Smart Fashion Recommender Application

A PROJECT REPORT

Submitted By

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BONAFIDE CERTIFICATE

Certified that this project report “Smart Fashion Recommender Application” is the bonafide work of **“JANICE AUSTIN , INDERA SALIL BHARATI, JERUSHA MISHAL J,MAHALAKSHMI S , ANJU M”** who carried out the project work under my supervision.

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CHENNAI	**CHENNAI**

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OVERVIEW

In recent years, the textile and fashion industries have witnessed an enormous amount of growth in fast fashion. On e-commerce platforms, where numerous choices are available, an efficient recommendation system is required to sort, order, and efficiently convey relevant product content or information to users.
With technological advancements, this branch of artificial intelligence exhibits a tremendous amount of potential in image processing, parsing, classification, and segmentation. Despite its huge potential, the number of academic articles on this topic is limited.The available studies do not provide a rigorous review of fashion recommendation systems and the corresponding filtering techniques. To the best of the authors' knowledge, this is the first scholarly article to review the state-of-the-art fashion recommendation systems and the corresponding filtering techniques. In addition, this review also explores various potential models that could be implemented to develop fashion recommendation systems in the future.
This paper will help researchers,academics, and practitioners who are interested in machine learning, computer vision, and fashion retailing to understand the characteristics of the different fashion recommendation systems.

According to different studies, e-commerce retailers, such as Amazon, eBay, and Shopstyle, and social networking sites, such as Pinterest, Snapchat, Instagram, Facebook, Chictopia, and Lookbook, are now regarded as the most popular media for fashion advice and recommendations]. Research on textual content, such as posts and comments, emotion and information diffusion, and images has attracted the attention of modern-day researchers, as it can help to predict fashion trends and facilitate the development of effective recommendation systems. An effective recommendation system is a crucial tool for successfully conducting an e-commerce business. Fashion recommendation systems (FRSs) generally provide specific recommendations to the consumer based on their browsing and previous purchase history. Social-network-based FRSs consider the user's social circle, fashion product attributes, image parsing, fashion trends, and consistency in fashion styles as important factors since they impact upon the user's purchasing decisions. FRSs have the ability to reduce transaction costs for consumers and increase revenue for retailers.

LITERATURE SURVEY

- OBJECTIVE

The growing number of fashion e-commerce digital platforms, customers can see and choose from a massive number of virtual fashion products merchandised virtually. There has been a dramatic shift in customers' purchasing behaviour, which is impacted by several factors, such as social media, fashion events, and so forth. Consumers now increasingly prefer to select their products from the immense pool of options and want them to be delivered in a very short time. It is challenging for fashion retailers to fulfill consumer demands in a short time interval. Therefore, it is crucial for fashion apparel retailers to make efficient and quick decisions concerning inventory replenishment in advance based on the forecast of future demand patterns. The textile and apparel industries have grown tremendously over the last years. Customers no longer have to visit many stores, stand in long queues, or try on garments in dressing rooms as millions of products are now available in online catalogues. However, given the plethora of options available, an effective recommendation system is necessary to properly sort, order, and communicate relevant product material or information to users. Effective fashion RS can have a noticeable impact on billions of customers shopping experiences and increase sales and revenues on the provider-side. The goal of this survey is to provide a review of recommender systems that operate in the specific vertical domain of garment and fashion products. We have identified the most pressing challenges in fashion RS research and created a taxonomy that categorizes the literature according to the objective they are trying to accomplish (e.g., item or outfit recommendation, size recommendation, explainability, among others) and type of side-information (users, items, context). We have also identified the most important evaluation goals and perspectives (outfit generation, outfit recommendation, pairing recommendation, and fill-in-the-blank outfit compatibility prediction) and the most commonly used datasets and evaluation metrics.

References

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4. Y. Huang, C. H. Chen, I. H. C. Wang, and L. P. Khoo, "A product configuration analysis method for emotional design using a personal construct theory," *International Journal of Industrial Ergonomics*, vol.

44, no. 1, pp. 120–130, 2014.

View at: Publisher Site | Google Scholar

With the exception of a single study from 2016 that focuses only on apparel recommendation systems, no current research presents recent advances in research on fashion recommendation systems. Therefore, the purpose of this paper is to present an integrative review of the research related to fashion recommendation systems. Moreover, Guan et al. cited research published until 2015. Therefore, the first objective of this paper is to review the most recent research published on this topic from 2010 to 2020. The previous study did not provide an in-depth analysis of the computational methods or algorithms corresponding to the fashion recommendation systems. This review study aims to fulfill this research gap and rigorously study the principles underlying, the methods used by, and the performance of the state-of-the-art fashion recommendation systems. To the best of our knowledge, this in-depth study is first of its kind. It includes research articles related to image parsing, clothing and body shape identification, and fashion attribute recognition, which are critical parts of fashion recommendation systems (FRSs). This review paper also provides a guideline for a research methodology to be used by future researchers in this field. The first section of this review discusses the history and background of FRSs. The second section presents a concise history and overview of recommendation systems. The third section aims to integrate the scholarly articles related to FRSs published in the last decade. The fourth section defines the metrics that are used by researchers to present and discuss recommendation results. The fifth section forms the major part of this review and focuses on various FRSs followed by different computational algorithmic models and recommendation filtering techniques used in fashion recommendation research. It will help researchers to understand these crucial parts of a FRS. The final section highlighted the existing challenges of using state-of-the-art recommendation systems followed by providing recommendations to overcome them and proposing a novel FRS based on the research findings discussed in section five. The study of the existing literature revealed that fashion recommendation systems have a huge impact on consumers' buying decisions. Hence, fashion retailers and researchers are exploring and developing state-of-the-art recommendation models to improve the accessibility, navigability and consumers' overall purchasing experience. One of the prime elements that has been continuously researched in these articles was the improvement of existing and the development of new algorithms relevant to the filtering techniques.

Recommendation System

Recommendation system (RS) is referred to as a decision-making approach for users under a multidimensional information environment. RS has also been defined as an e-commerce tool, which helps consumers search based on knowledge that is related to a consumer's choices and preferences. RS also assists in augmenting social processes by using the recommendations of other users when there is no abundant personal information or knowledge of the alternatives . RS handles the complication of information overload that consumers usually encounter by offering customised service, exclusive content, and personalised recommendations. There are multiple phases involved in the recommendation system that develop the foundation of any state-of-the-art recommendation system. These are defined as the information collection phase, the learning phase, and the recommendation phase.The interrelationship of these phases involved in the recommendation process. It shows that information collection is the initial stage of RS, which is followed by the learning phase and the recommendation phase. The recommendation provided in the last phase can be generated based on information gathered during the information collection phase.

Recommendations can also be provided by combining the learned information with the rating matrix to recommend learning resources]. Researchers reported improved recommendation accuracy using hybrid models in comparison with product content-based or other user preference-based collaborative models. Articles published from January 2010 to June 2020 have been considered for the review purpose of this article. Various online literature resources or databases such as Scopus, Web of Science, Science Direct, and Design and Applied Arts Index (DAAI) have been used to find the literature. Boolean operator techniques i.e., "AND" or "OR" strategies were used to search articles from these sources. Keywords grouped in three categories as listed below were used to conduct the final search.

Group 1: Fashion OR Style OR Apparel OR Clothing.

Group 2: Recommend*.

Group 3: Filtering Technique OR Algorithm OR Model OR Artificial Intelligence OR Neural Network OR Deep Learning OR Meta-Learning OR Fuzzy Techniques OR Model OR Image Processing OR Image Retrieval OR Image Feature extraction.

Final Search = Group 1 AND Group 2, Group 1 AND Group 2 AND Group 3.

Overall, 230 scholarly articles and 9 web sources have been reviewed. Among these, 214 scholarly articles were found containing the required keywords when using the search strategy mentioned above. Among these, 132 articles are indexed in Scopus, 26 in Web of Science, 3 in Science Direct and 1 in the Design and Applied Arts Index (DAAI) database. In addition, 50 articles and 2 patents were found in Google Scholar, published in different peer-reviewed journals and conferences.

The performance of a recommendation algorithm is evaluated by using some specific metrics that indicate the accuracy of the system. The type of metric used depends on the type of filtering technique. Root Mean Square Error (RMSE), Receiver Operating Characteristics (ROC), Area Under Cover (AUC), Precision, Recall and F1 score is generally used to evaluate the performance or accuracy of the recommendation algorithms.

Root-mean square error (RMSE). RMSE is widely used in evaluating and comparing the performance of a recommendation system model compared to other models. A lower RMSE value indicates higher performance by the recommendation model. RMSE, as mentioned by, can be as represented as follows:

$$RMSE = \sqrt{\frac{1}{N_p} \sum_{u,i} (p_{ui} - r_{ui})^2} \tag{1}$$

where, Np is the total number of predictions, pui is the predicted rating that a user u will select an item i and rui is the real rating.

Precision. Precision can be defined as the fraction of correct recommendations or predictions (known as True Positive) to the total number of recommendations provided, which can be as represented as follows:

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \tag{2}$$

It is also defined as the ratio of the number of relevant recommended items to the number of recommended items expressed as percentages. Recall. Recall can be defined as the fraction of correct recommendations or predictions (known as True Positive) to the total number of correct relevant recommendations provided, which can be as represented as follows:

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \tag{3}$$

It is also defined as the ratio of the number of relevant recommended items to the total number of relevant items expressed as percentages.

F1 Score. F1 score is an indicator of the accuracy of the model and ranges from 0 to 1, where a value close to 1 represents higher recommendation or prediction accuracy. It represents precision and recall as a single metric and can be as represented as follows:

$$F1\ score = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Coverage. Coverage is used to measure the percentage of items which are recommended by the algorithm among all of the items.

Accuracy. Accuracy can be defined as the ratio of the number of total correct recommendations to the total recommendations provided, which can be as represented as follows:

$$Accuracy = \frac{TP + FN}{TP + FN + TN + FP} \tag{5}$$

Intersection over union (IoU). It represents the accuracy of an object detector used on a specific dataset .

$$IoU = \frac{TP}{TP + FN + FP} \tag{6}$$

ROC. ROC curve is used to conduct a comprehensive assessment of the algorithm's performance

AUC. AUC measures the performance of recommendation and its baselines as well as the quality of the ranking based on pairwise comparisons [5]. Rank aware top-N metrics. The rank aware top-N recommendation metric finds some of the interesting and unknown items that are presumed to be most attractive to a user. Mean reciprocal rank (MRR), mean average precision (MAP) and normalized discounted cumulative gain (NDCG) are three most popular rank aware metrics.

MRR. MRR is calculated as a mean of the reciprocal of the position or rank of first relevant recommendation MRR as mentioned by can be expressed as follows:

$$MRR = \frac{1}{N_u} \sum_{u \in N_u} \frac{1}{L_u^n [k] \in R_u} \tag{7}$$

where u, Nu and Ru indicate specific user, total number of users and the set of items rated by the user, respectively. L indicates list of ranking length (n) for user (u) and k represents the position of the item found in the he lists L. MAP: MAP is calculated by determining the mean of average precision at the points where relevant products or items are found. MAP as mentioned by can be expressed as follows.

$$MAP = \frac{1}{N_u |R_u|} \sum_{k=1}^{n} 1 (L_u^n [k] \in R_u) P_u@k \tag{8}$$

where Pu represents precision in selecting relevant item for the user. NDCG: NDCG is calculated by determining the graded relevance and positional information of the recommended items, which can be expressed as follows [65].

$$NDCG_u = \frac{\sum_{k=1}^{n} G(u, n, k) D(k)}{\sum_{k=1}^{n} G^* (u, n, k) D(k)} \tag{9}$$

where D (k) is a discounting function, G (u, n, k) is the gain obtained recommending an item found at k-th position from the list L and G* (u, n, k) is the gain related to k-th item in the ideal ranking of n size for u user. FRS can be defined as a means of feature matching between fashion products and users or consumers under specific matching criteria. Different research addressed apparel attributes such as the formulation of colors, clothing shapes, outfit or styles, patterns or prints and fabric structures or textures. Guan et al. studied these features using image recognition, product attribute extraction and feature encoding. Researchers have also considered user features such as facial features, body shapes, personal choice or preference, locations and wearing occasions in predicting users' fashion interests. A well-defined user profile can differentiate a more personalised or customised recommendation system from a conventional system. Various research projects on apparel recommendation systems with personalized styling guideline and intelligent recommendation engines have been conducted based on similarity recommendation and expert advisor recommendation systems. Image processing, image parsing, sensory engineering, computational algorithms, and computer vision techniques have been extensively employed to support these systems.

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1. Barnard, M. Fashion as Communication, 2nd ed.; Routledge: London, UK, 2008.
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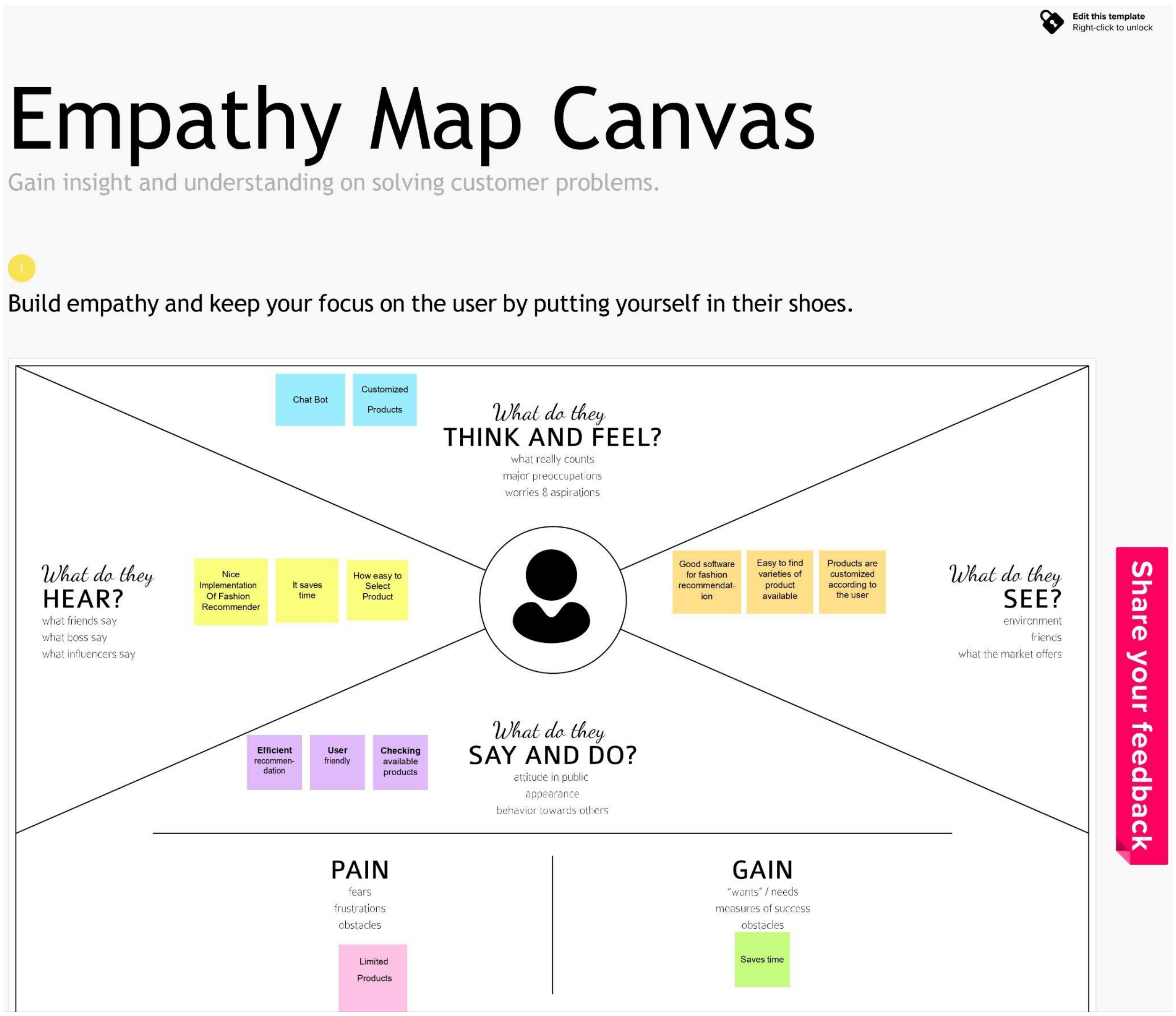
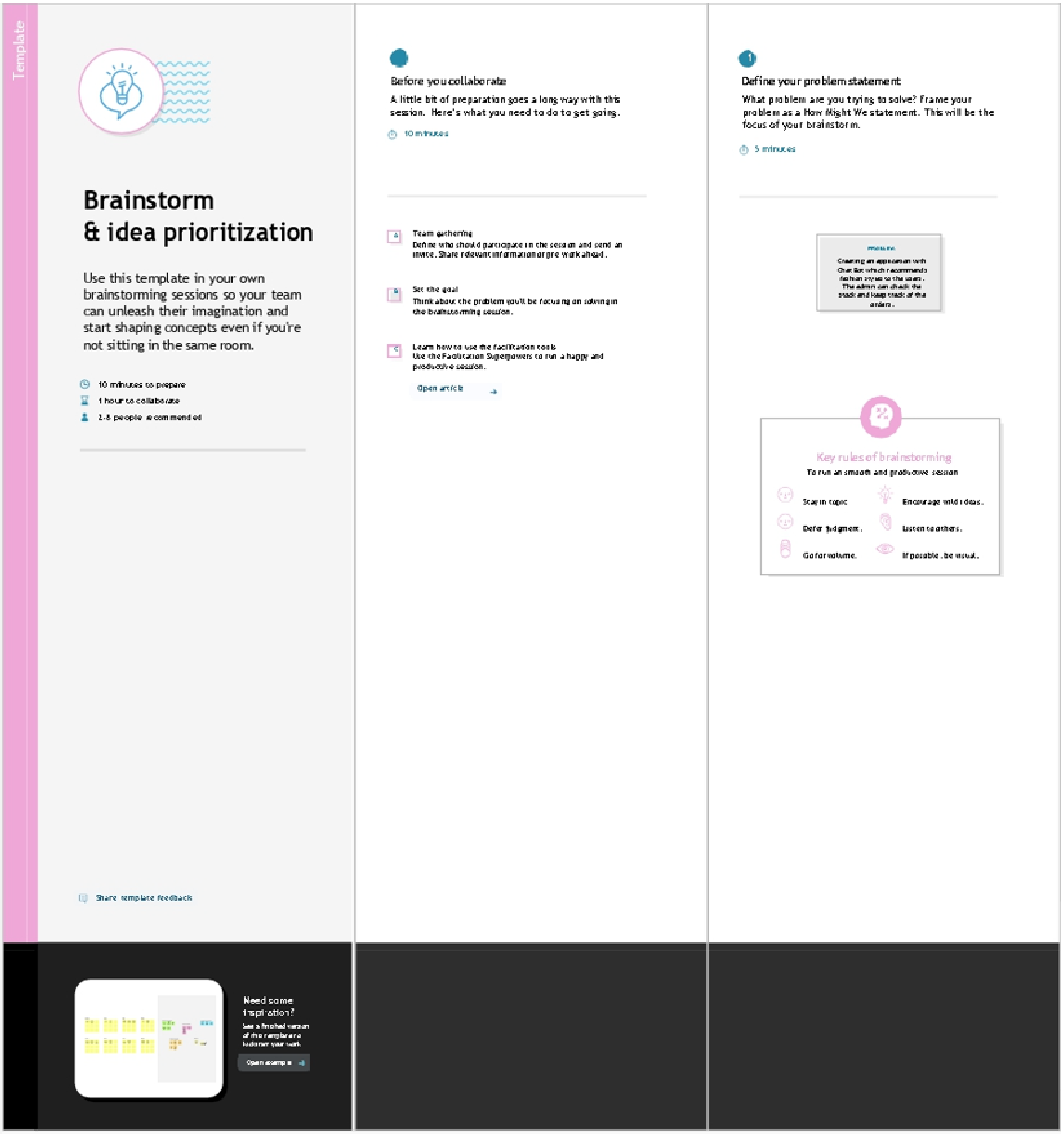
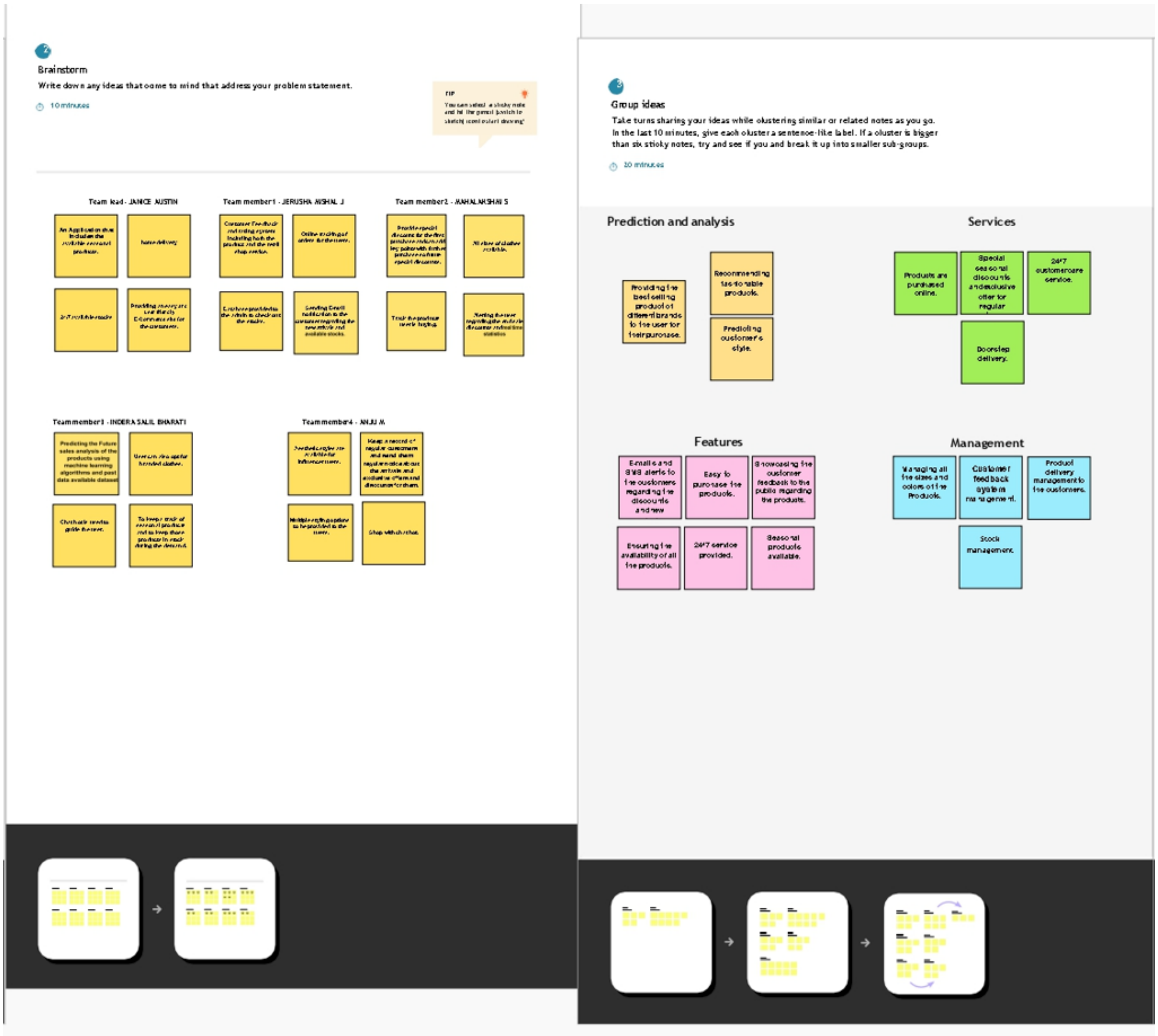
IDEATION & PROPOSED SOLUTION :

3.1. EMPATHY MAP CANVAS :



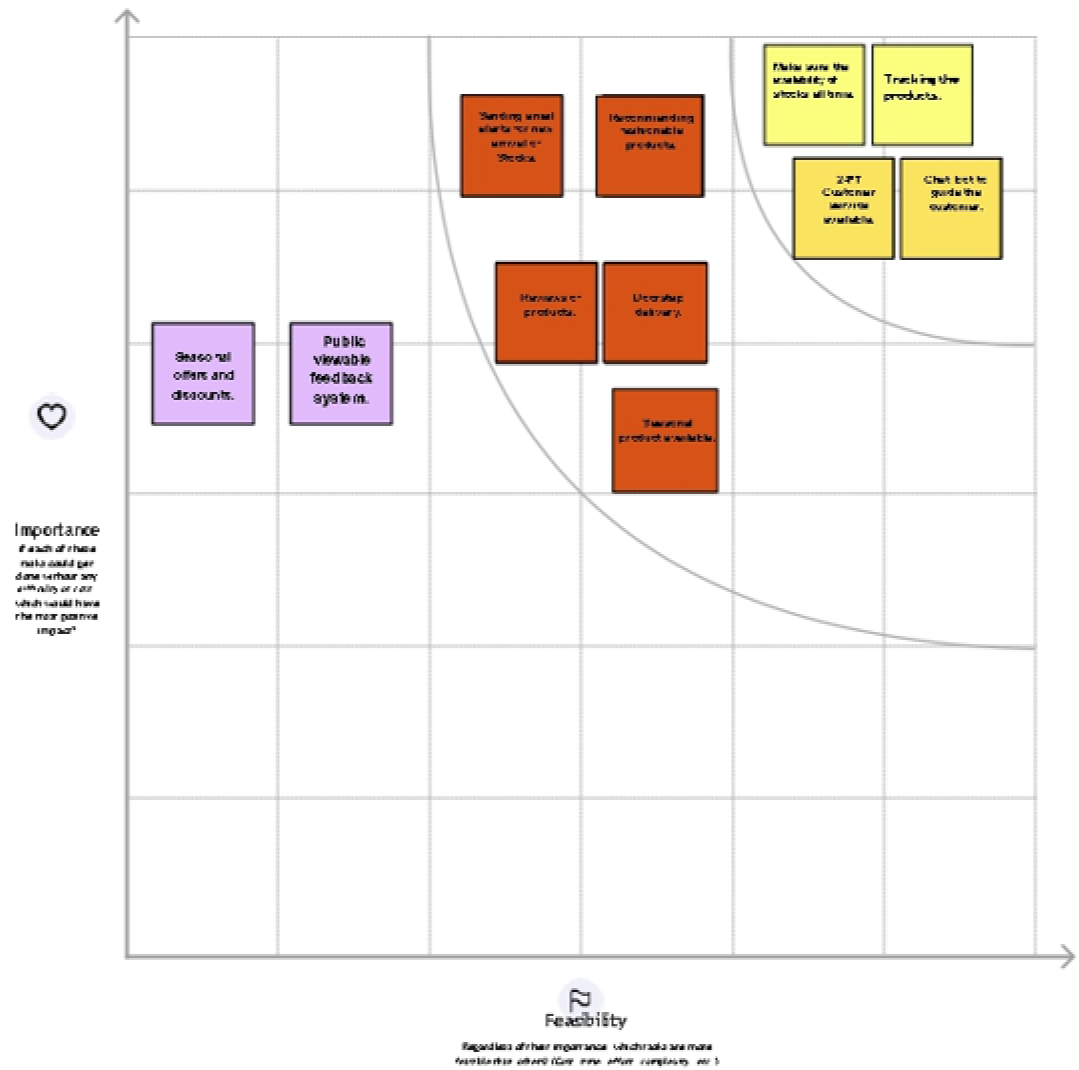

Template
Brainstorm
& idea prioritization
Use this template in your own brainstorming sessions so your team can unleash their imagination and start shaping concepts even if you're not sitting in the same room.
10 minutes to prepare
1 hour to collaborate
Share template feedback
Before you collaborate
A little bit of preparation goes a long way with this session. Here's what you need to do to get going.
10 minutes
Team gathering
Define who should participate in the session and send an invite. Share relevant information or pre-work ahead.
Set the goal
Think about the problem you'll be focusing on solving in the brainstorming session.
Learn how to use the facilitation tools
Use the Facilitation Superpowers to run a happy and productive session.
Open article
Define your problem statement
What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.
5 minutes
Key rules of brainstorming
To run an smooth and productive session
Stay in topic.
Encourage wild ideas.
Defer judgment.
Listen to others.
Go for volume.
If possible, be visual.
Need some inspiration?

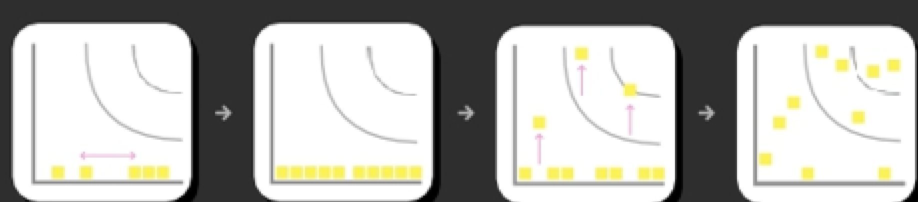

Brainstorm
Write down any ideas that come to mind that address your problem statement.
10 minutes
Team lead - JANICE AUSTIN
Team member1 - JERUSHA NISHAL J
Team member2 - MAHALAKSHMI S
Teammember3 - INDERA SALIL BHARATI
Predicting the Future sales analysis of the products using machine learning algorithms and past data available dataset
Teammember4 - ANJU M
Group ideas
Take turns sharing your ideas while clustering similar or related notes as you go. In the last 10 minutes, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.
20 minutes
Prediction and analysis
Providing the best selling product of different brands to the user for their purchase.
Recommending fashionable products.
Predicting customer's style.
Services
Products are purchased online.
Special seasonal discounts and exclusive offer for regular
24*7 customercare service.
Doorstep delivery.
Features
E-mails and SMS alerts to the customers regarding the discounts and new
Easy to purchase the products.
Showcasing the customer feedback to the public regarding the products.
Ensuring the availability of all the products.
24*7 service provided.
Seasonal products available.
Management
Managing all the sizes and colors of the Products.
Customer feed back system management.
Product delivery management to the customers.
Stock management.

Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

20 minutes





3.3. PROPOSED SOLUTION:

Proposed Solution:

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	As Fashion is not something that is only depends on personal taste or past activity of the customer, we seek to bring the dynamic and ever changing fashion industry in the hands of the people who do not have time to keep up with the up and coming trends
2.	Idea / Solution description	The user will login into the web application and go through the items which the website provides. The user can directly chat with the Chatbot regarding their needs.Thereby getting recommendations based on information provided by the user.
3.	Novelty / Uniqueness	This Web application will let the user decide clothes based Occasion, Type of Outfits and Aesthetics
4.	Social Impact / Customer Satisfaction	Customer Satisfaction will be attained as they will get a set of recommendations depending on their interests ,without requiring to go through tons of products for shortlisting
5.	Business Model (Revenue Model)	The chatbot is present to guide the customers. Admin can keep a track of stocks.
6.	Scalability of the Solution	The system must be scalable enough to maintain optimal performance during traffic

3.4. PROBLEM SOLUTION FIT :

Project Title:Smart Fashion Recommender Application **Project Design Phase-I - Solution Fit Template** **Team ID:** PNT2022TMID25340

Define CS, fit into CC

1. CUSTOMER SEGMENT(S) CS

- Online shopping persons all are our customers
- Shoppers who prefer the ease of contacting a chatbot to buy a product instead of search

6. CUSTOMER CONSTRAINTS CC

- Website speed and search function
- Customers cannot bargain
- Customer cannot bargain
- Customer can't able to touch the Product.
- Customer needs an active internet connection

5. AVAILABLE SOLUTIONS AS

- Quick finding of customer related products.
- Customer can return the product and exchanged it.
- If the product get delayed ,they can contact us and check the reason.

Explore AS, differentia

Focus on J&P, tap into BE, understand RC

2. JOBS-TO-BE-DONE / PROBLEMS J&P

- The chatbot helps in resolving customer queries.
- Availability
- Sort and show products relevant to customer.
- Track order option
- Refund and return policies.
- Customer Review

9. PROBLEM ROOT CAUSE RC

- Network issues
- Due to improper guidance , the customer can face difficulties while placing the order.
- Cross- Shopping
- Poor Logistics

7. BEHAVIOUR BE

- Complain in the Suggestion Area or Customer Care
- Identify the issue
- Cross check and compare with other sites
- Purchase the product and write a review •

Focus on J&P, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS TR

- Social proof and novelty
- No need to spend a lot of time searching for their style of clothing.

10. YOUR SOLUTION SL

- Chat bot will recommend the product and give detailed information about the product.
- We can compare various models or brands
- Write review to give their feedback about the product bought.

8. CHANNELS of BEHAVIOUR CH

ONLINE

- Chat with chatbot
- Buy items
- Less effort and can save time.

OFFLINE

- Search for a shop that sells their style
- Search for products

Identify strong TR & EM

4. EMOTIONS: BEFORE / AFTER EM

Feeling Sad and Frustration and unable to keep up with trends > Self Confidence is boosted and able to express themself

4. REQUIREMENT ANALYSIS:

4.1. FUNCTIONAL REQUIREMENT:

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form
FR-2	User Interaction	Confirmation via Email
FR-3	Display Products	Chat Bot recommends based on previous choices and preferences
FR-4	Purchasing Products	Payment done through third party
FR-5	Shipping Details	Shipping and Tracking details will be displayed in ChatBot in partnership with a logistics company
FR-6	Product Feedback	Will be obtained in a form

Non-functional Requirements:

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	The interface will be user-friendly
NFR-2	**Security**	The user data will be stored securely in IBM cloud.
NFR-3	**Reliability**	The system must perform without failure in 95 percent of use cases
NFR-4	**Performance**	The page must provide a quick response time in a desktop browser, including the rendering of text and images
NFR-5	**Availability**	The services are available 24/7
NFR-6	**Scalability**	The system must be scalable enough to maintain optimal performance during traffic

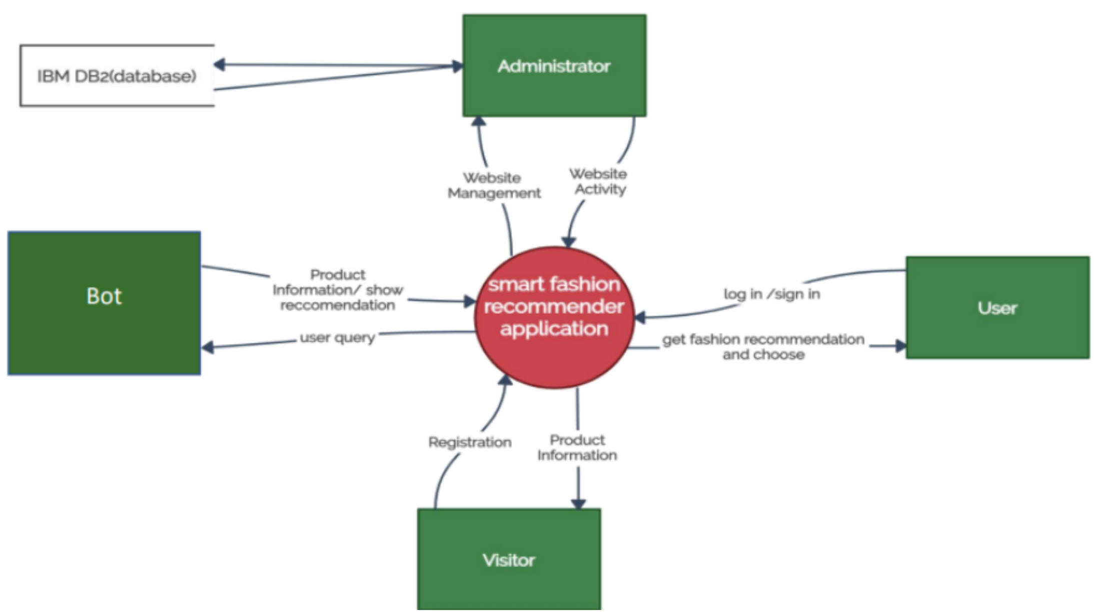
5. PROJECT DESIGN:

5.1. DATA FLOW DIAGRAMS:

Data Flow Diagrams:

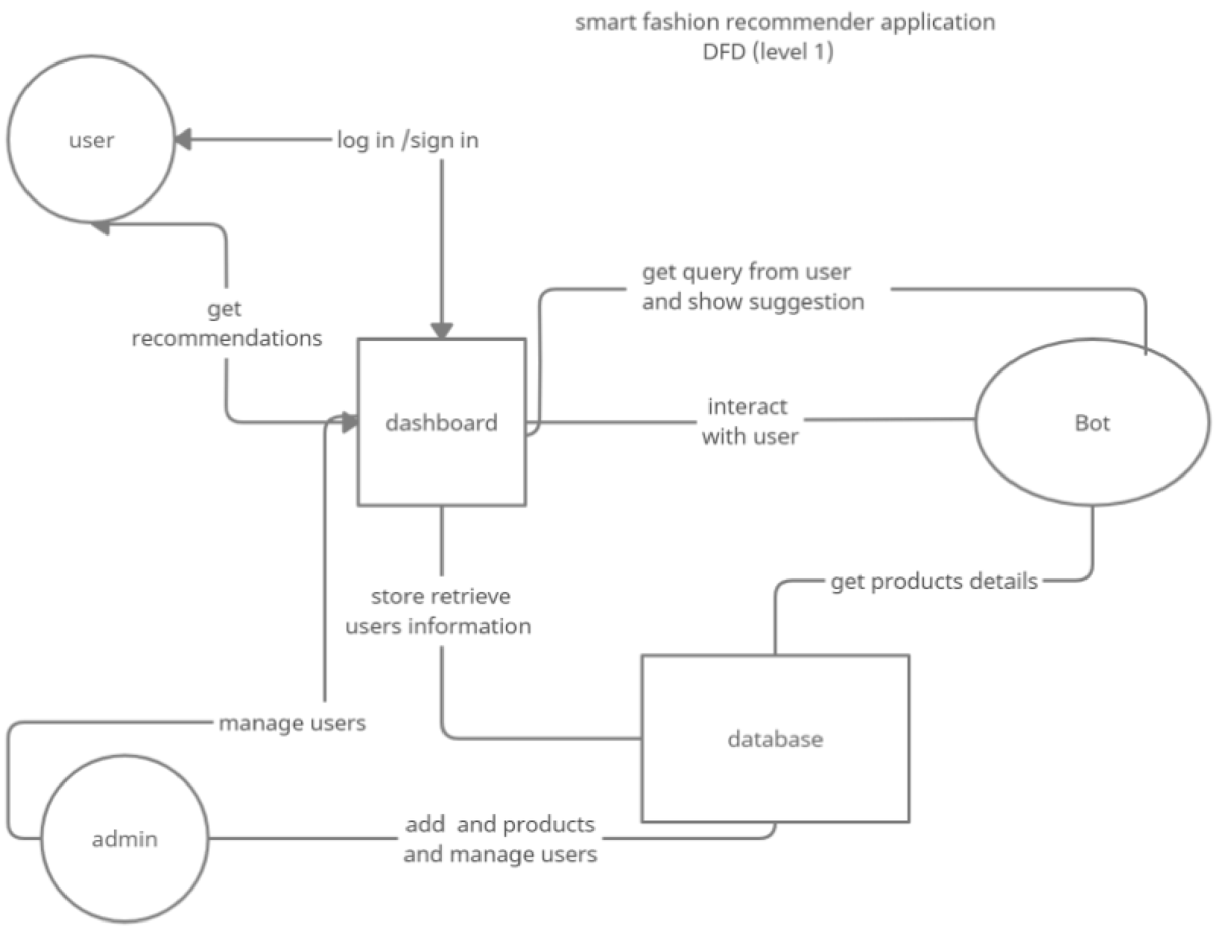
Data Flow Diagrams:

DFD (level 0):



5.2. SOLUTION & TECHNICAL ARCHITECTURE :

DFD (level 1):



User Stories

User Type	Functional Requirement (Epic)	User Story Number / User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1 As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2 As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1

		USN-3 As a user, I can register for the application through Gmail	I can use my gmail credentials instead of manually entering my details	Medium	Sprint-1
	Login	USN-4 As a user, I can log into the application by entering email & password	I can retrieve my information	High	Sprint-1
	Dashboard	USN-5 As a user, I can continue my old progress	I can continue where I left	Medium	Sprint-1
	chatbot	USN-6	I can interact with the bot	Medium	Sprint-2
Customer (Web user)	Registration	USN-1 As a user, I expect a bot to assist me	I can access my profile	High	Sprint-1
Customer Care Executive	login Dashboard Chatbot Contact with Customers	USN-2 As a user, I will receive a confirmation and greeting mail from the web application USN-3 As a user, I can register for the application through Gmail USN-4 As a user, I can log into the application by entering email & password USN-5 As a user , I can view the dashboard and by products USN-6 As a user, I expect a bot to assist me USN-7 As a Customer customers care executive, I solve the customer Requirements and feedback	I can receive the confirmation and greeting mail I can use my gmail credentials instead of manually entering my details I can retrieve my profile I can continue where I left I can interact with the bot I can receive calls from customers	High Medium High Medium High High	Sprint-1 Sprint-1 Sprint-1 Sprint-2 Sprint-1 Sprint-1
Administration	Login	USN-1 As a admin, login on admin page	I can access admin menu	High	Sprint-2
		USN-2 As a admin, access the admin menu using admin credentials	I can log in using admin credentials	High	Sprint-2
	Dashboard	USN - 3 As a admin, manage the application through admin panel	I can access admin panel	High	Sprint-3
		US N - 4 As a admin, add and remove available products from database	I can access database	High	Sprint-3
	Check stock and Price , orders	USN-8 As a Administrator , I can Check the database And stock details and buying and selling prices	I am the administrator of the company	High	Sprint-1

6. PROJECT PLANNING & SCHEDULING:
6.1. SPRINT PLANNING & ESTIMATION:

Product Backlog, Sprint Schedule, Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story points	Priority	Team Members
Sprint-1	Setting up App environment	USN-1	As a user, I can register in ICTA Academy and create IBM cloud account.	2	High	Mahalakshmi
Sprint-1		USN-2	As a user, I will create a flask project	1	Low	Janice Austen
Sprint-1		USN-3	As a user, I will install IBM Cloud CLI	2	Medium	Jerusha Mishal J
Sprint-2	Setting up App environment	USN-4	As a user, I can install Docker CLI	1	Low	Indera salil Bharati
Sprint-2		USN-5	As a user, I will Create an account in sendgrid	2	Medium	Anju M
Sprint-3	Implementing web application	USN-6	As a user, I Create UI to interact with the application	1	High	Janice Austen Indera Salil Bharati
Sprint-3		USN-7	As a user, I Create IBM DB2 and connect with Python	3	High	Mahalaks

						hmi Jerusha Mishal J
Sprint-3	Integrating sendgrid service	USN-8	As a user, I will integrating sendgrid with python code	2	High	Janice Austen Anju M
Sprint-3	Developing a chatbot	USN-9	As a user, I have to build a chatbot and Integrate to application	1	Medium	Jerusha Mishal Indera Salil Bharati
Sprint-4	Development of App in IBM Cloud	USN-10	As a user, I will Containerize the App	1	Low	Mahalakshmi Jaince Austen
Sprint-4		USN-11	As a user, I will upload image to IBM Container registry	2	Medium	Anju M Jerusha Mishal
Sprint-4		USN-12	As a user, I will deploy App in Kebernetes cluster	3	High	Indera Salil Bharati
Sprint-4	User panel		As a Users, • Register, Login, Email, • Verification • Manual Search • Order placement, Order	3	High	Jaince Austen Indera Salil Bharati Mahalakshmi Jerusha Mishal Anju M

			• Details			

7. CODING & SOLUTIONING:
7.1. FEATURE 1:

HTML CODE FOR LOGIN

```
<html>
<head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width,
    initial-scale=1"> <title>Bootstrap demo</title>
    <link
href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/css/bootstrap.min.cs
s" rel="stylesheet" integrity="sha384-
Zenh87qX5JnK2Jl0vWa8Ck2rdkQ2Bzep5IDxbcnCeuOxjzrPF/et3URy9Bv1WTRi "
crossorigin="anonymous">
    <link rel="stylesheet" href="/images/css/styles.css">

  </head>
<section class="h-100 gradient-form" style="background-color:
  #eee;"> <div class="container py-5 h-100">
    <div class="row d-flex justify-content-center align-items-center
      h-100"> <div class="col-xl-10">
        <div class="card rounded-3 text-black">
          <div class="row g-0">
            <div class="col-lg-6">
              <div class="card-body p-md-5 mx-md-4">

                <div class="text-center">
                  <img src="/images/products-img/logo.jpeg"
                    style="width: 185px;" alt="logo">
                    <h4 class="mt-1 mb-5 pb-1">We are The Ingenious Minds</h4>
                </div>

                <form action="/mainpage" method="POST">
                    <% if (messages.error){ %>
```

```
                <div class="alert alert-danger">
                    <strong><%= messages.error %></strong>
                </div>
              <% } %>
            <p>Please login to your account</p>

            <div class="form-outline mb-4">
                <input type="email" name="email" class="form-control"
                  placeholder="name or email address" />
              <label class="form-label"
for="form2Example11">Email</label>
            </div>

            <div class="form-outline mb-4">
                <input type="password" name="password" class="form
control" />
              <label class="form-label"
for="form2Example22">Password</label>
            </div>

            <div class="text-center pt-1 mb-5 pb-1">
            <button class="btn btn-primary btn-success" type="submit"
>Log
                in</button></a>



                <a class="text-muted" href="#!">Forgot password?</a>
            </div>

            <div class="d-flex align-items-center
justify-content-center pb-4">
                <p class="mb-0 me-2">Don't have an account?</p>
                <button type="button" class="btn btn-outline-warning"
onclick="myFunction()">Create new</button>
              <script>
               function myFunction(){
                      window.location.href="/register";
                  }
                </script>

            </div>

          </form>
```

```
          </div>
        </div>
        <div class="col-lg-6 d-flex align-items-center
          gradient-custom-2"> <div class="text-white px-3 py-4 p-md-5
          mx-md-4">
              <h4 class="mb-4 title">Smart Fashion Recommender
Application</h4>
              <p class="small mb-0 sub">We have come up with a new
innovative solution through which you can directly do your online shopping
based on your choice without any search. It can be done by using the
chatbot. </p>
          </div>
        </div>
      </div>
    </div>
   </div>
  </div>
 </div>
</section>

<script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/js/bootstrap.bundle.m
in .js" integrity="sha384-
OERcA2EqjJCMA+/3y+gxIOqMEjwtxJY7qPCqsdltbNJuaOe923+mo//f6V8Qbsw3 "
crossorigin="anonymous"></script>
</html>
```

CSS CODE FOR LOGIN

```
<html>
<head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width,
    initial-scale=1"> <title>Bootstrap demo</title>
    <link
href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/css/bootstrap.min.cs
s" rel="stylesheet" integrity="sha384-
Zenh87qX5JnK2Jl0vWa8Ck2rdkQ2Bzep5IDxbcnCeuOxjzrPF/et3URy9Bv1WTRi "
crossorigin="anonymous">
    <link rel="stylesheet" href="/images/css/styles.css">

  </head>
<section class="h-100 gradient-form" style="background-color:
```

```
#eee;"> <div class="container py-5 h-100">
   <div class="row d-flex justify-content-center align-items-center
     h-100"> <div class="col-xl-10">
       <div class="card rounded-3 text-black">
         <div class="row g-0">
           <div class="col-lg-6">
             <div class="card-body p-md-5 mx-md-4">

               <div class="text-center">
                 <img src="/images/products-img/logo.jpeg"
                   style="width: 185px;" alt="logo">
                 <h4 class="mt-1 mb-5 pb-1">We are The Ingenious Minds</h4>
               </div>

               <form action="/mainpage" method="POST">
                   <% if (messages.error){ %>
                         <div class="alert alert-danger">
                             <strong><%= messages.error %></strong>
                         </div>
                       <% } %>


                 <p>Please login to your account</p>

                 <div class="form-outline mb-4">
                     <input type="email" name="email" class="form-control"
                       placeholder="name or email address" />
                   <label class="form-label"
for="form2Example11">Email</label>
                 </div>

                 <div class="form-outline mb-4">
                     <input type="password" name="password" class="form
control" />
                   <label class="form-label"
for="form2Example22">Password</label>
                 </div>

                 <div class="text-center pt-1 mb-5 pb-1">
                 <button class="btn btn-primary btn-success" type="submit"
>Log
                     in</button></a>
```

```
                        <a class="text-muted" href="#!">Forgot password?</a>
                    </div>

                    <div class="d-flex align-items-center
justify-content-center pb-4">
                        <p class="mb-0 me-2">Don't have an account?</p>
                        <button type="button" class="btn btn-outline-warning"
onclick="myFunction()">Create new</button>
                      <script>
                       function myFunction(){
                              window.location.href="/register";
                          }
                         </script>

                    </div>
                  </form>

                </div>
              </div>
              <div class="col-lg-6 d-flex align-items-center
                gradient-custom-2"> <div class="text-white px-3 py-4 p-md-5
                mx-md-4">
                    <h4 class="mb-4 title">Smart Fashion Recommender
Application</h4>
                    <p class="small mb-0 sub">We have come up with a new
innovative solution through which you can directly do your online shopping
based on your choice without any search. It can be done by using the
chatbot. </p>
                </div>
              </div>
            </div>
          </div>
        </div>
      </div>
    </div>
</section>

<script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/js/bootstrap.bundle.m
in .js" integrity="sha384-
OERcA2EqjJCMA+/3y+gxIOqMEjwtxJY7qPCqsdltbNJuaOe923+mo//f6V8Qbsw3 "
crossorigin="anonymous"></script>
</html>
```

HTML CODE FOR REGISTRATION

```
<html lang="en">
  <head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width,
    initial-scale=1"> <title>Bootstrap demo</title>
    <link
href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/css/bootstrap.min.cs
s" rel="stylesheet" integrity="sha384-
Zenh87qX5JnK2Jl0vWa8Ck2rdkQ2Bzep5IDxbcnCeuOxjzrPF/et3URy9Bv1WTRi "
crossorigin="anonymous">
  </head>
  <section class="vh-100" style="background-color: #eee;">
  <div class="container h-100">
   <div class="row d-flex justify-content-center align-items-center h-100">
      <div class="col-lg-12 col-xl-11">
        <div class="card text-black" style="border-radius:
          25px;"> <div class="card-body p-md-5">
            <div class="row justify-content-center">
                <div class="col-md-10 col-lg-6 col-xl-5 order-2 order-lg-1">

                  <p class="text-center h1 fw-bold mb-5 mx-1 mx-md-4
mt-4">Sign up</p>

                  <form class="mx-1 mx-md-4" action="/register" method="POST">

                    <% if (messages.error){ %>
                          <div class="alert alert-danger">
                              <strong><%= messages.error %></strong>
                          </div>
                        <% } %>



                    <div class="d-flex flex-row align-items-center mb-4">
                      <i class="fas fa-user fa-lg me-3 fa-fw"></i>
                      <div class="form-outline flex-fill mb-0">
                        <input type="text" name="name" id="form3Example1c"
class="form-control" />
                        <label class="form-label" for="form3Example1c">Your
Name</label>
                    </div>
                  </div>
```

```
                    <div class="d-flex flex-row align-items-center mb-4">
                      <i class="fas fa-envelope fa-lg me-3 fa-fw"></i>
                      <div class="form-outline flex-fill mb-0">
                        <input type="email" name="email" id="form3Example3c"
class="form-control" />
                        <label class="form-label" for="form3Example3c">Your
Email</label>
                      </div>
                    </div>

                    <div class="d-flex flex-row align-items-center mb-4">
                      <i class="fas fa-lock fa-lg me-3 fa-fw"></i>
                     <div class="form-outline flex-fill mb-0">
                        <input type="password" name="password"
id="form3Example4c" class="form-control" />
                      <label class="form-label"
for="form3Example4c">Password</label>
                      </div>
                    </div>
                        <div class="form-check d-flex justify-content-center
                             mb-5"> <input class="form-check-input me-2"
                                            type="checkbox"
value="" id="form2Example3c" />
                      <label class="form-check-label" for="form2Example3">
                        I agree all statements in <a href="#!">Terms of
service</a>
                      </label>
                    </div>

                   <div class="d-flex justify-content-center mx-4 mb-3 mb-lg
4">
                        <button type="submit" class="btn btn-primary btn
lg">Register</button>
                    </div>

                  </form>

                </div>
                <div class="col-md-10 col-lg-6 col-xl-7 d-flex align-items
center order-1 order-lg-2">

                     <img src="https://mdbcdn.b-cdn.net/img/Photos/new
templates/bootstrap-registration/draw1.webp"
                    class="img-fluid" alt="Sample image">
```

```
              </div>
            </div>
          </div>
        </div>
      </div>
    </div>
  </div>
</section>
 <script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.2/dist/js/bootstrap.bundle.m
in .js" integrity="sha384-
OERcA2EqjJCMA+/3y+gxIOqMEjwtxJY7qPCqsdltbNJuaOe923+mo//f6V8Qbsw3 "
crossorigin="anonymous"></script>
 </html>
```

CONCLUSION

Recommendation system (RS) is referred to as a decision-making approach for users under a multidimensional information environment. RS has also been defined as an e-commerce tool, which helps consumers search based on knowledge that is related to a consumer's choices and preferences. RS also assists in augmenting social processes by using the recommendations of other users when there is no abundant personal information or knowledge of the alternatives . RS handles the complication of information overload that consumers usually encounter by offering customised service, exclusive content, and personalised recommendations. There are multiple phases involved in the recommendation system that develop the foundation of any state-of-the-art recommendation system. These are defined as the information collection phase, the learning phase, and the recommendation phase.The interrelationship of these phases involved in the recommendation process. It shows that information collection is the initial stage of RS, which is followed by the learning phase and the recommendation phase. The recommendation provided in the last phase can be generated based on information gathered during the information collection phase.