its ability to streamline the meal planning and preparation process.

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## **LIST OF ABBREVIATIONS**

<b>ACRONYM</b>	<b>ABBREVIATIONS</b>
AICS	ARTIFICIAL INTELLIGENCE COOK SYSTEM
CRS	COOK RECIPE SYSTEM
CRCRS	CONTEXTUAL RECIPE CONTENT RECOMMENDATION SYSTEM
CRARS	COOK RECIPE ADVISORY AND RECOMMENDATION SYSTEM
ICRRS	INTELLIGENT COOK RECIPE RECOMMENDATION SYSTEM
RRSR	RECIPE RECOMMENDATION AND SUGGESTION SYSTEM
RCRS	RECIPE CHOICE AND RECOMMENDATION SYSTEM
RRS	RECIPE RECOMMENDATION SYSTEM

# CHAPTER 1

## INTRODUCTION

In today's digital era, the internet has become an indispensable tool for individuals worldwide, shaping various aspects of daily life. From communication to commerce, the internet offers unparalleled convenience and accessibility. With the global internet user population reaching approximately 4.5 billion, the online landscape has witnessed unprecedented growth and transformation. Among the myriad activities facilitated by the internet, e-commerce stands out as a prominent phenomenon, revolutionizing the way consumers shop for goods and services.

E-commerce encompasses a diverse array of online transactions, ranging from retail purchases to digital subscriptions and service bookings. According to recent statistics, around 2.1 billion people engage in online commerce, highlighting the widespread adoption and popularity of digital transactions. This surge in online shopping can be attributed to several factors, including advancements in technology, evolving consumer preferences, and the proliferation of digital platforms.

One of the key drivers of e-commerce growth is the inherent convenience it offers to consumers. Unlike traditional brick-and-mortar stores, online shopping allows individuals to browse, compare, and purchase products from the comfort of their homes or on the go. The accessibility and flexibility of e-commerce platforms enable consumers to shop anytime, anywhere, without the constraints of physical proximity or operating hours.

Furthermore, the expansive range of products and services available online provides consumers with unparalleled choice and diversity. From household essentials to niche specialty items, e-commerce platforms cater to a wide spectrum of consumer needs and preferences. This abundance of options empowers consumers to explore alternative brands, compare prices, and discover unique offerings that may not be readily available in traditional retail outlets.

However, amidst the convenience and abundance offered by e-commerce, consumers are increasingly grappling with a phenomenon known as information overload. The internet serves as a vast repository of information, encompassing product details, reviews, recommendations, and promotional content. While this wealth of information can be valuable, it also poses challenges for consumers in terms of information processing and decision-making. Information overload occurs when consumers are inundated with an excessive amount of information, making it difficult to discern relevant insights from noise. This overload can lead to cognitive overload, decision fatigue, and ultimately, decision paralysis, where consumers feel overwhelmed and unable to make informed choices.

To mitigate the challenges posed by information overload, Recommendation Systems (RSs) have emerged as a strategic solution. RSs leverage algorithms and user data to provide personalized recommendations tailored to individual preferences and interests. These systems analyze user behavior, past interactions, and contextual data to generate relevant suggestions, thereby simplifying the decision-making process for consumers.



Popular examples of RS implementations include Amazon's "Customers who bought this item also bought" feature, which recommends products based on past purchase behavior, and Netflix's personalized film recommendations, which suggest movies and TV shows based on viewing history and preferences. Similarly, Spotify utilizes RS algorithms to curate personalized music playlists and recommendations tailored to each user's taste in music.

Beyond the realm of entertainment and retail, RSs have found application across various sectors, including education, healthcare, and food. In the food sector, RSs play a pivotal role in recommending food items, meal plans, recipes, restaurants, and grocery options based on consumer preferences and dietary requirements. These systems not only cater to individual tastes but also promote healthy eating choices, track eating behaviors, and address health concerns such as obesity and dietary restrictions.

Despite their potential benefits, food RSs are still in their infancy, with challenges related to accuracy, trustworthiness, and reliability. Enhancing the performance of these systems requires a deep understanding of consumer preferences, decision-making processes, and the nuances of the food industry. Moreover, as the landscape of e-commerce continues to evolve, there is a growing need to align RSs with the dynamic needs and expectations of consumers.

To address these challenges and capitalize on the opportunities presented by food RSs, it is essential to explore their application through the lens of the consumer decision-making process. By understanding how RSs influence consumer choices and behaviors at each stage of the decision-making journey, businesses can optimize their recommendations to better meet the needs and preferences of their target audience.

## **Research Questions**

To guide this exploration, the following research questions are formulated:

- a) What types and approaches of recommendation systems have been applied in the food sector?
- b) How can these food recommendation systems be classified based on the consumer decision-making process?
- c) What are the current challenges and solutions for food recommendation systems?

By addressing these questions, this paper aims to provide insights into the landscape of recommendation systems in the food sector, their alignment with consumer decision-making processes, and the key challenges and solutions in this domain. Through this exploration, we can better understand how food RSs can effectively support consumers in making informed choices and promote healthier lifestyles.

## **CHAPTER 2**

### **LITERATURE SURVEY**

#### **2.1 A Recipe Recommendation System Based on Regional Flavor Similarity:**

The food choices we make are often influenced by our flavor preferences. Whether it's the tangy spices of Indian cuisine, the savory umami of Japanese dishes, or the bold flavors of Mexican fare, each region's culinary traditions reflect a unique blend of ingredients and seasonings. However, despite the diversity in flavors, there are often similarities among cuisines from geographically adjacent regions. Leveraging these flavor similarities, researchers have developed a recipe recommendation system aimed at helping users discover dishes from various Chinese regional cuisines based on their flavor preferences.

This paper introduces a novel approach to recipe recommendation, focusing on flavor similarity as a key criterion. By analyzing the ingredient preferences of different regional cuisines and calculating their flavor profiles, the system aims to identify dishes that share similar flavor characteristics. The methodology employed involves several steps, including the use of the TF-IDF algorithm to calculate ingredient preferences, cosine similarity to measure flavor similarities, and the Tidal-Trust algorithm for recommendation selection.

The first step in the process involves analyzing the ingredient preferences of various Chinese regional cuisines. The TF-IDF algorithm, which stands for Term Frequency-Inverse Document Frequency, is utilized to quantify the importance of ingredients within each cuisine. This algorithm assigns a weight to each ingredient based on its frequency of occurrence in recipes from a particular region, while also considering its rarity across all recipes. By calculating these ingredient preferences, the system can create a profile for each regional cuisine, highlighting the key ingredients that contribute to its flavor profile.

Once the ingredient preferences are established, the next step is to measure the flavor similarities among the regional cuisines. This is achieved using the cosine similarity metric, which quantifies the similarity between two sets of data by measuring the cosine of the angle between them. In the context of recipe recommendation, cosine similarity is employed to compare the flavor profiles of different regional cuisines. By computing the cosine similarity between the ingredient preference vectors of each cuisine, the system can identify regions with similar flavor characteristics.

Finally, the Tidal-Trust algorithm is utilized to select and recommend dishes with the most similar flavors to the user. The Tidal-Trust algorithm, inspired by social network analysis, assigns trust values to recommendations based on the trustworthiness of their sources. In the context of recipe recommendation, this

algorithm evaluates the credibility of each dish recommendation based on its similarity to the user's flavor preferences. By considering both the flavor similarities among regional cuisines and the trust values assigned to each recommendation, the system can provide users with personalized and relevant dish suggestions.

The effectiveness of the recipe recommendation system is evaluated through a questionnaire-based study involving professional chefs. The results of the evaluation indicate that the recommendations generated by the system are considered reasonable and acceptable from a culinary perspective. This validation demonstrates the potential of the system to assist users in discovering new and flavorful dishes from various Chinese regional cuisines.

In summary, the recipe recommendation system presented in this paper offers a novel approach to culinary exploration by leveraging regional flavor similarities. By analyzing ingredient preferences, measuring flavor similarities, and employing trust-based recommendation algorithms, the system provides users with personalized and relevant dish suggestions. With further refinement and validation, this system has the potential to enhance culinary experiences and promote cultural appreciation through food exploration.

## **2.2 Constraint based recipe recommendation using forward checking algorithm:**

With the evolution of lifestyle and dietary habits alongside the rise in work-related stress, there has been a corresponding increase in the prevalence of various chronic diseases, including diabetes, hypertension, and heart problems. Many of these conditions can be managed to a certain extent through dietary modifications and healthy lifestyle choices. Therefore, understanding and adopting suitable dietary habits have become paramount for maintaining overall health and well-being.

The objective of our proposed recommendation system is to assist individuals, both those with existing health conditions and those without, in making informed dietary choices that promote optimal health. By recommending recipes tailored to the specific needs and preferences of each user, the system aims to support individuals in adopting healthy eating habits that align with their dietary goals and restrictions.

To achieve this objective, our recommendation system utilizes constraint-based knowledge recommendation methods in conjunction with a forward checking algorithm. Unlike traditional recommendation approaches that may suffer from the "ramp-up problem," wherein the system requires extensive user interaction or historical data to generate accurate recommendations, our approach overcomes this limitation by leveraging explicit knowledge about user preferences and dietary requirements.

The recommendation process begins by capturing user profiles, including information about their health status, dietary preferences, and any specific dietary restrictions or requirements. This explicit knowledge serves as the foundation for generating personalized recipe recommendations that cater to the individual needs of each user.

Additionally, the system takes into account users' favorite food items and recipe details, further enhancing the relevance and suitability of the recommendations provided. By incorporating this rich dataset of user preferences and recipe information, the system can generate highly tailored recommendations that not only meet users' dietary requirements but also align with their taste preferences and culinary interests.

The constraint-based recommendation approach allows the system to impose constraints on the

recommendation process, ensuring that the recommended recipes adhere to specific criteria or guidelines established by the user. For example, individuals with diabetes may require recipes that are low in sugar and carbohydrates, while those with hypertension may benefit from recipes that are low in sodium.

Furthermore, the forward checking algorithm efficiently explores the solution space by systematically evaluating potential recipe recommendations against the constraints defined by the user. This iterative process eliminates infeasible options early on, allowing the system to focus on generating recommendations that satisfy the user's requirements while minimizing computational overhead.

In conclusion, our proposed recommendation system offers a novel approach to supporting individuals in making healthy dietary choices. By leveraging constraint-based knowledge recommendation methods and the forward checking algorithm, the system can provide personalized recipe recommendations that align with users' health goals and dietary preferences. Through this approach, we aim to empower individuals to adopt healthier eating habits and improve their overall well-being.

## **2.3 Implementation of a Goal-Oriented Recipe Recommendation System:**

The proliferation of recipe websites has led to an increase in the number of people turning to online platforms for culinary inspiration and guidance. However, for individuals without professional knowledge of nutrition, selecting recipes that align with their health goals can be challenging. To address this issue, we introduce a goal-oriented recipe recommendation system designed to assist users in finding recipes tailored to specific health conditions, leveraging nutrition information available on the internet.

Our proposed system aims to simplify the process of selecting recipes that contribute to improving overall health by utilizing natural language queries related to specific health concerns. For example, users can input queries such as "I want to cure my acne" or "I want to recover from my fatigue," allowing the system to recommend recipes that are believed to be beneficial for addressing these health issues.

### **Key features of our recommendation system include:**

#### **Natural Language Processing:**

The system utilizes natural language processing techniques to interpret user queries and extract relevant health-related information. By understanding the intent behind user queries, the system can generate personalized recipe recommendations that address specific health concerns.

#### **Nutrition Information Retrieval:**

The system retrieves and analyzes nutrition information available on the internet, including nutrient composition data for various ingredients and recipes. By leveraging this information, the system can assess the nutritional value of recipes and identify those that align with users' health goals.

#### **Goal-Oriented Recommendation:**

Our recommendation system is designed to prioritize recipes that are known or believed to have beneficial effects on specific health conditions. By focusing on goal-oriented recommendations, the system helps users make informed dietary choices that support their health objectives.

To evaluate the effectiveness of our system, we conducted experiments using a dataset comprising 1000 dishes. We compared the recommendations generated by our system to those obtained through manual calculation of the nutrient information. The evaluation metrics used included F-Measure, which assesses the system's performance in terms of precision and recall.

## **2.4 An overview of recommender systems in the healthy food domain:**

Recently, Food recommender systems have become increasingly important in promoting healthy living, with a focus on providing personalized recommendations tailored to individual users' preferences and health goals. Existing studies in the food domain predominantly concentrate on recommending suitable food items for individuals based on factors such as dietary preferences, nutritional requirements, and health conditions. However, as social dining experiences become more common, there is a growing demand for group recommendation functionalities within food recommender systems.

Group recommendation functionalities play a crucial role in scenarios where multiple individuals are involved in meal planning, such as organizing a dinner party at home or celebrating a birthday at a restaurant. In such cases, the system must consider the preferences and dietary restrictions of all group members to ensure a satisfying dining experience for everyone involved.

This poses significant challenges for food recommender systems, as they need to effectively balance the diverse tastes and requirements of multiple users.

In this paper, we provide an overview of recommendation techniques tailored to both individuals and groups in the healthy food domain. For individual recommendations, the focus is on leveraging user preferences, health profiles, and nutritional guidelines to suggest suitable food choices that align with each user's dietary objectives. These recommendations may take into account factors such as calorie intake, macronutrient composition, and ingredient preferences to provide personalized meal suggestions.

On the other hand, group recommendation techniques aim to address the complexities of coordinating meal plans and catering to the preferences of multiple users simultaneously. These techniques may involve collaborative filtering approaches, where the system analyzes the collective preferences of group members to identify common interests and recommend food options that appeal to the majority. Additionally, group recommendation algorithms may consider factors such as dietary restrictions, allergies, and cultural preferences to ensure inclusive and satisfaction among all participants.

Overall, our paper aims to explore the various recommendation techniques employed in the healthy food domain, highlighting the unique challenges and considerations associated with both individual and group recommendations. By providing an overview of these techniques, we hope to contribute to the development of more robust and effective food recommend systems that support healthy eating habits.

## CHAPTER 3

### SYSTEM REQUIREMENTS

#### 3.1 SOFTWARE REQUIREMENTS:

The Software requirements play a crucial role in defining the features and functionalities of a target system. They serve as a road map for developers, conveying the expectations and needs of users from the software product. In this section, we will delve into the software requirements for the system, focusing on two key components: Jupyter Notebook and Python.

##### **Jupyter Notebook:**

The Jupyter Notebook is an open-source web application that revolutionizes the way developers create and share documents containing live code, equations, visualizations, and text. With its interactive interface, Jupyter Notebook enables users to write and execute code snippets in real-time, making it an indispensable tool for data scientists, researchers, and educators alike.

##### **The components of Jupyter Notebook include:**

**Notebook web application:** The interactive web interface where users can write, run, and edit code cells, as well as author narrative text, equations, and multimedia content. The notebook web application provides a seamless environment for experimentation and collaboration.

**Kernels:** Separate processes initiated by the notebook web application to execute code written in various programming languages. While Jupyter ships with the IPython kernel by default, users have the flexibility to choose from over 100 other kernels, including those for languages like R, Julia, and Scalar. Kernels handle computations, provide tab completion, and support interactive widgets.

**Notebook documents:** Self-contained files that encapsulate the content displayed within the notebook web application, including code inputs, outputs, text explanations, images, and more. Notebook documents offer a portable and shareable format for documenting and disseminating code-based projects.

##### **Python:**

Python is an object-oriented, high-level programming language renowned for its simplicity, readability and versatility. Widely used in web and application development, Python boasts integrated dynamic semantics and a rich ecosystem of libraries and frameworks that facilitate rapid development.

## **Key features of Python include:**

**Readability:** Python's syntax emphasizes readability, making it easy for developers to write and understand code. With its clean and concise syntax, Python fosters a productive and collaborative coding environment.

**Dynamic typing:** Python offers dynamic typing, allowing developers to create variables without explicitly specifying their data types. This flexibility simplifies code development and enhances code re-usability across different contexts.

**Dynamic binding:** Python supports dynamic binding, enabling objects to be bound to methods and attributes at runtime. This dynamic behavior enhances code flexibility and adaptability, facilitating agile development practices.

**Modular design:** Python encourages modular design principles, enabling developers to organize code into reusable modules and packages. This modular approach promotes code maintainability and scalability, facilitating collaboration and code sharing across projects.

**Rich ecosystem:** Python boasts a vast ecosystem of libraries and frameworks that extend its functionality for various use cases, including data analysis, machine learning, web development, and scientific computing. Popular libraries such as NumPy, pandas, and Tensor Flow empower developers to tackle complex tasks with ease.

In conclusion, the software requirements for the system encompass the Jupyter Notebook as the primary development environment and Python as the programming language of choice. Together, these tools provide a robust foundation for creating interactive, data-driven applications with ease and efficiency. By leveraging the features and capabilities of Jupyter Notebook and Python, developers can build powerful software solutions that meet the diverse needs of users across industries and domains.



## **SOFTWARE REQUIREMENTS:**

1. Operating System: Windows OS IDE: Eclipse
2. Environment: Anaconda Navigator Storage: Local storage
3. Data Set: Local CSV.

## **CHAPTER 4**

### **THEORITICAL FRAMEWORK**

#### **4.1 RECOMMENDATION SYSTEM**

##### **4.1.1 General Introduction**

Recommendation System (RS) has emerged as a pivotal technology in the realm of e-commerce, offering personalized suggestions to users based on their preferences, behavior, and demographics. This section provides a comprehensive overview of RSs, tracing their evolution from the early stages of research to their current prominence in online platforms. We delve into the general process of RSs, exploring the stages involved in understanding consumers, identifying and delivering recommendations, and measuring their impact on consumers, companies, and the market.

##### **Introduction to Recommendation Systems:**

The concept of RSs gained traction in the 1990s, propelled by the growth of e-commerce and the need to enhance user experience and facilitate decision-making. RSs are also known by various terms such as interactive decision aid systems, recommendation agents, and shopping bots. Adomavicius and Tuzhilin's three-stage process model provides a foundational framework for understanding the functioning of RSs.

##### **Understanding the Consumer:**

The first stage of the RS process involves collecting consumer information and building consumer profiles. This can be done through explicit methods such as questionnaires or implicit methods like clickstream and social media data. While explicit methods yield more accurate recommendations, a combination of both methods enhances accuracy further. Consumer knowledge plays a crucial role, with RSs adapting their approach based on the consumer's familiarity with the product or service.

##### **Identifying and Delivering Recommendations:**

In the second stage, RSs focus on identifying products or services that match the consumer's profile using various matchmaking approaches. The choice of approach depends on the information used to build the consumer profile. RS presentation or interface design is critical to ensuring that recommendations are understood and acted upon by users. Factors such as the number of recommendations shown, sorting cues, and instructional facilities influence the effectiveness of the recommendations.

### Measuring Impact and Adjusting Recommendations:

The third stage involves measuring the impact of RSs on consumers, companies, and the market. Feedback from customers is essential for adjusting recommendations and improving the overall effectiveness of the RS. This iterative process ensures that RSs evolve to meet the changing needs and preferences of users and remain relevant in the dynamic landscape of e-commerce.

### Impact of Recommendation Systems on Consumers:

RSs have a profound impact on consumers, influencing their purchasing decisions, satisfaction levels, and overall shopping experience. By providing personalized recommendations, RSs enhance user engagement, increase conversion rates, and foster loyalty. However, concerns regarding privacy, algorithmic bias, and over-reliance on recommendations necessitate careful consideration and mitigation strategies.

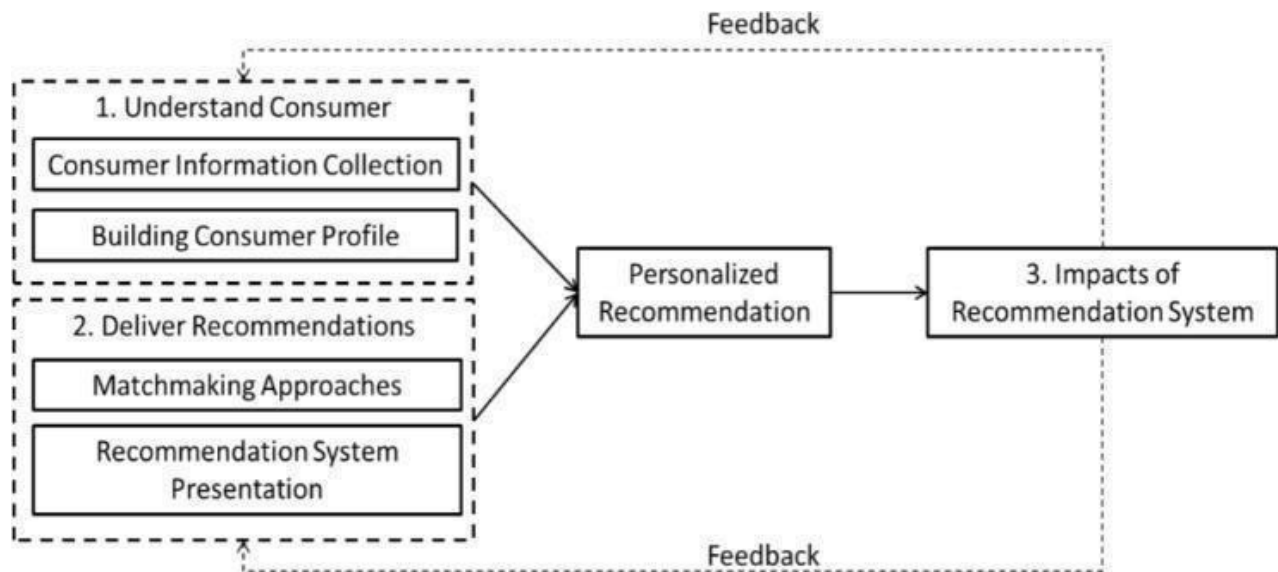


Fig.4.1 RECOMMENDATION SYSTEM

#### 4.1.2 Matchmaking Approaches of Recommendation Systems

Matchmaking approaches are fundamental to the functioning of Recommendation Systems (RSs), as they determine how recommendations are generated for individual consumers. In this section, we explore the various matchmaking approaches employed by RSs, each with its unique methodology and underlying principles.

##### Content-Based Approach:

The content-based approach relies on analyzing the attributes of products or

services, as well as the historical interactions of users with these items. By examining user ratings, purchase history, and preferences for specific product attributes, the RS predicts users' preferences and recommends items that are similar to those they have previously rated highly or purchased. This approach emphasizes personalized recommendations tailored to individual user profiles and preferences.

#### **Collaborative Filtering Approach:**

Collaborative filtering is one of the most common RS types, leveraging the preferences and ratings of like-minded individuals to predict users' preferences. Users implicitly or explicitly rate items, and the RS recommends items that similar users have also liked. This approach harnesses the collective wisdom of the user community to generate recommendations, making it highly effective in identifying relevant items for users based on their interests and preferences.

#### **Knowledge-Based Approach:**

The knowledge-based approach elicits explicit information from users to build a comprehensive user profile. By understanding users' criteria and preferences, the RS matches items to the user's specific requirements. This approach provides users with explanations for why certain items are recommended, enhancing transparency and trust in the recommendation process. Examples of knowledge-based approaches include constraint-based and case-based recommendation systems, which utilize user input and past successful recommendations to generate personalized suggestions.

#### **Demographic Approach:**

The demographic approach leverages demographic information such as age, gender, occupation, and preferences of other users with similar demographic characteristics. By analyzing reviews, ratings, and preferences of users with comparable demographics, the RS generates recommendations that are likely to resonate with the target user. This approach recognizes the influence of demographic factors in shaping consumer preferences and tailors recommendations accordingly.

#### **Context-Based Approach:**

Context-based recommendation systems consider not only consumer characteristics and item attributes but also contextual information such as the purpose of the purchase and the intended recipient. By understanding the situational context surrounding a user's decision-making process, the RS can generate recommendations that are relevant and meaningful in specific contexts.

#### **Social Network-Based Approach:**

Social network-based recommendation systems utilize data from users' social networks, such as prior purchases of their Facebook friends or connections. By incorporating social

influence and network dynamics into the recommendation process, these systems can identify items that align with users' social circles and preferences.

### **Hybrid Approach:**

The hybrid approach combines multiple techniques from other RS approaches to generate recommendations. By leveraging the strengths of different methods, hybrid RSs can overcome limitations and improve recommendation accuracy. For example, hybrid systems may integrate collaborative filtering with content-based methods to address the "new-item problem".

In conclusion, the diverse array of matchmaking approaches employed by RSs underscores the complexity of recommendation systems and the importance of tailoring recommendations to individual user preferences and contexts. By leveraging a combination of these approaches, RSs can deliver personalized and relevant recommendations that enhance user satisfaction and engagement in various domains of e-commerce and beyond.

## **4.1.3 Impact of Recommendation Systems on Consumers**

Matchmaking approaches within Recommendation Systems (RSs) encompass various methodologies tailored to provide personalized recommendations for individual users. These approaches include content-based, collaborative filtering, knowledge-based, demographic, context-based, social network-based, and hybrid methods. The content-based approach analyzes product attributes and user interactions to predict preferences, while collaborative filtering harnesses collective user ratings to recommend items liked by similar users. Knowledge-based approaches elicit explicit user information to match items to specific requirements, enhancing transparency. Demographic approaches leverage demographic data to tailor recommendations, while context-based systems consider situational factors. Social network-based RSs incorporate social influence from users' networks. Hybrid approaches combine multiple techniques to overcome limitations and improve recommendation accuracy. These diverse approaches underscore the complexity of RSs and highlight the importance of catering to individual user preferences and contexts to enhance user satisfaction and engagement in e-commerce and beyond. Recommendation Systems employ diverse matchmaking approaches to generate personalized recommendations for users. Content-based analysis examines product attributes and user interactions, while collaborative filtering leverages collective user ratings. Knowledge-based methods elicit explicit user information, enhancing transparency. Demographic and context-based approaches tailor recommendations based on user demographics and situational context. Social network-based systems incorporate social influence, while hybrid approaches combine multiple techniques for improved accuracy. These approaches underscore the complexity of RSs and their role in enhancing user satisfaction and engagement in e-commerce and other domains.

## **4.2 ONLINE CONSUMER DECISION-MAKING**

### **4.2.1 General Introduction**

As Consumer decision-making is a multifaceted process influenced by various factors, and over the years, several models have been proposed to elucidate its complexities. Among these models, the Engle, Kollat, and Blackwell (EKB) model, established in 1968, stands out as a foundational theory in understanding offline consumer decision-making. This model delineates the decision-making process into five sequential stages: problem recognition, information search, evaluation of alternatives, purchase, and post-purchase evaluation.

However, with the advent of the internet and the proliferation of online shopping, consumer behavior underwent significant transformations, necessitating adaptations to existing decision-making models. While the fundamental stages remained consistent, the manner in which consumers navigated through each stage evolved to accommodate the online environment.

In response to these changes, various online consumer decision-making models have emerged to delineate the unique dynamics of digital commerce. These models recognize the distinct actions and decisions undertaken by consumers as they navigate the online landscape. In an online consumer decision-making process model, the stages typically mirror those of the traditional EKB model, but with nuanced differences tailored to the digital realm. For instance, in the problem recognition stage, consumers may identify needs or wants through online browsing, social media interactions, or exposure to targeted advertisements. Subsequently, the search for information stage may involve scouring online reviews, comparison websites, and social media platforms for product recommendations and insights. The evaluation of alternatives stage may entail the exploration of various online retailers, analyzing product features, prices, and user ratings to make informed choices.

The purchase stage sees consumers executing transactions through online platforms, choosing from a myriad of payment and delivery options. Finally, the post-purchase evaluation stage involves reflecting on the overall online shopping experience, including satisfaction with the product and vendor, as well as any issues encountered during the transaction process.

While these online consumer decision-making models provide valuable insights into the digital purchasing journey, it is essential to recognize the myriad external factors that influence consumer behavior. These factors encompass individual characteristics such as motivation, knowledge, and lifestyle, as well as social influences from culture, social class, and reference groups.

Moreover, situational and economic factors such as time constraints, financial considerations, and the online environment itself play a significant role in shaping consumer decisions. For instance, the

design and functionality of e-commerce websites, the quality of product information, and the security of online transactions can impact consumer perceptions and behaviors.

Despite the advancements in understanding online consumer decision-making, these models are not without limitations. They may oversimplify the complexity of consumer behavior or fail to account for individual variations and contextual factors. Additionally, the rapid evolution of technology and changing consumer preferences necessitate ongoing revisions and updates to these models.

In conclusion, while the traditional EKB model laid the groundwork for understanding offline consumer decision-making, the rise of e-commerce has spurred the development of online consumer decision-making models. These models offer valuable insights into the intricacies of digital commerce and underscore the importance of adapting to the evolving landscape of online shopping. By considering the influence of external factors and addressing the shortcomings of existing models, researchers and practitioners can enhance our understanding of consumer behavior in the digital age and develop effective strategies to assist consumers in their online decision-making journey.

#### **4.2.2 Online Consumer Decision-Making Process Model**

The Combining Maçik (2016) and Darley et al. (2010) models yields a comprehensive online consumer decision-making process. This unified model integrates the five stages of the EKB model. Referencing Figure 2, an illustrative visual representation of this amalgamated model is presented. It encapsulates the journey from problem recognition to post-purchase evaluation. This synthesis provides a holistic understanding of how consumers navigate online choices. By amalgamating these frameworks, we enhance comprehension of the dynamic digital consumer landscape. This model serves as a roadmap for marketers to tailor strategies at each stage effectively. It elucidates the intricate interplay of factors influencing online consumer behavior. This unified model offers insights for businesses striving to optimize their online presence and engagement strategies. Expand 300 words

##### **Chat GPT**

The amalgamation of the Maçik (2016) and Darley et al. (2010) models results in a comprehensive framework for understanding the online consumer decision-making process. By integrating the five stages of the EKB model, this unified approach offers a cohesive depiction of how consumers navigate the digital landscape from problem recognition to post-purchase evaluation.

Figure 2 visually represents this amalgamated model, providing a clear illustration of the sequential stages involved in online decision-making. From identifying needs or wants to evaluating alternatives, making a purchase, and reflecting on the experience, the model encapsulates the entire consumer journey in the online realm.

This synthesis of frameworks enables a holistic understanding of the dynamic factors influencing

online consumer behavior. By combining insights from Maçık (2016) and Darley et al. (2010), marketers gain valuable insights into the nuanced decision-making processes of online shoppers.

Moreover, the unified model serves as a road map for marketers to tailor their strategies effectively at each stage of the online consumer journey. Understanding how consumers progress through each stage allows businesses to optimize their online presence, enhance user experience, and maximize engagement.

Furthermore, this model sheds light on the intricate interplay of internal and external factors that shape online consumer behavior. From individual characteristics and preferences to social influences, situational factors, and the online environment, the model provides a comprehensive framework for analyzing consumer decision-making in the digital age.

The amalgamated model offers actionable insights for businesses seeking to optimize their online strategies and drive consumer engagement. By leveraging a deeper understanding of the online decision-making process, marketers can tailor their approaches to meet the evolving needs and preferences of digital consumers, ultimately driving business growth and success in the online marketplace.

The consumer decision-making process is a complex journey that encompasses multiple stages, each playing a crucial role in shaping the final purchasing decision. Let's delve deeper into each stage to understand its significance and the factors influencing consumer behavior.

### **Stage 1 – Problem Recognition:**

At this initial stage, consumers identify an unfulfilled need or want. Whether it's a desire for a new smartphone, a craving for a particular cuisine, or a need for a reliable household appliance, this stage marks the inception of the decision-making process. Consumers may recognize their needs through internal cues, such as personal preferences or experiences, or external stimuli like advertisements, social media, or recommendations from friends and family.

### **Stage 2 – Searching for Information:**

Once the need is recognized, consumers embark on a quest for information. They actively seek out relevant details and insights to inform their decision-making process. This stage involves gathering information from various sources, both internal and external. Consumers rely on their own experiences, memories, and knowledge, while also exploring external channels such as websites, social media platforms, and word-of-mouth recommendations. Advertisements, promotional sales, and salespersons further contribute to their information pool, shaping their perceptions and preferences.

The internet plays a pivotal role in this stage, serving as a vast repository of product information, reviews, and comparisons. Social media platforms amplify consumer discussions and



influence preferences, making it essential for businesses to maintain a strong online presence and provide credible information across diverse channels.

### **Stage 3 – Evaluating Alternatives:**

Armed with information, consumers proceed to evaluate the available alternatives systematically. They assess products or services based on predefined selection criteria, considering factors such as functional features, brand reputation, and emotional appeal. Through a cost-benefit analysis, consumers weigh the trade-offs between different options, balancing search costs against expected utility. This deliberative process leads to the formation of a 'choice set', comprising the most viable options that align with their needs and preferences.

### **Stage 4 – Purchasing:**

In the purchasing stage, consumers make the final decision to acquire the chosen product or service. This decision encompasses not only selecting the item itself but also determining the preferred purchase channel, platform, and seller. The Theory of Reasoned Action (TRA) offers insights into the underlying factors influencing consumer purchase intentions. These include beliefs about their capability to perform the intended behavior, attitudes towards the behavior, and perceptions of benefits, trust, and risk associated with the transaction. Positive attitudes towards online purchasing, driven by perceptions of convenience, reliability, and security, often translate into higher purchase intentions.

### **Stage 5 – Post-purchase Evaluation:**

After following the purchase, consumers conduct a post-purchase evaluation to gauge satisfaction and experiences. This introspection determines whether their expectations were met. Positive experiences cultivate brand loyalty and foster future purchase intentions, solidifying the brand-consumer relationship. Conversely, negative encounters may breed dissatisfaction and prompt consumers to disengage from the brand, potentially seeking alternatives. This critical evaluation phase highlights the significance of delivering exceptional customer experiences and ensuring that products or services align with consumer expectations to nurture long-term relationships and drive repeat business.

In conclusion, comprehending each stage of the consumer decision-making process is vital for businesses aiming to influence purchasing behavior positively. By discerning the intricacies of these stages and the factors that influence them, businesses can craft targeted strategies to engage consumers effectively. From problem recognition to post-purchase evaluation, each phase offers opportunities for businesses to enhance customer satisfaction, build brand loyalty, and drive favorable outcomes. Through strategic alignment with consumer decision-making processes, businesses connections with their target audience, ultimately fostering long-term success in the marketplace.

In this context, consumer satisfaction hinges on the alignment between their perception and expectations regarding a product, service, or vendor. If the perceived performance surpasses expectations, consumers typically experience satisfaction, reinforcing their positive beliefs about the offering. Conversely, if the perceived performance falls short of expectations, dissatisfaction ensues, undermining their beliefs and eroding trust in the product, service, or vendor.

Following consumption, consumers may encounter cognitive dissonance, wherein they experience conflicting thoughts or emotions about their purchase decision. This internal conflict arises when their expectations do not match their post-purchase experiences, prompting reassessment of their beliefs and attitudes towards the product or service.

Ultimately, the culmination of these factors influences consumer behavior, guiding decisions such as disinvestment, where consumers may choose to resell, recycle, or discard the product. Disinvestment reflects consumers' final verdict on their satisfaction or dissatisfaction with the offering, shaping their perceptions and future interactions with the brand. As such, businesses must prioritize delivering on consumer expectations to foster positive experiences, mitigate cognitive dissonance, and cultivate enduring relationships with their clientele.

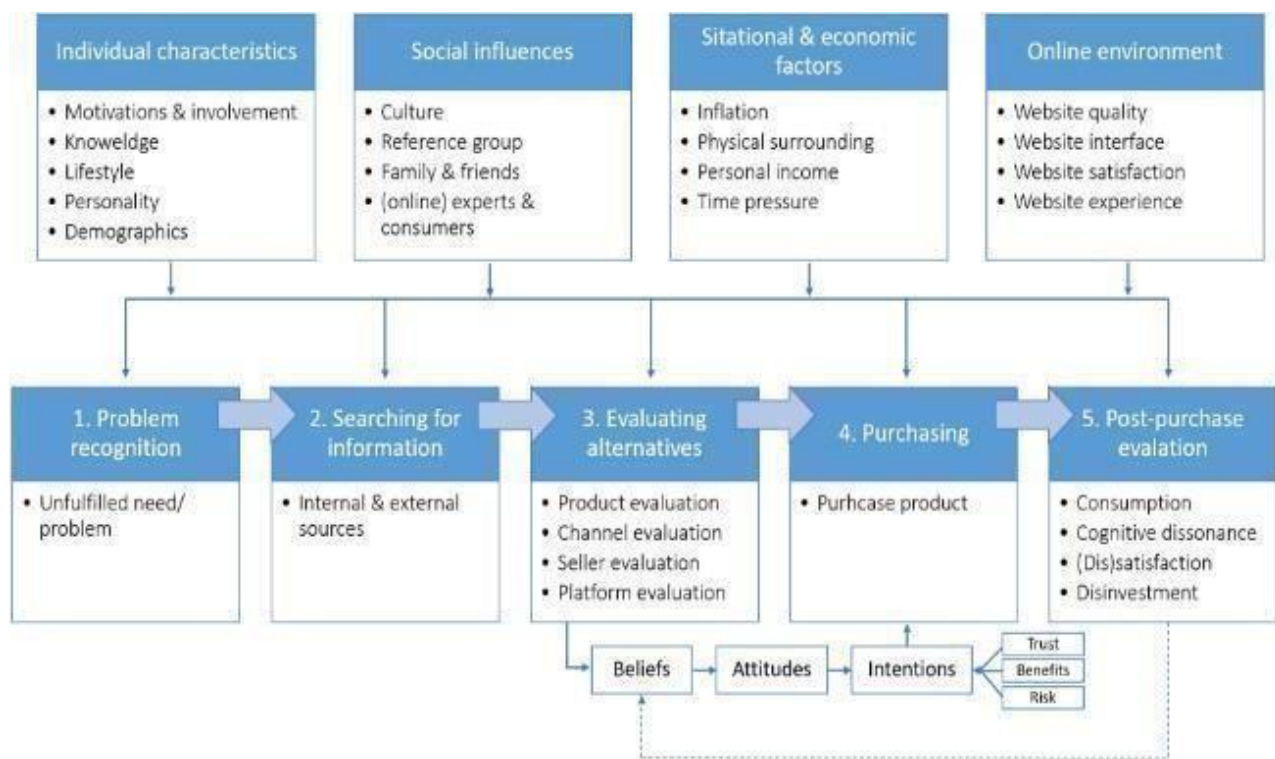


Fig.4.2.2 ONLINE CONSUMER DECISION-MAKING PROCESS MODEL

### 4.2.3 Influence of External Factors

At every stage of the consumer decision-making process, external factors exert a significant influence on individuals' choices and behaviors. These external influences encompass a wide range of dimensions, each contributing to shaping consumer decisions in unique ways.

#### Individual Characteristics:

One of the primary external factors that influence consumer decision-making is individual characteristics. These characteristics include motivations, levels of involvement, knowledge, values, personality types, education levels, lifestyles, and demographics. Each individual possesses a unique set of predispositions and preferences shaped by these characteristics. For example, a consumer's level of involvement in a particular product category may influence their decision-making process, with highly involved individuals conducting more extensive research before making a purchase. Similarly, demographics such as age, gender, income level, and occupation can impact consumer preferences and behaviors.

**Social Dynamics:**

Social influences also play a crucial role in shaping consumer decisions. Consumers are influenced by their cultural background, social class, reference groups, familial connections, peer circles, and media exposure. These social dynamics can sway consumer perceptions, preferences, and purchase intentions. For instance, individuals may be more likely to adopt certain consumption behaviors if they perceive them to be aligned with the norms and values of their social group. Moreover, recommendations and opinions shared by friends, family members, experts, and other consumers through various channels such as reviews, blogs, social media, and word-of-mouth can significantly impact consumer decision-making.

**Situational and Economic Variables:**

Consumer decision-making is further influenced by situational and economic factors. These factors encompass both macroeconomic indicators such as inflation and micro-level variables like physical surroundings, personal income, and time constraints. For example, consumers may adjust their purchasing behaviors in response to changes in economic conditions or personal financial circumstances. Similarly, situational factors such as the availability of time or the urgency of a need can influence the decision-making process. Marketers must be cognizant of these situational and economic variables to adapt their strategies accordingly and meet consumers' evolving needs.

**Online Environment:**

In today's digital age, the online environment plays a pivotal role in shaping consumer decision-making. Consumers navigate websites, social media platforms, and other online channels to gather information, compare products, read reviews, and make purchasing decisions. The quality of the online experience, including website design, information accuracy, privacy safeguards, security measures, and financial transaction risks, significantly influences consumer satisfaction and overall experience. Marketers must prioritize effective management of these online factors to foster positive customer experiences and drive conversions.

In essence, the interplay of individual characteristics, social dynamics, situational and economic variables, and the online environment intricately shapes consumer decision-making processes. Recognizing and understanding these multifaceted influences is paramount for marketers striving to craft targeted strategies that resonate with consumers' needs, preferences, and behaviors across diverse channels and touch points. By leveraging insights into these external factors, businesses can tailor their marketing efforts to effectively engage consumers at each stage of the decision-making journey, driving favorable outcomes and fostering long-term customer relationships.

#### **4.2.4 Shortcomings of the Online Consumer Decision-Making Model**

The Online Consumer Decision-Making Model offers a comprehensive framework for understanding how consumers navigate the digital landscape to make purchasing decisions. However, like any model, it has its limitations and shortcomings that need to be addressed for a more accurate depiction of consumer behavior.

One notable limitation of the model is its portrayal of the decision-making process as a linear progression through distinct stages. In reality, consumers often move back and forth between stages, revisiting information or reconsidering alternatives as they gather more data or encounter new stimuli. This dynamic nature of decision-making suggests that the process is more fluid and iterative than the linear model suggests.

Moreover, the model assumes that consumers primarily engage in System 2 thinking, characterized by rational, deliberate decision-making. However, research indicates that consumers frequently rely on System 1 thinking, which is intuitive, emotional, and automatic. This discrepancy highlights the influence of factors such as hunger, stress, or emotional states on consumer choices, particularly in the context of food-related decisions. Consumers may prioritize immediate gratification over long-term health considerations, leading to suboptimal choices.

The bounded rationality theory proposed by Simon (1972) further elucidates consumers' cognitive limitations in processing information and making optimal decisions. Due to constraints in time, information, and cognitive capacity, consumers often resort to heuristics or mental shortcuts to simplify complex decision-making tasks. These heuristics, while expedient, may result in biased or suboptimal decisions, particularly in situations with numerous alternatives and competing attributes.

Additionally, the model lacks specificity regarding food-related characteristics that may influence consumer decision-making. Factors such as nutritional value, dietary preferences, health considerations, taste preferences, and cultural influences play a significant role in food choices but are not explicitly addressed in the general model. Consequently, there is a need to augment the model to include food-specific variables that impact decision-making in the context of nutrition, dietary habits, and culinary preferences.

In conclusion, while the Online Consumer Decision-Making Model offers a valuable framework for understanding consumer behavior in the digital age, it is essential to recognize its limitations and refine the model to better reflect the complexities of real-world decision-making processes. By addressing these shortcomings and incorporating food-specific characteristics, marketers and researchers can develop more.

## **CHAPTER 5**

### **RESEARCH METHOD**

#### **5.1 DESIGNING THE REVIEW**

The landscape of recommendation systems (RSs) in the food sector has witnessed significant growth and evolution in recent years. As consumers increasingly turn to digital platforms for culinary inspiration, the role of RSs in guiding food choices has become paramount. This literature review aims to provide insights into the application of recommendation systems for individual users in the food sector. Specifically, it seeks to address three key sub-questions:

- a) What types and approaches of recommendation systems have been applied in the food sector?
- b) How can these food recommendation systems be classified based on the consumer decision - making process?
- c) What are the current challenges and solutions for food recommendation systems?

To achieve these objectives, an umbrella review was conducted to synthesize existing literature reviews on food RSs, focusing on recent developments and challenges. Additionally, original articles and recent papers were identified and analyzed to categorize food RSs based on the consumer decision-making process model.

##### **Umbrella Review: Summary of Literature Reviews on Food RSs**

The umbrella review encompassed a comprehensive analysis of existing literature reviews on recommendation systems in the food sector. By synthesizing findings from multiple sources, it aimed to provide a comprehensive overview of the types, approaches, challenges, and solutions in this domain.

##### **Several key themes emerged from the umbrella review:**

##### **Types and Approaches of Food RSs:**

Literature reviews highlighted various types of recommendation systems applied in the food sector, including content-based, collaborative filtering, knowledge-based, demographic-based, context-based, and hybrid approaches. Each approach offers unique advantages and challenges in recommending food items to individual users.

**Challenges in Food RSs:**

Common challenges identified in literature reviews include data sparsity, cold-start problem, user preference modeling, diversity-accuracy trade-off, and scalability issues. These challenges stem from the inherent complexity of food recommendation tasks and the diverse preferences of users.

**Solutions and Innovations:**

Researchers and practitioners have proposed innovative solutions to address the challenges facing food RSs. These include leveraging machine learning algorithms for personalized recommendations, incorporating contextual information for enhanced relevance, and integrating user feedback mechanisms to improve recommendation accuracy over time.

**User Satisfaction and Engagement:**

Literature reviews underscored the importance of user satisfaction and engagement in the success of food RSs. Effective recommendation systems should not only provide accurate and relevant suggestions but also consider user preferences, dietary restrictions, and cultural nuances to enhance overall satisfaction and engagement.

**Categorization of Food RSs Based on Consumer Decision-Making Process**

Building upon insights from the umbrella review, original articles and recent papers were analyzed to categorize food RSs based on the consumer decision-making process model. This model, depicted in Figure 2, encompasses five stages: problem recognition, searching for information, evaluating alternatives, purchasing, and post-purchase evaluation.

**Stage 1: Problem Recognition**

Food RSs assist users in identifying unfulfilled needs or desires related to food consumption. By analyzing user preferences, dietary requirements, and historical interactions, these systems help users recognize the need for culinary inspiration or dietary guidance.

**Stage 2: Searching for Information**

During this stage, consumers actively seek information on food options, recipes, ingredients, and nutritional content. Food RSs provide personalized recommendations based on user profiles, past behavior, and contextual factors, facilitating informed decision-making and exploration of diverse culinary choices.

**Stage 3: Evaluating Alternatives**

Consumers systematically evaluate food alternatives based on various criteria, including taste preferences, dietary restrictions, health considerations, and cultural preferences. Food RSs offer tailored recommendations that align with user preferences, streamlining the evaluation process and enhancing decision confidence.

#### **Stage 4: Purchasing**

Food RSs facilitate the final purchasing decision by guiding users to preferred food items, recipes, or meal plans. Integration with e-commerce platforms enables seamless transactions, allowing users to order ingredients or meals directly from recommended sources.

#### **Stage 5: Post-Purchase Evaluation**

After consuming the recommended food items, users engage in post-purchase evaluation to assess satisfaction levels, taste experiences, and overall culinary enjoyment. Feedback mechanisms within food RSs enable users to provide reviews, ratings, and feedback, contributing to the refinement of future recommendations.

#### **Conclusion**

In conclusion, this literature review provides a comprehensive overview of recommendation systems for individual users in the food sector. Through an umbrella review of existing literature reviews and categorization based on the consumer decision-making process model, key insights into types, approaches, challenges, and solutions in food RSs have been elucidated. Moving forward, continued research and innovation in this field are essential to address emerging challenges and meet the evolving needs of consumers



## 5.2 SEARCHING FOR LITERATURE

The literature search for this review commenced on May 25th, 2020, and concluded on June 12th, 2020. To ensure comprehensive coverage of relevant literature, three major databases were selected: Scopus, Web of Science, and Google Scholar. These databases were chosen for their accessibility and broad coverage across various scientific disciplines, including those relevant to food recommendation systems.

The search strategy involved using key terms such as "literature review," "recommendation systems," and "food," or their synonyms, in the title or abstract of articles. By employing these keywords, the aim was to retrieve studies that specifically focused on reviewing the existing literature on recommendation systems in the food sector. This targeted approach helped narrow down the search results to articles relevant to the research question.

After conducting the initial search, the retrieved articles underwent screening to ensure their relevance and adherence to the inclusion criteria. Only articles written in English were included, as English is the predominant language in scholarly communication, and including articles in other languages might have posed challenges in interpretation and synthesis.

Three literature reviews met the inclusion criteria and were selected for further analysis. These reviews were chosen based on their comprehensive coverage of recommendation systems in the food sector and their relevance to the research question. Each review provided valuable insights into the types, approaches, challenges, and solutions related to food recommendation systems, contributing to the overall understanding of the topic.

By utilizing multiple databases and employing a targeted search strategy, the literature search aimed to identify a diverse range of sources encompassing various perspectives and approaches to food recommendation systems. This approach helped ensure the comprehensiveness and rigor of the literature review, enabling a thorough analysis of existing research in the field.

Moving forward, the insights gleaned from the selected literature reviews served as a foundation for further exploration and analysis of recommendation systems for individual users in the food sector. By synthesizing findings from these reviews and incorporating additional original articles and recent papers, the review aimed to provide a comprehensive and nuanced understanding of the subject matter.

For the original studies included from the literature reviews, only studies that were used as example

within the text or in the tables were looked at, see Supplementary Materials. It was decided to include studies from all publication years, since the literature reviews used older studies in their whole research, meaning that it would have been impossible to refer to the literature reviews as they are based on studies older than 2015. Furthermore, it gives a better overview of the food RSs over the past few decades. The key words ‘food’, ‘recommendation system’ and ‘consumer’ or synonyms in the title or abstract were used. The synonyms used for RSs are ‘recommendation agents’, ‘recommender systems’, ‘shopping agents’, ‘shopping bots’, ‘interactive decision aid systems’, and ‘comparison shopping agents’. The synonyms for ‘food’ are ‘meal planning’, ‘recipes’, ‘ingredients’, ‘coffee shops’, ‘menus’, and ‘grocery shopping’. Lastly, consumers can be called ‘users’, so this was also included in the search term.

For the more recent studies, also the key words ‘food’, ‘recommendation system’ and ‘consumer’ or synonyms in the title or abstract were used. The only difference with the original studies from the literature review is that publications of the last 5 years (2015-2020) were included.

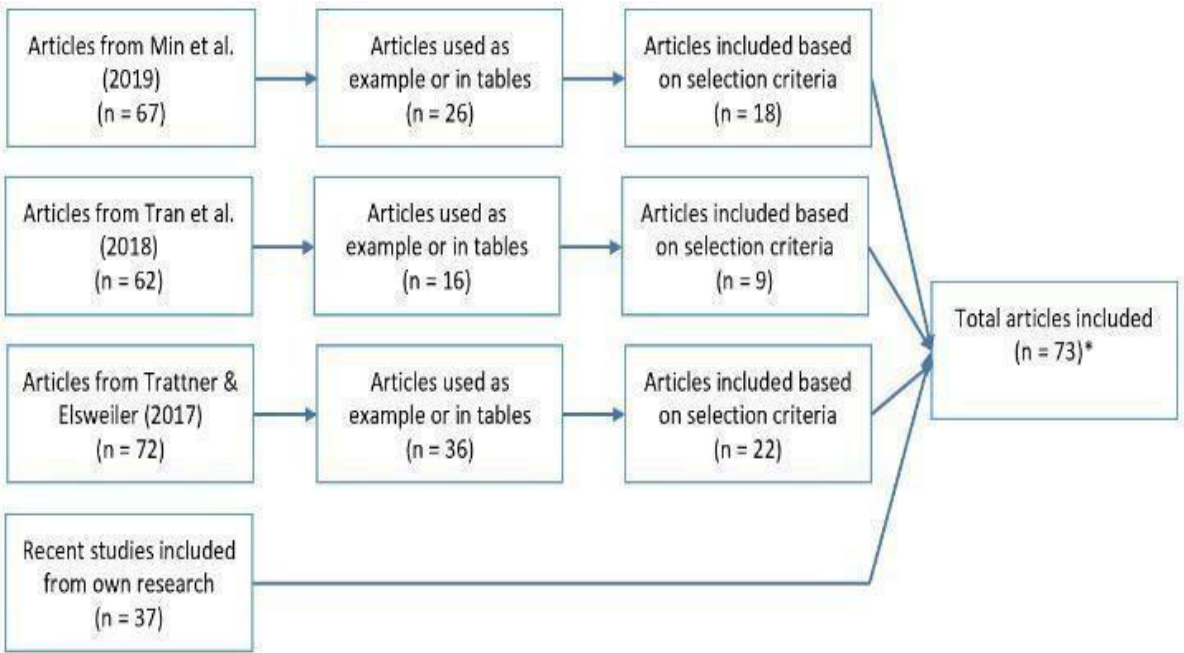


Fig.5.2. TYPES OF RECOMMENDATION SYSTEM IN THE FOOD SECTOR

### 5.3 SYNTHESIS

After collecting all articles their data was extracted. First, the texts of the literature reviews were merged to make an overview of the types of food RSs, the challenges and solutions, and future research suggestions. A color code was used to make this process easier, see Supplementary Material. After that, a table was made with the descriptive information of the total amount of studies per: publication year, food type, RS approach, decision-making stage, RS type, and type of study. Lastly, a thematic analysis was done per article see Tables 2-4. Those tables were divided per food RSs type and contained further details on: author, publication year, topic of the study, type of food, type of study, RS approach(es), and which decision-making stage it influences. It was decided to separate the tables per food type, as this gives additional information about the kind of food RSs made in that specific research area. The data of the articles were compared to each other to identify themes and categories that can be useful to answer the sub-questions.

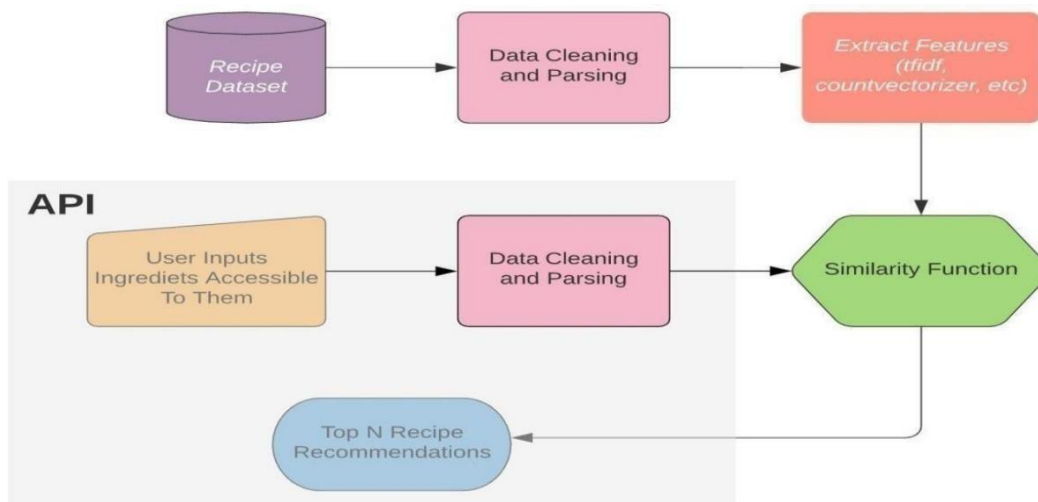
## CHAPTER 6

### ANALYSIS AND RESULTS

#### 6.1 TYPES OF RECOMMENDATION SYSTEMS IN THE FOOD SECTOR

There are different ways to categorize food RSs. For example, divide food RSs into recommendations for recipes, meal plans, groceries, and menus. However, this study will divide the food RSs based on the study of Tran et al. (2018), as this categorization focuses more on the function and the food RSs in general. Furthermore, there are more types of food related things (e.g. restaurants, food items, ingredients, and coffee shops) that are not covered by the division of Trattner & Elsweiler (2017). According to Tran et al. (2018) food RSs can be divided into four types, based on the information they use for their recommendations.

**The first type of food RSs focuses on user preferences.** These RSs focus on the user's food preferences derived from for example, the user's food ratings or eating history (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017). An example is Fatchum from Cruz, Alpay, Depeno Altabirano & Bringula (2017), that recommends recipes based on the user's search terms or ingredient input.



**Fig.6.1 Building a recipe recommendation system**

## **The second type of food RSs focuses on health and nutritional needs of users.**

For example, by substituting unhealthy ingredients by healthy ingredients or by generating a healthy food plan (Minetal., 2019). According to Trattner & Elswailer (2017), this is the most studied food RS type. The recommendations are, for instance, based on user's health information and contextual information (Minetal, 2019; Tran et al., 2018). To estimate the healthiness of a meal nutrition and health resources (e.g., USDA or BLS), a visual food analysis (e.g. recognizes food and estimates food quantity from a photo) and/or nutritional food standards (e.g., Food Standards Agency's (FSA) and World Health Organisation's (WHO)) are used in there commendation approach. Also, a traffic light system can be used to inform the users about the healthiness of the food item, with red being unhealthy, green being healthy, and orange being neither unhealthy nor healthy (Min et al., 2019; Trattner & Elswailer, 2017). One example of this food RS type is the RS from Alian, Li & Pandey (2018).

## **The third type is a trade-off food RS, that considers both user preferences and health and nutritional needs.**

According to Tran et al. (2018) this type leads to more optimal food recommendations. The reason for this is that by considering user preferences the recommended food items are more attractive and relevant for the user. This in turn makes the user more engaged and interested in using the food RSs. Furthermore, by considering the user's nutritional needs, physical activity, demographics, and health problems the recommended food items are healthier for the user. An example of a trade-off RS is SousChef from Ribeiro, Vasconcelos, Vieira & de Barros (2018). SousChef is a meal planner for the Portuguese elderly that keeps track of the user's food intake, user food preferences through meal ratings, and activity monitoring (see Figure 7). It also serves as grocery list.

**The fourth type is group food RSs**, as people often make food decisions with friends, families, or colleagues. For instance, people often decide together what they are going to eat during a Christmas dinner (Tran et al., 2018; Trattner & Elswailer, 2017). However, this type will not be discussed in this paper, since there is a lack of research in this area and this paper focuses on food RSs for individual users. Classification of Food Recommendation Systems on the Online Consumer Decision Making Process

In total seventy-three articles were analyzed, of which thirty-five articles were from the reference lists of the three literature reviews, and thirty-eight articles were from own research. Although it was possible to look at all search results from Scopus and Web of Science, Google Scholar retrieved too many search results. So only the first twenty pages of the search results were used, due to time constraints. The descriptive information of the included articles can be found in Table 1 and the thematic analysis can be found in Tables 2-4. As can be seen in Table 1, most studies in this analysis were from 2019, followed by 2015, 2017 and 2018. Furthermore, most food RSs were used to recommend recipes and after that meal planning. The main approach used was the hybrid approach, followed by knowledge-based and context-based approaches. Next to this, no studies used a demographic or social-network based approach. However eight studies included demographic characteristics and three studies included information from a social media network in their RS. Next to this, almost all studies

recommended alternatives to the user, which helped them with stage 3: evaluating alternatives. Moreover, the most used RS type was user preference, followed by the trade-off RS type. Lastly, there are more articles that did an experiment with their RS, than articles that explained their RS. All experiments tested the performance, except for the following three studies: Adaji, Sharmaine, Debrowney, Oyibo & Vassileva(2018), tested if there was a connection between personality types and recipe categories, tested if there was a relation between the demographics of the participants and how they rated the RS; and Freyne, Berkovsky, Baghaei, Kimani & Smith (2011), tested the effect of personalized and non-personalized tools on user interaction, information access and user motivation with the RS.

In the ‘Discussion & Conclusion’ section more information will be given about these findings. The last finding is that although most studies focus on food or users in general, five articles are made for a specific regional cuisine: Calabrian food items RS, Filipino recipes RS, Chinese regional recipes RS, Balinese food stalls RS and Indian recipes R.S Furthermore, eleven articles are specially made for certain users: meal plan RS for elderly, recipe RS for American Indians with diabetes, restaurant RS for tourists, recipe RS for users that suffer from a chronic disease, meal plan RS for obese youth, recipe RS for toddlers, food item RS for people suffering from common diseases, food item RS for travelers, and recipe RSfor peoplewith health problems.

## 6.2 Challenges and Current Solutions for Food Recommendation Systems

There are several challenges and solutions for food RS discussed in the literature reviews.

- 1. Predicting the user’s food preferences:** according to Min et al. (2019), Tran et al. (2018) and Trattner & Elswailer (2017) solutions to predict user food preferences are using psychology and neuroscience research methods; user food data from social media and recipe-sharing website (e.g., Yummly, Allrecipes, Meishijie, Foodspotting); user ratings; mobile and sensing devices; and user food journal. However, the accuracy of food RSs is poorer than RSs in other domains, as food preferences are complex and influenced by (contextual) factors that can be hard to obtain or model.
- 2. Food journal:** food journals are a solution to better predict user’s food preferences. In a food journal users can keep track of their eating history, for example their portion size and calories. Yet, a food journal costs a lot of the user effort to keep track of what they eat, and users easily forget or give wrong information. To decrease the user effort a visual analysis can be made of a photo the user made, to recognize the food ingredients, food categories, cooking instructions and estimate food intake. However, more research is needed to improve the food recognition of the visual analysis.
- 3. User ratings:** user ratings are also a solution to better learn the user’s food preference. Unfortunately, it is challenging to collect enough user’ ratings while keeping the food RSs convenient and saving the user effort. Furthermore, it is difficult to persuade users to keep rating dishes, recipes, or food items.
- 4. Accurately measuring the nutritional value:** one solution is to standardize the names and quantities.

Nevertheless, different names and units or quantities are still used for the same recipe, ingredient, or food item. Furthermore, food can be prepared in different ways, which influences the nutritional value.

**5. Food availability:** including the availability of food in the household is a solution to save the user money and prevent food waste. However, this requires a lot of effort from users to register all food items they consume and have in stock.

**6. Balancing between a big database and user satisfaction:** a big database is an advantage as the food RSs has more food items to recommend that better match the user's health situation or food preferences. Nevertheless, food RSs should find a balance between the amount of food items included in the database and user satisfaction with the system's response time. For example, if the database is too large, the RSs has to check more constraints or rules, which will take longer and can lead to user dissatisfaction.

## **CHAPTER 7**

### **DISCUSSION**

#### **7.1 DISCUSSION**

This literature review created an overview of three recent literature reviews and seventy-three studies in the field of food RSs for individual users and how they influence consumer decision making. With this overview the research question can be answered: How have the recommendation systems for individual users been applied in the food sector? The analyzed articles were mostly applied in the recipe domain, which is in line with the research from Trattner & Elswailer(2017). However, no studies were found on RSs for coffee shops or ingredients. An interesting finding was that all restaurant RSs focused on the user preference, as they do not consider health in their recommendations. Also as mentioned before, almost all food RSs can be applied for all different types of cuisines or users, except for sixteen articles. The majority of the studies in this analysis were from 2015, 2017, 2018 and 2019, which can be the result of the search strategy, as for the current studies only studies from 2015-2020 were allowed.

#### **7.2 IMPLICATIONS**

The exploration of food recommendation systems (RSs) within this paper offers a rich tapestry of insights and challenges, ripe for further exploration and application across diverse fields. Researchers, in particular, stand to benefit immensely from the nuanced understanding garnered from this examination. Armed with a comprehensive overview of current research, scholars are poised to embark on new avenues of inquiry, leveraging the identified challenges and future research suggestions as catalysts for innovation.

One pressing area for research pertains to the development of robust evaluation methodologies tailored specifically to the performance assessment of food RSs. As these systems grow in complexity and sophistication, the need for standardized evaluation metrics becomes increasingly imperative. Researchers can thus direct their efforts towards devising rigorous evaluation frameworks that capture the multifaceted dimensions of food recommendation efficacy, encompassing aspects such as accuracy, relevance, and user satisfaction.

Furthermore, the insights gleaned from this review hold profound implications for (e-commerce) food companies seeking to enhance their competitive edge through the design and implementation of superior food RSs. By leveraging the wealth of knowledge distilled from existing research, companies can glean valuable insights into successful strategies and design principles. For instance, grocery retailers may draw



inspiration from the Nutrismart system proposed by Talekar et al. (2019), incorporating its features and functionalities.

Moreover, the utility of food RSs extends beyond the realm of commerce, permeating into the domains of healthcare and nutrition. Nutritionists and dietitians, in particular, can leverage the plethora of existing RSs to augment their patient care strategies. For instance, the food RS elucidated by Ali et al. (2018), which facilitates diet menu planning and provides tailored nutritional guidance, holds immense promise for practitioners seeking to empower their clients towards healthier dietary choices. By incorporating such RSs into their practice, professionals can amplify the efficacy of dietary interventions, fostering improved health outcomes for their patients.

From a consumer perspective, the advent of enhanced food RSs heralds a paradigm shift in the shopping experience, underpinned by heightened personalization and informed decision-making. Effective RSs have the potential to streamline the user journey, facilitating seamless navigation through vast culinary landscapes while minimizing cognitive effort and search costs. Moreover, by recommending foods that strike a delicate balance between healthfulness and palatability, these systems hold sway over consumer eating behaviors, nudging individuals towards more wholesome dietary patterns.

In essence, the implications of food RSs are far-reaching and multifaceted, spanning across research, commerce, healthcare, and consumer behavior. As researchers continue to probe the depths of this burgeoning field, and as companies strive to capitalize on its commercial potential, the transformative impact of food RSs is poised to reverberate throughout society, reshaping the way we eat, shop, and engage with food.

### **7.3 LIMITATIONS**

There are some limitations that need to be considered. First of all, the method used was not a systematic literature review, which can make it less comprehensive, more biased and subjective, and less easy to replicate. Also, the literature review was done by one person. This means that there was no inter-rater agreement on the interpretation of the articles. This can harm the reliability and internal validity of the research, since two researchers can discuss and double check the interpretation of the other. Nevertheless, the steps for the literature review were explained thoroughly to achieve transparency, which improved the quality and credibility of this research. Moreover, as a result of writing this paper in only two and a half months' time, it was decided to exclude unpublished research, as it seemed unattainable within this short time frame. However, according to the publication bias this can threaten the internal validity of the conclusion, since published studies are more likely to have significant results. For example, there could be meal planning or grocery food RSs that are not published. That is why a future systematic literature review might be useful to including also unpublished research. Furthermore, it was decided in the 'Analysis & Results' section to refer to the three

literature reviews of Tran et al. (2018), Trattner & Elswailer (2017) and Min et al. (2019) instead of the original articles, except for section 4.3. This can make this paper less transparent, as people cannot immediately see in which original article these assumptions or results were found.

However, this strategy was used to make it easier to compare the information of the literature reviews. Furthermore, due to the limited time of this research it was decided to spend more time on searching for more recent articles than reading the original articles. Finally, this research only focused on the food RSs types, approaches, categorization of studies based on the online consumer decision-making process, challenges and solutions, and future research suggestions. Nonetheless, due to the limited time the external factors, such as individual, social influence, situational, and economic variables that influence the consumer decision-making process and other contextual factors that can be used to build a user profile for food RSs were not analyzed (Darley et al., 2010; Maçik, 2016). The same holds for the types of evaluation methods that were not incorporated in the article analysis. Moreover, as explained before, group food RSs were also not covered in this paper. That is why another literature review can be useful that will include these interesting.

### 7.3 FUTURE LIMITATIONS

The future research directions in the food RSs based on this research are as followed:

- 1. Food types:** more food RSs are needed to be developed in other areas than recipe RSs. For example, food RSs for grocery shopping, coffee shops, ingredients, restaurants, and food items. Something that might be interesting is to develop a restaurant RS that takes the healthiness of restaurant menus into consideration.
- 2. Evaluation methods:** a more standardized and specialized method must be developed to evaluate food RSs on prediction accuracy and diversity. Furthermore, full-online evaluations need more attention, as there are very limited researches that do this. The experimental researches included in this literature review can be used to make an overview of what current evaluation methods exist.
- 3. Literature review:** another literature review can be useful that includes topics such as group food RSs, external and contextual factors of current food RSs, unpublished research, and all current evaluation methods of food RSs. This in turn, will improve the understanding of how food RSs can change eating behavior.
- 4. Food RSs:** more food RSs can be developed that focus on other decision-making stages than stage 3: evaluating alternatives. For example, a food RS can be developed that provide product information or suggests different selection criteria that the user can use when choosing (healthy) grocery products. This helps people with stage 2: searching for information.

The future research direction in the food RSs based on the three literature reviews:

**1. User preference:** according to Min et al. (2019) and Trattner & Elswailer (2017), further research should improve the development of user profiles and the performance of the food RSs. One topic that asks for more attention is implicit methods (e.g., recipe reviews) to elicit user's food preferences, as explicit methods require user effort and cannot fully capture user preferences.

**2. Sensing devices:** the current sensing devices that measure the real-time user's state cannot measure everything. Some topics that need further research are fusing discrete and continuous contextual variables together in a joint model; innovating sensors to measure or 39 methods to quantify hard or up to now not available variables (e.g., smell and taste); and making more accurate sensors (Min et al., 2019).

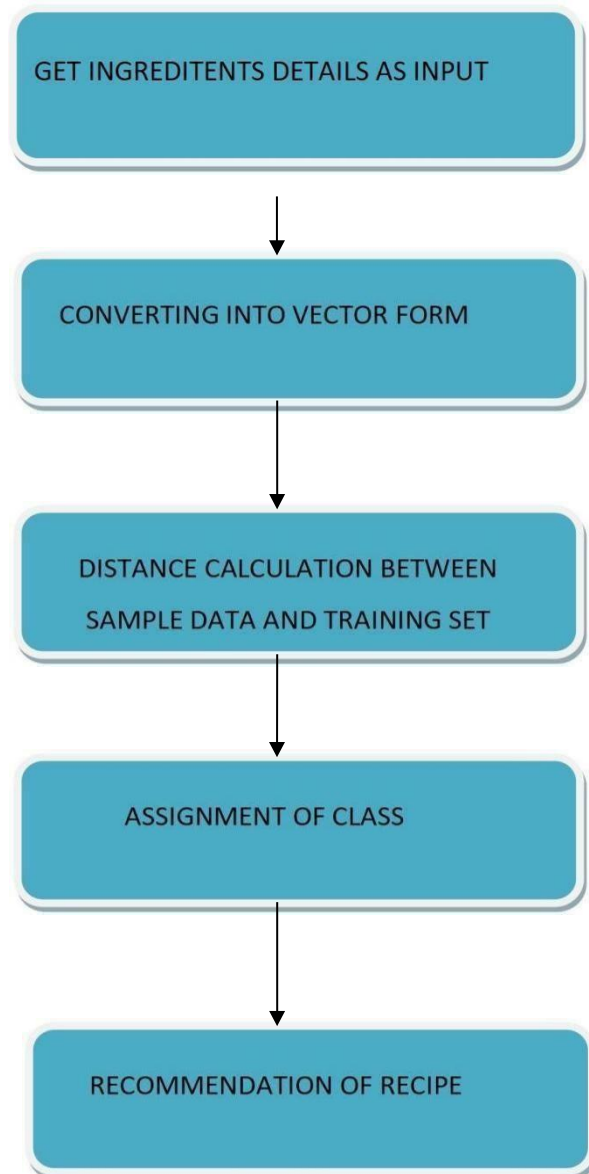
**3. Visualization of food items:** visual food analysis can serve as a solution for food journals, however, they need to be improved as most visual analysis are only effective for RSs in general. The reason for this is that food is non rigid and has no distinctive or structured form, which makes it harder to visually analyze it.

**4. Group food RSs:** according to Tran et al. (2018), more research needs to be done to achieve fast consensus in group decision-making and to make meal planning recommendations for one or more than one day (bundled recommendations). Especially group constraints, such as a food allergy of one individual is important to take into consideration. Next to this, more research should focus on the influence of social situations on (group) food choices.

**5. Other resources:** some resources that might improve food RSs have not yet been implemented, such as the Health Eating Index as nutrition and health resource; Food subs as food substitution database to replace unhealthy food items, meals or ingredients with healthy alternatives; Food log as information source to learn the user's food prefer.

## CHAPTER 8

### BLOCK DIAGRAM



## **CHAPTER 9**

### **CONCLUSION**

In conclusion, An intelligent cooking recipe recommendation system stands poised at the forefront of culinary innovation, offering a plethora of benefits for individuals seeking personalized recipe suggestions tailored to their preferences and dietary requirements. Through the amalgamation of cutting-edge technologies such as machine learning algorithms and natural language processing, these systems transcend mere recipe databases, becoming intuitive culinary companions that revolutionize the cooking experience.

At the core of these systems lies their ability to provide tailored recommendations, leveraging sophisticated algorithms to analyze user preferences, past choices, and dietary restrictions. By harnessing the power of machine learning, these systems continuously refine their suggestions, adapting to evolving tastes and preferences over time. This personalized approach not only enhances user satisfaction but also empowers individuals to explore diverse cuisines while adhering to their dietary needs, whether it be gluten-free, vegan, or low-sodium options.

Moreover, the integration of natural language processing enables seamless interaction, allowing users to effortlessly convey their culinary preferences and receive relevant recipe suggestions in return. This intuitive interface eliminates barriers to entry, catering to individuals with varying levels of culinary expertise, from novice cooks to seasoned chefs.

Beyond mere convenience, intelligent recipe recommendation systems play a pivotal role in promoting healthier eating habits. By curating recipes based on nutritional content and dietary guidelines, these systems empower users to make informed choices that align with their wellness goals. Whether striving to reduce calorie intake, increase fiber consumption, or incorporate more nutrient-dense ingredients, users can rely on these systems to steer them towards recipes that prioritize health without compromising on flavor.

Furthermore, these systems serve as invaluable allies in the fight against food waste. By analyzing pantry inventories and expiration dates, they suggest recipes that utilize ingredients on the brink of spoilage, thereby minimizing waste and fostering a more sustainable approach to cooking. This not only conserves resources but also cultivates a mindset of resourcefulness, encouraging users to creatively repurpose ingredients that might otherwise have been discarded.

In essence, the benefits of an intelligent cooking recipe recommendation system extend far beyond the realm of mere culinary convenience. They represent a paradigm shift in the way we approach cooking, transforming it from a mundane chore into a dynamic and rewarding experience. By fostering a deeper connection between individuals and their food, these systems inspire creativity, promote wellness, and instill a sense of stewardship towards the environment.

As we navigate an increasingly fast-paced world, where time and resources are precious commodities, the role of these systems becomes all the more indispensable. They not only streamline the cooking process but also empower individuals to make choices that resonate with their values and aspirations. Thus, an intelligent cooking recipe recommendation system emerges not just as a tool for culinary exploration, but as a catalyst for

personal growth, wellness, and sustainability.

## **FUTURE ENHANCEMENT**

There are several potential future enhancements for an intelligent cooking recipe recommendation system, including:

**1. Incorporating user preferences:** One way to improve the recommendation system is to incorporate user preferences into the algorithm. For example, the system could ask users to rate recipes they have tried and enjoyed or disliked, and use this feedback to generate more personalized recipe recommendations.

**2. Using machine learning algorithms:** Machine learning algorithms could be used to analyze large amounts of recipe data and identify patterns in ingredient combinations, cooking techniques, and flavor profiles that are likely to be popular with users. These algorithms could also be used to predict which recipes are most likely to be successful based on factors such as ingredient availability, cooking time, and user feedback.

**3. Integrating with smart kitchen appliances:** As more homes become equipped with smart kitchen appliances, an intelligent cooking recipe recommendation system could be integrated with these devices to make cooking even more convenient. For example, the system could suggest recipes that can be cooked using a specific appliance or provide step-by-step cooking instructions on a connected device.

**4. Including dietary restrictions:** Another way to enhance the system is by incorporating dietary restrictions and preferences into the recommendations. Users could specify dietary restrictions such as gluten-free, vegetarian, or low-sugar, and the system would generate recipe recommendations that meet those criteria.

**5. Adding nutritional information:** The system could also be enhanced by including nutritional information for each recipe, such as calorie counts, macronutrient breakdowns, and vitamin and mineral content. This would allow users to make more informed decisions about the meals they prepare and consume.

## APPENDIX 1

```

import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
import matplotlib.pyplot as plt

workloads = pd.read_csv('/content/drive/MyDrive/Copy of PP_recipes.csv')
workloads.dtypes

from google.colab import drive
drive.mount(' / content/drive ')

workloads['name_tokens'] = pd.to_numeric(workloads['name_tokens'],
errors='coerce')
workloads['ingredient_tokens'] =
pd.to_numeric(workloads['ingredient_tokens'], errors='coerce')
workloads['steps_tokens'] = pd.to_numeric(workloads['steps_tokens'],
errors='coerce')
workloads['techniques'] = pd.to_numeric(workloads['techniques'],
errors='coerce')
workloads['calorie_level'] = pd.to_numeric(workloads['calorie_level'],
errors='coerce')
workloads['ingredient_ids'] = pd.to_numeric(workloads['ingredient_ids'],
errors='coerce')

workloads=workloads.fillna(0).astype(np.int64,errors='ignore')

```

```
X = workloads.iloc[:,0:7]
```

```
Y = workloads.iloc[:,7].values
```

```
print(Y)
```

```
train_x,test_x,train_y,test_y = train_test_split(X,Y,test_size =15)
```

```
rfc = RandomForestClassifier(n_estimators=70,criterion='gini')
```

```
rfc.fit(train_x,train_y)
```

```
y_pred3 = rfc.predict(test_x)
```

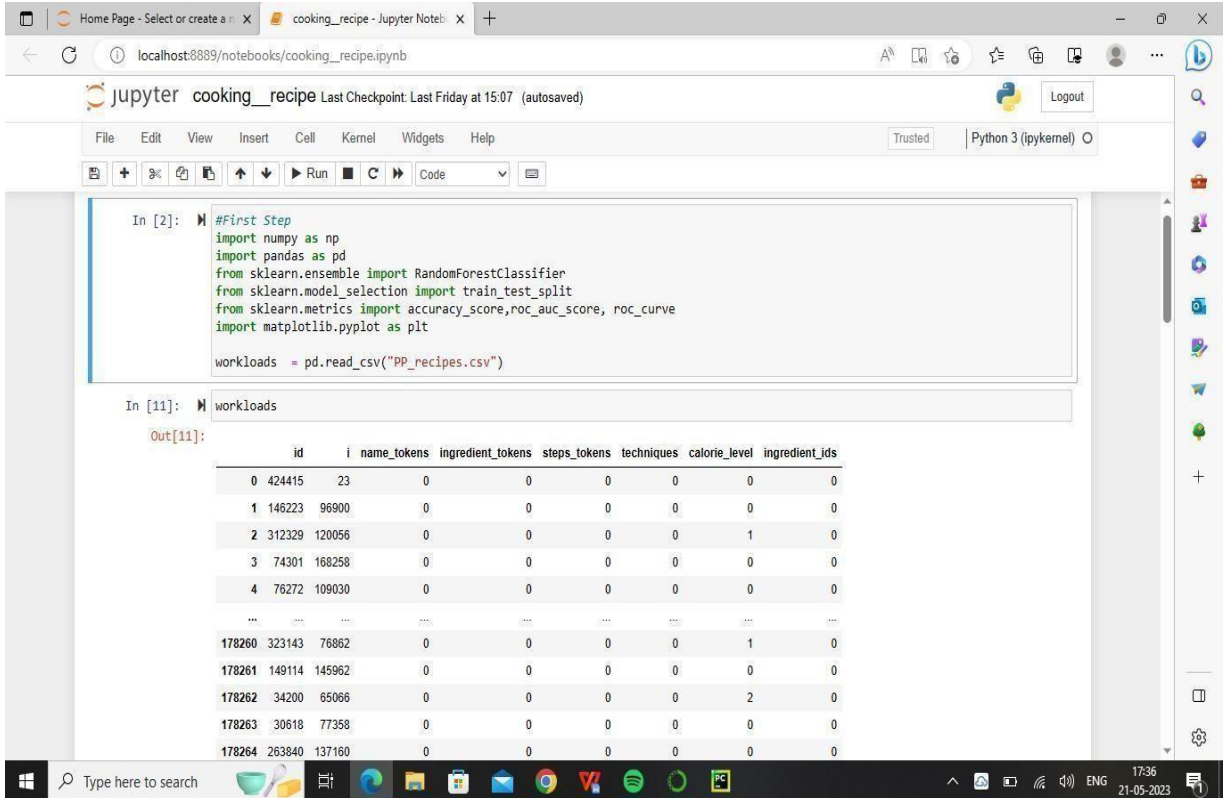
```
print('Accuracy Score of Random Forest Classifier : ',  
accuracy_score(y_pred3,test_y))
```

```
from sklearn.metrics import classification_report
```

```
print(classification_report(test_y, y_pred3))
```



## APPENDIX 2



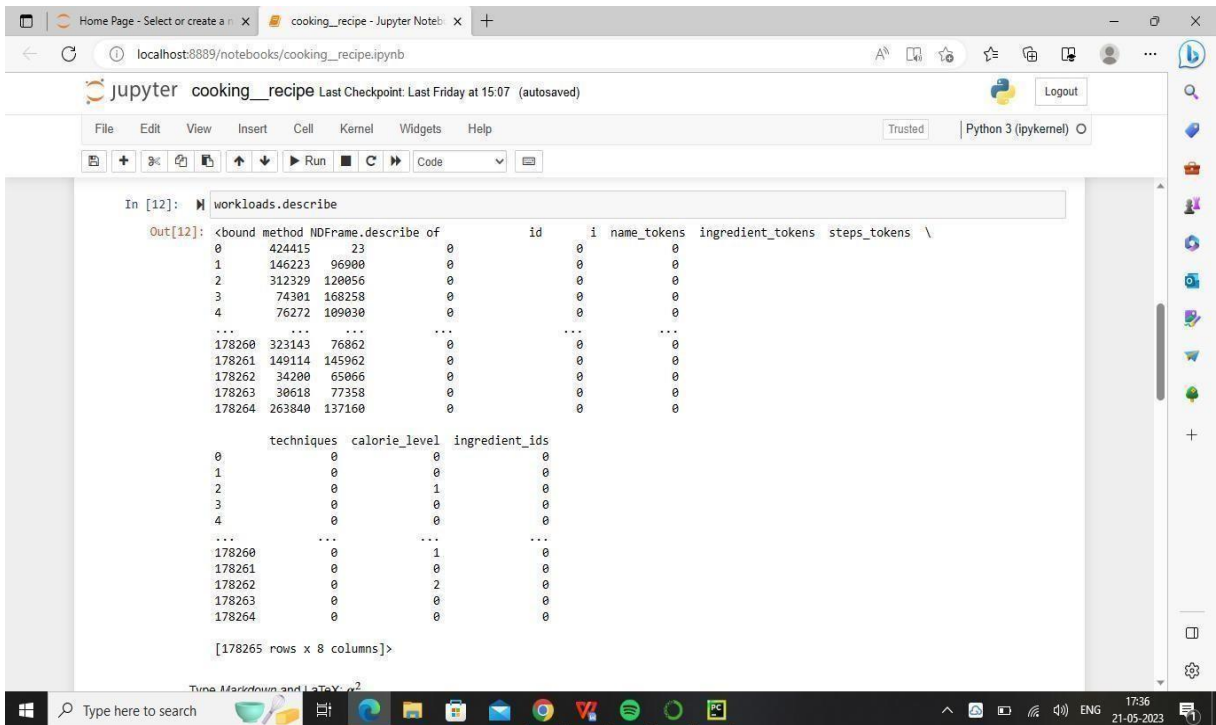
```
In [2]: #First Step
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
import matplotlib.pyplot as plt

workloads = pd.read_csv("PP_recipes.csv")
```

```
In [11]: workloads
```

```
Out[11]:
```

	id	i	name_tokens	ingredient_tokens	steps_tokens	techniques	calorie_level	ingredient_ids
0	424415	23	0	0	0	0	0	0
1	146223	96900	0	0	0	0	0	0
2	312329	120056	0	0	0	0	1	0
3	74301	168258	0	0	0	0	0	0
4	76272	109030	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
178260	323143	76862	0	0	0	0	1	0
178261	149114	145962	0	0	0	0	0	0
178262	34200	65066	0	0	0	0	2	0
178263	30618	77358	0	0	0	0	0	0
178264	263840	137160	0	0	0	0	0	0



```
In [12]: workloads.describe
```

```
Out[12]: <bound method NDFrame.describe of
```

	id	i	name_tokens	ingredient_tokens	steps_tokens	techniques	calorie_level	ingredient_ids
0	424415	23	0	0	0	0	0	0
1	146223	96900	0	0	0	0	0	0
2	312329	120056	0	0	0	0	1	0
3	74301	168258	0	0	0	0	0	0
4	76272	109030	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
178260	323143	76862	0	0	0	0	1	0
178261	149114	145962	0	0	0	0	0	0
178262	34200	65066	0	0	0	0	2	0
178263	30618	77358	0	0	0	0	0	0
178264	263840	137160	0	0	0	0	0	0

```
[178265 rows x 8 columns]>
```

Home Page - Select or create a notebook | cooking\_recipe - Jupyter Notebook | +

localhost:8889/notebooks/cooking\_recipe.ipynb

jupyter cooking\_recipe Last Checkpoint: Last Friday at 15:07 (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

In [8]:

```
train_x, test_x, train_y, test_y = train_test_split(X, Y, test_size=15)
rfc = RandomForestClassifier(n_estimators=70, criterion='gini')
rfc.fit(train_x, train_y)
y_pred3 = rfc.predict(test_x)
print("Accuracy Score of Random Forest Classifier : ", accuracy_score(y_pred3, test_y))
```

Accuracy Score of Random Forest Classifier : 1.0

In [9]:

```
from sklearn.metrics import classification_report
print(classification_report(test_y, y_pred3))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	15
accuracy			1.00	15
macro avg	1.00	1.00	1.00	15
weighted avg	1.00	1.00	1.00	15

In [14]:

```
# Example of making predictions on a sample input
sample_input = [[23, 10, 5, 0, 2, 1, 1000]] # Replace with your own sample input

# Make predictions on the sample input
sample_output = rfc.predict(sample_input)

# Print the predicted output
print("Predicted Output for Sample Input: ", sample_output)
```

Predicted Output for Sample Input: [0]

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17:37 21-05-2023

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