# AGE-BASED HEALTH RECOMMENDATION SYSTEM

## ABSTRACT

A study involving a survey of over 1000 participants aged 20 and above examined public awareness and perceptions of the term age-friendly. Results revealed that 81% of respondents were familiar with the term, although older adults demonstrated lower awareness. The term was primarily linked to communities 57% and health systems 41%. Unexpectedly, most participants believed it was applicable to all age groups, contrary to its intended focus on older adults. These findings underscore the need for enhancing comprehension and communication within the age friendly framework, presenting valuable opportunities for refinement.

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| AI | Artificial Intelligent |
| ML | Machine Learning |
| ABHRS | Age Based Health Recommendation System |
| TF-IDF | Term Frequency-Inverse Document Frequency |
| CF | Collaborative Filtering |

# CHAPTER 1
# INTRODUCTION

## 1.1 Overview

In today's rapidly evolving digital landscape, the challenge of delivering personalized user experiences has become paramount. With a diverse user base spanning various age group, it has become increasingly essential to tailor recommendations to align with users' unique preferences, needs, and life stages. Traditional one-size-fits-all recommendation systems often fall short in providing relevant content, products, or services to users of different ages. To address this issue, a novel approach emerges by harnessing the capabilities of machine learning and data visualization tools like Power BI to create an Age-Based Recommendation System.

The examination of public perceptions and familiarity with the term age-friendly among individuals aged 20 and above has provided invaluable insights into the understanding and implications of this concept across different age cohorts. By conducting an extensive survey involving over participants, this study aimed to discern not only the recognition but also the associations linked to the term. The results revealed that a substantial 81% of the respondents were well-acquainted with the term age-friendly. Nonetheless, a notable divergence emerged among older adults, who exhibited comparatively lower levels of awareness. This observation points towards a potential need for targeted communication efforts, specifically tailored to address this age group's concerns and interests, which are integral to the successful implementation of age-friendly initiatives.

As digital platforms and businesses strive to stay competitive in a world inundated with choices, the Age-Based Recommendation System offers a forward-looking approach to delivering content that resonates with users of all ages. This system stands as a testament to the power of merging technology and user-centricity, paving the way for more engaging, relevant, and valuable user experiences.

## 1.2 Motivation for the project

The scope of this project encompasses the development of a comprehensive age-based recommendation health system, leveraging collaborative filtering, content-based filtering techniques, and Power BI for data visualization and insights. The motivation behind this endeavour is to empower individuals of all ages with personalized, evidence-based health recommendations, promoting informed healthcare decisions and improved well-being while utilizing data analytics to continually enhance the system's performance and user satisfaction**.**

## 1.3 Problem Definition

In the context of healthcare and wellness, there exists a critical need for a sophisticated age-based recommendation system that leverages user age data to provide tailored health recommendations. Existing health recommendation systems often lack personalization based on age, which results in suboptimal user engagement and potentially ineffective guidance for individuals across different life stages. This project aims to address this gap by developing a data-driven recommendation system that considers users' ages as a key factor in suggesting health content, services, and interventions. The system should be scalable, adaptive, privacy-conscious, and capable of utilizing various data sources to offer evidence-based and age-appropriate health advice, ultimately enhancing user health outcomes and satisfaction.

## 1.4 Organization of the Report

The following is the thesis's structure is as follows. Chapter 1 introduces the motivation and problem definition of the project in detail. The reference document that was collected for this project, as well as the takeaways, are noted in the Literature Survey. In Chapter 3, the Project Description is mentioned along with existingwork, proposed work, and benefits of project. In Chapter 4, the Architecture Design is mentioned along with full explanation for the project. In Chapter 5, the Software and Hardware Requirements and technologies being implemented in the project is mentioned.

In Chapter 6, the Module Description of the project is mentioned and the subdivisions are explained in detail. In Chapter 7, the whole implementation of the project is discussed. In Chapter 8 , the Results and Explanations are mentioned and theoutcomes of every module are shown in graphic detail.

In Chapter 9, a Conclusion for this project is made and the further enhancements are also mentioned. In Chapter 10, the Individual Report of the Team Members is mentioned along with the objective, role, and contribution of each member

## 1.5 Summary

An age health recommendation system is a digital tool that offers personalized health advice based on an individual's age. It analyzes user data and considers age-specific health needs to provide tailored recommendations for diet, exercise, and preventive healthcare measures. By utilizing advanced algorithms, it ensures evidence-based and up-to-date guidance for users. This system empowers individuals to make informed decisions and take proactive steps towards better health as they age.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Introduction

This chapter examines the numerous papers that have been published up to this point., as well as the project details that are supplied and addressed in length in the analysis of the article.

## 2.2 Literature Review

**Awareness and Perceptions of "Age-Friendly": Analyzing Survey Results from Voices in the United States (**May 2023, Dunning, L.; Ty, D.; Shah, P.; McDermott)

The survey findings provide the age-friendly ecosystem field with the context in which it is vying for in the mindshare of adults over 40. Most respondents reported being aware of the term age-friendly, with adults aged 40–64 leading the sample in being at least Somewhat aware and those over 65 lagging in their self-reported extreme awareness. Age-friendly was most often associated with cities and communities and most respondents perceive the term as applying to all ages. Taken together, the results suggest that the depth and specificity of awareness of the term age-friendly is lacking and that it is perceived quite broadly, beyond the intended scope of some efforts. As AFHSs strive to align the care preferences of older adults with the care they receive, their target population may not clearly associate the term with an older demographic. Knowledge- and awareness building, alongside the systemic changes that age-friendly initiatives aim to produce, can be an avenue for further examination to determine the potential contribution to outcomes and overall success.

**Differences in awareness of positive and negative age-related changes accounting for variability in health outcomes** (February 2022, Serena Sabatini, Obioha C. Ukoumunne, Allyson Brothers, Manfred Diehl)

This was the first study exploring the potential coexistence of AARC gains and losses and identifying which profiles of AARC gains and losses were common in the population. Among middle-aged and older individuals with above average perceived physical health and intact cognitive abilities, there were different profiles of coexistence of perceived AARC gains and losses. Most frequently, individuals perceived many age-related gains and few age-related losses, whereas the experience of both many gains and losses were the least frequent. This was also the first study exploring whether different profiles of AARC gains and losses are related to physical, mental, and cognitive health. Profiles with different combinations of AARC gains and losses differed with respect to physical, mental, and cognitive health, suggesting that assessing the coexistence of gains and losses is important when relating AARC to health.

**Recommender systems in the healthcare domain: state-of-the-art and research issues** (December 2020, Alexander Felfernig, Christoph Trattner, Andreas Holzinger)

Health recommender systems have emerged as tools to support patients and healthcare professionals to make better health-related decisions. In this article, we have given insights into recommendation scenarios offered by these systems, such as food recommendation, drug recommendation, health status prediction, physical activity recommendation, and healthcare professional recommendation. For each recommendation scenario, various algorithms have been employed, which are based on recommendation techniques (e.g., CF, CB, KB, HYR, and context-based recommendations) or machine learning techniques (e.g., classification, clustering, decision tree, natural language processing, logic programming, ontologies, and semantic technologies). Although the proposed HRS bring many benefits in terms of health-related improvements, there still exist a few challenges that need to be tackled for the better development of these systems in the future.

**Evaluating the Age-Based Recommendations for Long-Term Follow-Up in Breast Cancer** (September 2021, Annemieke Witteveen, Linda de Munck, Catharina G.M, Groothuis-Oudtshoorn)

The current consensus-based follow-up recommendations after 5 years (annual for <60 years after 5 years of follow-up, biennial for 60–74, consider stopping >74) use suboptimal age cutoffs leading to an imbalance between risk of LRR and SP and intensity of the follow-up following the 5 years of clinical follow-up. Patients aged 50–60 years have a lower risk for recurrence compared with patients <50 and could have a less intensive schedule. The proposed alternative cutoffs (<50, 50–69, >69) will lead to a more balanced risk-based follow-up frequency considering the risk of both LRR and SP and will be a start toward more efficient allocation of resources. However, to get truly personalized follow-up, more risk factors as well as the benefits and harms of follow-up should be considered to provide accurate individualized risk estimates and follow-up schedules.

**Deep Learning Based Health Recommender System Using Collaborative Filtering** (May 2019, Abhaya Kumar Sahoo, Chittaranjan Pradhan, Rabindra Kumar Barik, Harishchandra Dubey)

Health Recommender systems are one of the new prevailing technologies for deriving supplementary information for a patient from healthcare data. These systems find recommended hospitals by calculating the similarity of patients' choices. Therefore, they play an important role in the medical sector. Modern state of the art technologies is required that can resolve the issues data security and privacy found in CF-based health recommender systems. In this paper, different privacy-preserving collaborative filtering methods, along with the deep learning method, are compared. The proposed RBM-CNN demonstrates better accuracy of the health recommender system as compared to others.

## 2.3 Conclusion

In conclusion, the presented research articles emphasize the need for improved awareness and specificity in age-friendly initiatives, the importance of considering coexistence of age-related gains and losses for health outcomes, and the potential of recommender systems in healthcare decision-making. These insights contribute to ongoing discussions and offer directions for future research and practical applications in healthcare and aging.

# CHAPTER 3
# PROJECT DESCRIPTION

## 3.1 Objective of the Project Work

The primary goal of our research is to develop an age-based health recommendation system capable of providing personalized health guidance to individuals. While there is substantial prior work in the field of health recommendation systems, our approach focuses on tailoring recommendations based on an individual's age. Furthermore, our system will offer the functionality for users to create unique accounts, allowing them to curate personalized health plans and recommendations specific to their age and health requirements.

## 3.2 Existing System

Age-based health recommendation systems have gained significant importance in the era of personalized healthcare. These systems are designed to cater to the diverse health needs and concerns of individuals across different age groups. Users are typically required to create profiles that include their age, gender, and health history, which serve as the foundation for tailored recommendations. Age segmentation is a fundamental component of these systems, as it allows for the precise targeting of advice and guidance. Dietary recommendations are tailored to meet the nutritional requirements and age-related dietary changes that vary from one age group to another.

Physical fitness plans are also part of these systems, accounting for varying fitness levels and health objectives that may differ across age groups. Furthermore, preventive care recommendations play a vital role in promoting early detection and proactive health management. The systems provide guidance on vaccinations, screenings, and wellness check-ups that are particularly relevant to a user's age. Medication reminders are integrated to ensure that users adhere to their prescribed treatments, especially for those with age-related health conditions.

Lifestyle guidance within the systems includes recommendations on sleep patterns, stress management, and addressing issues such as alcohol and tobacco use. Community and social support features facilitate connections with others in the same age group, fostering a sense of camaraderie and emotional support. To enhance accuracy and real-time monitoring, many systems integrate with wearable devices that track users' physical activity, heart rate, and other relevant health metrics.

In summary, age-based health recommendation systems serve as invaluable tools in empowering individuals to make informed health decisions, considering their unique age-related needs and circumstances. These systems are a manifestation of the healthcare industry's commitment to personalized care, considering the individuality of each user and their age-specific health journey.

## 3.3 Proposed Solution

Developing a collaborative filtering-based health recommendation system using Power BI represents an innovative approach to offer users personalized health advice. The system initiates by collecting and cleansing health-related content and medical conditions data, followed by harnessing Power BI's data transformation capabilities to prepare this data for analysis.

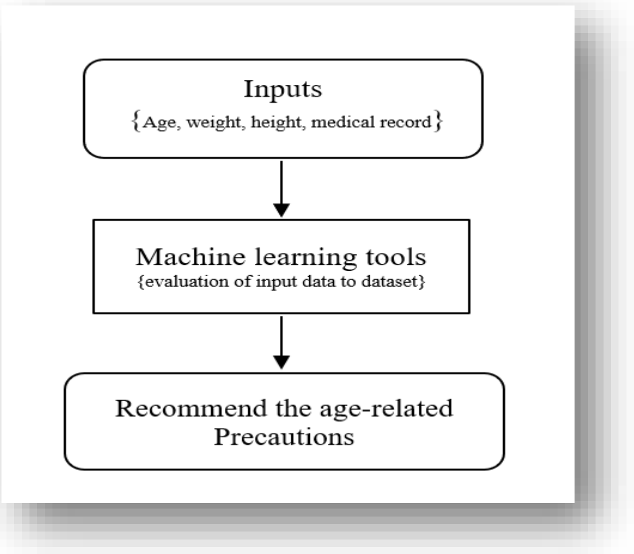


Fig 3.1: Structure of ABHRS model

In the modeling phase, Power BI assumes a central role in constructing a collaborative filtering model that evaluates user behavior and content preferences. This model serves as the cornerstone for generating customized health recommendations based on user interactions. The recommendation engine, at the heart of the system, employs collaborative filtering algorithms to compute similarity scores between users and content items, guiding users towards health content aligned with their age, BMI, and medical conditions. In addition, the system provides a user-friendly interface within Power BI, enabling users to input their age, BMI, and medical conditions. The system processes this data to furnish personalized recommendations. Utilizing Power BI's reporting and visualization capabilities, interactive reports and dashboards are created to effectively present these recommendations. Furthermore, the integration of user accounts enables users to manage profiles, preferences, and interactions, while rigorous testing and validation procedures guarantee recommendation accuracy. Once deployed, the system empowers users with personalized health guidance, all within Power BI's seamless and user-friendly interface.

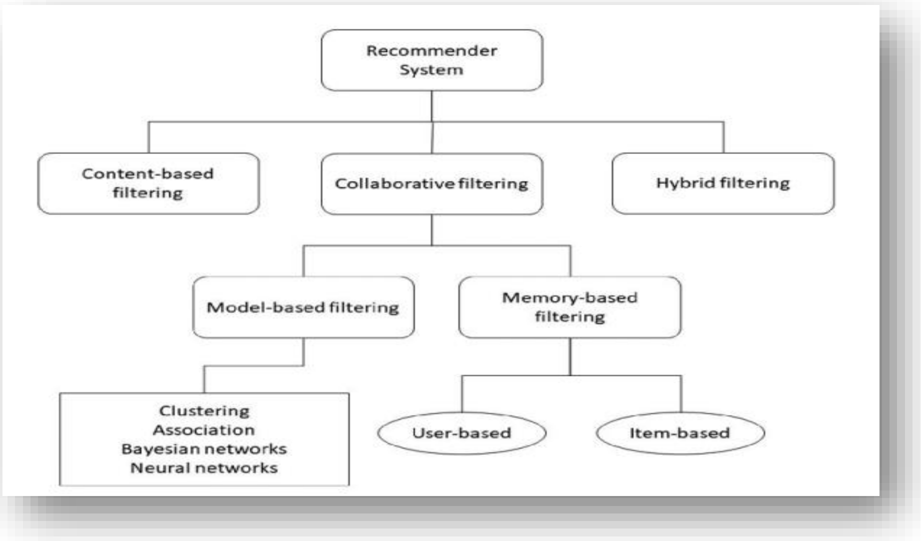


Fig 3.2 Collaborative Filtering-CF Method

## 3.4 Benefits of Proposed System

The proposed collaborative filtering-based health recommendation system using Power BI offers personalized health guidance, promoting better health outcomes and user engagement. It also provides valuable data insights, supports user feedback, and ensures data privacy, contributing to cost-effective and efficient health management.

# CHAPTER 4
# SYSTEM DESIGN

## 4.1 SYSTEM ARCHITECTURE

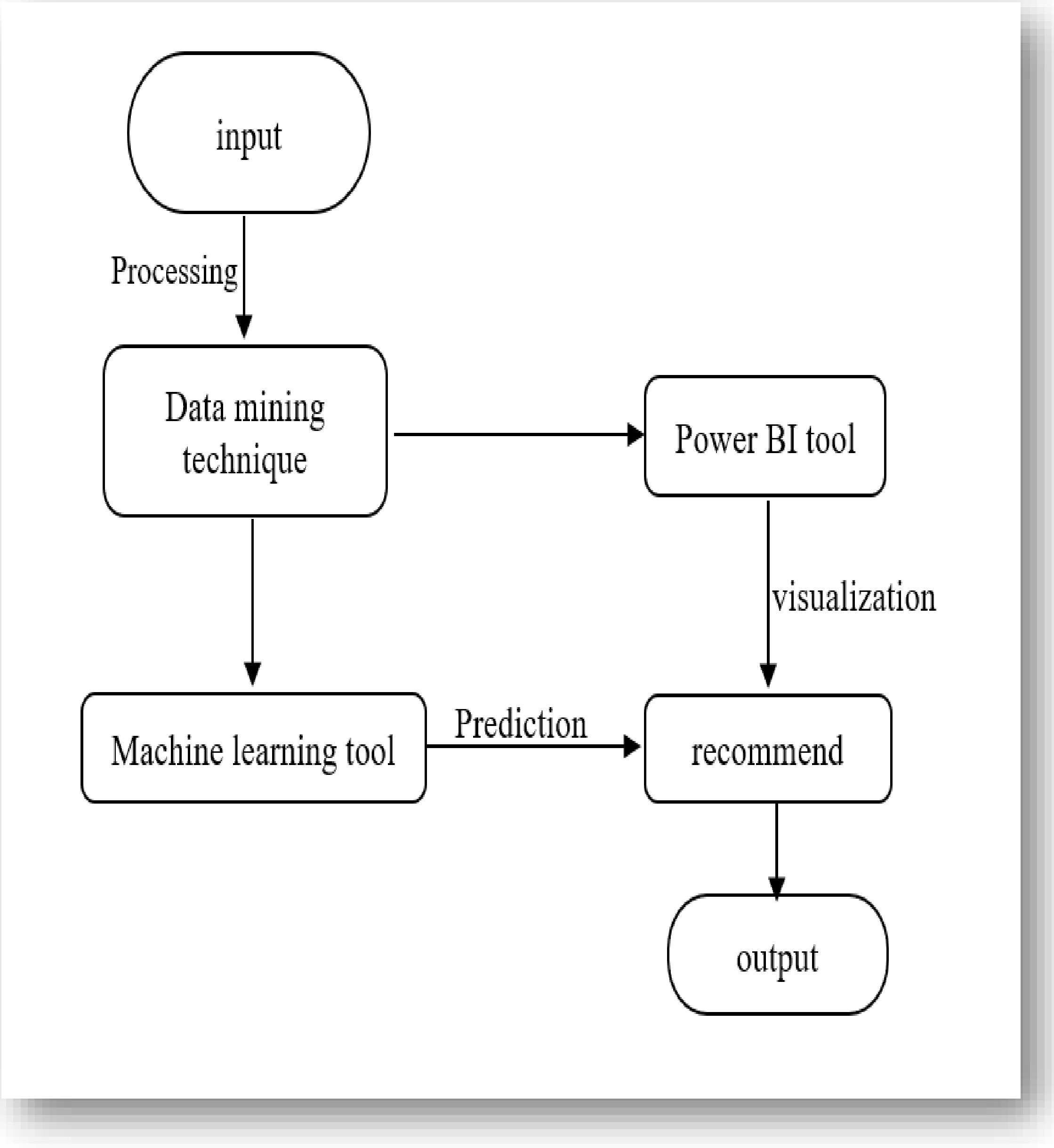


Fig 4.1: Flow Diagram of ABHRS

The architecture of the age-based health recommendation system is illustrated in the diagram, outlining the flow and design of the model. Initially, the user's age is identified, and relevant health information is collected. The user's data is pre-processed to create a personalized health profile, including age-specific recommendations. The system then matches the user's age to predefined health guidelines, and personalized health recommendations are generated accordingly. Only recommendations suitable for the user's age group are provided, and they are tagged with the user's age for reference. If the user's age is accurately matched and recommendations are available, the system proceeds with the recommendation process; otherwise, it concludes the process. Users can view and act upon the recommendations to improve their health. In summary, the system leverages age information to tailor health recommendations, ensuring that users receive guidance aligned with their specific age-related health needs. This approach enhances the relevance and effectiveness of the health recommendations provided to the users.

# CHAPTER 5
# PROJECT REQUIREMENTS

## 5.1 Hardware and Software Specification

### 5.1.1 Python

Python is a computer programming language often used to build websites and software, automate tasks, and conduct data analysis. Python is a general-purpose language, meaning it can be used to create a variety of different programs and is not specialized for any specific problems.

### 5.1.2 Flask

Flask is used for developing web applications using python, implemented on Werkzeug and Jinja2. Advantages of using Flask framework are: There is a built-in development server and a fast debugger provided.

### 5.1.3 Power BI

Microsoft Power BI is used to find insights within an organization's data. Power BI can help connect disparate data sets, transform, and clean the data into a data model and create charts or graphs to provide visuals of the data. All of this can be shared with other Power BI users within the organization.

### 5.1.4 Window 11

Windows 11 is a Microsoft operating system known for its modern interface and improved performance, offering enhanced multitasking and gaming features. It supports Python programming, offering a compatible environment for Python development and execution.

## 5.2 Summary

The hardware and software specifications for the system include Python for versatile programming, Flask for web application development, and Power BI for data insights. Windows 11, with its modern interface and Python support, serves as the operating system for this comprehensive solution.

# CHAPTER 6
# MODULE DESCRIPTION

## 6.1Modules

Module 1 discuss about Collaborative Filtering (CF) for Recommendation. In module 2 we implemented TF-IDF Vectorization using for similarity age group findings and another module Power BI used for different age group insights and recommend the system and last module flask which combined the all modules for recommend the precaution for different age groups.

### 6.1.1Collaborative Filtering

In this Module, Collaborative filtering is a popular technique in recommendation systems that provides personalized recommendations to users based on their historical behaviour and preferences, as well as the behaviour and preferences of other users. It assumes that users who have agreed on certain issues in the past are likely to agree on other issues as well. Collaborative filtering can be broadly categorized into two types:

**User-Based Collaborative Filtering**: In this approach, recommendations are generated based on the similarity between users. The idea is to find users who are like the target user and recommend items that those similar users have liked or interacted with it.

**Item-Based Collaborative Filtering:** In this approach, recommendations are generated based on the similarity between items. The idea is to find items that are like those the target user has already liked or interacted with it.

### 6.1.2 TF-IDF Vectorization

In this module, TF-IDF (Term Frequency-Inverse Document Frequency) vectorization is a widely used technique in natural language processing. It transforms a collection of textual documents into numerical vectors. It assigns a weight to each term in a document based on its frequency within that document (Term Frequency) and inversely proportional to its frequency across all documents in the collection (Inverse Document Frequency). This process is crucial for tasks like text classification, information retrieval, and sentiment analysis, as it helps represent text data in a format that machine learning models can work with effectively.

It prioritizes important terms while reducing the influence of common words, making it a powerful tool for text analysis.

### 6.1.3 Power BI Using ABHRS

In this module Power BI, a versatile data visualization and business intelligence tool, can be employed effectively in an age-based health recommendation system. It allows the creation of interactive dashboards and reports to present personalized health recommendations to users based on their age group. By integrating Power BI, the system can offer visually appealing insights and trends related to age-specific health guidance. Users can access and explore their recommendations in a user-friendly manner, enhancing their understanding and engagement with the health advice provided. Moreover, Power BI supports data analysis and tracking, enabling users to monitor their health progress over time and make informed decisions for their specific age demographic. This robust integration of Power BI enhances the system's ability to deliver relevant and actionable health recommendations, contributing to improved health outcomes.

### 6.1.4 Flask Web Framework

In this Flask module is integral in the age-based health recommendation system, serving as the framework for building web applications that enable users to input their age and access personalized health recommendations. Flask's simplicity and speed, along with built-in development tools, make it a suitable choice for creating user-friendly interfaces for age-specific health guidance. Users can conveniently input their age, allowing the system to process the information and provide tailored recommendations using Flask's capabilities. Flask plays a key role in the system's front-end, ensuring an intuitive user experience, and facilitating the seamless interaction between users and their personalized health recommendations. Flask, the system efficiently manages user input, integrates it into the recommendation process, and enhances user engagement with age-appropriate health advice.

## 6.2 Summary

The age-based health recommendation system is structured into four essential modules: Collaborative Filtering for personalized suggestions, TF-IDF Vectorization for textual analysis, Power BI for age-specific health insights, and Flask for user-friendly web interactions. Collaborative Filtering includes user-based and item-based techniques to generate recommendations based on historical user behavior and preferences. TF-IDF Vectorization transforms textual data into numerical vectors, vital for text analysis. Power BI enhances the system with visually appealing age-specific health insights and data analysis, while Flask serves as a user-friendly framework to facilitate age-appropriate health recommendations and engagement.

# CHAPTER 7
# IMPLEMENTATION

The proposed method implementation of a health recommendation system using Flask, pandas, and scikit-learn in Python. It starts by reading health-related content and medical conditions from CSV files, utilizes TF-IDF vectorization to analyze textual content, and calculates the cosine similarity between content items. The system takes user input for age, weight, height, and medical conditions through a Flask web interface. It then leverages the user's information and preferences to generate personalized health recommendations based on the content's relevance and similarity scores.

The recommendations include both general and condition-specific advice, enhancing the system's effectiveness. This implementation offers a user-friendly and interactive platform for individuals to access age-specific health guidance, and it demonstrates the integration of data analysis, recommendation algorithms, and web development in Python, providing valuable insights for health-conscious users. The depicted flowchart illustrates a comprehensive data processing system, showcasing the journey from data input to valuable insights and recommendations. Beginning at the input stage, data is acquired from diverse sources, spanning databases, online feeds, and user-generated content.

It is then channeled into the processing phase, where data is cleansed, normalized, and transformed to align with subsequent analytical stages. The core of the system lies in the application of data mining techniques, including clustering, classification, and regression, to unveil intricate patterns and correlations within the data. These insights serve as the foundation for the implementation of machine learning tools, which construct predictive models capable of forecasting outcomes or automating decision-making based on learned patterns. Simultaneously, the flow branches to Power BI, a dynamic business analytics service.

It leverages interactive visualizations and reporting, facilitating the communication of findings. In the visualization step, Power BI is instrumental in creating compelling visual representations of data, simplifying the comprehension and dissemination of results.

Ultimately, the system provides recommendations and actionable insights based on predictions, which can be delivered as reports, dashboards, or automated actions to enhance decision-making processes. To implement this system effectively, a harmonious integration of data sources, processing tools, data mining libraries, machine learning frameworks, and Power BI is vital, ensuring seamless data flow and an efficient pathway from input to output for end-users or applications.

## 7.1 Summary

The proposed health recommendation system, implemented using Flask, pandas, scikit-learn, and TF-IDF vectorization in Python, offers personalized health advice based on user input and content analysis. The system incorporates data mining techniques and machine learning tools to provide tailored recommendations, combining general and condition-specific guidance for enhanced effectiveness.

Additionally, the system is depicted in a comprehensive data processing flowchart, highlighting data acquisition, cleansing, data mining, and machine learning stages. It leverages Power BI for interactive data visualization and presentation, ensuring the delivery of actionable insights and recommendations. This integrated approach provides valuable health guidance and insights for users in a user-friendly and efficient manner.

# CHAPTER 8
# RESULT & ANALYSIS

## 8.1 Results Obtained

A Collaborative Filtering used for recommend the precautions of different ages for user Based filtering and power BI shows the insights of different age groups variance BMI between average BMI and different ages and their precautions.

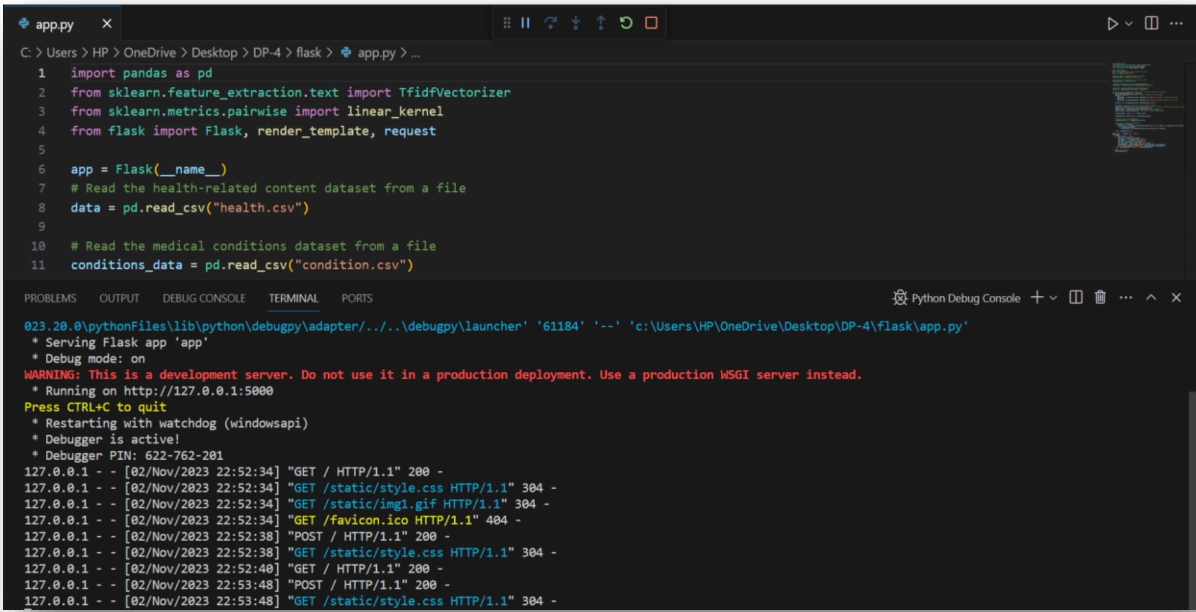


Fig 8.1: Flask framework

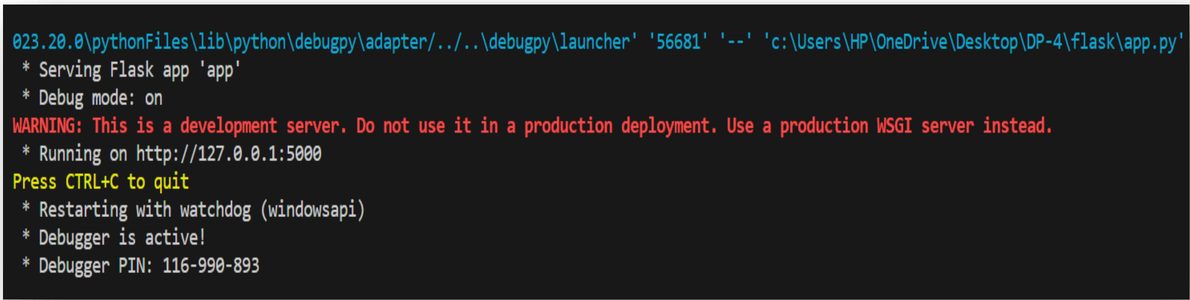


Fig 8.2: Flask server Running Successfully

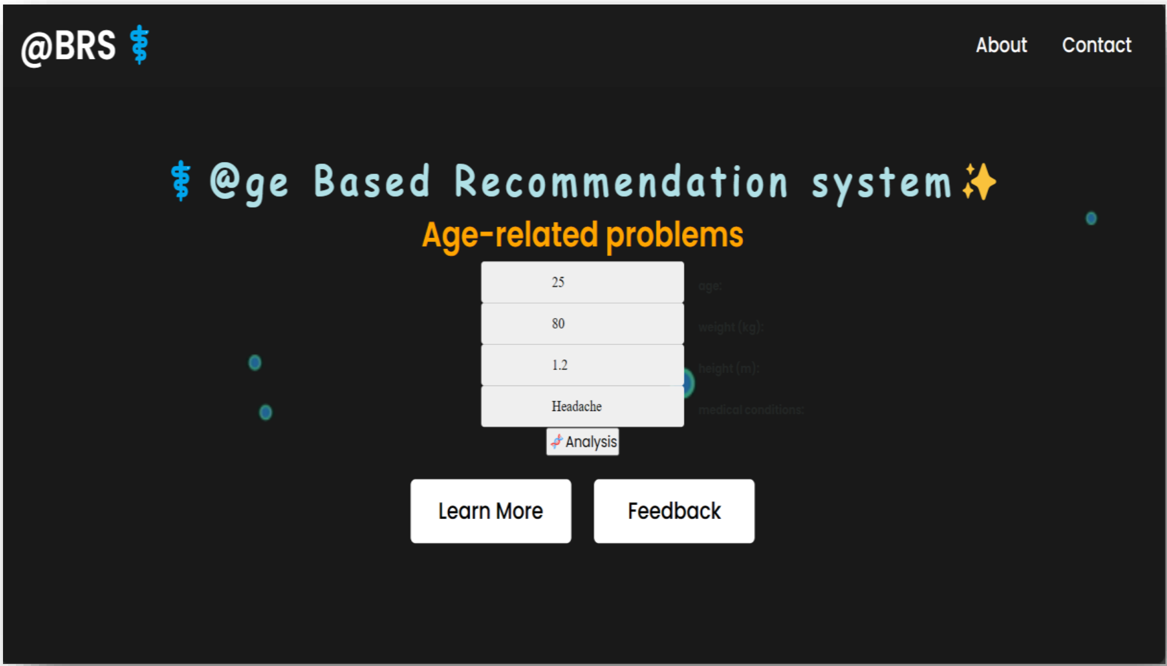


Fig 8.3: Index page

Here fig 8.2 Shows that index page of ABHRS system. This page shows the age, weight, height, and medical condition they are input of ABHRS system. User will be placed their values in those places. After that when click analysis button it shows the recommendations.

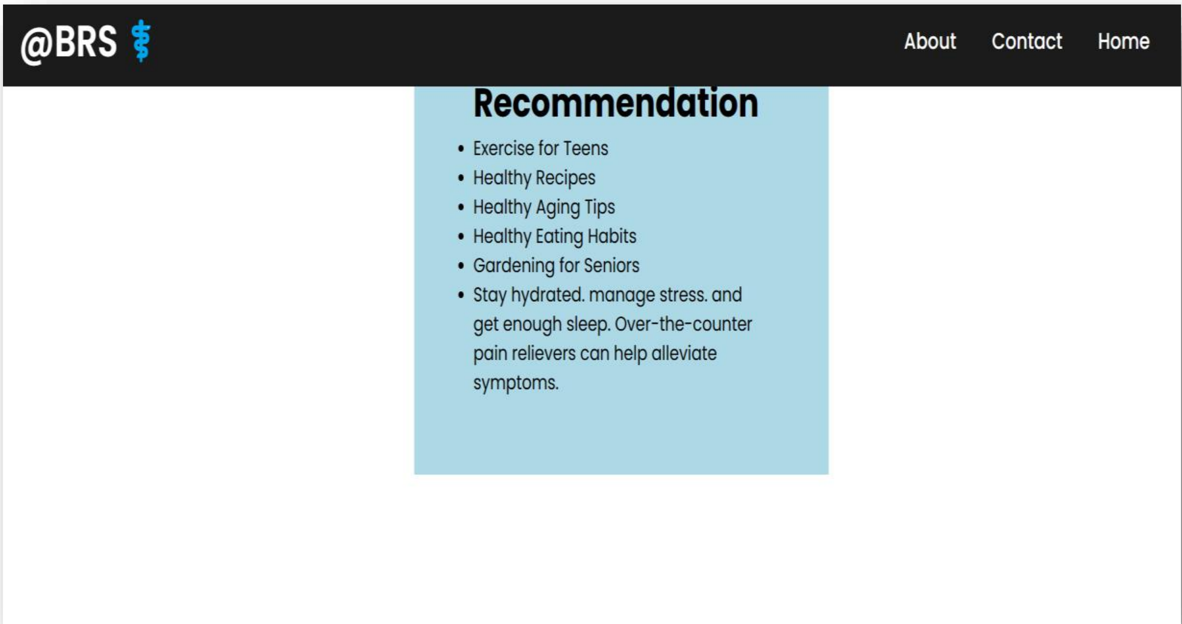


Fig 8.4: Recommendation Page

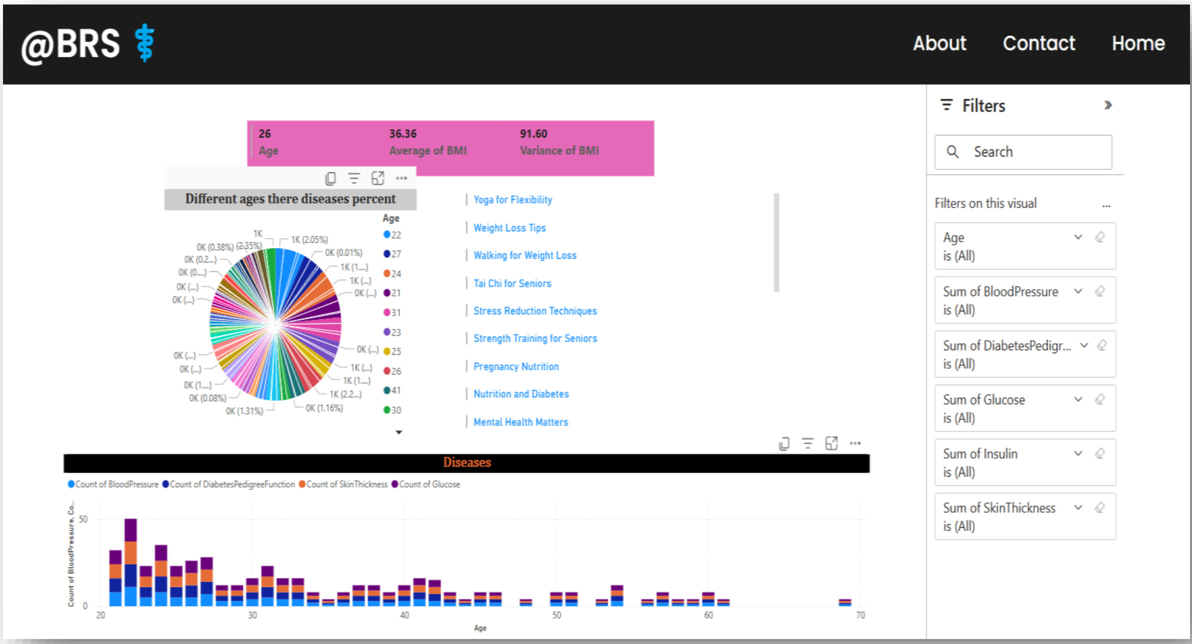


Fig 8.5: Power BI insights Page

Here fig 8.4 shows that insights of different age groups. This age groups shows their average BMI and variance BMI and prediction of different age groups.

# CHAPTER 9
# CONCLUSION AND FUTURE WORK

## 9.1 Conclusion

In conclusion, the Age Based Recommendation System developed through the integration of machine learning and Power BI stands as a powerful solution to address the challenge of delivering personalized recommendations tailored to users' age groups. This innovative system empowers businesses and platforms to provide a more engaging and relevant experience to their users, ultimately fostering increased user satisfaction and retention. By leveraging machine learning algorithms, the system identifies intricate patterns within age related data, enabling precise recommendations that align with the unique preferences and needs of different age segments. The real-time adaptability of the system ensures that the recommendations remain current and effective as user behaviors and trends evolve. Power BI's visualization capabilities add a new dimension to the system by translating complex data insights into visually appealing and easy-to-understand dashboards. This empowers decision-makers to gain valuable insights into user preferences, system performance, and recommendation effectiveness, thus guiding continuous improvement efforts. In essence, the Age-Based Recommendation System introduces a paradigm shift in personalized user experiences, exemplifying the potential of combining cutting-edge technologies. As businesses strive to differentiate themselves in competitive landscapes, this system opens avenues for better customer engagement, increased loyalty, and the ability to navigate the challenges of catering to diverse user demographics. As we embark on the journey of enhanced recommendation systems, the Age-Based Recommendation System stands as a beacon of innovation and customer-centricity in the digital age.

## 9.2 Future Work

Future work for the age-based health recommendation system involves expanding its capabilities and enhancing its personalization. This can include incorporating more advanced machine learning models to fine-tune recommendations based on individual health histories and genetic factors. Additionally, integrating real-time health data from wearables and IoT devices would allow for continuous health monitoring and dynamic adjustments to recommendations. The system can also explore incorporating social and environmental factors to provide a holistic approach to health guidance. Furthermore, enhancing user engagement and interactivity through mobile applications and chatbots could improve the user experience, making it more accessible and convenient for individuals of all ages to access and act upon health recommendations. Finally, ongoing data analysis and user feedback collection will be essential for refining the system and ensuring it remains up-to-date with the latest health research and guidelines.

## 9.3 Summary

In conclusion, the Age-Based Recommendation System, a result of machine learning integration and Power BI, revolutionizes personalized user experiences by offering tailored recommendations based on age groups. This innovative system not only enhances user satisfaction but also drives increased user engagement and retention. Leveraging advanced algorithms, it delivers precise recommendations, adapting in real-time to evolving user behaviours and preferences. Power BI's visualization tools translate complex data insights into user-friendly dashboards, guiding continuous improvement efforts. As businesses seek differentiation in competitive markets, this system paves the way for improved customer engagement, loyalty, and effectively catering to diverse user demographics. In terms of future work, expanding capabilities, personalization, and incorporating real-time health data, social and environmental factors, and improved user engagement through mobile applications and chatbots will further elevate the system's efficacy and relevance. Continuous data analysis and user feedback will be crucial for its evolution and alignment with current health research and guidelines.

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# APPENDIX A
# SAMPLE CODE

**Python File Save as app.py**

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel
from flask import Flask, render_template, request
app = Flask(__name__)
# Read the health-related content dataset from a file
data = pd.read_csv("health.csv")
# Read the medical conditions dataset from a file
conditions_data = pd.read_csv("condition.csv")
# Initialize the TF-IDF vectorizer for health content
tfidf_vectorizer = TfidfVectorizer()
# Create a TF-IDF matrix for the health-related dataset
tfidf_matrix = tfidf_vectorizer.fit_transform(data['Content'])
# Calculate the cosine similarity between content items
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
# Function to get recommendations based on user's age, BMI, and medical conditions
def get_recommendations(age, bmi, conditions):
    age_group = data[data['Age Group'] == 'All']  # Content for all age groups
    if age >= 30:
        age_group = pd.concat([age_group, data[data['Age Group'] == '30+']])  # Content for users 30+
    if age >= 40:
        age_group = pd.concat([age_group, data[data['Age Group'] == '40+']])  # Content for users 40+
        indices = pd.Series(age_group.index, index=age_group['Content'])
    # Calculate cosine similarity based on user's selected content
    content_idx = indices['Exercise for a Healthy Heart']  # You can choose a different content item as a reference
    similar_scores = list(enumerate(cosine_sim[content_idx]))
    similar_scores = sorted(similar_scores, key=lambda x: x[1], reverse=True)
    similar_scores = similar_scores[1:6]  # Get the top 5 similar content items
    content_indices = [i[0] for i in similar_scores]
    recommendations = data['Content'].iloc[content_indices]
    # Create a list of recommendations
    recommendations_list = recommendations.tolist()
    # Add condition-specific recommendations
    for condition in conditions:
        condition_row = conditions_data[conditions_data['Condition'].str.lower() == condition.strip().lower()]
        if not condition_row.empty:
            recommendations_list.append(condition_row['Recommendation'].values[0])
    return recommendations_list
@app.route('/', methods=['GET', 'POST'])
```

```
def index():
    if request.method == 'POST':
        user_age = int(request.form['age'])
        user_weight = float(request.form['weight'])
        user_height = float(request.form['height'])
        user_bmi = user_weight / (user_height ** 2)
        user_conditions = request.form['conditions'].split(",")
        recommendations = get_recommendations(user_age, user_bmi, user_conditions)
        return render_template('Recommend.html', recommendations=recommendations)
    return render_template('index.html', recommendations=None)
if __name__ == '__main__':
    app.run(debug=True)
```

**Html File Save as Index.html**

```
<!DOCTYPE html>
<html>
<head>
    <title>@bhrs ⚕ </title>
    <link rel="stylesheet" href="{{ url_for('static', filename='style.css') }}">
    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-
awesome/5.15.2/css/all.min.css"/>
</head>
<body>
  <nav>
    <div class="menu">
      <div class="logo">
        <a href="http://127.0.0.1:5000/">@BHRS ⚕ </a>
      </div>
      <ul>
        <li><a href="#">About</a></li>
        <li><a href="#">Contact</a></li>
      </ul>
    </div>
  </nav>
  <div class="img"></div>
  <div class="center">
    <div class="title"> ⚕ @ge Based Health Recommendation system ✨ </div>
    <div class="sub_title">Age-related problems</div>
    <div class="row">
    <form method="POST">
        <input class="clean-slide" type="number" name="age" required><label
for="age">Age:</label><br>
        <input class="clean-slide" type="number" name="weight" required><label
for="weight">Weight (kg):</label><br>
        <input class="clean-slide" type="number" name="height" step="0.01" required><label
for="height">Height (m):</label><br>
        <input class="clean-slide" type="text" name="conditions">
<label for="conditions">Medical Conditions:</label><br>
```

```
        <input type="submit" value="🧬 Analysis">
    </form>
  </div>
      <div class="btns">
         <a href="#"><button>Learn More</button></a>
           <button>Feedback</button>
         </div>
    </div>
</body>
</html>
```

**RECOMMEND.HTML**

```
<!DOCTYPE html>
<html>
<head>
    <title>@bhrs ⚕ </title>
    <link rel="stylesheet" href="{{ url_for('static', filename='style.css') }}">
    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-
awesome/5.15.2/css/all.min.css"/>
</head>
<body>
  <nav>
    <div class="menu">
      <div class="logo">
        <a href="http://127.0.0.1:5000/">@BHRS ⚕ </a>
      </div>
      <ul>
        <li><a href="#">About</a></li>
        <li><a href="#">Contact</a></li>
        <li><a href="http://127.0.0.1:5000/">Home</a></li>
      </ul>
    </div>
  </nav>
  <div class="result">
    <h1>Recommendation</h1>
    {% if recommendations %}
        <ul>
            {% for recommendation in recommendations %}
                <li>{{ recommendation }}</li>
            {% endfor %}
        </ul>
    {% endif%}
    </div>
    <iframe title="data visualization" width="1140" height="541.25"
src="https://app.powerbi.com/reportEmbed?reportId=6431de9d-8f45-4e32-9d73-
7271b913b424&autoAuth=true&ctid=a5840ece-7ae5-48e0-9ebe-248ceb407d8b"
frameborder="0" allowFullScreen="true"></iframe>
</body> </html>
```

# APPENDIX B
# SAMPLE SCREEN