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MINISTERE DE L'ENSEIGNEMENT SUPERIEUR ET DE LA RECHERCHE SCIENTIFIQUE

**UNIVERSITE IBN KHALDOUN - TIARET**

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Par :

**ZITOUNI Hamdane Abdelkader**
**RAHOUANI Toufik**

**Sur le thème**

# Medical Prescription Assistance System Using Recommendation Systems

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| | | | |
|---|---|---|---|
| Mr BOUDAA Boudjemaa | MCA | Université de Tiaret | Président |
| Mme LAAREDJ Zohra | MAA | Université de Tiaret | Encadrant |
| Mr KOUADRIA Abdelrahmane | MCB | Université de Tiaret | Examinateur |

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بسم الله الرحمن الرحيم

# Abstract

Patient safety is an area of healthcare that has emerged with the increasing complexity of healthcare systems and the rise of harm to patients it is about preventing and reducing risks, errors and harm to patients in the context of health care. Patient safety is first and foremost about continuous improvement, through learning from errors and adverse events. In this context, the health sector must achieve the conditions for the protection of patients throughout the duration of treatment, taking into account the situation of each patient separately. Among the conditions of protection of our patients, the writing of a good appropriate prescription which does not lead to undesirable effects. And given the presence of several factors that can give undesirable and sometimes fatal results and effects to our patients following the wrong prescription. It has become necessary to take this area seriously by improving the editorial quality of medical prescriptions.

.

**Keywords:** Medical Prescription, Medication Errors, Recommender System, Health Recommender System, Content-Based Filtering.

## خلاصة


سلامة المرضى هي مجال من مجالات الرعاية الصحية التي ظهرت مع التعقيد المتزايد لأنظمة الرعاية الصحية وتزايد الضرر الذي يلحق بالمرضى ، فهي تتعلق بمنع وتقليل المخاطر والأخطاء والأضرار التي تلحق بالمرضى في سياق الرعاية الصحية. تتعلق سلامة المرضى أولاً وقبل كل شيء بالتحسين المستمر ، من خلال التعلم من الأخطاء والأحداث السلبية. وفي هذا السياق ، يجب على القطاع الصحي توفير شروط حماية المرضى طوال مدة العلاج ، مع مراعاة حالة كل مريض على حدة. من بين شروط حماية مرضانا ، كتابة وصفة طبية مناسبة لا تؤدي إلى آثار غير مرغوب فيها. ونظراً لوجود عدة عوامل يمكن أن تعطي نتائج وتأثيرات غير مرغوب فيها وأحياناً قاتلة لمرضانا باتباع وصفة طبية خاطئة. لقد أصبح من الضروري التعامل مع هذا المجال بجدية من خلال تحسين الجودة التحريرية للوصفات الطبية.



الكلمات المفتاحية: الوصفة الطبية ، أخطاء الدواء ، نظام التوصية ، نظام التوصية الصحية ، التصفية القائمة على المحتوى.

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I would also like to thank my work colleagues for their understanding and continued support, I thank my parents, my brothers and all the faculty at Ibn Khaldoun University of Tiaret Computer Science, Thank you.

# Dedications

I dedicate this modest work:

To my dear parents

To my brothers and my sister

All my friends

RAHOUANI  Toufik

# Dedications

I dedicate this modest work:

To my dear parents

To my brothers and my sister

All my friends

ZITOUNI Hamdane Abdelkader

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# Acronyms

| | |
|---|---|
| **AI** | **A**rtificial **I**ntelligence |
| **CBR** | **C**ontent **B**ased **R**ecommender |
| **CBRS** | **C**ontent **B**ased **R**ecommender **S**ystem |
| **CF** | **C**ollaborative **F**iltering |
| **CLI** | **C**ommand **L**ine **I**nterface |
| **EHRs** | **E**lectronic **H**ealth **R**ecords |
| **HIT** | **H**ealth **I**nformation **T**echnology |
| **HRS** | **H**ealth **R**ecommender **S**ystem |
| **IOM** | **I**nstitute **O**f **M**edicine |
| **IT** | **I**nformation **T**echnology |
| **GUI** | **G**raphical **U**ser **I**nterface |
| **LLA** | **L**ong **L**asting **A**ffection |
| **LSTM** | **L**ong **S**hort **T**erm-**M**emory |
| **LT** | **L**ong **T**ail |
| **MAE** | **M**ean **A**bsolute **E**rror |
| **PHR** | **P**ersonal **H**ealth **R**ecord |
| **RS** | **R**ecommender **S**ystem |
| **VSM** | **V**ector **S**pace **M**odel |
| **VS Code** | **V**isual **S**tudio **C**ode |
| **WHO** | **W**orld **H**ealth **O**rganization |

# General Introduction

## A. Background

In the advanced development of science and technology, information technology is applied in many fields: economics, education, medical, transportation. In health, the application of information technology contributes much to enhancing system quality, improving care quality, and early detection of infectious disease outbreaks [1]. To a study [2] by RAND Health, the US healthcare system could save more than 81$ billion annually if health information technology (HIT) were taken on. In 2019, the Vietnamese Ministry of Health approved the project on the Application of Health Information technology in 2019–2025 about principal policies such as investment in infrastructure technology, application development, healthcare, hospital management system, and health administration. The primary purpose is that by 2030, 95% of the population can manage their health, and all medical facilities around the country use electronic health records (EHRs). Besides, people control their personal health information through electronic applications [1]. Artificial intelligence (AI) is a current technology that is considered among the best techniques applied in different fields. In the field of health, artificial intelligence is gradually becoming a hot spot for research. A recommendation system is a type of artificial intelligence technology that uses machine learning algorithms to suggest products, services, or information to users.

In fact, Owing to the large amount of information available in health institution databases, including medical treatments, diagnostic tests, clinical histories, and drug characteristics, there is a need to implement recommender systems (RSs) that support medical staff in activities related to health control and management. The main concept of an RS is to suggest items that are particularly suitable for the user based on their profile or historical preferences. In the context of health, these items can be drugs, medical treatments, health videos, and patients sharing the same disease [57].

According the report of the Institute of Medicine (IOM) published in 2000, which revealed that an estimated 44,000 to 98,000 people die annually from medical errors [58] . According to the Report, “more people die in a given year as a result of medical errors than motor vehicle accidents (43,458), breast cancer (42,297), or AIDS (16,516)”. The Report also estimates that total national costs encompassing lost income, lost household production, disability, and health care costs of preventable adverse events are estimated to be between $17 and $29 billion annually, 50% of which are direct health care costs.  The medical errors issue is anticipated to receive a lot of attention by the federal government and Congress in the year 2000.

In the 2016 and 2017 medicine error reports from Norway’s incident reporting system of more than 64 hospitals, the wrong dosage accounted for 38%, wrong medication 15%, missed medication 23%, causing 0.8% of deaths [4].

Therefore, it became necessary to closely manage the medical prescription, in this context, several works and studies are developed to help the doctor to identify the list of medication described in the prescription as well as their dosage.

Nevertheless, the application of recommendation systems in the field of medical prescription remains minimal, despite the fact that these systems are imposed as an effective means in several sectors. Following this, we decided to examine recommendation systems in the field of medical prescribing in order to support clinical decision-making.

Drug recommendation systems can help both doctors prescribe drugs and pharmacists review prescribed drugs, and can thus reduce medical errors that have serious and sometimes fatal effects.

## B. Work context

The work presented in this thesis takes place as part of a project to implement and create a medical prescription support system by applying recommendation systems. This project is led by Ms. LAAREDJ Zohra Assistant professor "A" at IBN Khaldoun University, Tiaret. The main idea of this project is the establishment of a support system when prescribing drugs by doctors.

The goal is to automate the process of medical prescription and reduce medical errors that may be introduced when writing a prescription, in order to make it usable by health institutions, pharmacists and patients by minimizing the cost associated with medical errors which is becoming increasingly high, thus guaranteeing the health of our population.

Our work is part of the first step in setting up a platform capable of recommending drugs and building an appropriate and relevant medical prescription. This task is of extreme importance linked to the reduction of medical errors which has received a lot of attention in recent years by all health institutions on an international scale.

As a result, we have focused on the implementation and development of a system dedicated to institutions and healthcare professionals to help them make faster and more accurate decisions.

## C. Problem Statement

The majority of health institutions, doctors as well as all health professionals and especially patients suffer from the problem of medical errors which have led to undesirable effects. This situation poses a serious problem for states worldwide, especially when these errors lead to the death of patients. And with the progress and the incessant development of computer technologies, which has led states and researchers to think of automating the process of medical prescription, the objective of which is to benefit from the advantages of these technologies in the field of drugs.

Although recommendation systems have shown good results in other domains such as e-commerce, education, social networks, etc investigating their usage in the health sector, more precisely in medial prescription, remains an open of research. The main research question of this thesis is thus formulated as:

What do recommendation systems bring to medical prescription?

## D. Research Objectives

As part of our end-of-study project, our main objective is to develop a medical prescription assistance system for healthcare professionals. The system implemented aims to support doctors and pharmacists during the preparation and delivery of medication to patients. In this context we focus specifically on how to get an appropriate prescription that contains no errors. To achieve this goal, we plan to implement a system based on recommendation systems. The developed system will recommend a patient's medications based on the history of patients who have similar symptoms and characteristics. The purpose of the proposed system at first is to write a medical prescription accurately and correctly to avoid any adverse consequences and impacts. This is done by tending towards an ideal prescription adapted to each patient.

## E. Approach

To answer the research question, a system using the content-based approach is presented. Our recommendation approach stems from the effectiveness of content-based recommendation systems in many areas. Furthermore this approach is able to recommend user needs accurately.

For our medical prescription problem, we used the vector space model (VSM) which is a widely used retrieval model in content-based recommender systems. The application of SVM in our developed system is based on the TF-IDF algorithm. TF-IDF or Term Frequency Inverse Document Frequency is a very common algorithm for transforming text into a meaningful representation of numbers which is used to tune the machine algorithm for prediction.

## F. Outline

This thesis is structured in five chapters besides a general introduction and a general conclusion:

- **INTRODUCTION**

An initiation to the use of science and technology information in health sector and the background, work context, problem statement, research objectives and our approach.

- **CHAPTER ONE: Detailed study on the fields of medical prescription**

In the 1st chapter we present a study of medical prescription, her Characteristics, legal formwork of the prescription, the instructions of the use of medicines, medication errors and her types…etc.

- **CHAPTER TWO: Recommendation Systems**

In the 2nd chapter we present a brief summary on the recommender systems, her types and her techniques.

- **CHAPTER THREE: The use of recommendation systems in the health sector**

The chapter number three is dedicate to the use of recommendation systems in the health sector

- **CHAPTER FOUR: Content Based Filtering**

In this chapter we describe then content based approach and his techniques.

- **CHAPTER FIVE: Experiences and Results**

The fifth chapter is devoted to the implementation and programming of the proposed system. In this part we presented the programming languages used, the database implemented.

- **CONCLUSION**

The last part of this work summarizes the main part of our work and draws the perspectives in general conclusion.

# Chapter 1 Detailed study on the fields of medical prescription

## 1.1. Introduction

The medical prescription is the initial step in the drug circuit, an important step under medical responsibility and certain professional categories. It is one of the links between the patient, the doctor and the pharmacist. It represents a symbolic step in the care process involving the patient and the healthcare professionals who are called upon to take care of him and thus embodies an essential communication tool.

In fact, a doctor's medical prescription is a handwritten paper that a doctor writes to prescribe the medicine to the patient according to the injury or sickness that the patient has been experiencing [3]. Prescriptions must comply with the standards of good prescriptions given its impact on the lives of patients, which can be serious in many cases. Therefore, establishing and improving the writing quality of prescriptions is becoming crucial.

In this chapter, we present a complete guide to medical prescriptions. We highlight the rules and elements of a prescription and an overview of prescription errors and its impact on patients' lives is given.

## 1.2. Definition

Prescription can be defined as an important component of medication administration [5]. A Doctor's medical prescription is a handwritten paper that a doctor writes to prescribe the medicine to the patient according to the injury or sickness that the patient has been experiencing [3].

According to the World Health Organization, the prescription is an instruction from a prescriber to a dispenser. The prescriber is not always a doctor but can also be a paramedical worker, such as a medical assistant, a midwife or a nurse. The dispenser is not always a pharmacist, but can be a pharmacy technician, an assistant or a nurse. Every country has its own standards for the minimum information required for a prescription, and its own laws and regulations to define which drugs require a prescription and who is entitled to write it. Many countries have separate regulations for opiate prescriptions [6].

## 1.3. History of the prescription

"Prescription" (from the Latin praescriptio "to write at the head") was an expressly formulated order in the sixteenth century. It was only around 1750 that it was commonly used to designate the recommendations that a doctor could make to his patient verbally or in writing.

In English, prescription refers to both the prescription (medium) and the prescription (content).

The official birth of medical prescription in France dates back to 1322, when a new royal edict prohibited apothecaries from selling or giving toxic or abortifacient laxatives without a doctor's prescription, which they were forbidden to renew.

In 1941 a new law that requires a prescription for abortive drugs and certain toxic drugs. Social security was created in 1946, so medical prescription became necessary again in order to allow the reimbursement of prescribed drugs. The first code of medical ethics appeared in 1947 formalizing the mentions concerning it that a doctor can put on his prescriptions[1].

## 1.4. Information on a prescription

The medical prescription is not an order sheet, but a patient-doctor-pharmacist communication tool, and thus, it should allow a good transmission of information between the doctor, the patient and the pharmacist. A good prescription must be complete and unambiguous [7], for this it must comply in its entirety, it must include the clear identification criteria of the prescriber, those of the patient and those of the drug [8].

In this section, we describe the different information that must be included in the drug prescription, based on the practical guide "Guide to Good Prescribing" from the World Health Organization.

### 1.4.1. Name and address of the prescriber with telephone number (if possible)

This is usually pre-printed on the form. If the pharmacist has any questions about the prescription (s) he can easily contact the prescriber[6].

### 1.4.2. Date of the prescription

In many countries the validity of a prescription has no time limit, but in some countries pharmacists do not give out drugs on prescriptions older than three to six months. You should check the rules in your own country [6].

### 1.4.3. Name and strength of the drug

R/ (not Rx) is derived from Recipe (Latin for ‘take’). After R/ you should write the name of the drug and the strength. It is strongly recommended to use the generic (nonproprietary) name. This facilitates education and information. It means that you do not express an opinion about a particular brand of the

[1] https://www.ordoclic.fr/titres-autorises-sur-une-prescription-medicale/

drug, which may be unnecessarily expensive for the patient. It also enables the pharmacist to maintain a more limited stock of drugs, or dispense the cheapest drug. However, if there is a particular reason to prescribe a special brand, the trade name can be added. Some countries allow generic substitution by the pharmacist and require the addition ‘Do not substitute’ or ‘Dispense as written’ if that brand, and no other, is to be dispensed [6].

### 1.4.4. Dosage form and total amount

Only use standard abbreviations that will be known to the pharmacist [6].

### 1.4.5. Information for the package label

S stands for Signa (Latin for ‘write’). All information following the S or the word ‘Label’ should be copied by the pharmacist onto the label of the package. This includes how much of the drug is to be taken, how often, and any specific instructions and warnings. These should be given in lay language. Do not use abbreviations or statements like ‘as before’ or ‘as directed’. When stating ‘as required’, the maximum dose and minimum dose interval should be indicated. Certain instructions for the pharmacist, such as ‘Add 5 ml measuring spoon’ are written here, but of course are not copied onto the label [6].

### 1.4.6. Prescriber's initials or signature.

### 1.4.7. Name and address of the patient; age (for children and elderly)

The data listed above are the core of every prescription. Additional information may be added, such as the type of health insurance the patient has. The layout of the prescription form and the period of validity may vary between countries. The number of drugs per prescription may be restricted. Some countries require prescriptions for opiates on a separate sheet. Hospitals often have their own standard prescription forms. As you can check for yourself, all prescriptions in this chapter include the basic information given above [6].

## 1.5. Characteristics of a medical prescription

It is essential that a medical prescription be [9]:

- Presentable: on clean, unwrinkled paper.
- Clear: including the name of the drug (preferably in capitals), its presentation (vials, tablets, etc.) and finally its dosage.

- Readable: the patient must be able to easily read and understand the instructions intended for him. This will allow the pharmacist to avoid errors and confusion between similar drug names.
- The prescriber can write the prescription manually or by microcomputer.

## 1.6. The legal formwork of the prescription

Medical writing is a dangerous exercise, because it can engage the civil, criminal or disciplinary liability of the writer, following this, a set of articles must be respected by the doctor when writing the prescription. These articles are mentioned in Algerian Medical Deontology.

Among these articles, we quote the articles which relate to the doctor[2]:

**Article 13** “The doctor is responsible for each of his professional acts, can only practice under his true identity, any document he issues must bear his name and signature”.

**Article 56** "any prescription, certificate, attestation or document drawn up by a doctor must be written legibly and allow the identification of the signatory and include the date and signature of the doctor".

**Article 57** “Without yielding to any unreasonable request from his patients, the doctor must endeavor to facilitate their obtaining the social benefits to which their state of health entitles them”.

**Article 58** “The issuance of a tendentious report or a certificate of convenience is prohibited”.

## 1.7. Instructions for the use of medicines

Patients need information, instructions and warnings to provide them with the knowledge to accept and follow the treatment and to acquire the necessary skills to take the drugs appropriately, especially when the patient is elderly. The six points listed below summarize the minimum information that should be given to the patient [6].

- **Effects of the drug**

  Why the drug is needed

  Which symptoms will disappear, and which will not

  When the effect is expected to start

  What will happen if the drug is taken incorrectly or not at all

[2] http://www.atds.org.tn/CODEDEDEONTOLOGIEALG.pdf

- **Side effects**

  Which side effects may occur

  How to recognize

  How long they will continue

  How serious they are

  What action to take

- **Instructions**

  How the drug should be taken

  When it should be taken

  How long the treatment should continue

  How the drug should be stored

  What to do with left-over drugs

- **Warnings**

  When the drug should not be taken

  What is the maximum dose

  Why the full treatment course should be taken

- **Future consultations**

  When to come back (or not)

  In what circumstances to come earlier

  What information the doctor will need at the next appointment

- **Everything clear?**

  Ask the patient whether everything is understood

  Ask the patient to repeat the most important information

  Ask whether the patient has any more questions.

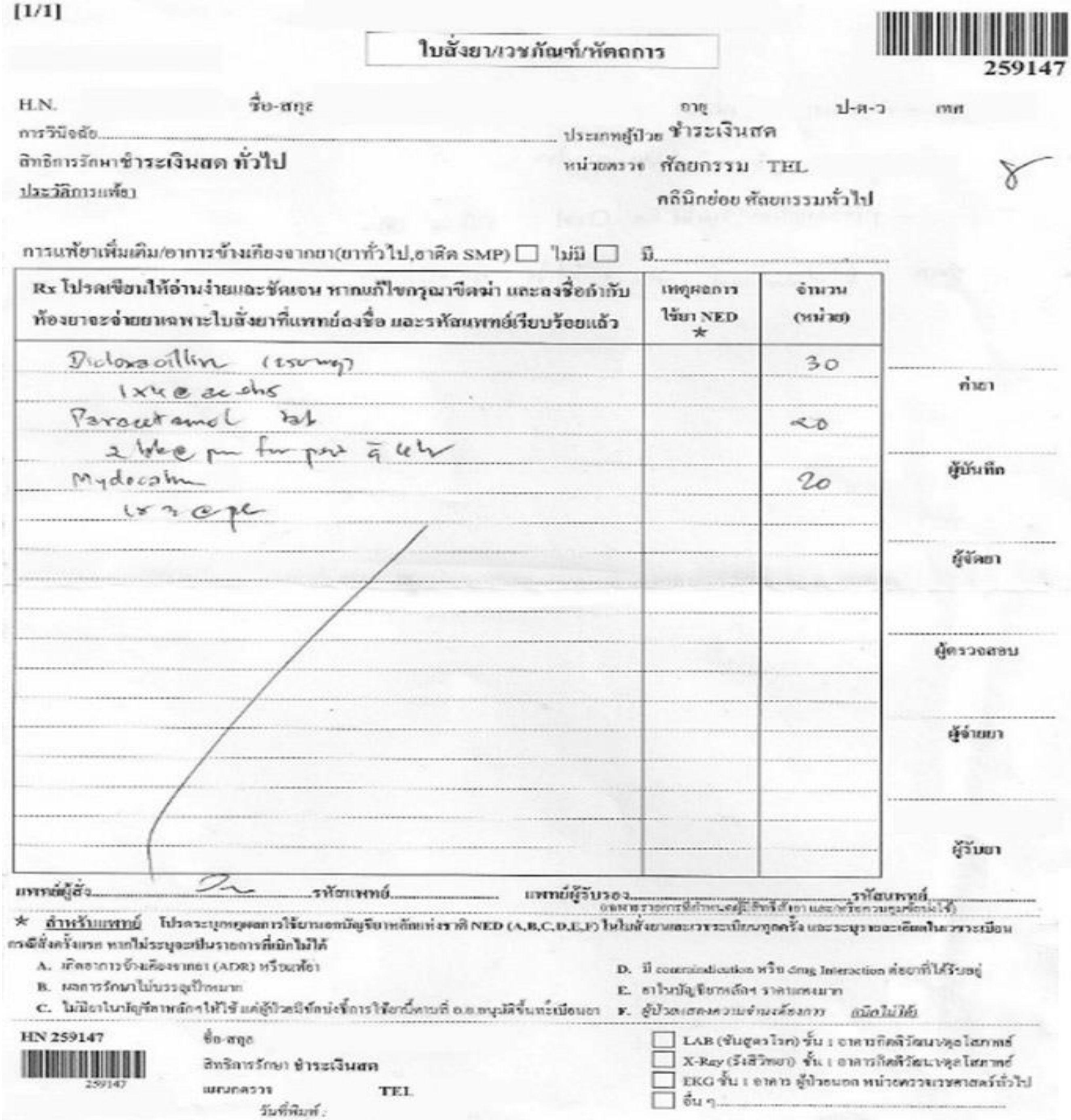
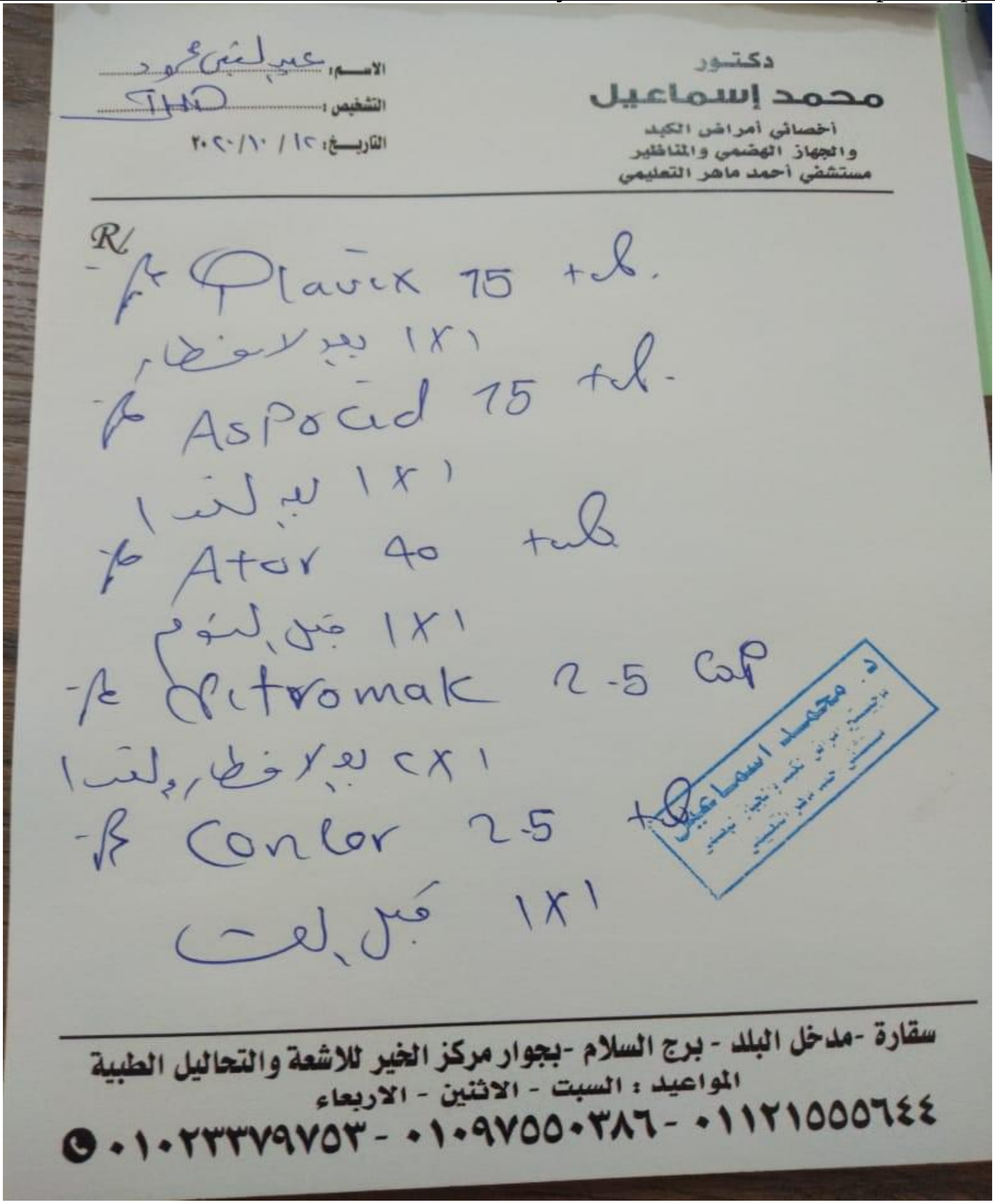



Figure 1.1: Example 1 of Prescription [10]


دكتور
محمد إسماعيل
أخصائي أمراض الكبد
والجهاز الهضمي والمناظير
مستشفى أحمد ماهر التعليمي

الاسم:
التشخيص: IHD
التاريخ: ١٢ / ١٠ / ٢٠٢٠

R/
Plavix 75 tab.
1x1
Aspocid 75 tab.
1x1
Ator 40 tab
1x1
Concor 2.5 tab
1x1

سقارة -مدخل البلد - برج السلام -بجوار مركز الخير للاشعة والتحاليل الطبية
المواعيد : السبت - الاثنين - الاربعاء
٠١٠٢٣٣٧٩٧٥٣ - ٠١٠٩٧٥٥٠٣٨٦ - ٠١١٢١٥٥٥٦٤٤

Figure 1.2: Example 2 of Prescription [3]

## 1.8. Types of medical prescriptions

The prescription nowadays can take five different aspects, in the following we detail these types[3],[4]:

### 1.8.1. The classic prescription

It's a simple prescription which all individuals know. This is the common medical prescription given out by most doctors.

### 1.8.2. The bizonal prescription

Intended for patients with LLA (Long Lasting Affection), which allows the doctor to distinguish on the same prescription, prescriptions intended for the treatment of LLA and non-LLA treatments.

### 1.8.3. The secure prescription

This is a prescription for the prescription of narcotic drugs such as certain anxiolytics or hypnotics which may be the subject of fraud or trafficking;

### 1.8.4. Prescriptions for drugs or exceptional products and services

Concerns the prescription of drugs with special conditions for reimbursement by Health Insurance.

### 1.8.5. The electronic prescription

It is a dematerialized prescription issued by the doctor online in the case of a teleconsultation

## 1.9. Quality of medication prescription

The notion of quality, stemming from the industrial world, has evolved a lot in recent years. This is not a new concern for health professionals and it has been the subject of several definitions, the most commonly accepted of which is that of the World Health Organization( WHO):

"Deliver to each patient the assortment of diagnostic and therapeutic procedures that will ensure the best result in terms of health, in accordance with the current state of medical science. At the best cost for the same result, at the lowest iatrogenic risk and for his greatest satisfaction in terms of procedures, results, and human contacts within the healthcare system."[17]

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[3] https://goodassur.com/mutuelle-sante/ordonnance-medicale

[4] https://www.lelynx.fr/mutuelle-sante/soins/medicaux/medecin-generaliste/ordonnance/

The quality of the drug prescription, which partly conditions the medical service rendered to the patient, remains one of the main concerns of doctors [18].

The quality of the drug prescription can thus be assessed according to several dimensions and quality criteria. Among these criteria, we find the specialty of the prescriber, the name of the drug, the duration of the treatment, the conformity of the drug as well as its dosage, etc[18].

And in order to measure the quality of a drug prescription, we must first study and identify the errors that may be present in the medical prescriptions,

Therefore, we are interested in the errors that can be introduced in the medical prescription in the following section.

## 1.10. Medication errors

A prescription is ‘a written order, which includes detailed instructions of what medicine should be given to whom, in what formulation and dose, by what route, when, how frequently, and for how long [11] .Thus, a prescription error can be defined as ‘a failure in the prescription writing process that results in a wrong instruction about one or more of the normal features of a prescription’. The ‘normal features’ include the identity of the recipient, the identity of the drug, the formulation and dose, and the route, timing, frequency and duration of administration (although this list is by no means exhaustive). Consequently, the definition of a medication error, a prescribing fault can be defined as ‘a failure in the prescribing process that leads to, or has the potential to lead to, harm to the patient [12].

In fact, medication errors are among the most serious incidents in most hospital institutions. According to the World Health Organization (WHO), medication errors cause at least one death every day and injure approximately 1.3 million people per year in the USA. The worldwide cost associated with medication errors has been estimated at US$ 42 billion per year or almost 1% of total global health expenditures [13].

### 1.10.1. Classification of medication errors

The best way to understand how medication errors happen and how to prevent them is to consider their classification, which can be contextual, modal, or psychological.

Contextual classification deals with the specific time, place, medicines, and people involved. Modal classification examines the ways in which errors occur (e.g. by omission, repetition, or substitution). However, classification based on psychological theory is to be preferred, as it explains events rather than merely describing them. Its disadvantage is that it concentrates on human rather than systems sources of errors. Psychologists consider an error to be a disorder of an intentional act, and they distinguish between errors in planning an act and errors in its execution. If a prior intention to reach a specified goal leads to action, and the action leads to the goal, all is well. If the plan of action contains some flaw, that is a‘mistake’. If a plan is a good one but is badly executed, that is a failure of skill [12].

This approach yields four broad types of medication error [14], Mistakes can be divided into

- Knowledge-based errors
- Rule-based errors.

Failures of skill can be divided into

- Action-based errors (’slips’, including technical errors)
- Memory based errors (‘lapses’).

Knowledge-based errors can be related to any type of knowledge, general, specific, or expert. It is general knowledge that penicillins can cause allergic reactions; knowing that your patient is allergic to penicillin is specific knowledge; knowing that co-fluampicil contains penicillins is expert knowledge. Ignorance of any of these facts could lead to a knowledge-based error.

Rule-based errors can further be categorized as

- The misapplication of a good rule or the failure to apply a good rule;
- The application of a bad rule.

An action-based error is defined as ‘the performance of an action that was not what was intended. A slip of the pen, when a doctor intends to write diltiazem but writes diazepam, is an example. Technical errors form a subset of action-based errors. They have been defined as occurring when ‘an outcome fails to occur or the wrong outcome is produced because the execution of an action was imperfect’. An example is the addition to an infusion bottle of the wrong amount of drug.

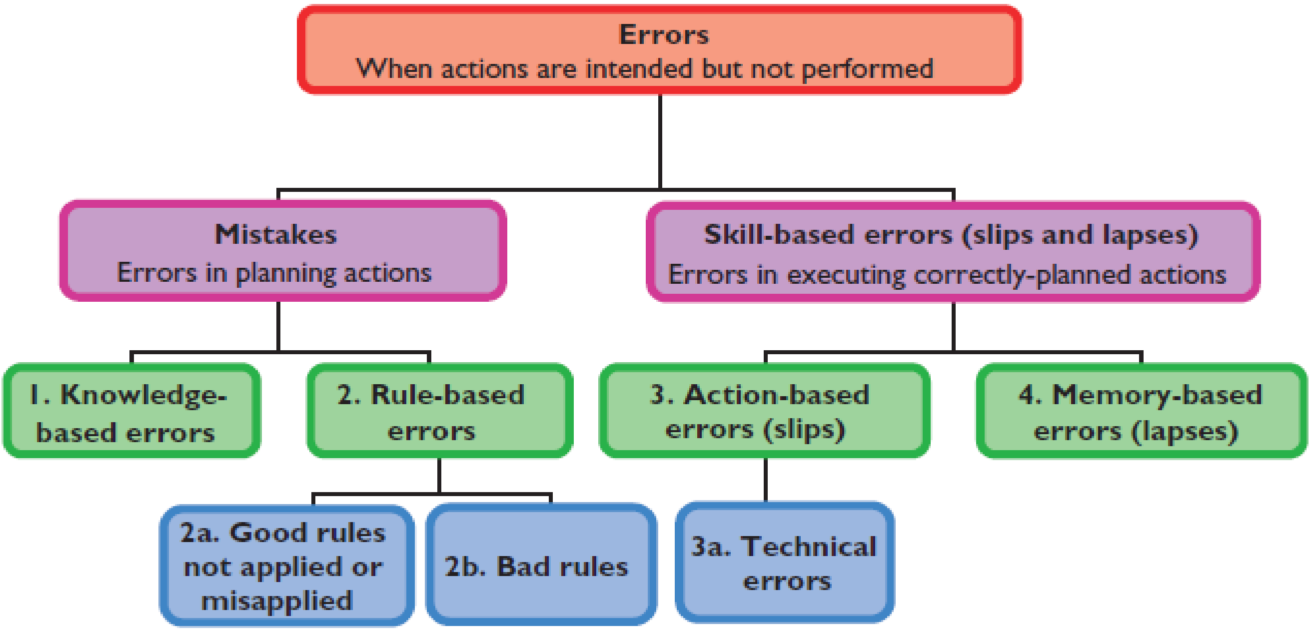



Figure 1.3: The classification of medication errors based on a psychological approach [12]

Medication errors, which can lead to adverse drug reactions, require clear and unambiguous definitions, so that patients, prescribers, manufacturers, and regulators can all understand each other. The classification of medication errors on the basis of the underlying psychological mechanisms, based on how errors occur, can suggest strategies that help to reduce their occurrence [12].

In this context, medication errors were categorized and defined as per the America Society of Hospital Pharmacists guidelines (table 01), which is also relevant in the Indian setting [15].

Table 1.1: Types of errors of medication prescription [14]

| **Types of errors** | **Working definitions** |
|---|---|
| Wrong dose | Unexplained deviation of more than 10% of normal, over/under the ordered dose |
| Wrong time | More than 30 min for emergency medicine |
| Wrong rate | Drug delivered slower or faster than the prescribed. Rate of infusion not mentioned. 24-hour volume of fluid more than 10% of over/under the ordered rate; or hourly rate more than 50% over/under the ordered rate |
| Wrong preparation | Incorrect dilution with correct drug dosage, mixing of incompatible drugs |
| Wrong route | Route other than the prescribed for the use in neonates |
| Omission | Failure to administer or omission of prescribed dose/drug type |
| Wrong transcription | Wrong copy of prescription in medical records for purpose of administration. Discrepancy in drug name, drug formulation, route, dose, dosing regimen, drugs which were not ordered |
| Others | Drug not authorised, wrong site, wrong patients, etc |
| Medication error per 100 prescriptions | Number of errors described as above, divided by the total number of prescriptions analysed expressed in terms of 100 prescriptions (percentage of medication errors) |
| Median medication error percentage | Calculated median of weekly values of medication error percentages expressed at each phase |
| Errors per prescription | Number of errors found in a single prescription |
| Mean errors/patient | Mean of errors occurred per patient included in the study in each phase |

## 1.11. Conclusion

A medical prescription is a medical act consisting in giving a formal and detailed order to dispense a drug or administer a necessary treatment to a person. It always follows a consultation and aims for treatment or prevention. The medical prescription engages the responsibility of the doctor; it must be easily usable by the pharmacist, the nurse and the patient or his relatives. Also, it obeys precise rules of drafting [16].

However, there are errors observed in the writing of prescriptions with potentially serious consequences.

By reviewing the medication prescription and its errors, as well as the impact of these errors on the lives of patients, and given the works that have illustrated this problem until today, we can see that research in the topic of medication prescription is challenging and at the same time the very interesting, in order to minimize medical prescription errors and improve the quality of writing this prescription. The next chapter will present the Recommender Systems.

# Chapter 02
# Recommendation Systems

## 2.1. Introduction

The explosive growth in the amount of available digital information and the number of visitors to the Internet have created a potential challenge of information overload which hinders timely access to items of interest on the Internet. Information retrieval systems, such as Google, DevilFinder and Altavista have partially solved this problem but prioritization and personalization (where a system maps available content to user's interests and preferences) of information were absent. This has increased the demand for recommender systems more than ever before [19]. Recommender systems (RSs) are information filtering systems that deal with the problem of information overload [20] by filtering vital information fragment out of large amount of dynamically generated information according to user's preferences, interest, or observed behavior about item [21]. Recommender system has the ability to predict whether a particular user would prefer an item or not based on the user's profile [19]. So, Recommender systems are primarily devised to assist individuals who are short on experience or knowledge to deal with the vast array of choices they are presented with [22].

In this context, we will establish in this chapter a general study on recommender systems, their types, their techniques and their impact in the world of information technologies.

## 2.2. Definition

A recommendation system is a type of artificial intelligence technology that uses machine learning algorithms to suggest products, services, or information to users. These systems are used in a variety of applications, such as e-commerce, online advertising, and social media.

Recommender system is defined as a decision making strategy for users under complex information environments [23]. Also, Recommender system was defined as a means of assisting and augmenting the social process of using recommendations of others to make choices when there is no sufficient personal knowledge or experience of the alternatives [24].

Recommendation systems use a variety of machine learning techniques, including clustering, decision trees, and neural networks, to analyze and interpret user behavior and generate recommendations. These systems can improve user experience and increase engagement, but they also raise important ethical concerns, such as issues of privacy, bias, and fairness.

## 2.3. Data used by recommender systems

Data used by RSs refers to three kinds of objects: items, users, and transactions, i.e., relations between users and items [22].

- **Items**: Items are the objects that are recommended. Items may be characterized by their complexity and their value or utility. The value of an item may be positive if the item is useful for the user or negative if the item is not appropriate and the user made a wrong decision when selecting it.
- **Users**: Users of a RS, may have very diverse goals and characteristics. In order to personalize the recommendations and the human-computer interaction, RSs exploit a range of information about the users .This information can be structured in various ways and again the selection of what information to model depends on the recommendation technique.
- **Transactions**: We generically refer to a transaction as a recorded interaction between a user and the RS. Transactions are log-like data that store important information generated during the human-computer interaction and which are useful for the recommendation generation algorithm that the system is using.

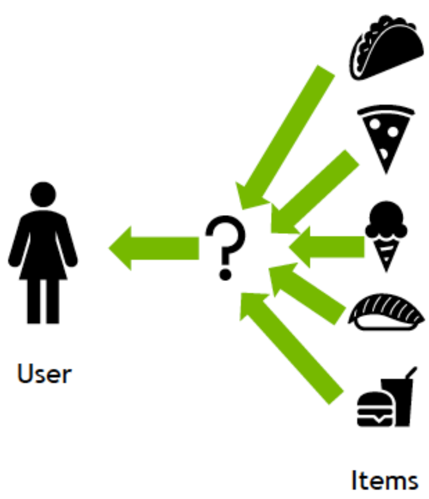



Figure 2.1: The Data used by recommender systems[5]

[5] https://www.nvidia.com/en-us/glossary/data-science/recommendation-system/

## 2.4. Phases of Recommendation Systems

The recommendation process is seen as an iterative cycle represented by three main phases. These are the information collection phase, learning phase, prediction/recommendation phase. In the following we will explain these different phases in detail.

### 2.4.1. Information collection(IC) phase

The information collection phase is an essential and an important part of the recommendation process phase. This phase gathers vital information about users and prepares user profiles based on the users' attribute, behaviors, or resources accessed. Without constructing a well-defined user profile, the recommendation engine cannot work properly. A recommendation system is based on inputs that are collected in different ways, such as explicit feedback, implicit feedback, and hybrid feedback [25].

#### 2.4.1.1. Explicit feedback

This system asks the users for their feedback to produce recommendations [26]. The user will provide ratings for items on a Likert scale. The rating scale will usually go from "I like it a lot" which expresses positive preferences to "I don't like it" which expresses negative user preferences.

The quality and efficiency of the RS relies on the user ratings. Despite of implicit feedback this system expects more work from the user [26].

#### 2.4.1.2. Implicit feedback

The system automates the user’s preferences by analyzing the user’s history, purchases, links clicked by the user and time spent on number of web pages, contents of emails and so on. The need for user’s action is not required for this kind of feedback instead it automatically provides recommendations by analyzing the above mentioned contents [26]. Implicit feedback can only be positive. For example, if a user did not listen to a track that does not imply he does not like the track.

#### 2.4.1.3. Hybrid feedback

The combination of both explicit and implicit feedback is known as hybrid feedback. The weaknesses of both indirect and direct feedbacks are removed and strengths of them are combined to form this hybrid feedback. This feedback can be attained by using the indirect data as an attribute for recommendation while allowing users to provide direct feedbacks and ratings [26].

The strengths of both implicit and explicit feedback can be combined in a hybrid system in order to minimize their weaknesses and get a best performing system. This can be achieved by using an implicit data as a check on explicit rating or allowing user to give explicit feedback only when he chooses to express explicit interest [19].

### 2.4.2. Learning phase

This phase applies learning algorithms on the user's data which are obtained from the feedbacks in information collection phase [19, 26]. The learning algorithms are the methods which are helpful in drawing out the patterns appropriate for application in certain situations [26].

### 2.4.3. Prediction/recommendation phase

This phase called prediction or recommendation phase. It the last phase in recommendation process. It recommends or predicts what kind of items the user may prefer. This can be made either directly based on the dataset collected in information collection phase which could be memory based or model based or through the system's observed activities of the user [19].

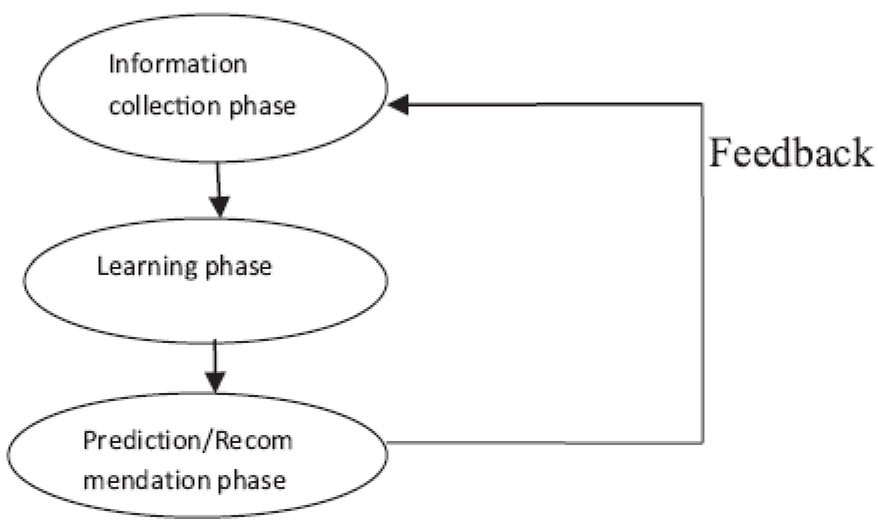



Figure 2.2: Recommendation phases [19]

## 2.5. How does are recommender systems work?

In order to help the user discover new products and services when shopping online, the recommendation systems guide the user to the product most likely to be purchased based on two types of information:

- Characteristic information: this is information about items (keywords, categories, etc.) and users (preferences, profiles, etc.).
- User-item interactions: this is information such as ratings, number of purchases, likes, etc.

## 2.6. Recommender systems types

Recommender systems [22, 27] are majorly categorized into six types which work primarily in the Media and Entertainment industry: collaborative filtering, content-based, utility-based, demographic-based, knowledge-based, and hybrid-based. In this section, a brief explanation of these categories is provided.

### 2.6.1. Collaborative-Filtering Recommendation Systems

Collaborative filtering (CF) is one technique for producing recommendations. Given a domain of choices (items), users can express their opinions (ratings) of items they have tried before. The recommender can then compare the user's ratings to those of other users, find the "most similar" users based on some criterion of similarity, and recommend items that similar users have liked in the past [23]. CF is classified into item-based filtering and user-based filtering [22].

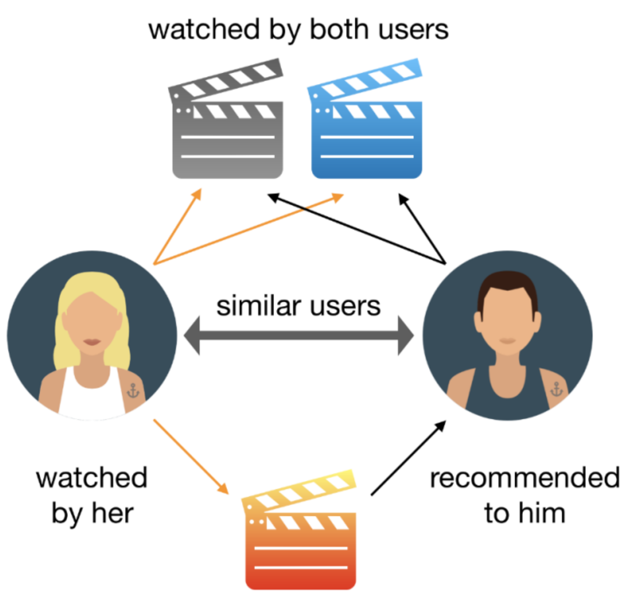



Figure 2.3: Collaborative-Filtering Recommendation System[6]

[6] https://vitalflux.com/recommender-systems-in-machine-learning-examples/#Collaborative_filtering_recommender_system

### 2.6.2. Content-Based Recommendation Systems

It’s basically a tag and keyword specific recommender system here keywords are used to describe the items. Measuring the utility of content-based filtering is commonly calculated by using heuristic functions, such as the cosine similarity metric. Content-based filtering can be employed in many cases, where the features’ values can easily be extracted. Content-based filtering is user-independent since this system only requires analyzing the items and user profile for recommendations [27].

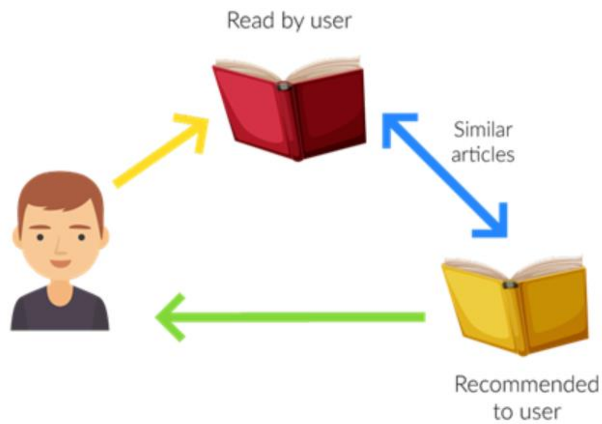



Figure 2.4: Content based recommender system[7].

### 2.6.3. Hybrid-Based Recommendation Systems

Hybrid systems are combining two or more techniques to obtain better performance. Their main target is to eliminate the drawbacks of the individual ones [27]. This is the most sought after Recommender system that many companies look after, as it combines the strengths of more than two Recommender systems and also eliminates any weakness which exists when only one recommender system is used.

One of the good examples for hybrid filtering is the Netflix, it compares the user’s and similar users history (i.e., Collaborative filtering) and offer movies based on the user ratings which contains common aspects (Content-based filtering) [26].

[7] https://vitalflux.com/recommender-systems-in-machine-learning-examples/#Collaborative_filtering_recommender_system

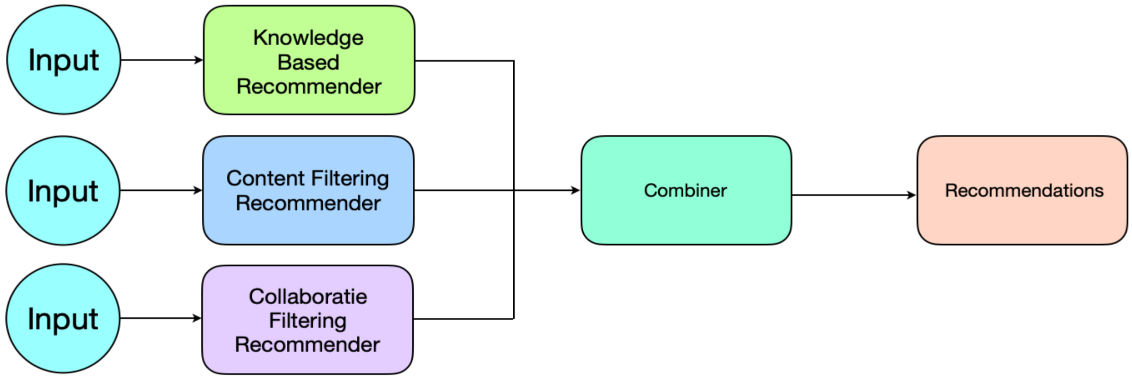



Figure 2.5: Hybrid RS combine Content-based, Collaborative filtering and knowledge-based system[8]

### 2.6.4. Demographic-Based Recommendation Systems

This type of systems assumes the possibility of partitioning the set of users based on their demographic profile. The demographic features such as the country or age of each user will decide to which class he belongs to. Then, a set of rules decides which recommendation to perform depending on the class to which the user belongs [28]. Demographic RSs are especially useful when the amount of product information is limited [27].

### 2.6.5. Utility-Based Recommendation Systems

Utility-based RS provides recommendations based on generating a utility model of each item for the user. This system builds multi-attribute users' utility functions and recommends the highest utility item based on each item's calculated user-utility explicitly [29]. Utility-based RSs are useful because they can factor non-product attributes into utility functions, such as product availability and vendor reliability. They generate utility computation, which allows them to check both real-time inventory and features of an item. It enables the visualization of its status to the user [27].

### 2.6.6. Knowledge-Based Recommendation Systems

Knowledge-based systems recommend items based on specific domain knowledge about how certain item features meet users needs and preferences and, ultimately, how the item is useful for the user. Knowledge-based RSs are noted to be advantageous for several purposes [22].

[8] https://www.width.ai/post/recommender-systems-recommendation-systems

## 2.7. Benefits of Recommendation Systems

Recommender systems are a critical component driving personalized user experiences, deeper engagement with customers, and powerful decision support tools in retail, entertainment, healthcare, finance, and other industries. Companies implement recommender systems since these systems offer several advantages. Among the key advantages of recommendation system we find[9], [10]:

- **Increased sales/conversion**

There are very few ways to achieve increased sales without increased marketing effort, and a recommendation system is one of them. Once you set up an automated recommendation system, you get recurring additional sales without any effort since it connects the shoppers with their desired products much faster.

- **Increased user satisfaction**

The shortest path to a sale is great since it reduces the effort for both you and your customer. Recommendation systems allow you to reduce your customers' path to a sale by recommending them a suitable option, sometimes even before they search for it.

- **Increased loyalty and share of mind**

By getting customers to spend more on your website, you can increase their familiarity with your brand and user interface, increasing their probability of making future purchases from you.

- **Reduced churn**

Recommendation system-powered emails are one of the best ways to re-engage customers. Discounts or coupons are other effective yet costly ways of re-engaging customers, and they can be coupled with recommendations to increase customers' probability of conversion.

[9] https://research.aimultiple.com/recommendation-system/

[10] https://divedeep.ai/benefits-of-recommendation-systems/

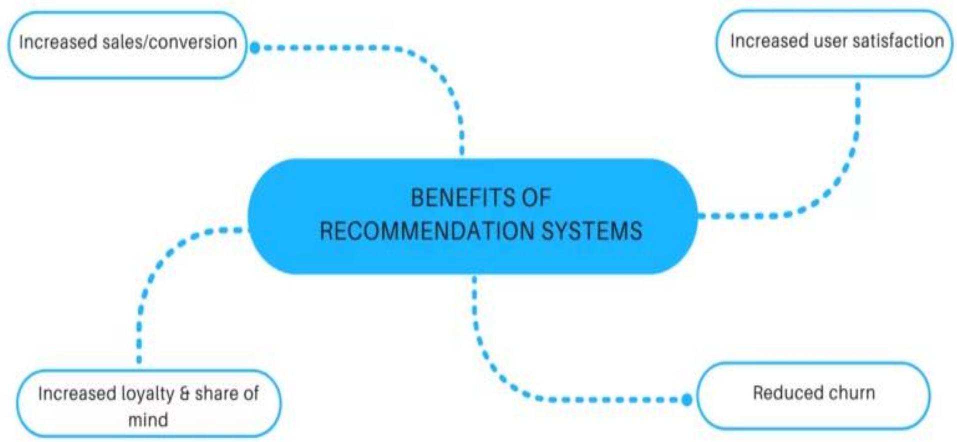



Figure 2.6: Benefits of Recommendation Systems[11]

## 2.8. Recommendation System Applications

The range of applications where recommendations can be done is wide and diverse. Therefore, in this section, we describe the main fields in which recommendation are applied nowadays:

### 2.8.1. Recommendation Systems in e-Commerce

The most common usage of recommendation systems is in the e-commerce sector. Companies and e-commerce stores use modern recommendation systems with sophisticated algorithms to filter data based on the customer's buying choices.

RSs can enhance sales of e-commerce sites in three ways [27].

- **Browsers into buyers**: Visitors to an e-commerce site often look over products without buying anything, but if a site displays relevant recommendations to a user, they are more likely to purchase.
- **Cross-sell**: Recommendation techniques suggest additional products to the users, apart from the one they are already buying. With this, the average order size should increase over time.
- **Loyalty**: In an era where a competitor's site can be visited by a mere click or two, loyalty is essential. RSs personalize the site for each user, which builds the user-site relationship. The more a customer uses a system, the more they are training the system, the more loyal a customer becomes, which also improves the quality of recommendations, over time.

[11] https://research.aimultiple.com/recommendation-system/

### 2.8.2. Recommendation Systems in Transportation

RSs can assist in diverse ways with the increasing use of Global Positioning System (GPS)-enabled devices, especially mobile devices. Because information overload problems become worse when using mobile devices. The development of wireless communication services and position detection techniques such as RFID or GPS has promoted location-based information systems. RSs play a significant role in path recommendation, smart transport application of goods, tourism industry, or venue recommendation. We have categorized applications of RSs in transportation into [27]:

- Recommending trip
- Recommending path
- Recommending popular activities in a location
- Recommending popular locations (restaurants)
- Recommending transporters (goods transporter, bus lines, drivers).

### 2.8.3. Recommendation Systems in the e-Health Domain

E-health and medical decisions are considered for RSs' research, aiming to help medical professionals take fast and proper medical decisions [27]. In recent years, a lot of research has been done in the field of e-health. More, different techniques of the recommendation system have been applied in the field of health [30]. For example, the authors in [31] developed a tailored hybrid RS incorporating demographic, utility-based, and content-based filtering techniques. They aimed to help smokers quit smoking by sending them motivational messages seeking to change their behavior. They evaluated their model using the F-measure, MAE, and the hit rate. The authors in [32] tackled the patients' dietary needs by proposing a novel method to recommend food, based on the patients' medical history. They also included other features such as age, weight, gender, calories, protein, and fat. They combined deep learning and machine learning methods such as naïve Bayes, recurrent neural network, and Long Short Term-Memory (LSTM) and applied them on a 30 patients' collected dataset.

In the context of applying recommendation systems in the field of health, more particularly medical prescription, we will describe this field and its challenges in chapter 3.

### 2.8.4.Recommendation Systems in Agriculture

In Agriculture, RSs have a significant impact on managing and using the resources efficiently, such as fertilizers, agrochemicals, irrigation [27].

### 2.8.5. Recommendation Systems in Media and Beyond

The technological developments and changes in media and the increasing number of people visiting cultural places have led to an increase in various cultural items and offers. Therefore, visitors are bombarded with the information, making it difficult for them to find their interests. Thus, recommendation systems have become a vital tool to provide suggestions that ease the information overload in this area [27]. In the media the system recommends to the user items like movie, music. . . The profit is usually made from advertising or subscription to the website [28].

## 2.9 Examples from companies that use a recommendation engine and her Impact[12]

- **Amazon.com:** Amazon.com uses item-to-item collaborative filtering recommendations on most pages of their website and e-mail campaigns. According to McKinsey, 35% of Amazon purchases are thanks to recommendation systems.

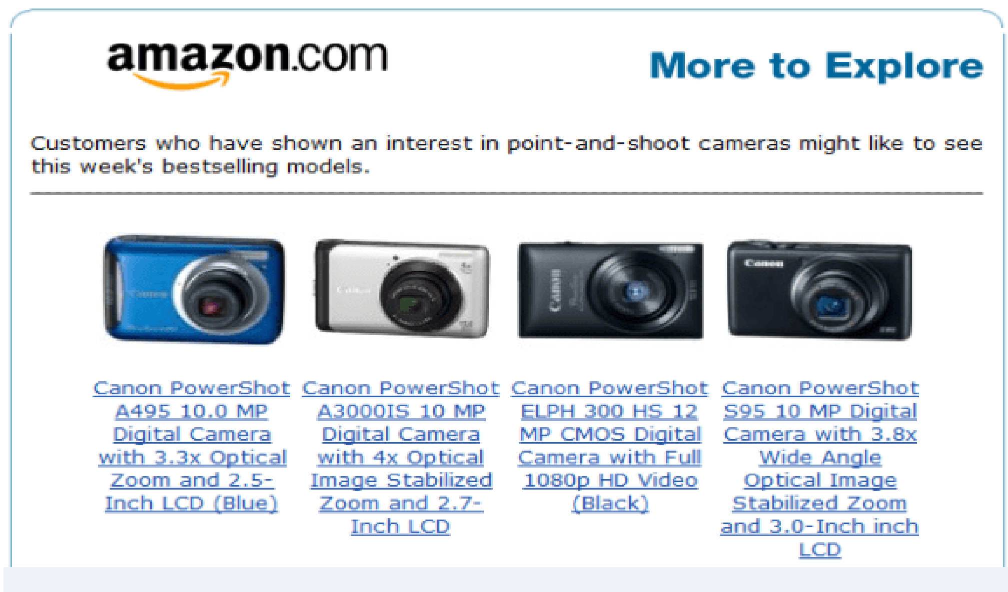



Figure 2.7: Example of where Amazon uses recommendation systems[13]

- **Netflix:** Netflix is another data-driven company that leverages recommendation systems to boost customer satisfaction. 75% of what people are watching on Netflix comes from

[12] https://research.aimultiple.com/recommendation-system/

[13] https://research.aimultiple.com/recommendation-system/

recommendations, according to McKinsey. Employing a recommender system enables Netix to save around $1 billion each year.

- **Linkedin:** LinkedIn uses "You may also know" or "You may also like" types of recommendations.

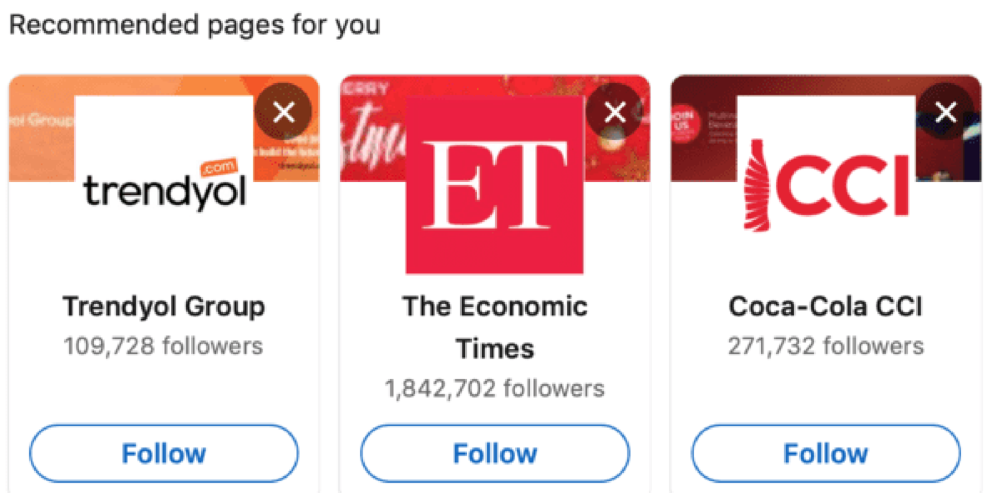



Figure 2.8: Recommended pages for user LinkedIn[14]

- **Spotify**: Every week, Spotify generates a new customized playlist for each subscriber called "Discover Weekly" which is a personalized list of 30 songs based on users' unique music tastes.

## 2.10 Problems of Recommender systems

To build an efficient recommender system, the companies or developers need to overcome some serious problems which restrain the effectiveness of these systems; they are, as shown below.

### 2.10.1 Lack of data and limited content analysis

The sizable issue encountered by the RS may reasonably is the lack of data but where RS needs lots of data to make an efficient model of recommendation system to make recommendations. As xplained in the phases of recommender system, a good RS is a one which mainly needs data about items and users first, then analyze user data, then the algorithms do its work to give recommends as a result [26].

[14] https://research.aimultiple.com/recommendation-system/

Therefore if the RS does not contain sufficient information about a user, the performance of the recommendation will be low. No CBR system can provide suitable suggestions if the analyzed content does not contain enough information to discriminate items the user likes from items the user does not like [33].

### 2.10.2 Over-specialisation

The aim of a RS is to help users explore new products. Diversity is an important feature of a good RS. Unfortunately, some recommendation algorithms may do exactly the opposite. They tend to recommend the popular and highly rated items which are liked by a particular user. This leads to lower accuracy as CBRS does not recommend items from a non-homogenous set of items. This is known as the over-specialisation problem [33].

### 2.10.3 Cold start

When a new item or a new user is introduced to an RS, the system will not have any past records (ratings, preferences, search history, etc.) on the basis of which recommendation should be made. This is known as the cold start problem. It is also termed as the new user problem or new item problem [33].

### 2.10.4 Sparsity

In practice, the RSs work with very large datasets. Hence, the user-item matrix used for CF is extremely sparse, which adversely affects the performances of the predictions or recommendations of the CF systems. It also takes place when a user, having used some particular product, did not bother to rate it. In other cases, users do not rate items that are not known to them [33].

### 2.10.5 Scalability

As the RSs work on large datasets, the complexity of the RSs increases in case of a huge number of users and millions of distinct items set. Many systems need to react immediately to online requirements and make recommendations for all users based on their purchases and rating history, which demands high scalability items [26, 33, and 34].

### 2.10.6 Synonymy

Synonymy refers to the problem of multiple words having similar meanings [35]. Most of the RSs are unable to find the same or similar items with different names (synonyms) [33].

### 2.10.7 Abbreviation

If the RS is not familiar with the abbreviations that the users often use during online interactions, it will not be able to recognise the item that the user is looking for. This generates an erroneous recommendation [33].

### 2.10.8 Long tail

If an item initially is not well-rated or not rated at all in an RS which follow a top-N recommendation, then over the time it will perish from the recommendation catalogue. Diversity is closely related to this problem. A user will miss recommendations for many necessary items just because he did not rate those items or did not have any access to them. This generally leads to the long tail problem (LT). It occurs when many items remain unrated or low rated [33].

### 2.10.9 Black-box problem

The efficiency of the RS is enhanced with the increase in the transparency of recommendation. The satisfaction of the user in the recommendation is entangled with the trust that the user places on the objectives of recommendation. The black box problem occurs in RSs when the system is opaque towards the end user, causing decreased levels of confidence in the system [33, 36].

## 2.11 Content-Based Recommender System

### 2.11.1 Definition

Content-based filtering is a recommendation technique used in information retrieval and recommendation systems to provide personalized recommendations to users. Content-based recommendation systems try to recommend items similar to those a given user has liked in the past [49].

Thus the content-based technique does not require the ratings of other users to make valuable recommendations [50]. Systems implementing a content-based recommendation approach analyze a set of documents and/or descriptions of items previously rated by a user, and build a model or profile of user interests based on the features of the objects rated by that user [49]

## 2.12 The process of content-based filtering

Content-based filtering try to match features of items stored in the user's profile. At the same time, the references are kept with the features of the newly presented items to make recommendations. Therefore, only items that the user previously liked will be recommended [50]. In content-based filtering, items are described by their attributes, such as keywords, genres, or features and user profiles are created based on their interactions with these attributes. Recommendations are then generated by comparing the attributes of items to the user's profile and selecting items that closely match their preferences. Unlike collaborative filtering, which focuses on user similarities and item relationships, content-based filtering emphasizes the content or characteristics of the items themselves to make recommendations.

The recommendation process is performed in three steps, each of which is handled by a separate component:

### 2.12.1Content Analyzer

The first step of the recommendation process is the one performed by the CONTENT ANALYZER that usually borrows techniques from Information Retrieval systems. In fact when information has no structure (e.g. text), some kind of pre-processing step is needed to extract structured relevant information. The main responsibility of the component is to represent the content of items (e.g. documents, Web pages, etc.) coming from information sources in a form suitable for the next processing steps [49]. This form is item representation which is stored in the repository Represented Items.

In this step, features are extracted from various sources to convert them into a keyword-based vector-space representation [56]. This step is important because, the proper extraction of the most informative features is essential for the effective functioning of any content-based recommender system [56].

### 2.12.2 Profile Learner

This module collects data representative of the user preferences and tries to generalize this data, in order to construct the user profile [49]. In order to achieve this goal, user feedback is leveraged, which may be manifested in the form of previously specified ratings (explicit feedback) or user activity (implicit feedback). Such feedbacks are used in conjunction with the attributes of the items in order to construct the training data. A learning model is constructed on this training data [56]. Usually, the generalization strategy is realized through machine learning techniques, which are able to a model of user interests starting from items liked or disliked in the past [49].

### 2.12.3 Filtering Component

This module performs the last step of the content-based recommendation process. It is important for this step to be very efficient because the predictions need to be performed in real time [56].

FILTERING COMPONENT exploits the user profile to suggest relevant items by matching the profile representation against that of items to be recommended. The result is a binary or continuous relevance judgment (computed using some similarity metrics), the latter case resulting in a ranked list of potentially interesting items [49]

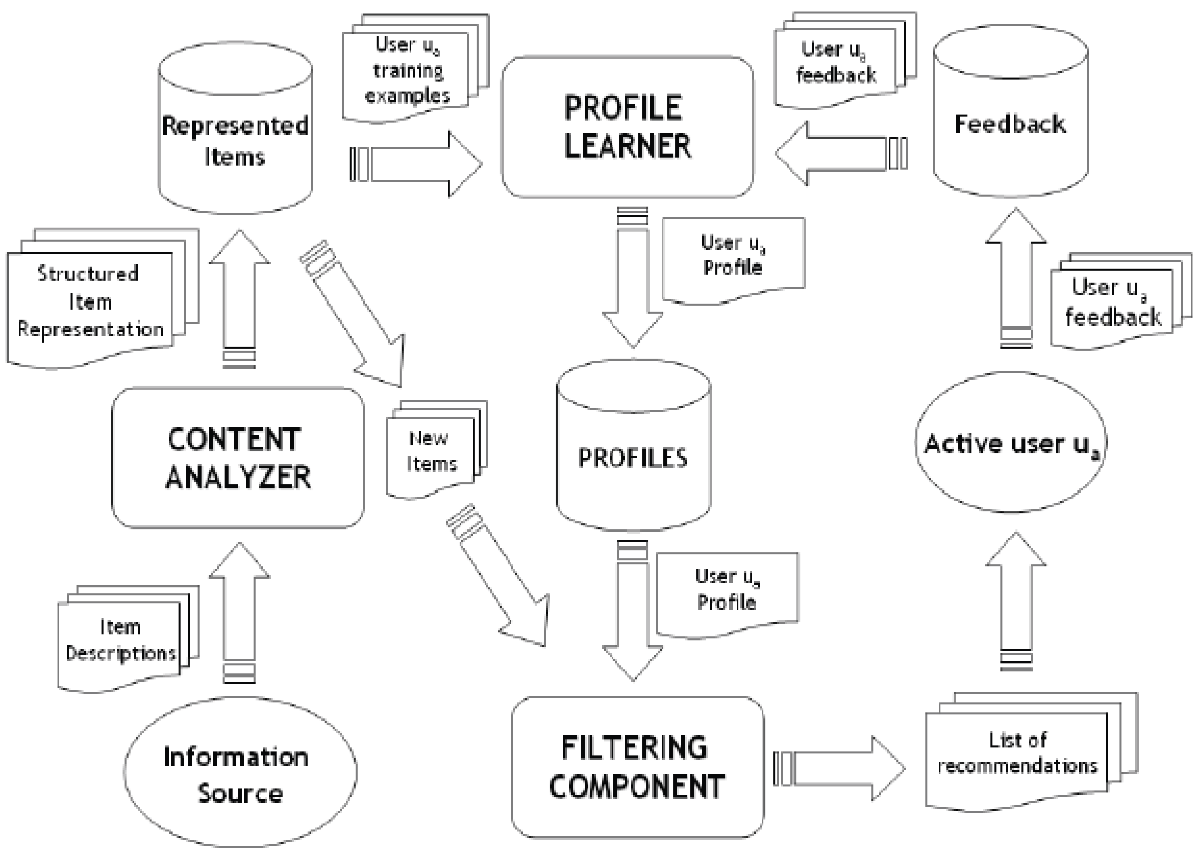



Figure 2.9: High level architecture of a Content-based Recommender [49]

## 2.13 Methods for Content Based Feature Selection

Three methods are used to select features in the content-based approach [51], [52], [53]:

### 2.13.1 Wrapper methods

Divide the features into subsets, run analysis on these subsets and then evaluate which of these subsets seems the most promising. As the number of all possible subsets is factorial in the number of features, different heuristics are used to choose “promising" subsets (forward-selection, backward-elimination, tree-induction, etc.). Wrapper methods are independent of the prediction algorithm.

### 2.13.2 Filter methods

Filter methods use heuristic methods to rate features on their content. They do not require training many models and therefore scale well for large datasets. Yet, filter methods cannot be naturally extended to recommender systems, in which the prediction target varies and depends both on the user's history and on the item under consideration.

### 2.13.3 Embedded methods

Family of algorithms in which the feature selection is performed in the course of the training phase. they are not based on cross-validation and therefore scale with the size of the data. However, since the feature selection is an inherent property of the algorithm, an embedded method is tightly coupled with the specific model: If the recommendation algorithm is replaced, features selection needs to be revisited;

## 2.14 Techniques of Content Based Approach

The content-based recommendation system works on two techniques, both of them using different models and algorithms. One uses the vector spacing method while the other uses a classification model.

### 2.14.1. Vector Space Model

Vector space model (VSM) is a relatively simple retrieval model which is widely used in content-based recommender systems [54]. The VSM is an algebraic model used for Information Retrieval. It represent natural language document in a formal manner by the use of vectors in a multidimensional space. The Vector Space Model (VSM) is a way of representing documents through the words that they contain [55]. In this n dimensional vector, each dimension corresponds to a separate term from the overall terms appeared in the collection of documents.

Formally, every document is represented as a vector in a n-dimensional space, where wi is the weight of term ti, which indicates the degree of relevance between a given document D and the term ti [54].

TF–IDF (term frequency–inverse term frequency) is a popular scheme to determine term weights, which is based on two empirical observations: the more frequent a word appears in a document, more relevant it is to the subject of the document, the more frequent a word appears throughout the documents in collection, the less efficiently it discriminates between documents .These suppositions are fully exemplified by the TF–IDF formula: [54].

$$w_i = tf_i \cdot \log\left(\frac{N}{df_i}\right)$$

The cosine distance between the vectors of the item and the user can use also to determine its preference to the user.

### 2.14.2. Classification method

Classification algorithms like Bayesian classifiers or decision tree models can be used to make recommendations. For example, every level of a decision tree can be used to filter out the various preferences of the user to make a more refined choice[15].

## 2.15. Advantages and Drawbacks of content-based recommendation system

### 2.15.1. Advantages

Content-based filtering offers several advantages over other recommendation techniques:

- **User Independence**: Content-based recommenders exploit solely ratings provided by the active user to build her own profile [49]. It is independent of any external factors such as user behavior, ratings, or social connections. This makes it less prone to the problems of popularity bias and spam that can affect other recommendation algorithms.

- **Transparency**: Explanations on how the recommender system works can be provided by explicitly listing content features or descriptions that caused an item to occur in the list of

[15] https://www.turing.com/kb/content-based-filtering-in-recommender-systems

recommendations. Those features are indicators to consult in order to decide whether to trust a recommendation [49].

- **New Item**: Content-based recommenders are capable of recommending items not yet rated by any user. As a consequence, they do not suffer from the first-rater problem [49].

- **Accuracy**: Content-based filtering is very accurate in recommending relevant content to users based on their interests and previous behavior. It analyzes the actual content of the item being recommended rather than relying solely on metadata or user ratings. This leads to higher accuracy in predicting user preferences and ensuring that recommended content is more relevant to the user.

- **Personalization**: Content-based filtering enables personalization of recommendations based on the user's interests, preferences, and behavior. This means that users are more likely to engage with the content and find it relevant and interesting.

- **Scalability**: Content-based filtering techniques can easily handle large datasets and can scale up to millions of users and items. This makes it suitable for large-scale recommendation systems.

- **Diversity**: Content-based filtering can increase the diversity of recommended content by using a wider range of features to represent items. This means that users are less likely to get stuck in a filter bubble, where they are only recommended items based on their past behavior.

### 2.15.2. Drawbacks

Content-based filtering has certain limitations and challenges [49]:

- **Cold Start Problem**: One of the major limitations of content-based filtering is the cold start problem. When a new user joins the system or anew item is added to the system, it becomes challenging to provide recommendations since there is no previous history or data available to analyze the user's preferences.

- **Over-Specialization**: Another limitation of content-based filtering is that it tends to provide recommendations that are too similar to the user's past preferences. As a result, it may hinder diversity in the recommendations, leading to over-specialization and limiting the user's exposure to new and potentially interesting items.

- **Limited Contextual Information**: Content-based filtering relies heavily on the content's intrinsic properties, such as keywords, genres, or topics. As a result, it may not be able to capture contextual information, such as the user's mood, social situation, or temporal factors, which are crucial in determining the relevance of the recommendation.

- **Inability to Handle Complex Preferences**: Content-based filtering works best when the user's preferences can be easily expressed as a set of features or properties. However, for some users, preferences may be more complex, such as a preference for a particular style or combination of styles. Such complex preferences are difficult to capture using simple feature-based representations.

## 2.16 The use of Content-based filtering recommender system for medical prescription

Before diving into the details of our work, it is useful to understand the reasons for applying one of the techniques of recommender systems to the field of medical prescription. It is evident that the integration of information technologies in the health sector becomes essential and crucial. In fact, information technologies play an increasingly important and preponderant role in the health sector. A multitude of IT solutions is available to healthcare establishments, healthcare providers, patients and the population as a whole. These include clinical information systems used in hospital organizations that allow, among other things, the management of computerized patient records, laboratory results and medical imaging.

Medical prescription domain is also part of the health sector, in fact in the practice of medicine; prescription is the act by which an authorized health professional orders therapeutic recommendations from a patient. And given the significant prevalence of adverse drug events, as well as the increasing risk of misuse of these drugs caused mainly by inappropriate prescribing and overuse, it has become necessary to find automatic solutions to minimize the risk of medical errors resulting from these inappropriate prescriptions. The automation of the medical prescription process is considered to be one of the most important projects that healthcare institutions worldwide seek to achieve today.

In fact, success in the domain of medical prescriptions depends on reducing the various errors present in it, which can threaten the lives of patients through the adverse effects they can cause and can lead to death.

According to the World Health Organization (WHO), medication errors cause at least one death every day and injure an estimated 1.3 million people a year in the United States. The global cost associated with medication errors has been estimated at US$42 billion per year, or nearly 1% of total global healthcare expenditure [13]. For this reason, it has become necessary to work hard in this field in order to diligently protect the health of citizens against the threat of medical errors, by finding an advanced method that allows to reduce and why not eliminate these medical errors which are have become a threat to the patient's health, this is done by integrating technologies that can be an effective way to change prescriptions, the objective of which is to avoid medical errors as much as possible.

In this context, several studies have focused on the errors that can occur in medical prescription and the various IT solutions with the aim of improving the quality of medical prescription and reducing medical errors. Several technologies have been used to reduce medication errors such as image processing [57], natural language processing [58], [59], [60]. In the context of applying recommendations in the field of drugs, there are some works based on ontology and rules, such as GelenOWL [61] who recommended drugs for patients using a medical reasoning approach and based on rules developed based on the patient's disease, allergies and known drug interactions for the drugs in the database. Another work [62] used an ontology-based approach based on diseases, medications, and allergies to provide a list of recommended medications. However, these algorithms required the development of extensive rules, which is difficult and time-consuming to achieve on a large scale [63]. Indeed, most studies of drug recommendations have relied on traditional classification methods [63].

The application of recommender systems in the area of prescribing is minimal despite the success of these systems in other areas. Recently, several studies have used recommender systems by applying several machine learning techniques such as the work presented in [64] which is used to generate a list of medications taking into account patient diagnoses and adverse drug effects. This is done by applying a high quality heterogeneous graph. Shan et al. [65], Yang et al. [66] used neural networks to develop a drug recommendation engine. The development of recommendations based on collaborative filtering is illustrated recently by Granda Morales et al in his article [67]. The developed drug recommendation is specific to diabetic patients.

In fact, the application of content-based recommendation systems in the field of medical prescription is a new idea that aims to reduce medical errors, solve problems related to this field and reduce the cost associated with these errors.

Therefore, by applying a recommendation system by adopting the content-based approach in the prescription of drugs can create an information system to support the medical decision, reduce errors during the medical act. It makes it possible to provide clinicians in useful times and places with information describing the clinical situation of a patient as well as the knowledge and prescriptions appropriate to this situation, correctly filtered and presented.

Our choice comes first is that content-based recommender systems are ranked among the best systems in terms of accuracy and user independence, compared to other recommender system techniques such as collaborative filtering. .

Another motivation for our choice lies in the novelty of this idea in the field of medical prescription which comes from the domain analysis, the undesirable and serious effects of bad medical prescription caused by several factors. Thus the previous studies which will not really solve the challenges presented in this area.

Therefore, the goal of our Medical prescription assistance system using recommendation systems is to provide a list of relevant and appropriate medications corresponding to patient diagnoses, based on the disease conditions of the patient and based on a history of patients with similar characteristics. Helping healthcare professionals make faster and more accurate decisions is another need that must be met by the application of recommender systems in the medical field.

## 2.17 Conclusion

During the last few decades, with the rise of Youtube, Amazon, Netflix and many other such web services, recommender systems have taken more and more place in our lives and are today unavoidable in our daily online journeys. In a very general way, recommender systems are a type of machine learning based systems that are used to predict the ratings or preferences of items for a given user.

Recommender systems are really critical in some industries as they can generate a huge amount of income when they are efficient or also be a way to stand out significantly from competitors. They open new opportunities of retrieving personalized information on the Internet. In this chapter, we have made literature survey of different phases and various techniques in the recommender systems. The impact, benefits and problems associated with recommendation systems are also studied in this chapter. The next chapter will present the use of recommendation systems in the health sector.

# Chapter 3

# The use of recommendation systems in the health sector

## 3.1. Introduction

Recommendation systems, also known as recommender systems, are widely used in many industries, including healthcare. These systems use algorithms to provide personalized recommendations for users based on their preferences, past behaviors, and other data.

In the healthcare sector, recommendation systems can be particularly useful in helping healthcare providers and patients make informed decisions about medical treatments, medications, and lifestyle changes. For example, a recommendation system may suggest a particular medication based on a patient’s medical history, symptoms, and genetic profile, or recommend certain lifestyle changes based on a patient age, gender, and other demographic factors.

Recommendation systems can also help healthcare providers identify patients who may be at risk for certain medical conditions, and provide personalized interventions to prevent or manage those conditions. Additionally, these systems can assist Healthcare providers in making more accurate diagnoses, by suggesting potential.

In this chapter, we will first describe what the health recommender system, his goals is. Next, we will explain areas where recommendation systems can be applied in healthcare and in the last section we will describe the criteria of evaluation of recommender system in a health domain.

## 3.2. Definition

Not much previous work on applying recommender system in health informatics or medicine exists. As of June 5th 2016 only 17 articles are found when searching for the terms “recommender system health” in web of science. The oldest article is from 2007 and the most cited article has only 14 citations [43].

In the context of integrating recommender systems in the medical environment, several definitions have been indicated, among which we cite the most recognized.

A health recommender system (HRS) is a specialization of an RS as defined by Ricci et al [22]. In the context of an HRS, a recommendable item of interest is a piece of non-confidential, scientifically proven or at least generally accepted medical information, which in itself is not linked to an individual’s medical history. However, an HRS’s suggestions are driven by individualized health data such as documented in a personal health record (PHR) [37]. According to [38] this source of information is considered the user profile of an recommender system.

A health recommendation system is a specialized recommender system that supplies a user with personalized health information, which is meant to be highly relevant to the user's health profile [37]. In addition, an HRS is capable of automatically identifying and recommending appropriate materials (such as recommending diagnoses, health insurance, clinical pathway-based treatment methods, and alternative medicines) to users based on their specific health conditions and needs [39]. Therefore, an HRS can empower people with relevant health information, enable them to have more control on their own health management, and engage them in important health decision-making [40]. HRS introduces an opportunity for the health care industry to transition from a traditional to a more personalized paradigm in a telehealth environment [39].

## 3.3. The goals of health recommender systems

The goal of an HRS is to supply its user with medical information which is meant to be highly relevant to the medical development of the patient associated with that PHR. Related may medical information be recommended to health professionals who work on or with the given PHR but also it may be recommended to laymen inspecting their own PHR. Depending on a user's medical expertise an HRS should suggest medical information, which is comprehendable to that user [37].

HRS offers a better personalization that increases the details of provided recommendations and improves users' understanding of their medical condition. These systems also provide patients with a better experience, improve their health condition, and motivate them to follow a healthier lifestyle [41].

HRS should analyze patients' health status and recommend personalized diets, exercise routines, medications, disease diagnoses, or other healthcare services. HRS's great concern is to send the necessary information to patients at the right time while ensuring the accuracy, trustworthiness, and privacy of patient information [42].

Another goal is needed in medical recommender systems this is to help healthcare professionals predict and treat disease. Moreover, these systems are expected to minimize the cost of the healthcare-related decision making process (in terms of time and effort) [43].

In fact, for a successful integration into any health related information system, it is important to consider the system context of an HRS. As depicted in Figure 3.1, a profile-based HRS component is implemented as an extension of an existing PHR system. Data entries in a PHR database (DB) constitute the medical history of a PHR owner. Supplied with medical facts, an HRS computes a set of potentially relevant items of interest for a target user (e.g., a PHR owner or an authorized health professional). Such items originate from trustworthy health knowledge repositories and may be displayed while he/she inspects the PHR online [37].

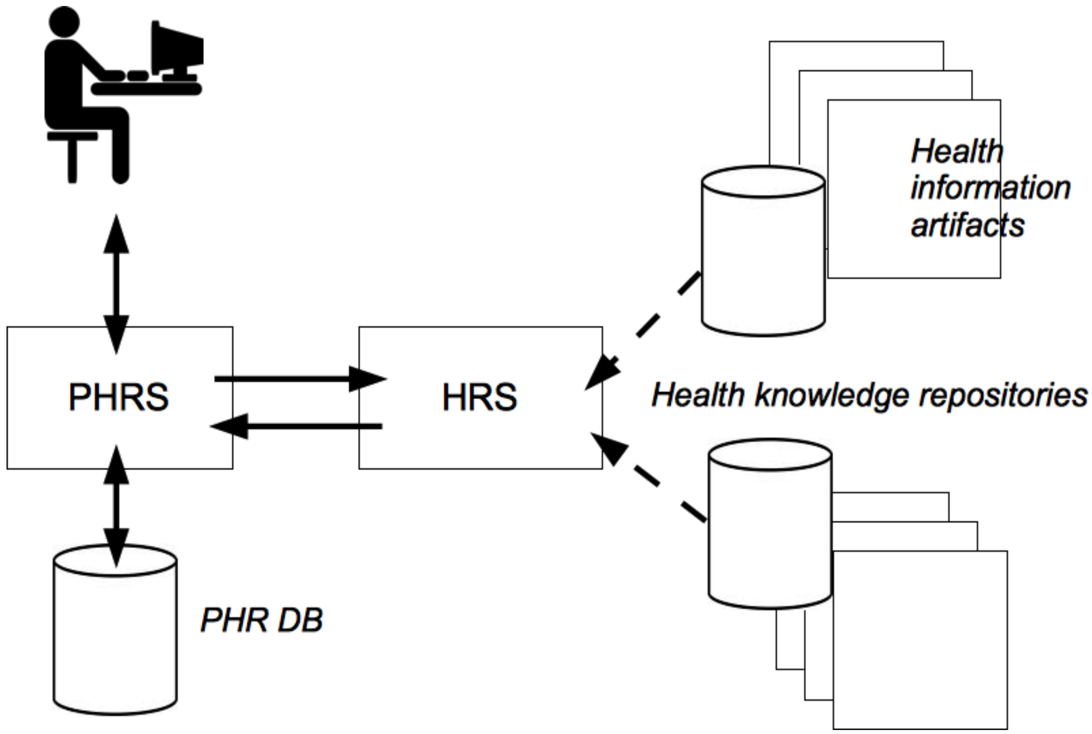



Figure 3.1: System context of an HRS-enabled PHR system [37].

## 3.4. The areas where recommendation systems can be applied in healthcare

HRS domain can be further classified into sub-domains namely health well-being, healthcare services, diagnosis, and treatment process and others sub-domains.

### 3.4.1. Healthcare services

For end users, HRS provides several health services such as nutritional information, medications, treatment plans, disease diagnosis/predictions, physical activities or other health services (e.g. finding good doctors or appropriate medical services for patients) [41].

### 3.4.2. Diagnosis and treatment recommendation

Recommendation systems can analyze patient data and provide healthcare professionals with recommendations for diagnosis and treatment. For example, a system can analyze a patient's symptoms and medical history and recommend a specific test or treatment. Diagnosis and Medication recommenders target patients and medical professionals. It depends on patient's diagnostic data, case history, expert rules, and social media data to train and build a model that can predict and recommend possible potential health risks, diagnose issues and suggest treatments [44].

A model proposed in Article [44] that uses patients' clinical health data at the diagnosis stage to map (recommend) the appropriate diagnosed health condition or treatment, whereas patients' personal health data and Patients' knowledge is used in the later stages to obtain precise treatment recommendations for the particular diagnosed condition.

### 3.4.3. Medication recommendation

Medication recommender systems have been developed to assist end-users and healthcare professionals in identifying accurate medications for a specific disease [41]. Furthermore, recommendation systems can help healthcare providers choose the most appropriate medication for a patient based on their medical history and current condition. This can help reduce the risk of adverse reactions and improve patient outcomes.

Therefore, the implementation of medication prescriptions based on a recommendation system becomes necessary because medical prescription is an important part of the process of treatment and care of patients and it's considered as a major component of nurse's function, and in the meantime patient safety has a particular importance [45].


Figure 3.3: Medication review[16]

### 3.4.4. Personalized care recommendation and Patient engagement

HRS is to empower people to monitor and improve their health through technology-assisted, personalized recommendations. As one approach of modern health care is to involve patients in the cocreation of their own health, rather than just leaving it in the hands of medical experts [46].

In this context, recommendation systems can help healthcare providers deliver personalized care to patients based on their medical history, lifestyle, and preferences. This can include recommendations for diet, exercise, and other lifestyle changes.

### 3.4.5. Clinical decision support

The recommendation system can be clinical decision support systems that provide recommendations for health care professionals [46], by providing them with relevant information and treatment options based on the patient's condition and medical history.

[16] https://familycaregiversonline.net/what-is-a-medication-review/

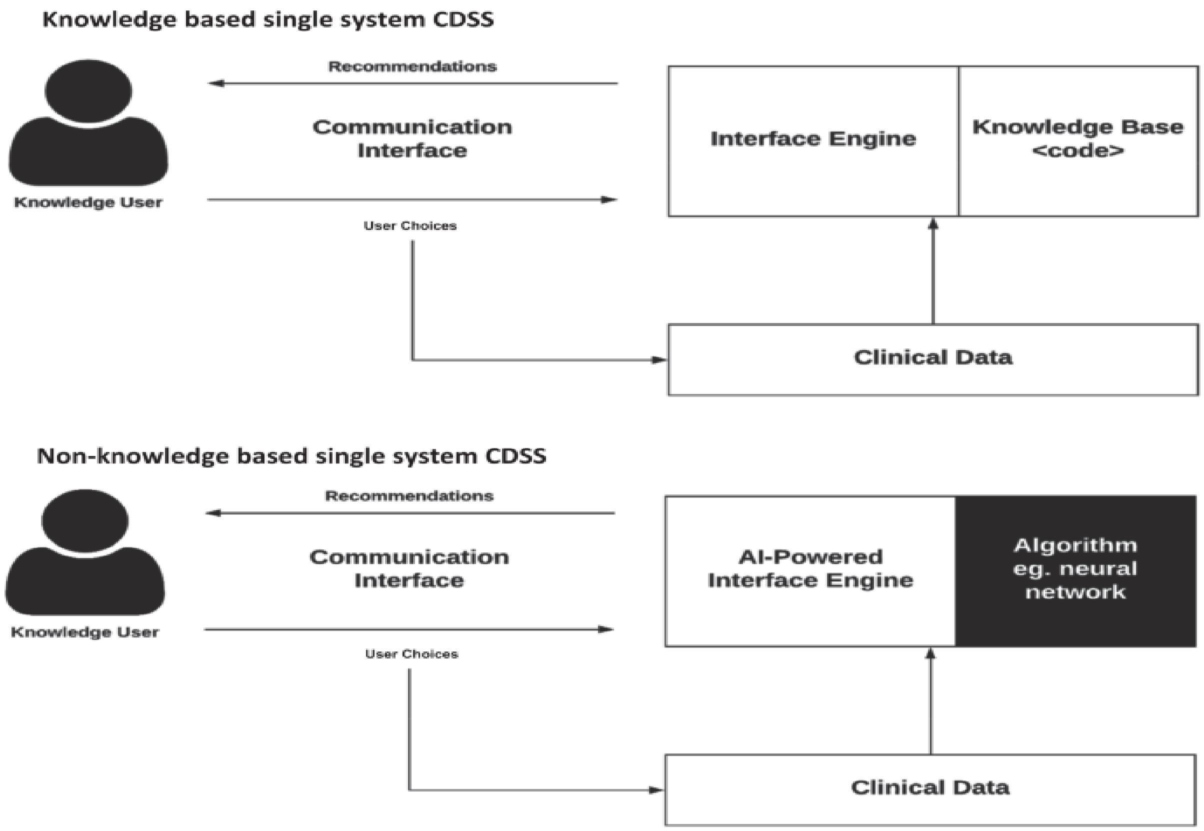



Figure 3.4: Clinical decision support [47]

### 3.4.6. Physical activity recommendation

Besides recommendations of disease treatment plans, suggestions on physical activities have become another focus of HRS. Providing recommendations on what physical activities to perform. May be applied to help in finding activities that are interesting and motivating and also match the users requirements and needs. A recommender could also include location-data and weather data to find activities that are optimal for the users context [43].

Physical-activity recommendations help to decrease the probability of becoming frail of patients and prevent them from further health complications. Moreover, they also encourage users to follow daily activities that meet their calorie-burn goals[17].

[17] https://medium.com/pathtoai/recommendation-systems-fb437f89d4ea

### 3.4.7. Healthcare professional recommendations

In recent years, there has been a significant increase in the amount of available medical information, which results in some difficulties for patients when searching for suitable doctors. What concerns patients greatly are how to find medical professionals with the best expertise for resolving their health issues[18]. In this context the implementation of system based on recommendations of doctors and available information about user is necessary

## 3.5. Evaluation of Health Recommender Systems

As with any medical technology it is crucial to measure and benchmark health recommender systems, particularly in regard to user acceptance and satisfaction [43]. Following this, several criteria for evaluating medical recommendation systems have been addressed by several authors. In the following, we will discuss these criteria in detail.

### 3.5.1. Serendipity and coverage

The question of serendipity and coverage, i.e. finding “interesting” as well as finding all relevant results, is important for health recommender systems, especially in rare diseases. In this context, there are algorithms to find a trade-off between serendipity and coverage for improved accuracy, e.g. recommending items with more data.

### 3.5.2. Satisfaction of users

In the case of health recommender systems, this prediction is peculiar, as there are different relevant user groups. Differences in expertise, overview knowledge, but also tasks must be understood to create recommender systems suitable to health practitioners, clinical doctors, biomedical researchers, care givers and patients.

### 3.5.3. Privacy of information user

Another very important research issue is trust in recommender systems. This is particularly true for health recommender systems, as they shall be used to provide end users with more proactive and personalized information relevant to their health. But, there are still many open research questions considering trust, privacy and intimacy in the use of medical technology. User diversity plays a role, with an emphasis on gender and age.

[18] https://medium.com/pathtoai/recommendation-systems-fb437f89d4ea

### 3.5.4. Uncertainty in a set of recommendations

As the outcome of health recommendations are inherently uncertain, communication of this uncertainty is highly important. Finding ways to visualize uncertainty in a set of recommendations is crucial to allow the user to evaluate the option adequately. This problem is linked to the risk and duration of the consequence of a choice. Picking a bad therapy could reduce quality of life for many years. One bad option in the first few recommendations could have drastic outcomes. The designer of health recommender systems must be careful and act responsibly in both generating recommendations and communicating them.

### 3.5.5. The effectiveness

The effectiveness of such a system must still be evaluated in regard to the users external behavior. Behavioral evaluations must be considered to measure the effectiveness of a health recommender system. For example, when giving recommendations about activities to conduct to improve fitness, the recommender system must track what activities have actually been conducted.

### 3.5.6. Measuring actual health impact

Is also important. Even when the users show long term adherence to recommended health behaviors, the next question is whether the conducted changes in behavior or therapy lead to the desired changes in health. We must consider which health parameters to assess and which medical tests to employ to ensure medical effectiveness. For example, crash diets may lead to reduced body weight (a superficial health parameter), but mostly because of reducing body muscle mass. This leads to rebounding effects because of reduced metabolism. Long-term weight loss is burdened.

Therefore before such an approach can be implemented in real-world medicine, it must be assured that such systems are sufficiently trustworthy [48]. Furthermore we must consider ethical considerations of recommender systems. (e.g. what do we do when health parameters used as an indicator for disease seem to not correlate with actual disease). The principle of “first do no harm” should be kept in mind. A recommender system might unintentionally provide health guidance that could in the hand of a person suffering from a mental illness steer a patient in an unhealthy direction (e.g. dieting tips for anorexic patients) [43].

## 3.6. Conclusion

The use of recommendation systems in the health sector has the potential to revolutionize the way healthcare is delivered through to improve population health. These types of systems can help healthcare providers make more informed decisions about patient care, reduce healthcare costs, and improve patient outcomes by studying and analyzing patient data and by providing personalized recommendations.

Recommender systems have a wide range of applications in healthcare, from personalized treatment recommendations to medication management, disease diagnosis, health monitoring, clinical decision support and patient engagement. However, it is important to ensure that these systems are designed and implemented in an ethical and transparent manner, and that patient privacy and data security are carefully protected.

However, it is important to ensure that these systems are designed and implemented in an ethical and transparent manner, and that patient privacy and data security are carefully protected. This is done by supporting criteria to increase the reliability of these systems. As technology continues to advance, it is likely that recommendation systems will become even more advanced and sophisticated, making a significant impact on the health sector in the years to come.

# Chapter 04
# The results

## 4.1. Introduction

After having presented the concept of medical prescription and its importance in relation to health professionals and patients, and after having studied the theory of recommendation systems and its application in the health sector, in the previous chapters, this chapter is devoted to the implementation of a medical prescription support system using a recommendation system approach. For this, we will first present the proposed architecture. The results of the implementation will also be presented and detailed in this chapter.

## 4.2. The proposed approach

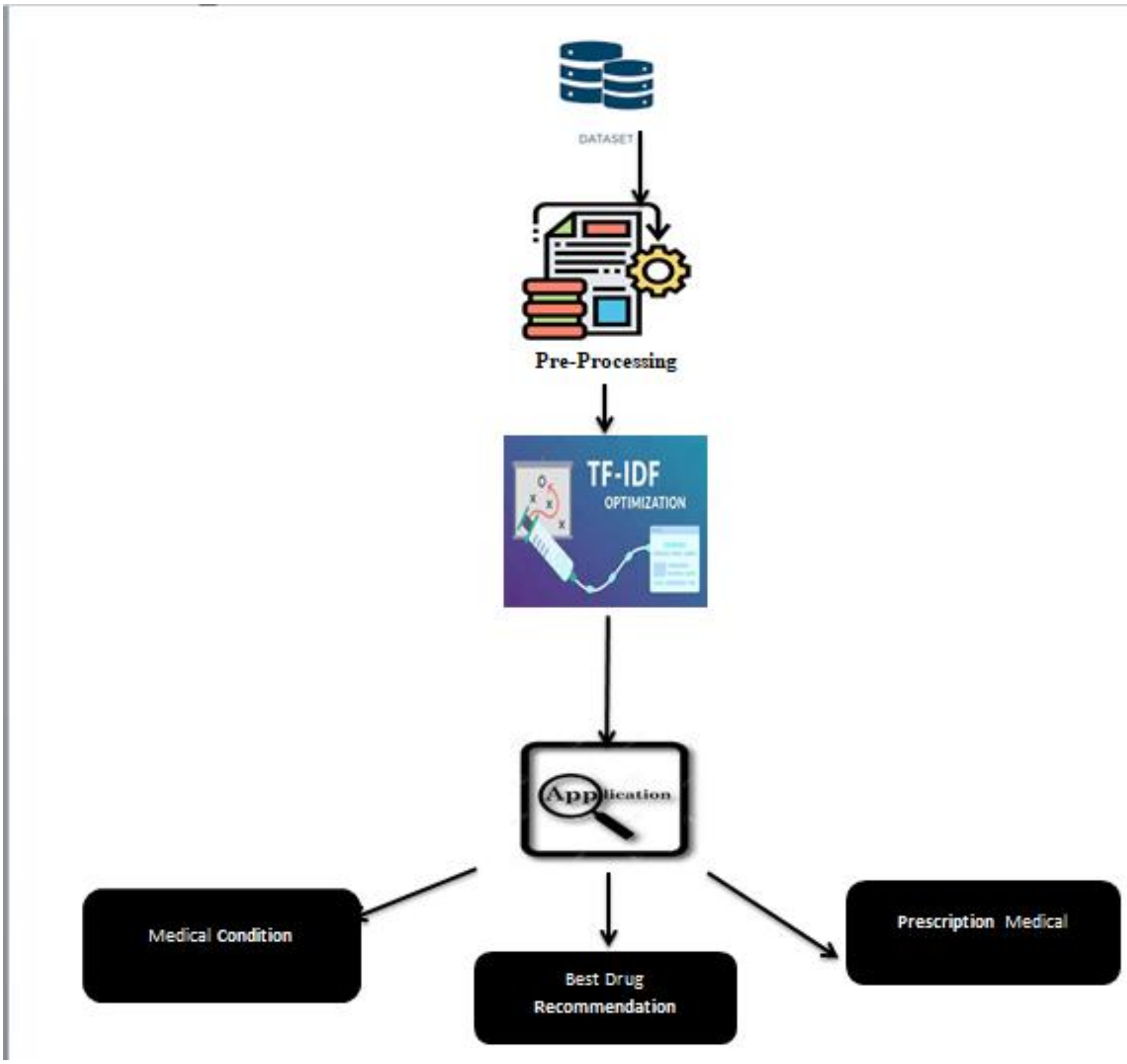



Figure 4.1: The proposed model

In this diagram, we have identified the steps involved, which are as follows:
Surveying the data base, and then we did some operations on it, such as Naïve Bayes and Passive Aggressive Classefie, then we made TF-IDF and then demoed our programmed app on Streamlet and the program shows the Drug Recommended and write the prescription.

### 4.2.1. Data source used

Our model aims to improve the writing quality of medical prescriptions and to help healthcare professionals in clinical decision-making. The model thus makes it possible to recommend a patient's medications based on the history of other patients who have similar symptoms.

In our research, we used the Drug Review Dataset database published in March 2018 and created by Surya Kallumadi from Kansas State University, Manhattan United States and Felix Grer from Dresden University in Germany. The dataset provides patient reviews on specific drugs along with related conditions and a 10 star patient rating reflecting overall patient satisfaction. The data was obtained by exploring online pharmaceutical journal sites.

The information that exists in this database is for example:
1. drugName (categorical): name of drug
2. condition (categorical): name of condition
3. review (text): patient review
4. rating (numerical): 10 star patient rating
5. date (date): date of review entry
6. usefulCount (numerical): number of users who found review useful

**Link Data source:**

**https://archive.ics.uci.edu/dataset/462/drug+review+dataset+drugs+com**

### 4.2.2. Passive Aggressive Classefie

The Passive-Aggressive algorithms are a family of Machine learning algorithms that are not very well known by beginners and even intermediate Machine Learning enthusiasts. However, they can be very useful and efficient for certain applications.

**Example**

```
pass_tf = PassiveAggressiveClassifier()
pass_tf.fit(tfidf_train_3, y_train)
pred = pass_tf.predict(tfidf_test_3)
score = metrics.accuracy_score(y_test, pred)
# st.write("accuracy:   %0.3f" % score)
cm = metrics.confusion_matrix(y_test, pred, labels=['Birth Control', 'Depression','Diabetes, Type 2','High Blood Pressure'])
plot_confusion_matrix(cm, classes=['Birth Control', 'Depression','Diabetes, Type 2','High Blood Pressure'])
```

## 4.2.3. Naïve Bayes Classifier Algorithm

The Naïve Bayes classifier algorithm is a simple probabilistic classifier that is based on Bayes' theorem with a strong assumption of feature independence. It is commonly used for text classification tasks, such as spam filtering, sentiment analysis, and document categorization. Despite its simplicity, Naïve Bayes has shown to be effective in many real-world applications.

The algorithm is called "naïve" because it assumes that the features are conditionally independent of each other given the class label. This means that the presence or absence of a particular feature does not affect the presence or absence of any other feature. While this assumption rarely holds true in practice, Naïve Bayes can still produce reasonable results and is often computationally efficient.

**Example**

```
mnb_tf = MultinomialNB()
mnb_tf.fit(tfidf_train_2, y_train)
pred = mnb_tf.predict(tfidf_test_2)
score = metrics.accuracy_score(y_test, pred)
# st.write("accuracy:   %0.3f" % score)
cm = metrics.confusion_matrix(y_test, pred, labels=['Birth Control', 'Depression','Diabetes, Type 2','High Blood Pressure'])
plot_confusion_matrix(cm, classes=['Birth Control', 'Depression','Diabetes, Type 2','High Blood Pressure'])
```

### 4.2.4. TF-IDF Vectorizer

The vectorization general process of turning a collection of text documents into numerical feature vectors. This specific strategy (tokenization, counting and normalization) is called the Bag of Words or “Bag of n-grams” representation. Documents are described by word occurrences while completely ignoring the relative position information of the words in the document.

**Example**

```
fromsklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(stop_words='english', max_df=0.8)
tfidf_train_2 = tfidf_vectorizer.fit_transform(X_train)
tfidf_test_2 = tfidf_vectorizer.transform(X_test)
```

### 4.2.5. Extract Best Drugs

```
deftop_drugs_extractor(condition):
df_top = df[(df['rating']>=9)&(df['usefulCount']>=100)].sort_values(by = ['rating', 'usefulCount'], ascending = [False, False])
drug_lst = df_top[df_top['condition']==condition]['drugName'].head(10).tolist()
returndrug_lst
```

## 4.3. Presentation of development tools

During the development of this simple program we used

### 4.3.1. Anaconda.Navigator

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda® Distribution that allows you to launch applications and manage conda packages, environments, and channels without using command line interface (CLI) commands. Navigator can search for packages on Anaconda.org or in a local Anaconda Repository. It is available for Windows, macOS, and Linux[19]

[19] https://docs.anaconda.com/free/navigator/index.html

Figure 4.2: Anaconda.Navigator[20]

### 4.3.2. VS Code

Visual Studio Code is a lightweight but powerful source code editor which runs on your desktop and is available for Windows, macOS and Linux. It comes with built-in support for JavaScript, TypeScript and Node.js and has a rich ecosystem of extensions for other languages and runtimes (such as C++, C#, Java, Python, PHP, Go, .NET)[21]

Figure 4.3: Visual Studio Code Logo[22]

### 4.3.3. Python

Python is[23] an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for rapid application development, as well as for use as a scripting or glue language to connect existing components together. Python simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and

[20] https://mvolkmann.github.io/blog/python/anaconda/

[21] , [4] https://code.visualstudio.com/docs

[23] https://www.python.org

packages, which encourages program modularity and code reuse. The Python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms, and can be freely distributed.

This reference manual describes the syntax and “core semantics” of the language. It is terse, but attempts to be exact and complete. The semantics of non-essential built-in object types and of the built-in functions and modules are described in the Python Library Reference. For an informal introduction to the language, see the Python Tutorial. For C or C++ programmers, two additional manuals exist: Extending and Embedding the Python Interpreter describes the high-level picture of how to write a Python extension module, and the Python/C API Reference Manual describes the interfaces available to C/C++ programmers in detail.

Figure 4.4: Python programming language logo[24]

### 4.3.4. Streamlit

Streamlit[25] is a free and open-source framework to rapidly build and share beautiful machine learning and data science web apps. It is a Python-based library specifically designed for machine learning engineers. Data scientists or machine learning engineers are not web developers and they're not interested in spending weeks learning to use these frameworks to build web apps. Streamlit allows you to create a stunning-looking application with only a few lines of code.

[24] https://www.python.org

[25], [26] https://www.datacamp.com/tutorial/streamlit

Figure 4.50: Streamlit framework[26]

## 4.4. Results

This section shows the different results obtained by our system

### 4.4.1. Execute Program

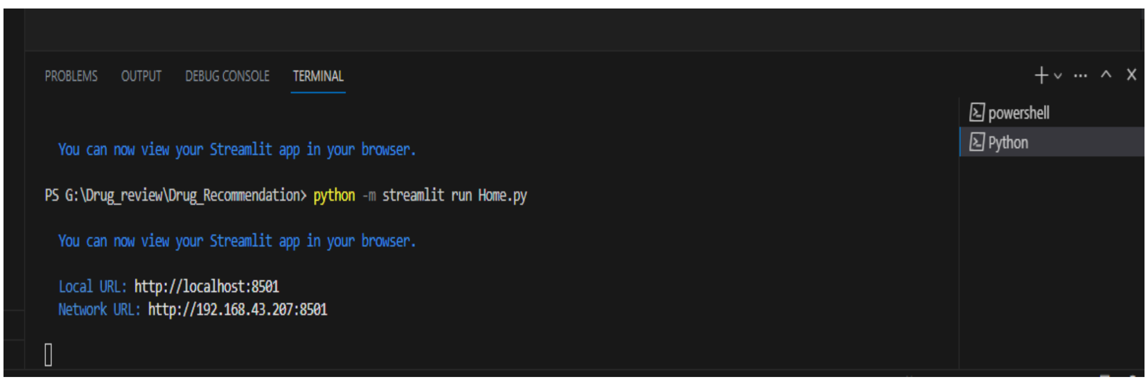



Figure 4.6: Execute App in Streamlit

### 4.4.2. Show Dataset

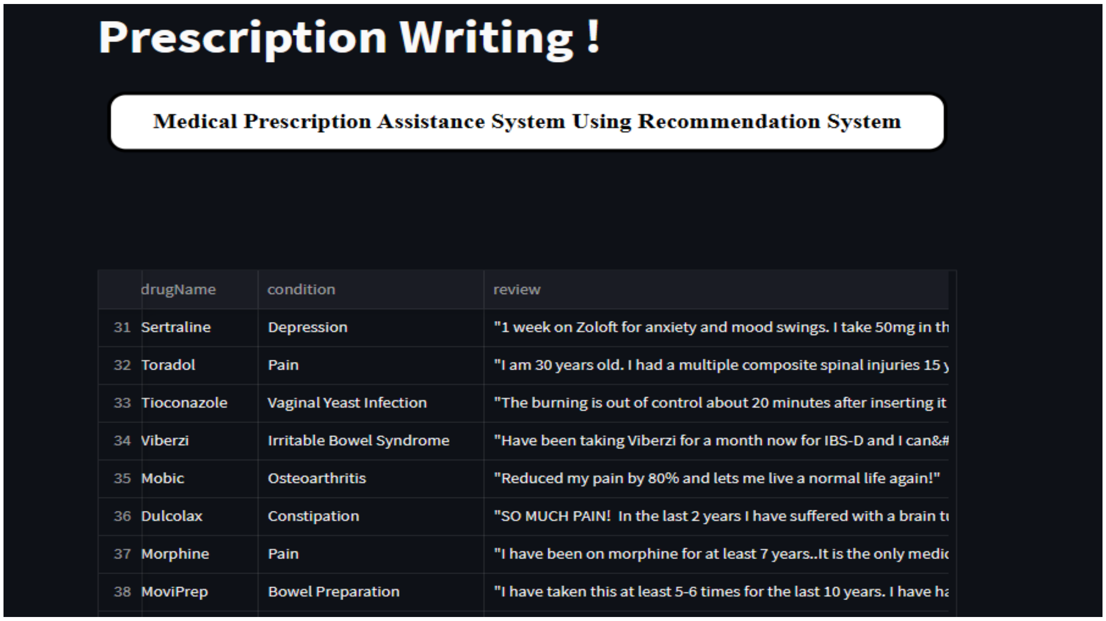



Figure 4.7: Show Dataset uses in Application

### 4.4.3. Present the patient's case

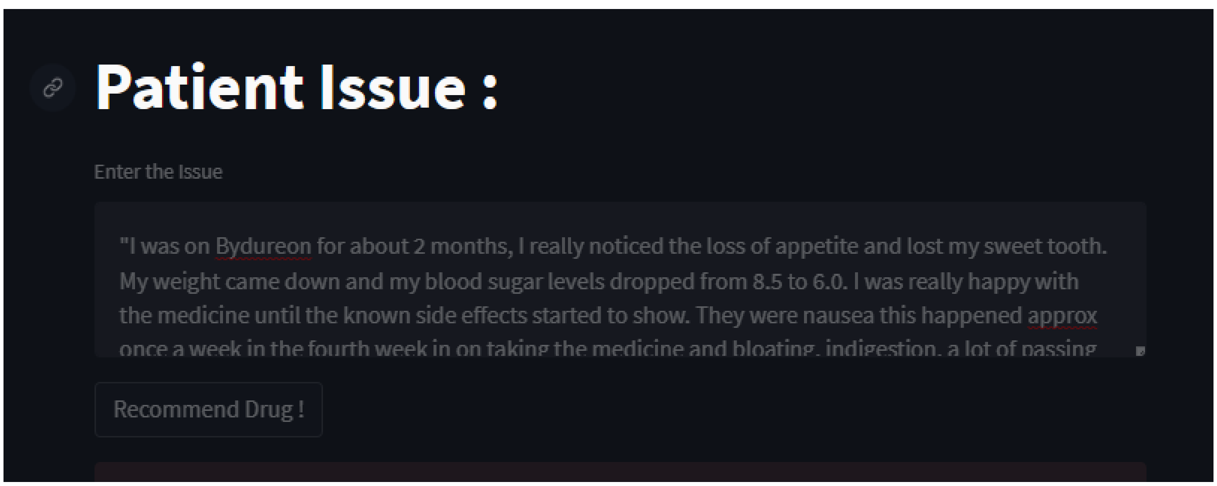



Figure 4.8: Form present Patient Issue

### 4.4.4. Result Drug Recommended

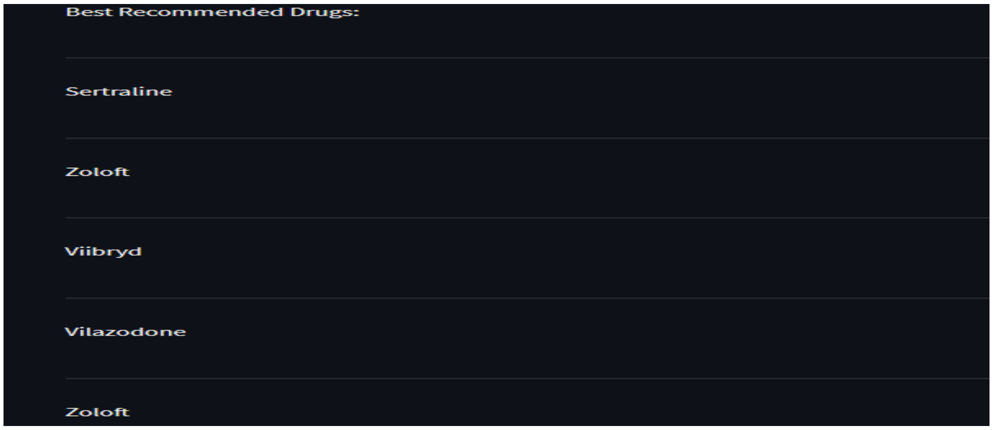



Figure 4.9: Show drug Recommended

### 4.4.5. Select Information for Patient

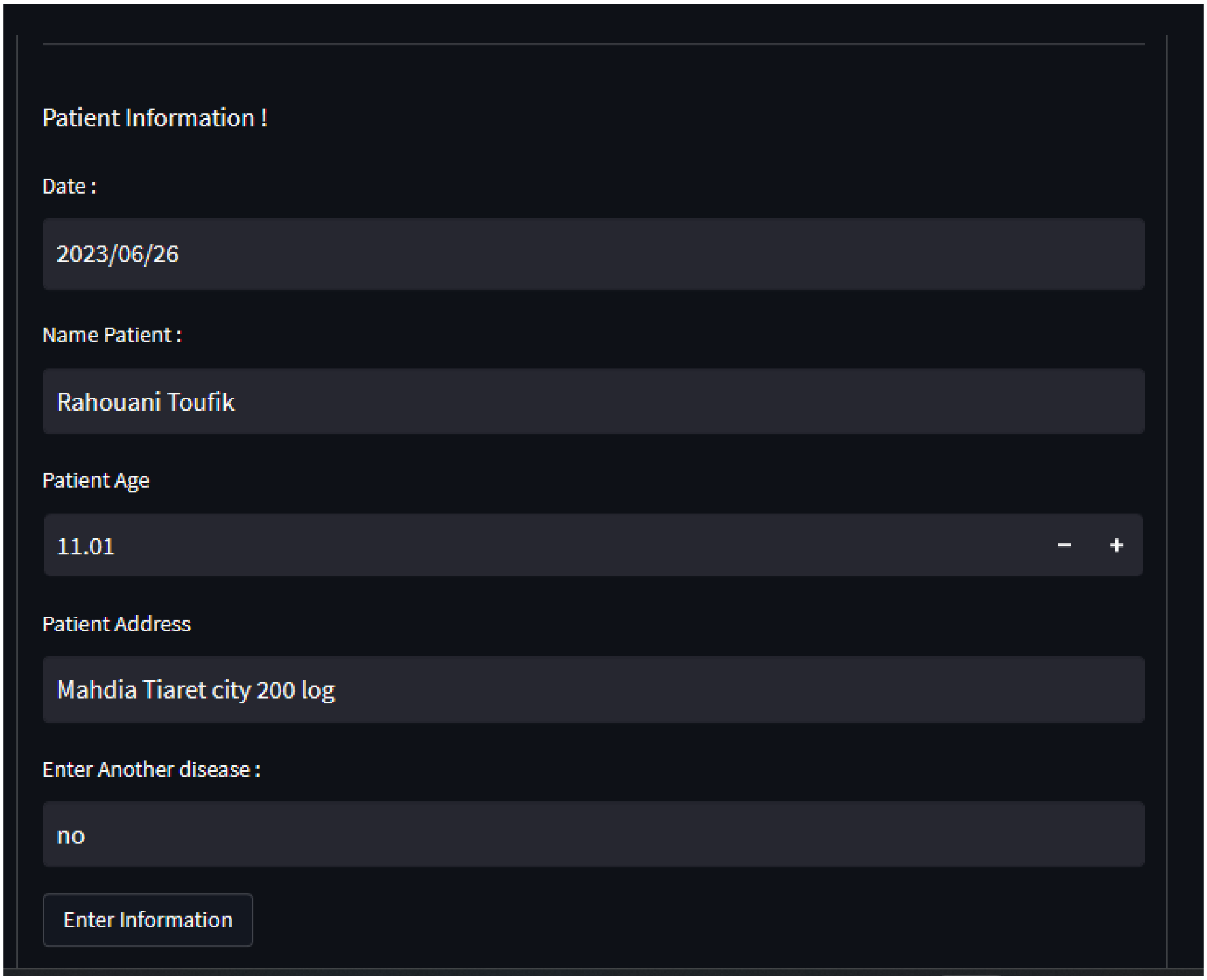



Figure 4.10: Form for Enter Information Patient

### 4.4.6. Select drug for Patient Children

After consulting the specialist doctor, children under 12 years of age

They may be prescribed one of these drugs Duloxetine; sertraline; Zoloft

And in a dose not exceeding 25mg, and at most only two medications ,

As for the elderly, most of the suggested medications can be prescribed to them

The dose can be increased from 50 mg to 100 mg

This is what we will see in the application.


Figure 4.11: Select Drug for Children

For Click button expert convert prescription to PDF File for print

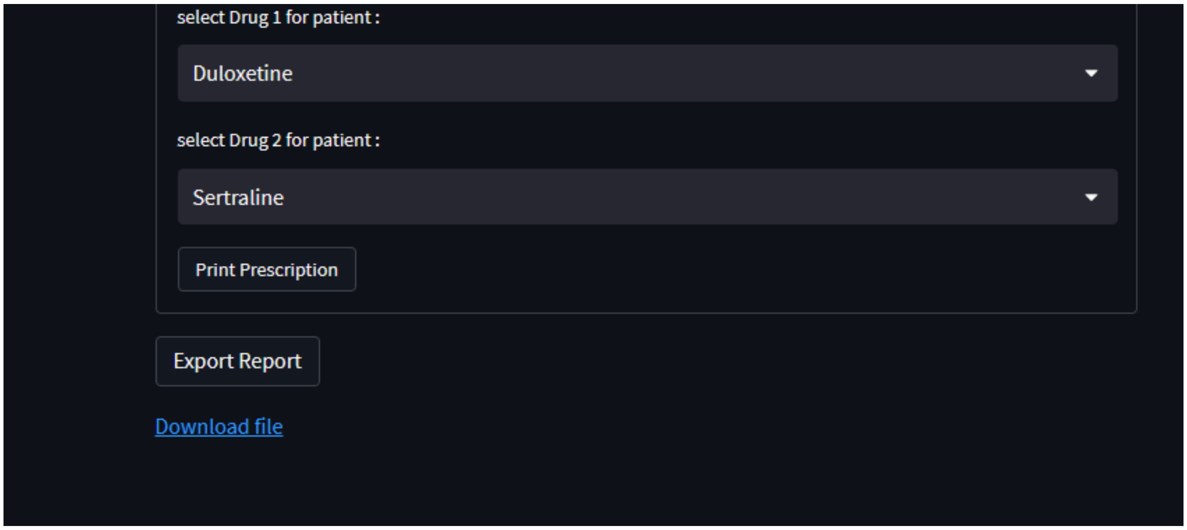



Figure 4.12: Download Prescription File PDF

## Download Prescription file PDF

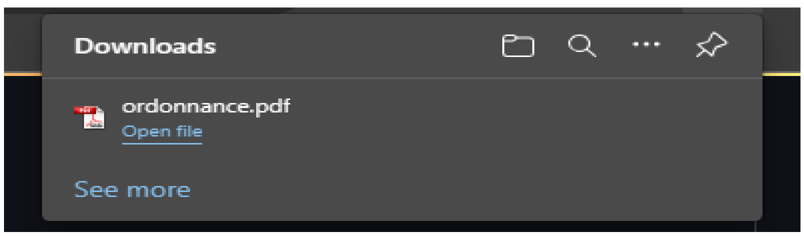



Figure 4.13: Prescription Download

**Show Result Prescription for Children**

Dr. Slaya Menad

**Specialist Général.**

Tel : 046463232.

--------------------------------------------------------------------------------

Name Patient : hamdane zitouni

Age : 10.0

Patient Address : challala tiaret

Ordonnance .

--------------------------------------------------------------------------------

1 -

Sertraline
25 Mg 2 cp / Day

--------------------------------------------------------------------------------

2 -

Duloxetine
25 mg 1 cp / Day

--------------------------------------------------------------------------------

Figure 4.14: Show Prescription PDF for children

### 4.4.7. Adult Patient

### Information for Adult Patient

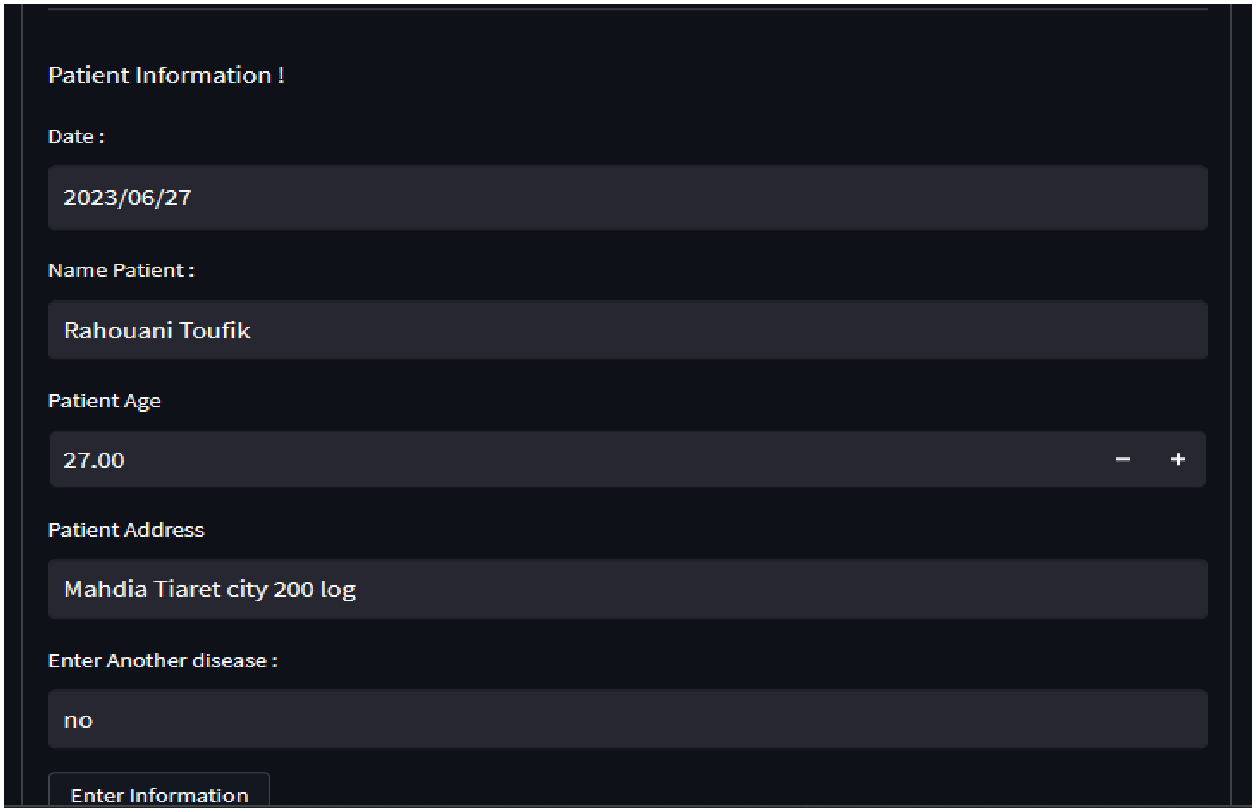



Figure 4.15: Enter Information for Patient Adult

### Select Drug for Adult Patient

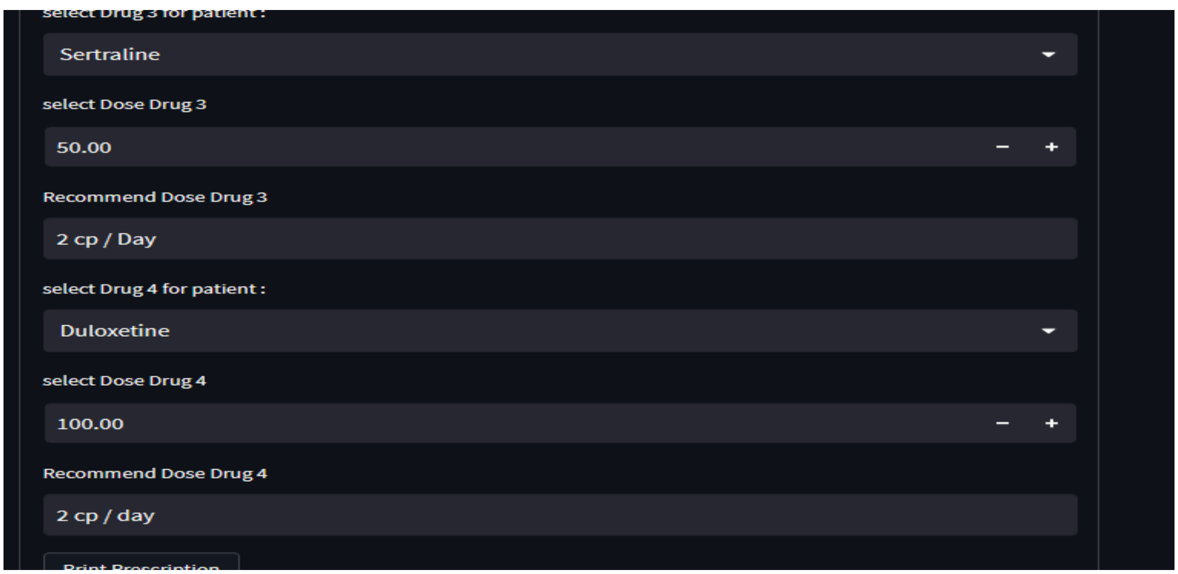
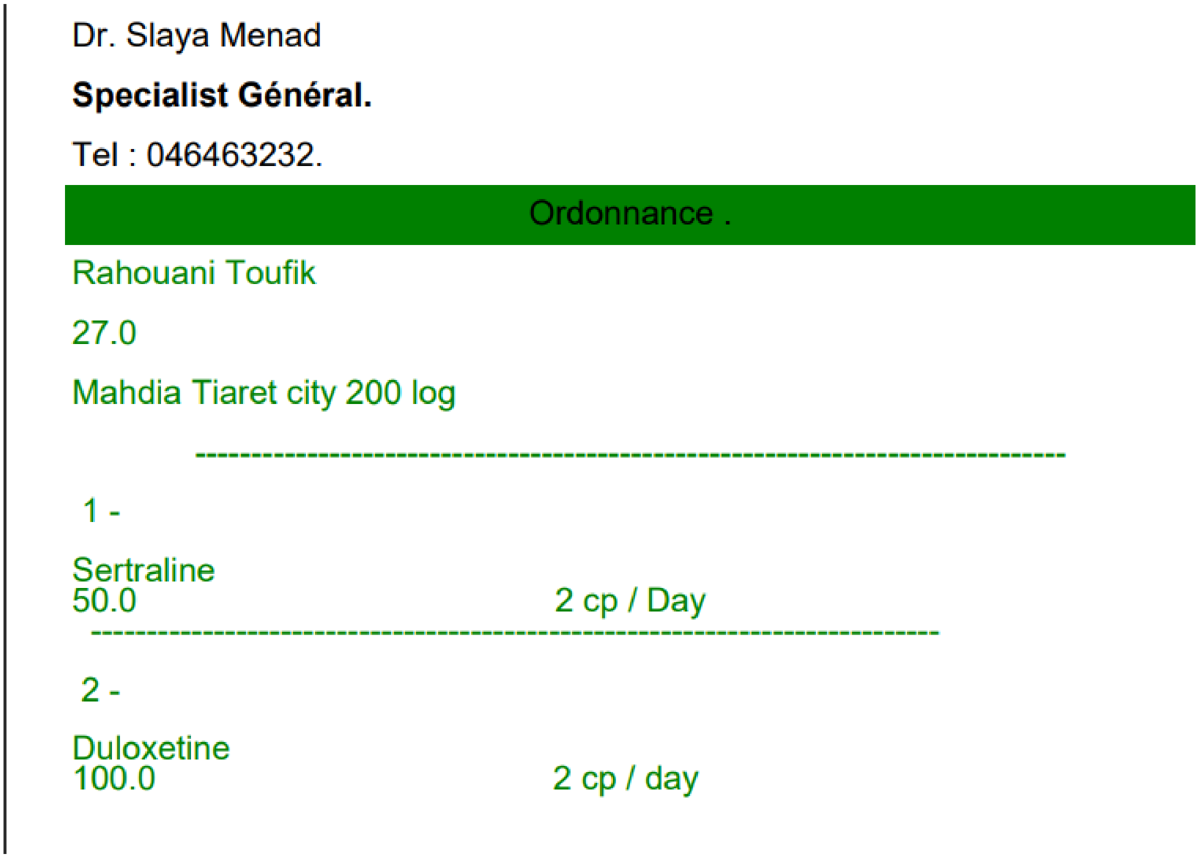



Figure 4.16: Select Drug

**Show Prescription in File PDF**



Dr. Slaya Menad

**Specialist Général.**

Tel : 046463232.

Ordonnance .

Rahouani Toufik

27.0

Mahdia Tiaret city 200 log

---

1 -

Sertraline
50.0 2 cp / Day

---

2 -

Duloxetine
100.0 2 cp / day

Figure 4.17: Show Prescription for Adult patient

## 4.5. Conclusion

In this chapter, we presented a recommendation system approach in medical prescription in order to improve the editorial quality of the latter. We also presented the different tools and languages that we used to implement our application. At the end, we presented the results of our application by giving some screenshots which better explains the purpose of our approach.

# General Conclusion

With the prevalence of information technology (IT), recommender system has long been acknowledged as an effective tool for addressing information overload problem. Furthermore, recommender systems have attracted substantial interest in various fields due to their ability to provide personalized recommendations to users.

In the health sector, these systems have shown great potential. In this context, they can help healthcare providers and patients in making informed decisions by providing personalized recommendations based on individual preferences, health conditions and medical history. These recommendations can range from suggesting appropriate treatments, medications, and healthcare providers to offering lifestyle recommendations for disease prevention and management.

In fact, interest in recommender systems in healthcare sector from the potential to enhance patient satisfaction, improve healthcare outcomes, optimize operations, and promote preventive healthcare. As technology continues to advance and more data becomes available, there is growing interest in exploring different applications and refining recommender systems to better support healthcare decision-making and patient care.

In the medical prescription domain, the recommendation system is attracting growing interest. Indeed, these systems have the potential to significantly improve healthcare outcomes by optimizing and personalizing medical prescription decisions.

The value of recommender systems in medical prescription arises from the potential to enhance patient outcomes, reduce medication errors, and support healthcare professionals in medical prescription.

Therefore, integrating recommender systems into medical prescription is becoming a necessity as they can help healthcare professionals make more informed decisions by providing personalized recommendations based on the patient's medical history, symptoms and other relevant factors. This can result in more accurate diagnoses and treatment plans, leading to improved patient outcomes. Recommender systems can also help reduce medical errors and adverse drug events.

In this project, we have tried to integrate recommender systems into medical prescription, so that they will provide an appropriate medical prescription that does not lead to adverse effects for patients. For this, we used content-based recommendation techniques the TF-IDF method to write a medical prescription automatically based on the patient's medical history which has similarities.

The choice of content-based recommender systems is justified by the simplicity and effectiveness of this type of recommendation. The objective of this work was to help doctors during medical prescription, improve the editorial quality of medical prescriptions, reduce medical errors and reduce the problem of misinterpretation of drug names by users and pharmacists. . This research came with a solution using medication recommendations to produce a relevant and appropriate medical prescription.

Finally, this work has made it possible to identify some perspectives:

This project can be approved at the level of health institutions and at the level of medical offices because of the actual training data,

In the future, other experiments can be performed using other data sets used in healthcare and comparing the model to a set of commonly used benchmarks to observe the effectiveness of the proposed method.

It will be interesting in the future to improve this system in order to be able to reduce other types of errors in medical prescription.

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