Master of Technology

Intelligent Reasoning System Project

Advanced Gym Recommender (AGR)

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1. EXECUTIVE SUMMARY

Exercise is undeniably an important aspect in our lives due to the countless benefits it brings such as reduction in chronic health issues, improvement in muscle strength and boosting our mental well-being. However, adopting an exercise routine may prove challenging to many as they do not possess adequate knowledge on the physical anatomy of the body and proper selection of exercises to meet their fitness goals. Engaging gym trainers may also not be a cost-effective solution due to the need to conduct dedicated personalisation for each individual. On the other hand, gym trainers may face difficulty in managing the requirements and schedules of their clients, and to design innovative exercise routines for them. With these challenges in mind, our team has designed an intelligent cognitive reasoning system, Advanced Gym Recommender (AGR), to enhance the exercise experience of our potential users.

Acquisition of exercise knowledge was conducted via data mining and manual elicitation, to extract key information and insight of our targeted fitness domain. The knowledge was represented in the form of rules, and was further incorporated into a flowchart model. A hybrid-reasoning system was developed to provide exercise recommendations at different stages of user experience. For the first pass recommendation, feature discovery was done via word count vectorisor approach and cosine similarity was applied to the user's implicit preferences. In subsequent recommendations, a model based collaborative filtering algorithm was implemented to extract user and item latent features, and the top set of predicted item scores was recommended to the user. Using the derived user latent features, similar profiles of users could be constructed and recommended as exercise companions to motivate users and improve the retention rate of our application.

Our cognitive reasoning system interfaces the backend algorithms with an interactive frontend UI to obtain and display relevant information. This was implemented using the Django web framework, which serves to connect the database memory and the reasoning backend engine to the frontend application. The frontend UI utilises the reactJS framework to provide an interactive and straightforward experience to our users, and also for our application to retrieve user data with ease. The collected user data are stored in a SQL database, which was designed with well defined data types and structure, to maintain the scalability, accessibility and integrity of our data. From the frontend UI, users may also access our database of exercise knowledge and routine records to monitor and customise their exercise routines.

The AGR application provides a full stack solution to exercise recommendation for the users of the fitness industry. Implementation of our project was demonstrated in a case study provided, highlighting the user experience from the frontend UI to the backend reasoning output. Finally, future improvements to the project in terms of data accuracy and scalability were also discussed.

2. PROBLEM STATEMENT & OBJECTIVES

2.1. Problem Statement

2.1.1. Exercise: Benefits, Needs & Challenges

Cultivating an exercise habit has an ever-increasing emphasis in our lives due to the many positive benefits it brings. An increase in physical activity can reduce the risk of chronic health issues such as heart disease, high blood pressure and Type 2 diabetes, in addition to maintaining bone and muscle strength. Exercising also helps to boost our emotional and psychological well-being by improving blood flow through the body and by releasing positive chemicals known as Endorphins, which is reported to relieve stress, uplift our mood and improve our energy levels [1]. This is especially relevant in today's world where many are increasingly leading sedentary lifestyles, consuming unhealthy diets and facing high levels of mental stress. In this aspect, the Singapore government have been promoting an active lifestyle by launching campaigns such as 'National Steps Challenge' and 'Move It', to cultivate an exercise habit among Singaporeans. Guidelines by the Health Promotion Board recommend at least 150 minutes of moderate to vigorous physical activity per week to reap the benefits of an active lifestyle [2].

However, picking up or adopting an exercise routine may prove daunting for many due to the lack of knowledge on the physical anatomy of the body and the wide range of exercises to choose from [3]. Psychological barriers which manifest in the form of embarrassment and self-consciousness of one's own body also hinder them from visiting the gym and seeking professional help. Often, many do not continue their exercise programs due to the lack of progress which arises from mismatched exercises that do not contribute to their training goals effectively [4, 5]. While signing up for a personal trainer may help new users better understand their exercise goals and personalise their training regime, often such personalised services are costly due to the need to cater to individual needs and differences, which may not be an affordable solution to many.

Personal/gym trainers on the other hand also face issues to cater the demands of gym users. New users often do not have much knowledge on exercise and hence are unable to communicate their training goals accurately. This makes it more difficult for trainers to design effective training programs for them. The need to cater to demanding customer schedules have also led to burnout in many personal trainers, as they are required to work extended hours in order to meet up with their clients [6, 7]. Assigning trainers on shift basis may not be viable due to the lack of understanding of user exercise preference. With the rise of online platforms and home exercises, gym businesses face a disruption to their operations as more users choose other exercise alternatives, which may provide more flexibility in terms of time schedule and exercise choices [8]. As such, gym businesses are required to adapt to technological changes to reach out to their customers more effectively.

2.2. Market Research

2.2.1. Fitness industry market size and trends

In 2020, the global gym industry is reported worth $96.7 billion and has approximately more than 184 million gym members worldwide [9]. It has an estimated growth rate of 2.9% per annum with a projected membership of 230 million by 2030 [10]. The rising interest in fitness is also apparent in Singapore, where there are about 2.9 million gym users in 2019, with an approximate increase of 470,000 from the year before. Even amid a pandemic, the gym, health and fitness market in Singapore was expected to generate $0.2 billion of revenue in 2020, and this translates to a compound annual growth rate (CAGR) of 2% between 2016 and 2020 [11, 12].

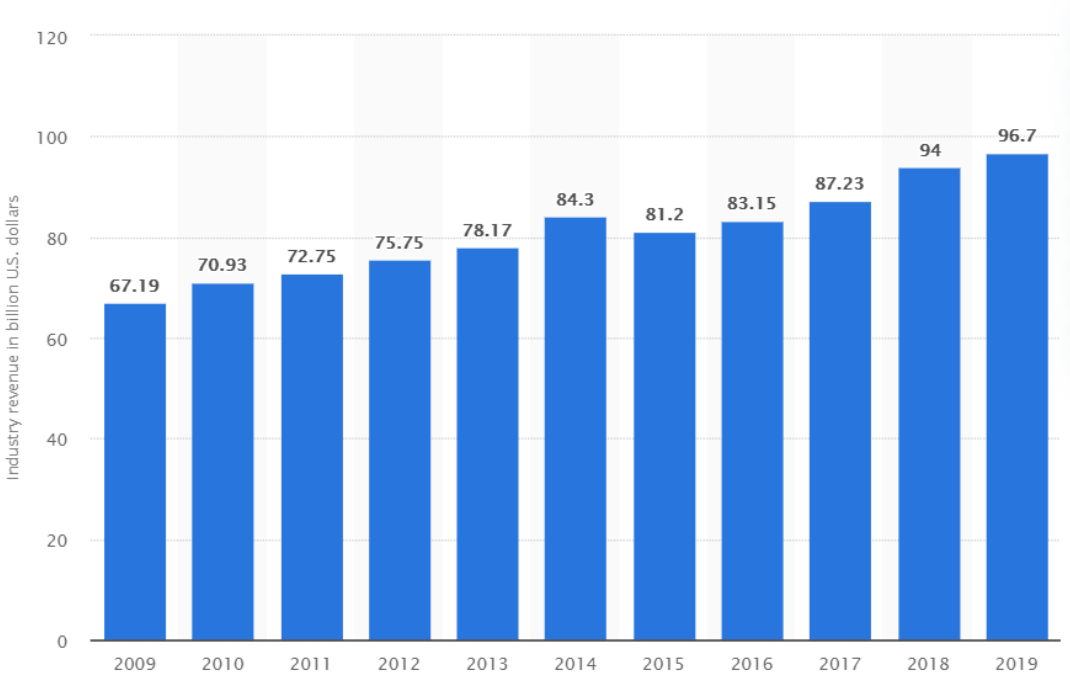


Figure 1: Market size of the global gym industry from 2009 to 2019 [9].

As reported by the Singapore Ministry of Culture, Community and Youth, a higher proportion of Singapore residents are participating in physical activity on a regular basis. 32.1% of Singapore residents engaged in regular exercise (1 to 2 times a week) in 2017, up from 27.6% in 2015. Participation in frequent exercise (a least 3 times a week) saw a larger increase from 26.4% to 35.9% during the same period [13]. Hence, the above statistics indicate an increase of interest towards physical activity, which generates a greater demand for goods and services in the health and fitness sector.

Table 1: Sports/Exercise participation rate of Singapore residents [13].

	2015	**2016**	**2017**
Regularly (1-2X/Week) Proportion of Singapore residents who had participated in some form of sports/exercise one to two times a week in the past three months.	27.6%	30.9%	32.1%
Frequently (at least 3X/Week) Proportion of Singapore residents who had participated in some form of sports/exercise at least thrice a week in the past three months.	26.4%	30.1%	35.9%

2.2.2. Emergence of digital fitness

With the introduction of online exercise and fitness apps, also known as "digital fitness", it has gained rising interest amongst exercise users, due to the convenience and flexibility to customise workout routines and plan exercise schedules according to different exercise goals. Cost effectiveness has also been cited as a top reason for using digital platforms, as such digital products are priced much lower than gym memberships [14, 15]. On average, subscription to exercise apps cost up to $15 a month, as compared to gym memberships at an average range of $65 - 125 per month. On top of gym membership, engaging a personal trainer may incur additional costs of around $50 – 86 per session. Table 2 below shows the price of gym membership and personal training in Singapore, while Table 3 shows the subscription price for fitness applications.

Table 2: Selected gym outlets and pricing [16, 17].

Gym name	Number of outlets across Singapore	Gym membership pricing	Personal trainer pricing
Anytime Fitness	69	From $90 / month	$150 for 3 sessions
Dennis Gym	4	From $64 / month	$157 for 3 sessions
Fitness First	18	From $125 / month	From $54 / session
Gymmboxx	7	From $65 / month	From $86 / session
Safra EnergyOne	6	From $80 / month	Not available

The global fitness app market size is expected to grow at a compounded rate of 21.6% from 2021 to 2028, with a current valuation of US$ 4.4 billion in 2020. With increasing penetration of digital platforms led by smartphones, 77% of the world population is expected to have mobile subscription by 2025. This would provide substantial market potential for applications providing personalised fitness programs. For example, MyFitness Pal app generated USD 6.7 million in revenue in 2020 for providing personalised activity and diet tracking [18].

2.2.3. Existing fitness application products, features and pricing

There have been several fitness personalisation apps launched in the past few years. More notable ones include MyFitness Pal, Nike Training Club, Runtastic and Fitbit Premium, which are developed by leading fitness brands such as Fitbit, Nike and Adidas. Table 3 below summarises the key features of these products.

Table 3 Selected fitness application products, features and cost [19, 20, 21, 22, 23, 24].

Product Name	Features	Number of Users	Pricing
MyFitnessPal	• Contains exercise database with >350 exercises with number of calories burnt. • Includes food and meal management.	200 million	$9.99 / month
Nike Training Club	• Access to over 190 workouts across strength, endurance, yoga and mobility. • Workout collection allows users to discover new workouts recommended by Nike Trainers.	1.8 million	$14.99 / month
Adidas Training/Running App	• Select from more than 190 exercises with HD videos for each exercise. • Guided videos by expert trainers and athletes	150 million	$9.99 / month
JEFIT Workout Planner Gym Log App	• Create your own custom workout plans and log your exercises. • Database containing over 1400 exercises.	5 million	$6.99 / month
Sworkit	• Collections include over 400 individual exercises and 300 unique workouts. • Able to customize workout time, length of each exercise and rest breaks. • Create custom workout from scratch.	10 million	$9.99 / month
Fitbit Premium	• Has a 'Challenge' function to motivate and compete with other users. • Includes wellness report and health coaching.	> 500,000	$9.99 / month

2.2.4. Areas for improvement

While fitness applications are gaining popularity for their ability to create customised workout routines based on user goals, users may find it difficult to sift through a large database to select and add exercises. Furthermore, users with less exposure to fitness concepts may not be able to find exercises which suit their preferences. For example, having to filter through over 1000 exercises in JEFIT database and figure out which might be closely related to the exercises you have previously liked may be time consuming and laborious. Hence, the process of creating workout routines may pose as a troublesome experience for some.

In addition, users with less workout experience may want to be exposed to exercises that they might not have tried before. Such recommendations can be done by matching other users of similar exercise preferences, and cross-recommending exercises from their routines. This ensures that the exercise recommendations are both unique and relevant at the same time.

Reports have indicated that building social connections are important to developing exercise habits. When working out in groups, users tend to run/cycle 21% further and workout 10% longer, while uploading 3 times more activities [25]. Social support, motivation and accountability are factors that help users to follow through their workout routines in the long run [26, 27].

Although some fitness applications allow access to online communities, it may be difficult to find users of closely matching exercises habits. This is a crucial component as exercise companions have to be compatible in terms of fitness level, exercise preferences and target goals. With databases containing millions of users, querying for exercise preferences and suitable user profiles are unlikely to be feasible without data-driven approaches.

2.3. Project Scope and Objectives

This project aims to build upon the existing fitness applications by addressing the areas for improvement as outlined in the above section:

- Item knowledge discovery to accelerate filtering of exercises.
- Use of model-based recommender system to curate unique and relevant workout routines.
- User-user recommendations to promote group exercises and improve app retention rate.

In order to develop a system for intelligent exercise recommender, the following components are to be included:

- Extraction of domain knowledge and design of business rules
- Data mining of exercise database & knowledge discovery of item features
- Optimisation of recommender system via model-based approach
- Development of interactive frontend UI

The intelligent exercise recommender system designed by our group will be deployed to assist exercise users in crafting workout routines that meet their exercise goals. Hybrid AI-enabled personalisation will be used to match user preferences through a combination of rule-based, similarity-based and collaborative filtering reasoning techniques. Our exercise reasoning system will enhance the existing solutions to provide an upgraded platform for the users of the fitness industry.

3. SOLUTION

3.1. Knowledge Modelling & Acquisition

3.1.1. Knowledge Acquisition

Before knowledge modelling can be implemented, some information is necessary to be gathered and reviewed to build up the initial knowledge base for the project. Various sources of information were pursued, from existing state-of-art to domain knowledge from websites and subject matter experts. More information of this can be found in the table below.

Table 4 Knowledge Acquisition Information and Insights Summary

Information source	Insights gained	Knowledge acquisition technique
Exercise recommender apps	• Provided the understanding of current state-of-art. • Provided the general framework for UI flow.	Manual elicitation through searching various
Fitness websites	• Provided information on general exercise goals for gym-goers. • Provided general information on fitness and workouts.	Web scrapping to obtain publicly available/documented information
Exercise enthusiast	Personal insights into the troubles of exercising in the gym such as: • Noticing beginners not knowing what to do in gym. • Providing input on what he as a non-beginner would find useful for an exercise recommender system.	Elicitation of tacit knowledge through the conduct of interview
Exercise information websites	• Provided information on exercises. • Provided ideas for exercise filtering categories.	Web scrapping to obtain publicly available/documented information

3.1.2. *Knowledge Representation*

After acquiring the data required for the project, the next step is to represent the knowledge. Representation of the knowledge involves the formalizing of description, conventions, and structure of information to make it usable by computer systems in an intelligent system.

First, based on the knowledge acquired we formalized the categorical data we will utilize in our recommender system as seen below:

Fitness level	Goals	Muscle groups	Exercise type
Beginner	General fitness	Abs	Cardio
Intermediate	Focused muscle building	Back	Olympic Weight Lifting
Advanced	Endurance training	Biceps	Powerlifting
		Chest	Strength
		Forearm	Stretching
		Glutes	
		Shoulders	
		Triceps	
		Upper legs	
		Lower legs	

Figure 2: Knowledge Data Type and Categories.

After defining the categorical data to be used, formal logic rules are then created with the categorical data:

Rules

WHEN personal fitness level = advanced
THEN exercise difficulty = expert OR intermediate

WHEN personal fitness level = intermediate
THEN exercise difficulty = intermediate or beginner

WHEN personal fitness level = beginner
THEN exercise difficulty = beginner

WHEN fitness mode = general fitness
THEN exercise type = ALL

WHEN fitness mode = muscle building
THEN exercise type = strength

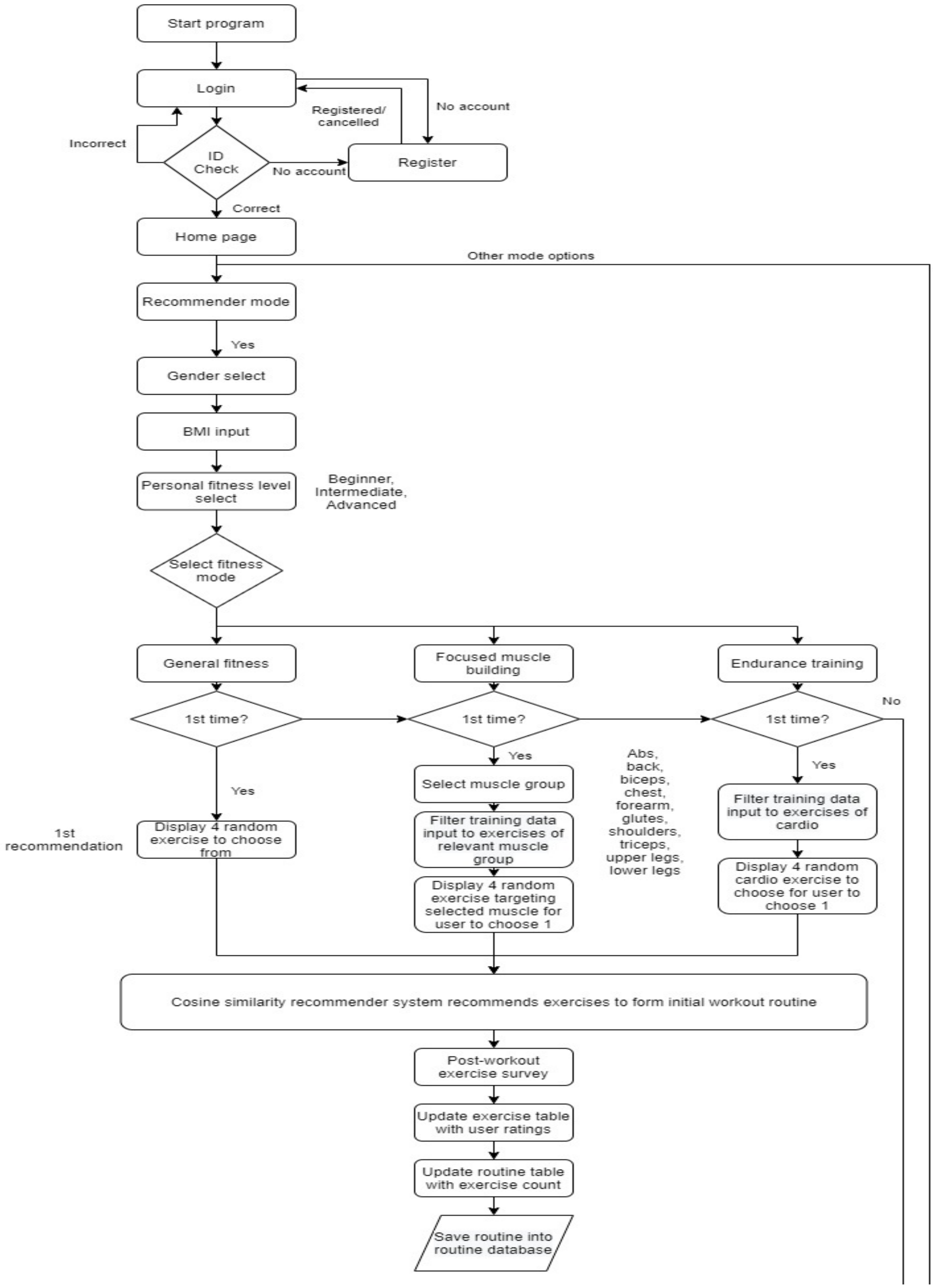
WHEN fitness mode = muscle building
THEN FILTER by MainMuscleGroup

WHEN fitness mode = endurance training
THEN exercise type = cardio

Figure 3: Knowledge Rules and Logical Inference.

3.1.3. Knowledge Implementation (Model)

Combining the tacit knowledge acquired, the categorical data and associated rules we develop the Flowchart to model the intelligent system. This guides the flow of how the knowledge and rules are utilized in a typical user workflow.



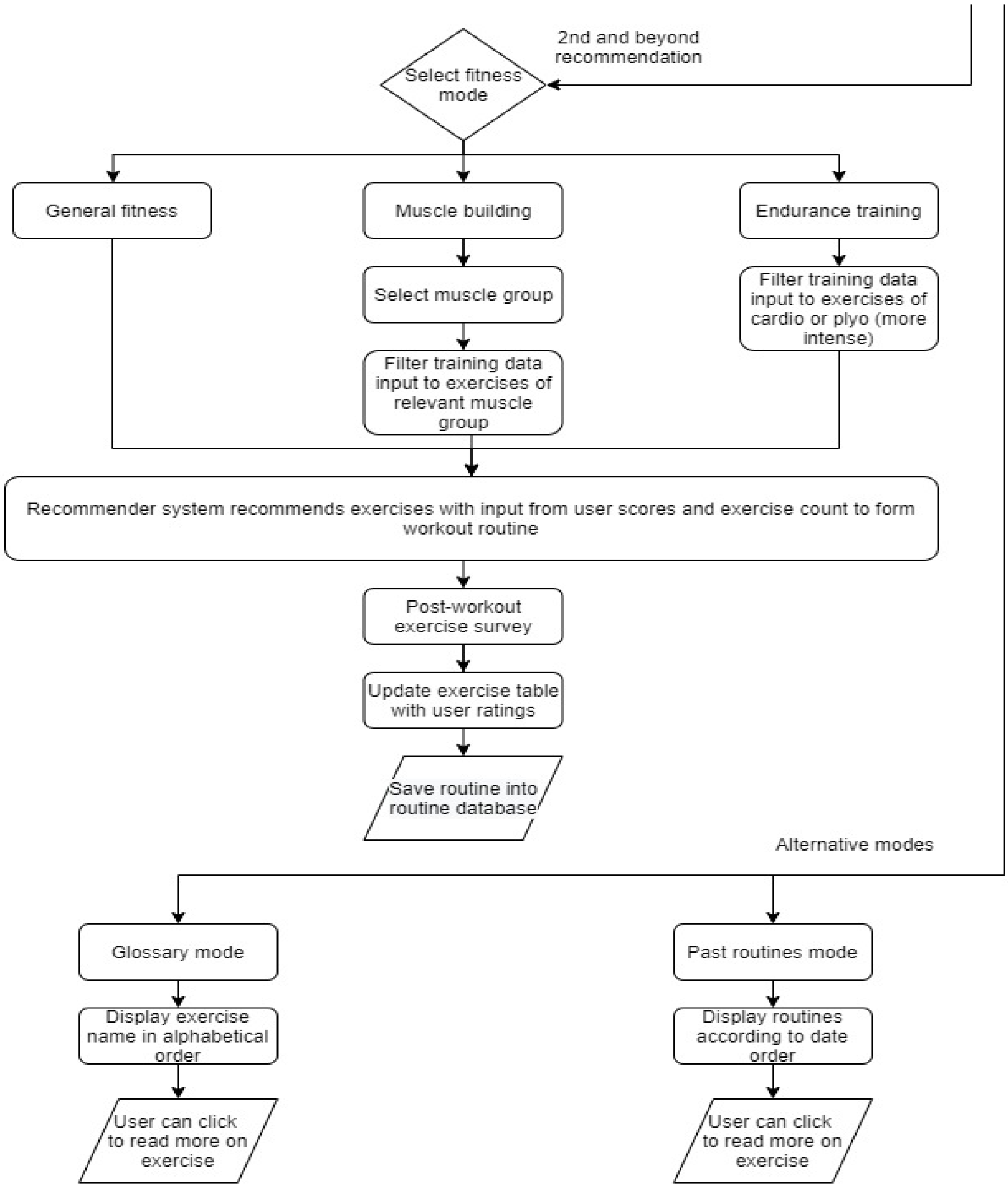


Figure 4: Knowledge Flow Chart and Diagram.

3.2. System architecture

The Advanced Gym Recommender (AGR) is a full-stack single page application solution which provided the user more friendly and immersive interaction. The full system architecture shown in Figure 5 mainly consist of two parts: client-side application and server-side application. By using Django a high-level Python Web framework, the front-end and backend application are fitted into a gapless application to perform better.

The client-side application is the web template which is based on the reactJS framework and generated by using webpack. The routing of the pages has been configured into the web template and this web template will then be served by the Django server under the main endpoints ('/').

Server-side applications will also be served with the Django server under separate endpoints ('/AGR/'). All the events to query or store data into the database will call the different web services to trigger different Recommender or Event Logic in the Django Framework. The serialized model also facilitates the data extraction from the database to efficiently query massive data from database.

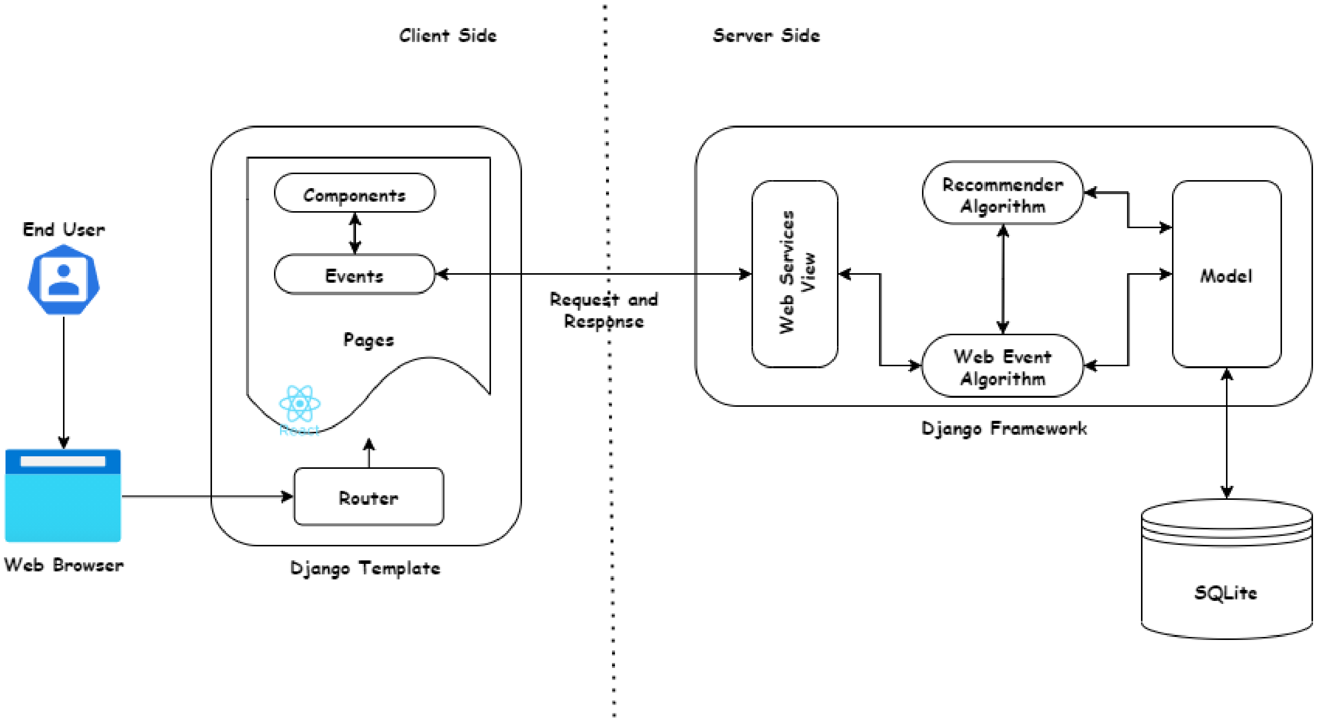


Figure 5: System Architecture of the AGR.

3.3. Recommender Logic

3.3.1. First user-exercise recommender

For the first pass recommendation of exercises, a cosine similarity-based recommendation algorithm was implemented. The reason why cosine similarity was applied instead of collaborative filtering (CF) was due to the fact that when a new person signs up to the app, we would only have his/her basic information such as: gender, fitness level, fitness goals, exercise intensity, exercise location and Body Mass Index (BMI).

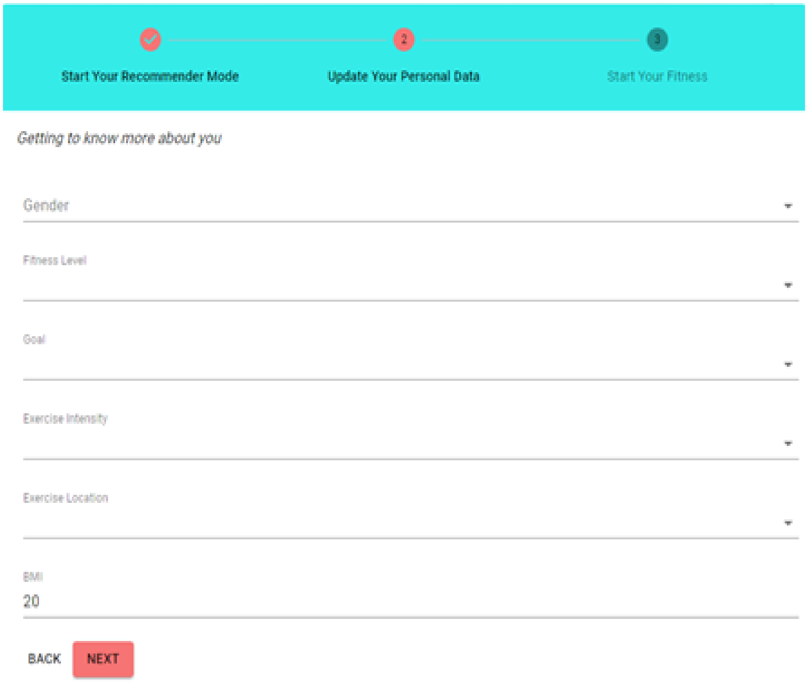


Figure 6: Basic information page where new users are required to fill up.

With such limited information, we will be unable to apply either item-based or user-based CF effectively. As such we developed a means of providing a meaningful first-pass recommendation using very limited data. After signing up, we present 4 random exercise based on the recommender mode selected.

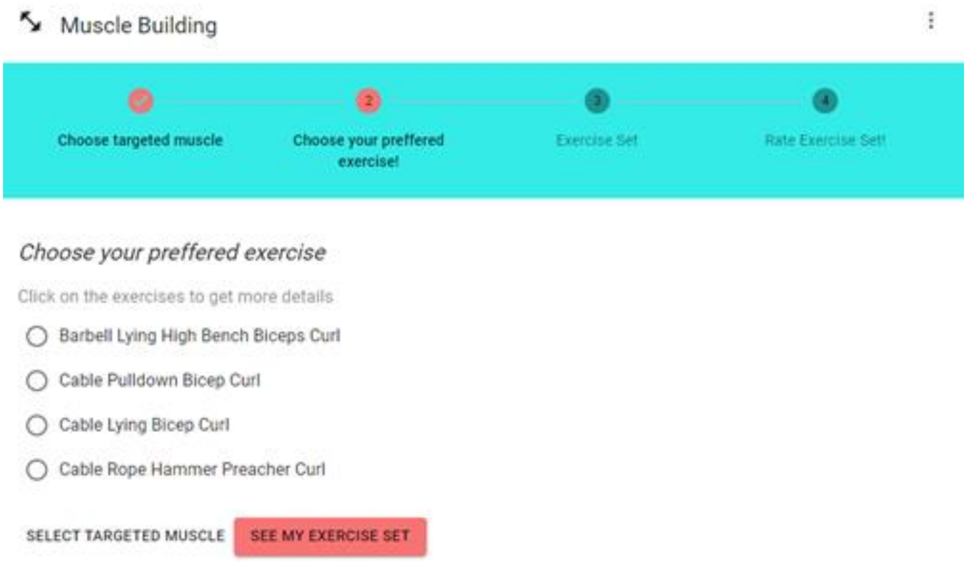


Figure 7: Example of exercises generated to get user's preference.

Using the exercise selected as an indication of the user's preference, we apply cosine similarity to find other similar exercises to recommend to the user as a 1st recommendation.

The workflow for the 1st pass recommendation is as seen in the diagram below:

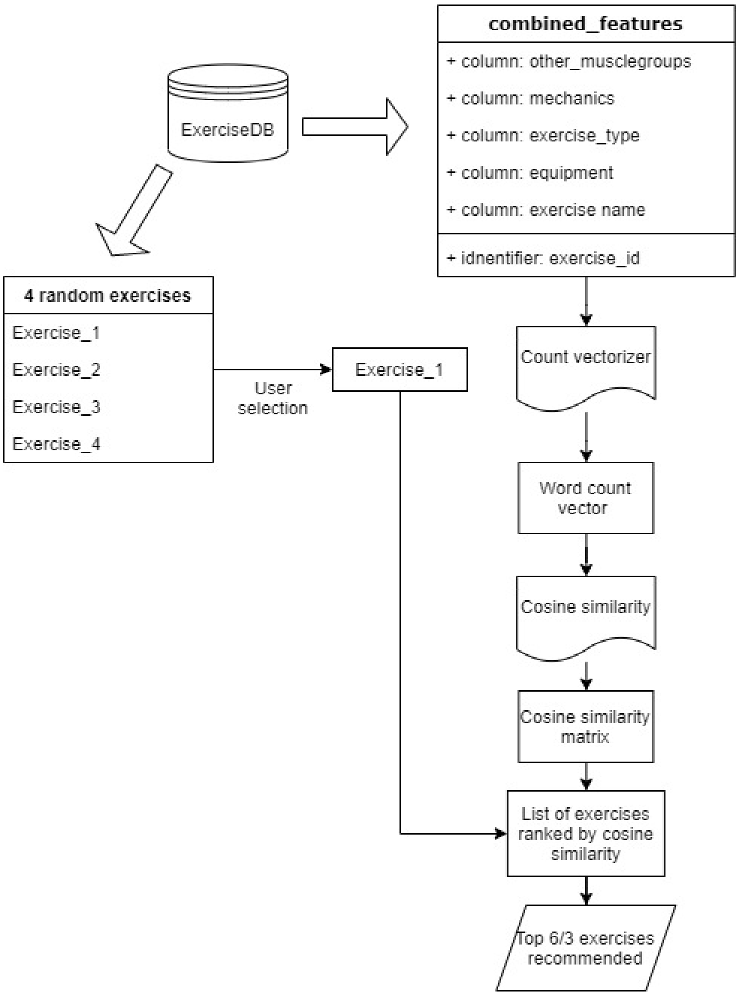


Figure 8: 1st recommendation schematics.

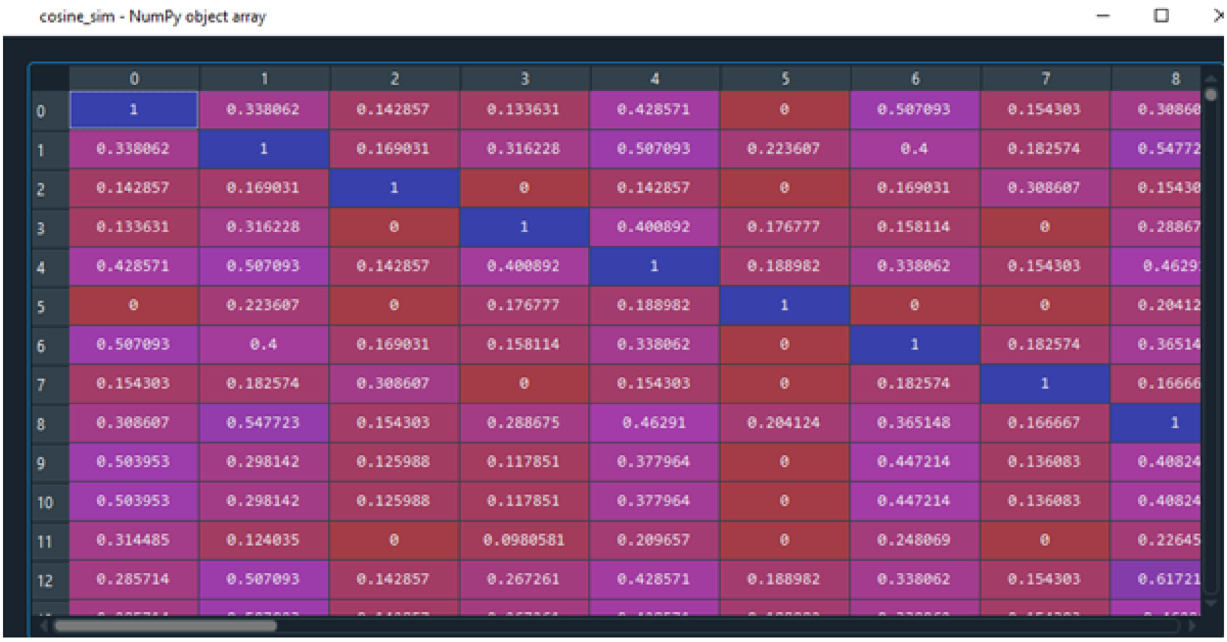
As seen in the diagram, we combine the columns (*other_musclegroups*, *exercise_type*, *mechanics*, *equipment* and *exercise_names*) inside *exercise_db* to get the *combined_features* column. The *combined_features* column represents the features of interest which we will use to derive our similar exercises to recommend.

To apply cosine similarity, we first have to convert the combined features column into a count of words that appear in that column for each exercise. That is done by applying the count vectorizer function and we get a word count vector as the output.

Cosine similarity is one metric used to measure how similar two items are. In math, it works by measuring the cosine angle between two vectors when projected in multi-dimensional space with an output from 0 to 1.

$$similarity = \cos(\theta) = \frac{A.B}{||A||\ ||B||} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2}\ \sqrt{\sum_{i=1}^{n} (B_i)^2}} \quad (1)$$

After applying cosine similarity to the word count vector, we get a cosine_sim numpy array, with exercises as the row and column headers and the data represents the cosine similarity score. As seen in the snapshot of the array below, there is a diagonal with 1s. This is true as exercise “0” in the column will be 100% similar to exercise “0” (itself) in the row.

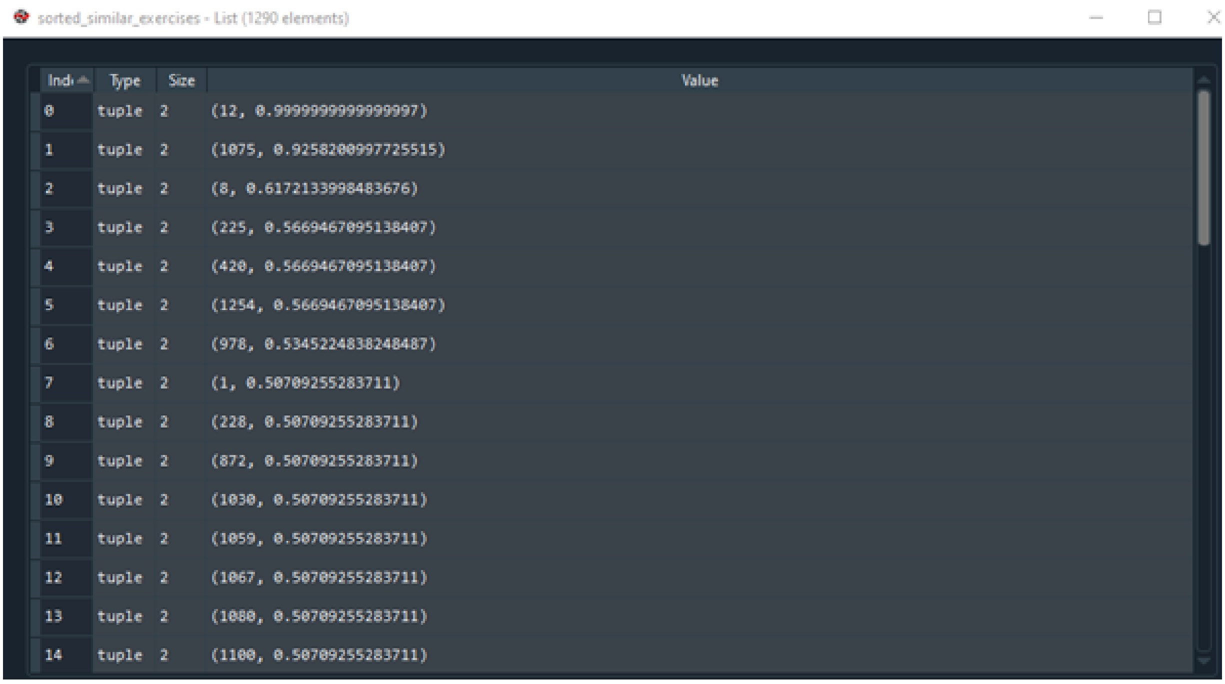


cosine_sim - NumPy object array

	0	1	2	3	4	5	6	7	8
0	1	0.338062	0.142857	0.133631	0.428571	0	0.507093	0.154303	0.30860
1	0.338062	1	0.169031	0.316228	0.507093	0.223607	0.4	0.182574	0.54772
2	0.142857	0.169031	1	0	0.142857	0	0.169031	0.308607	0.15430
3	0.133631	0.316228	0	1	0.400892	0.176777	0.158114	0	0.28867
4	0.428571	0.507093	0.142857	0.400892	1	0.188982	0.338062	0.154303	0.4629
5	0	0.223607	0	0.176777	0.188982	1	0	0	0.20412
6	0.507093	0.4	0.169031	0.158114	0.338062	0	1	0.182574	0.36514
7	0.154303	0.182574	0.308607	0	0.154303	0	0.182574	1	0.16666
8	0.308607	0.547723	0.154303	0.288675	0.46291	0.204124	0.365148	0.166667	1
9	0.503953	0.298142	0.125988	0.117851	0.377964	0	0.447214	0.136083	0.40824
10	0.503953	0.298142	0.125988	0.117851	0.377964	0	0.447214	0.136083	0.40824
11	0.314485	0.124035	0	0.0980581	0.209657	0	0.248069	0	0.22645
12	0.285714	0.507093	0.142857	0.267261	0.428571	0.188982	0.338062	0.154303	0.61721

Figure 9: Cosine Similarity between exercises.

We then generate a list of similar exercises using the initial preferred exercise (Exercise_1 in Figure 8) selected by the user. After generating the list, we then sort the exercises similarities in descending order to get the most similar exercises on the top.



sorted_similar_exercises - List (1290 elements)

Index	Type	Size	Value
0	tuple	2	(12, 0.9999999999999997)
1	tuple	2	(1075, 0.9258200997725515)
2	tuple	2	(8, 0.6172133998483676)
3	tuple	2	(225, 0.5669467095138407)
4	tuple	2	(420, 0.5669467095138407)
5	tuple	2	(1254, 0.5669467095138407)
6	tuple	2	(978, 0.5345224838248487)
7	tuple	2	(1, 0.50709255283711)
8	tuple	2	(228, 0.50709255283711)
9	tuple	2	(872, 0.50709255283711)
10	tuple	2	(1030, 0.50709255283711)
11	tuple	2	(1059, 0.50709255283711)
12	tuple	2	(1067, 0.50709255283711)
13	tuple	2	(1080, 0.50709255283711)
14	tuple	2	(1100, 0.50709255283711)

Figure 10: Exercises Similarity to user preferred exercise with the most similar exercises on the top.

As can be seen in the image above, the exercise_id "12" has the highest cosine similarity score of 0.999 because it is the exercise the user has chosen initially. From here we can then select the top N number of exercises to pass to the user as the first recommendation.

With the first set of exercises recommended, the user will then rate the exercises afterwards. This user-item ratings will serve as inputs for the second and subsequent user exercises recommender.

3.3.2. Second & subsequent user-exercises recommender

For the second pass recommendation of exercises, a model based collaborative filtering (CF) algorithm was implemented. In order to provide better recommendations, collaborative filtering was used to extract latent features of each exercise, which are derived from user-item ratings across the database. After users have completed their first pass rating of exercises, these ratings are stored in a database of past user-item ratings. As not all users would have rated all exercises, the database of ratings forms a sparse matrix, as seen in Figure 11 below.

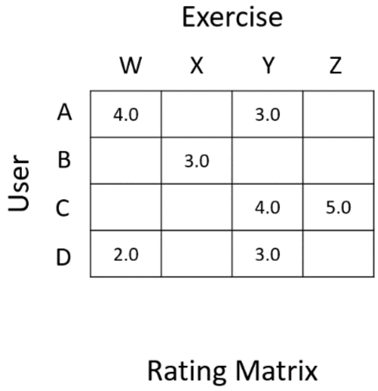


Figure 11: Sparse matrix illustration.

In the model-based approach, the ratings matrix $(N_u \times N_i)$ undergoes further factorization to obtain its latent features L, where low rank matrices $U^T V = (N_u \times N_i)$. The model-based approach was selected due to its higher capabilities to handle sparse matrices as compared to memory-based approach like similarity and correlation.

This forms the matrix of latent features, which can be expressed as

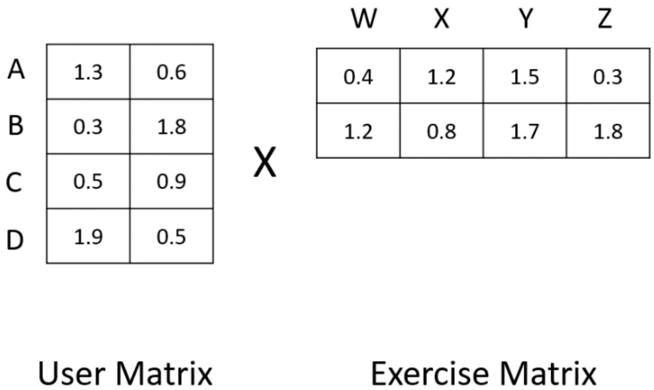


Figure 12: Matrix factorization creating latent features.

The model-based CF and factorization was implemented using the Scikit-Surprise package [28]. In this package, the prediction equation is given by

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \tag{2}$$

where $\hat{r}_{ui}$ is the predicted score, μ is the baseline average, b is the bias, q is the latent item matrix and p is the latent user matrix.

In this implementation, a general average μ was used to represent the baseline rating of all exercises. The user and item specific features are represented by a matrix and bias, which are then added to the general average to derive the final predicted score for the missing exercises. These parameters are optimized by stochastic gradient descent, where the regularized squared error is minimized:

$$\sum_{r_{ui} \in R_{train}} (r_{ui} - \hat{r}_{ui})^2 + \lambda\left(b_i^2 + b_u^2 + \|q_i\|^2 + \|p_u\|^2\right) \tag{3}$$

where λ is the regularization term. The values for bias and latent matrix are updated by the error $e = r_{ui} - \hat{r}_{ui}$, and learning rate γ. These values are randomly initiated and updated by the assigned number of epochs.

$$b_u \leftarrow b_u + \gamma(e_{ui} - \lambda b_u) \tag{4}$$

$$b_i \leftarrow b_i + \gamma(e_{ui} - \lambda b_i) \tag{5}$$

$$p_u \leftarrow p_u + \gamma(e_{ui} \cdot q_i - \lambda p_u) \tag{6}$$

$$q_i \leftarrow q_i + \gamma(e_{ui} \cdot p_u - \lambda q_i) \tag{7}$$

After performing minimization on the training set, prediction is conducted on the missing values in the sparse matrix. For each user, the predicted item scores are subsequently ranked in order of highest ratings, where the top n exercises are then recommended to the user. The recommended set of exercises ID is returned and displayed on the frontend UI, along with detailed exercise information retrieved from the database.

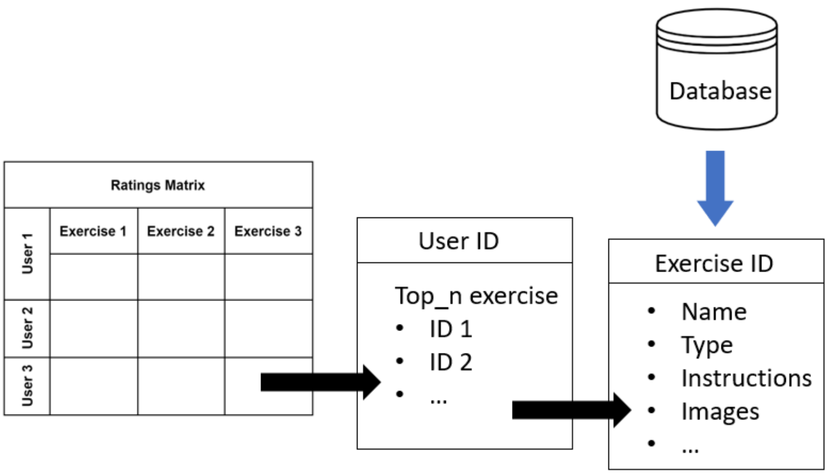


Figure 13: Overview of recommendation system information flow schematics.

3.3.3. Group user-user recommender

As an added feature in our exercise recommender application, we would like to establish exercise companions by connecting users with other users of similar exercise preferences. This function is implemented by utilizing the matrix of latent user features, which is obtained through the database of past user-exercise ratings. For each user, an analogical reasoning technique is used to find similar latent feature information. This can be done by computing the Euclidean distance for n latent features and obtaining the lowest distance values, which represents closely related users.

$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \quad (8)$$

It may be stated that no two users would have exactly similar exercise preferences and hence recommendations. Therefore, in order to generate a common set of exercises, the latent features across the two users are averaged and it is then used to derive the predictions for exercise scores. This is analogous to the generation of a "new user" which is a representation of the two individuals. These exercises are then displayed along with the recommended companions, which are ranked by their highest similarity index.

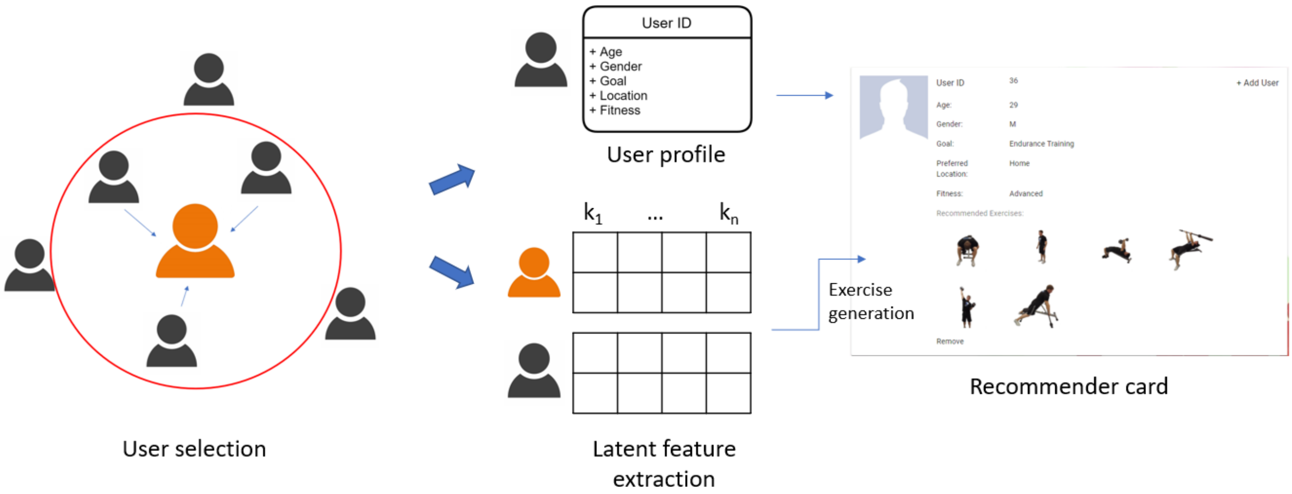


Figure 14: Exercise buddy schematic on similarity algorithm and logic.

This concept may be extended to a group of users, where the list of exercises may be defined by the group administrator or determined by averaging of latent features is conducted over all users in the group. Users would then be able to select exercise groups which fit their schedules, exercise preferences and fitness goals.

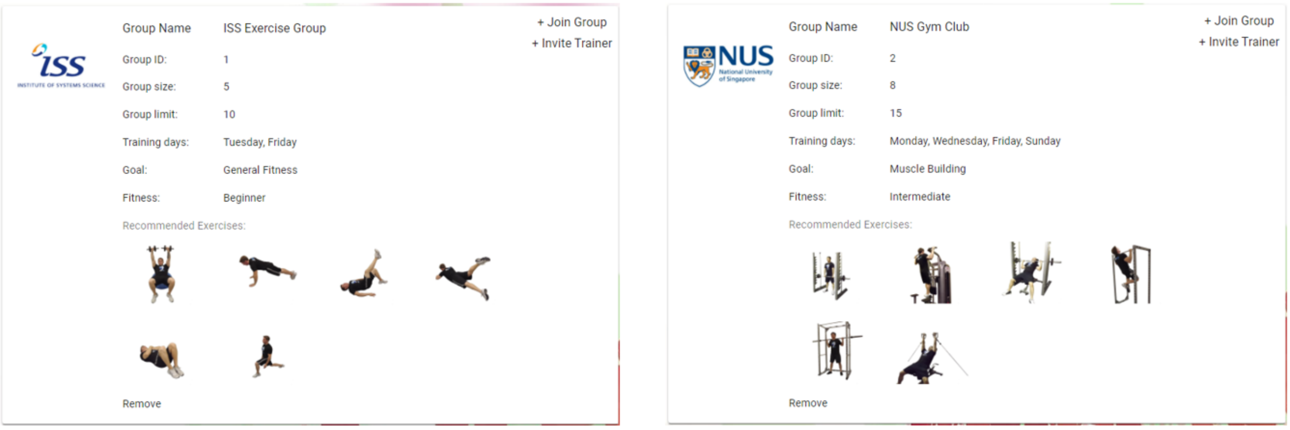


Figure 15: Examples of exercises group recommender.

3.4. Model and Database

Data collection and alignment are always most prioritised concern to be resolved. Although the current data used in this project is still relatively small and all the data are easily stored in corresponding table for easy access, we must simplify the data structure for the ease of data retrieval and avoid the duplicate data stored to achieve a high scalability in the AGR's database for the future work in mind.

Django framework provided a favourable method to create and define the SQL database. Data type and structure are defined clearly in the Django Model and the relation of the primary keys and foreign keys between the tables gave us data integrity on the low level to prevent creating a record which does not fulfil the relation. The application data are divided into 6 SQL tables with each table representing a clear data boundary to reduce the storage size. Data in the *Exercise* SQL table was populated from web scrapping of exercise information from JEFIT website [29], while there remaining SQL tables are filled from user interaction. The databases representation detail shown in Table 5 and their connection best described in the database diagram below (Figure 16).

Table 5: Database table and event representation.

SQL Table	Event (row) representation
User	A unique user admin data
UserData	A unique user exercises related data
Exercise	A unique exercise
Routine	A unique exercise set given to a user
Routine Exercise	An exercise from an exercise set
User Exercise Rating	The rating of an exercise for specific user. The rating score can be changed overtime.

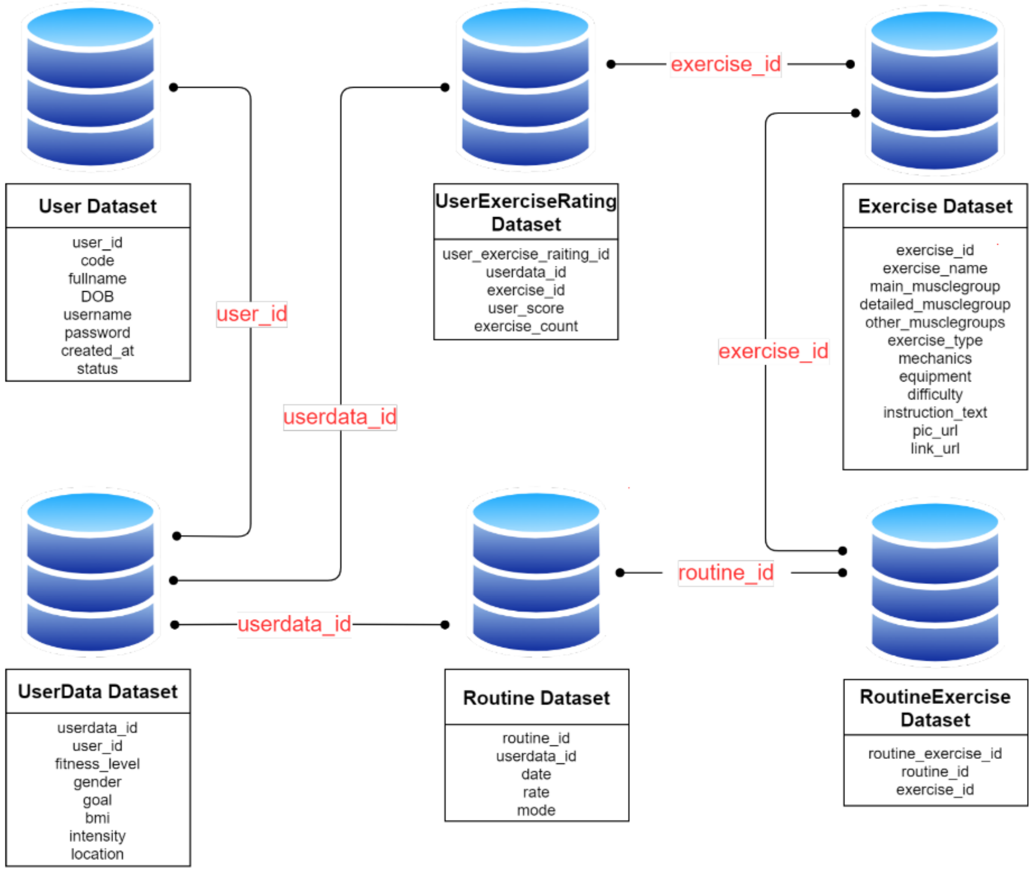


Figure 16: Database graph showing their features and connections.

3.5. Front-end (UI interface)

The ultimate purpose of front-end is to create a smooth user experience while interacting with the knowledge model and application logic (back-end). AGR uses Django and react to deliver a web-app user interface that is accessible through any browsers and devices and ease the integration with back-end as Django uses python as the primary programming language. As user interface is not the focus of the project, this section will emphasis on implementation overview and overall design of the front-end web app.

3.5.1. *Implementation overview*

User-Application interaction can be simplified, as shown earlier in Figure 5. In description, all the users can interact with the UI in web browser in their devices. By using the HTTP protocol, the web browser will fetch the web resources, such as HTML documents, pictures, JSON data etc. Some of the webpage event services are defined in the client side to send separate GET/POST http request to the Django Framework, which will eventually pass the data to back-end application logic to handle the request. The response is then complied, and web browser will receive the response from the server to render the components or views.

3.5.2. *Webpage connections design*

The web-application contains 17 web pages, which are broadly categorized into two groups. *The administrative pages collection* are webpages for created for administrative purposes, log in to the account, updating user data, etc. *The interactive recommender pages* where AGR recommender logic and functions are served to the users. The interconnection/linkage between the pages are captured in the graph representation below (Figure 17). Each individual page layout and details are documented in User Guide (page 36).

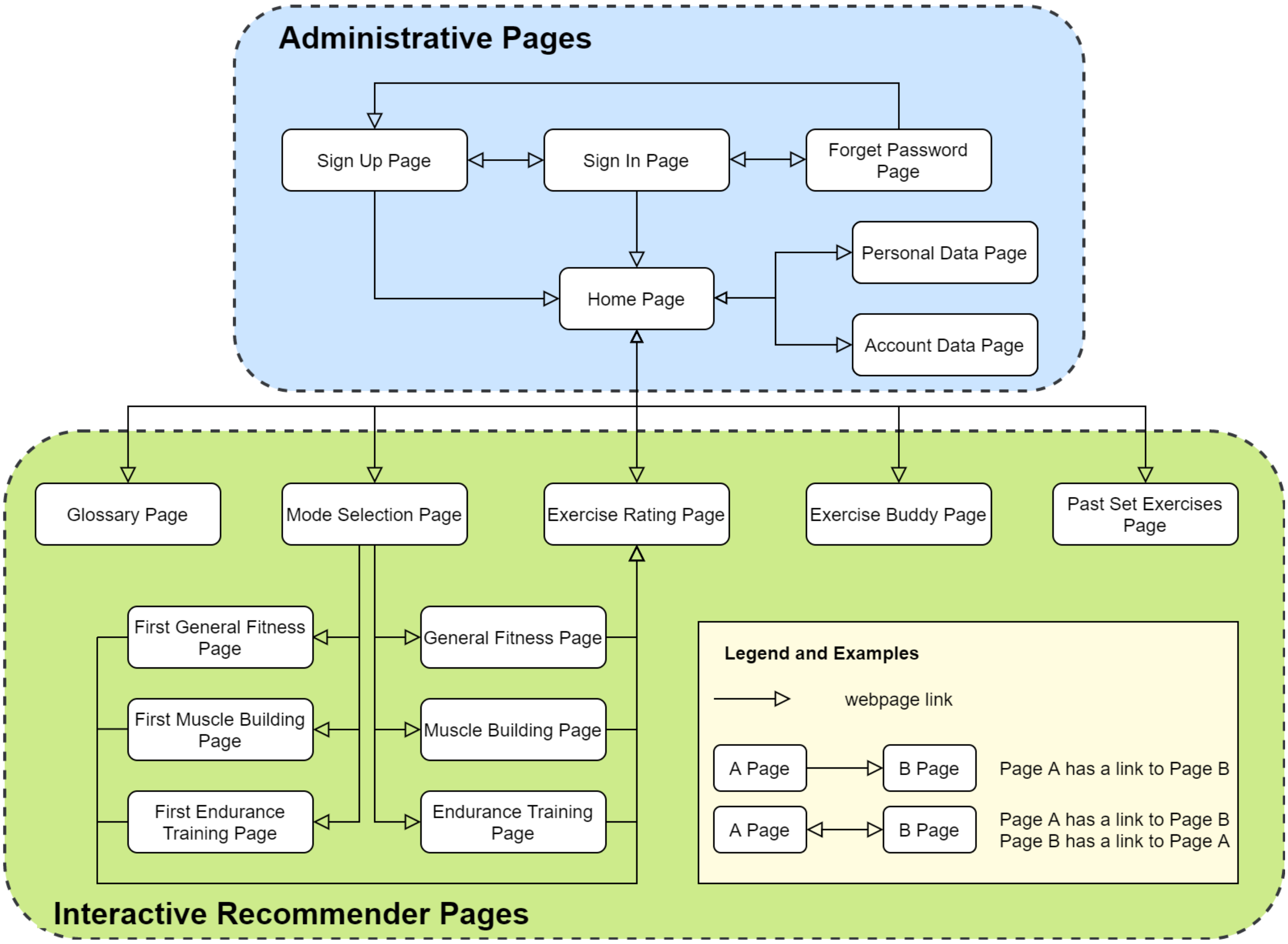


Figure 17: Webpage Linkage Graph.

Each page is designed to deliver the user a better informative visualization. The widgets in the pages are understandable from the user's perspective and the informative visualization will favor user more to know about the exercise details. There are still many improvements and adaptability on the user interface and the functionalities of the AGR but this simplified webpage provides the most comprehensive knowledge to the user. The details of the pages are written in 8.3.2.

3.6. System Feature

3.6.1. System Robustness

Most of recommender system require past user's data to start recommending specific item to the user. However, in AGR there is recommendation for everyone including for the first-time user. AGR achieved this through distinguishing recommender model used in first time recommender as discussed in section *3.3 Recommender Logic*. This feature gives AGR competitive edge as compared to its competing exercising application in suggesting items that are more compatible to user preferences.

AGR also offer non recommendation knowledge sharing through *glossary mode* which is informative for user who would like to query about any exercises that AGR have in the database. Making a AGR as a user friendly one stop for all exercise application.

3.6.2. Accessibility and Convenience

AGR is a cross platform web application which is accessible to all browsers from all devices including, mobile phones and tablets. Users can switch browsing devices simply by login into the same account. The web-application uses the Cookies to keep track of the signed in users to cut down repeated login steps before users can use the application.

3.6.3. Scalability

AGR is built for high scale application that can support million users through efficient data storage. The matrix factorization technique able to store the pre-trained matric in lighter space as compared full data stack which can be easily pulled in by the users.

4. PROJECT IMPLEMENTATION: A CASE STUDY

Case study:

Jane is a new user who has recently gained interest in exercising. She would like to start off with toning her muscles, specifically the abs region. In addition, recently her company is providing a subsidy to gym membership to promote an active lifestyle among the employees. Jane would like to utilise the company benefits by enrolling in a gym nearby her house, as she prefers machine assisted workouts. However, she has not been exercising regularly and does not have much knowledge on the different types of exercises. Hence, she has decided to utilise the AGR application to assist her in selecting the right exercises for her fitness goals.

Profile of Jane:

- 25 years old, Female
- Fitness level: Beginner
- Goal: Muscle building
- Muscle group: Abs
- Preferred type of exercises: Machine assisted

Upon entering the AGR application, she registers for an account and enters her personal fitness details. She then walks through the mode selection based on her exercise goals (details in section 3.5):

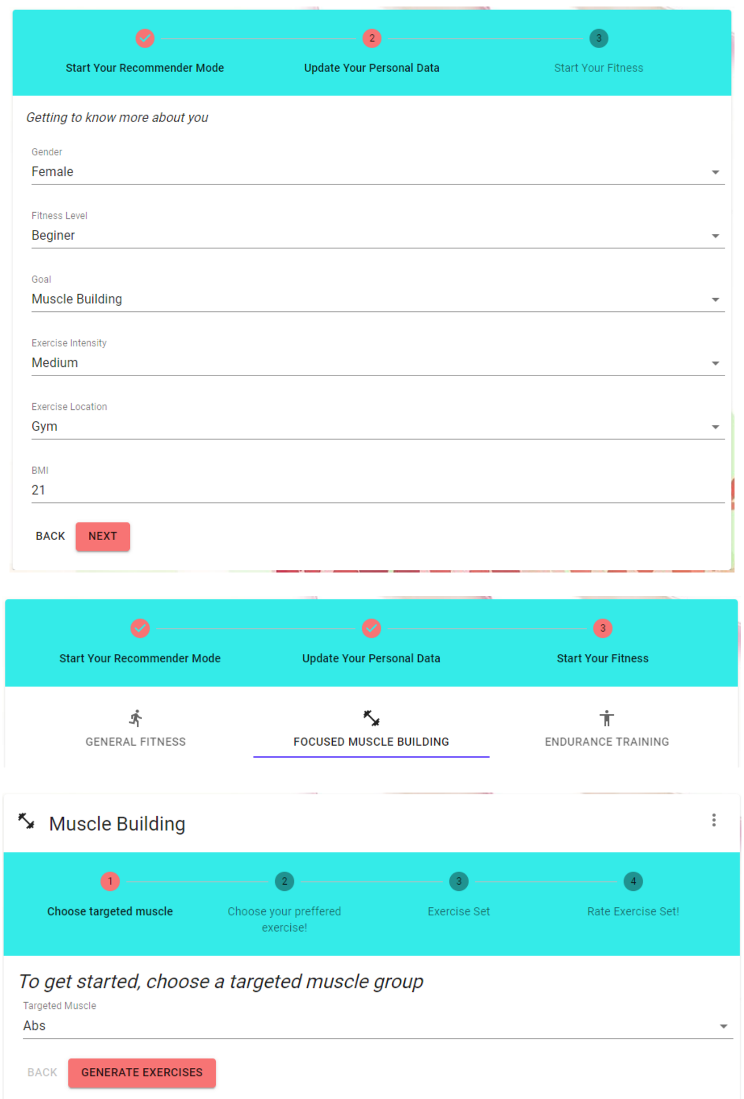


Figure 18: Mode selection of case study user.

In order to retrieve more information on her personal exercise preferences, 4 exercises in this targeted muscle group are generated. She then makes a selection, which in this case relates to her preference of "Machine-assisted" exercises in a gym. Her selection gives an implicit rating on her preferences and the first 6 set of exercises are recommended to her based on exercise description similarity in the database (details in section 3.3.1). Upon completion of her first set of exercises, she provides a rating which explicitly expresses her preferences.

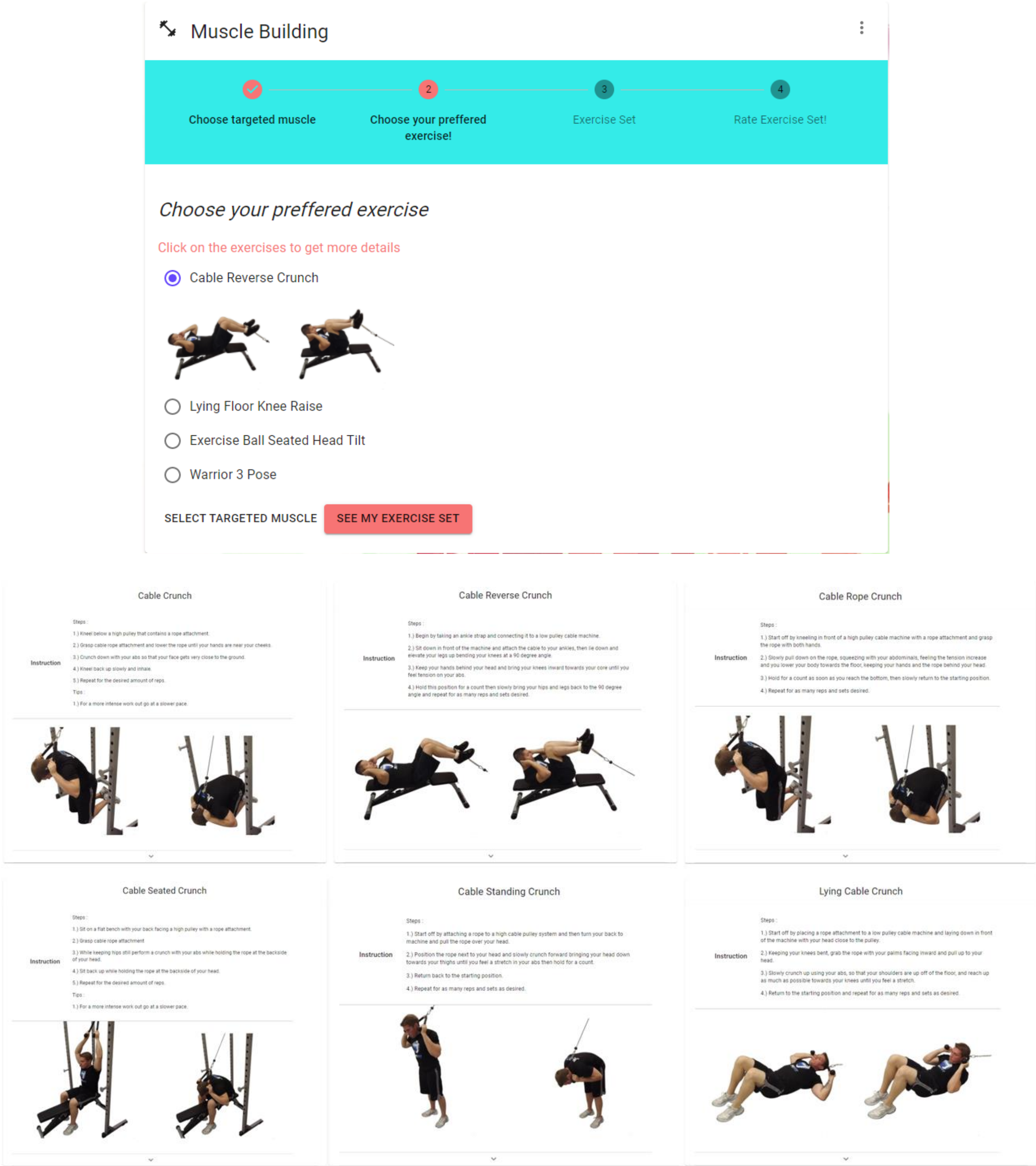


Figure 19: First pass recommendation for case study user.

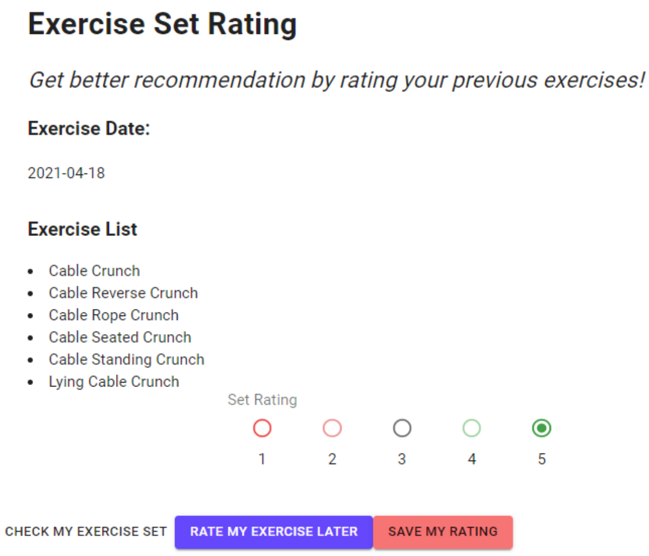


Figure 20: Exercise rating for case study user.

In subsequent visits to the gym, she is now recommended exercises based on collaborative filtering over the database of users and exercises (details in section 5.3.2). As seen from the list of exercises recommended, these exercises match her preference of "Machine-assisted", and they provide a mix of exercises by her own preference together with what she might like based on other users with similar preferences.

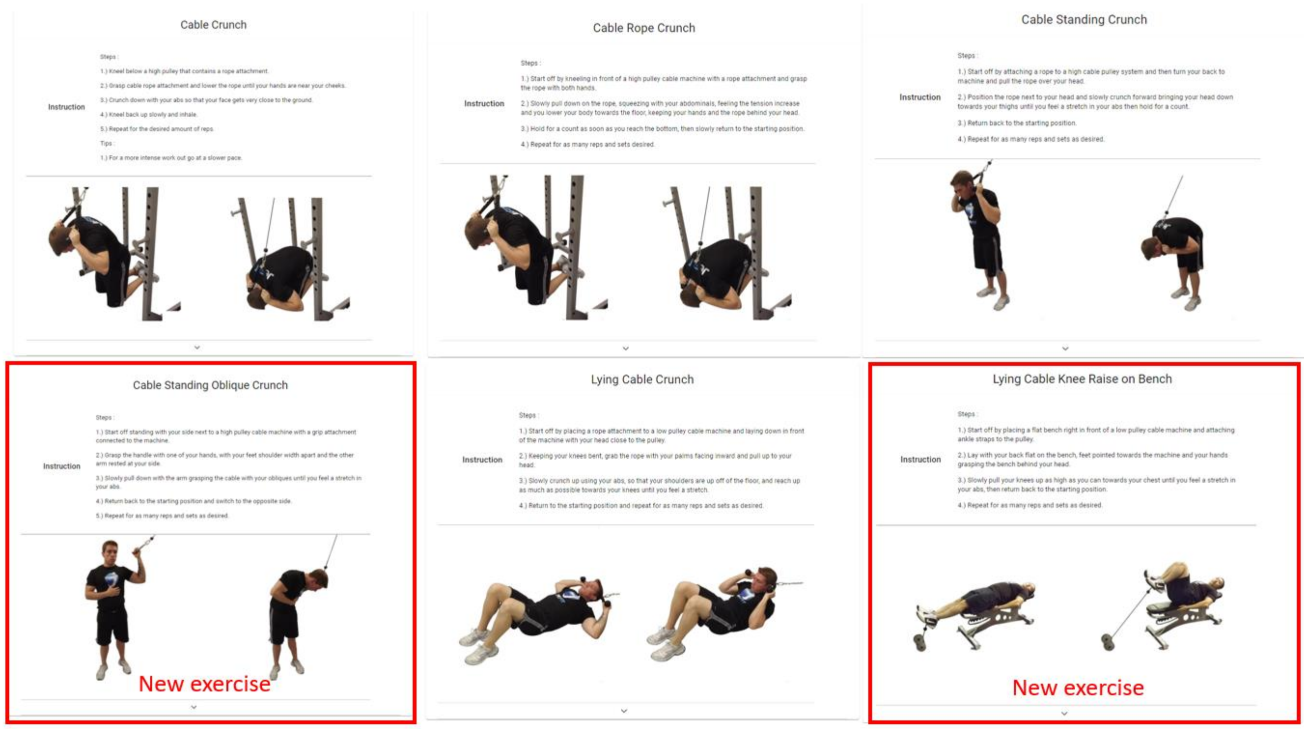


Figure 21: Subsequent exercise recommendation for case study user.

As Jane is new to the gym and would like to have an exercise companion to motivate one another, she navigates to the home page and select the “Exercise Buddy” mode. Within the page, she can select from a number of users which are recommended to her based on similar exercise preferences (details in section 5.3.3). A recommended set of exercises are also displayed which would match both their interests.

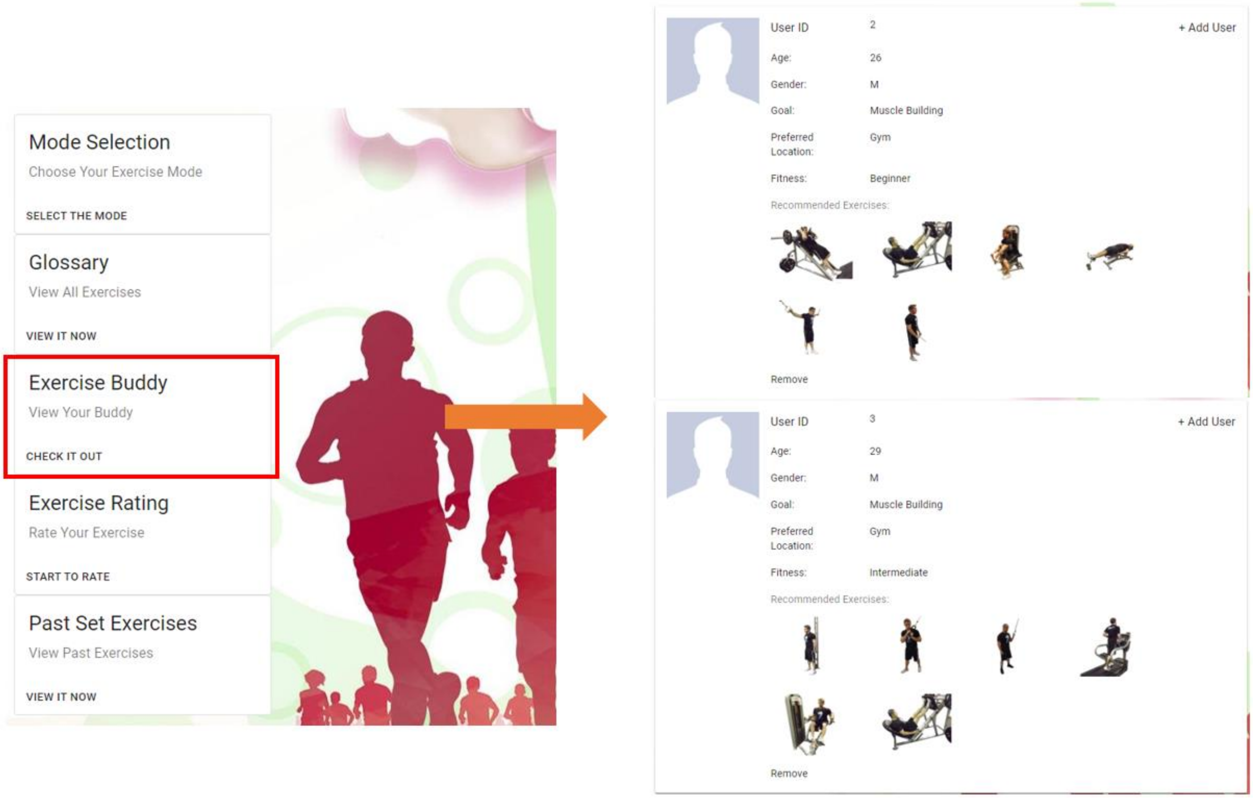


Figure 22: Exercise buddy recommendation for case study user.

This case study of Jane shows the learning and reasoning capabilities of the application to the user preferences. The user interface provides a quick evaluation and extraction of the user profile while the hybrid-reasoning systems uses different reasoning approaches to recommend the most suitable exercises at each stage of the user selection. Further value-added features such as buddy selection and group exercise recommendations enhance the overall user experience and likelihood of achieving their exercise goals.

5. PERFORMANCE VALIDATIONS AND LIMITATION

As the AGR is a basic implementation of our project, it has only gone through some integration testing with existing exercises and user data stored in the database. User profiles were generated by creating hundreds of user account and randomizing the respective personal data like BMI, age, fitness level etc. The AGR performance was validated through repeated generation and testing, where users were assigned to select specific type of exercises and monitoring the next recommended exercises from the fitness mode. Ideally, the 6 most suitable exercises will be recommended to user and the AGR will learn and store the user preferences, provided all the exercises are rated accurately.

However, the AGR is still deficient in generating precise user data and exercises rating. To achieve higher cognitive ability in AGR, the system requires gathering and storing a larger amount of real user data with personalised ratings. This would improve the reasoning algorithm by utilising accurate user-item preferences to provide more relevant predictions.

For now, our AGR system serves as a proof of concept which has been designed to operate in a local machine. In future developments, the system and network architecture are likely to be enhanced by migrating into cloud server and serving as a public address as the cloud will have much more scalability to increase the computation and memory of the machine.

Moreover, the user interface could be further improved to enhance the user experience in areas of webpage layout, design and navigation. This could be done by obtaining constructive comments from the real user to improve its system functionalities and interaction. Working towards being a better SaaS application, our AGR system seeks to deliver a user-friendly platform and accurate exercise recommendations.

6. CONCLUSION

The booming of the information technology impacts all the human activities and interest. Nowadays, we cannot stay away from the smart devices and objects connected to the internet. All the personal data related to the behaviour, interest and thought stored in the cloud or premises are increasingly precious than any of the physical commodities. The data analytics has also played a growingly crucial role in the ecommerce and social media industry because of the more predictable user preferences from the data collected from each individual. As such, we have proposed a data-driven intelligent solution to be applied in the fitness industry, in the form of an Advanced Gym Recommender (AGR) system.

By obtaining the personal data and behaviour from the users, the AGR has addressed the difficulties to pick up the exercises and the mistakes of selecting unfavourable routines. It has successfully extracted the domain knowledge and translated them into exercise reasoning system. Our exercise reasoning system can assist exercise users in crafting workout routines that meet their exercise goals and match user preferences through a combination of rule-based, similarity-based and collaborative filtering reasoning techniques. In addition, buddy and group recommender was included as a further value-added feature to incorporate social connections and strive towards building a motivated exercise community. These implementations will enhance the existing solutions to provide an upgraded platform for the users of the fitness industry.

Certainly, there are still further improvements our team would like to include, such as using larger datasets of real user ratings, performing cloud implementations and incorporating other AI techniques of computer vision for Active Gym Coaching. Nonetheless, the AGR is unarguably an impactful solution in the fitness industry as everyone could own their restless personal fitness trainer which provides affordable, smarter and more intuitive recommendation.

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8. APPENDIXES

8.1. Appendix A: Project Proposal

GRADUATE CERTIFICATE: Intelligent Reasoning Systems (IRS)

PRACTICE MODULE: Project Proposal

Date of proposal:

14 February 2021

Project Title:

Advanced Gym Recommender (AGR)

Sponsor/Client: *(Name, Address, Telephone No. and Contact Name)*

Institute of Systems Science (ISS) at 25 Heng Mui Keng Terrace, Singapore
NATIONAL UNIVERSITY OF SINGAPORE (NUS)
Contact: Mr. GU ZHAN / Lecturer & Consultant
Telephone No.: 65-6516 8021
Email: zhan.gu@nus.edu.sg

Background/Aims/Objectives:

Background

With the growing health and wellness awareness, there are increasing number of people thinking to start exercises regularly. However, there are many factors that are inhibiting them to start or continue to exercises. A couple examples of the push factor are boredom of the repetitive training for regular individual as well as overwhelm by the number of possible exercises for beginner.

Aim

Advanced Gym Recommender (AGR) aid users to achieve their goal with easy to user interface for recommendation system. AGR gives user a personalized set of gym exercises that are similar to past exercises, which tailored to achieve user's desired goal. AGR have a database of more than 1200+ exercises aid regular individual with new exercises and expand their exercises knowledge and for beginner AGR provides a focus in their training without the overwhelming choices of possible exercises in the gym and discovering exercises that they like.

Objective

At heart, AGR aim to recommend exercises which are similar to the user past preferences (rating) which are align to the user goal (fitness/muscle building/endurance training).
In order to retain users and easy usage, AGR also aim to provide smooth UI experience in a form of web-app that will be able to be accessible through all browsers through any devices

Extension

The team is planning to create a two parts integrated project with AGR as the gym exercise recommender and Active Gym Coaching (AGC) through computer vision to act as a real time active gym coach that can give users feedback of their posture while doing the exercises. The two app will work hand in hand as a guidance for user in achieving their goal and perfecting their exercise posture to give a holistic feedback for the users.

Requirements Overview:

- Research ability
- Programming ability
- System integration ability
- Basic front end developing ability

- Excellent understanding of recommendation algorithm

Resource Requirements (please list Hardware, Software and any other resources)

Hardware proposed for consideration:

- CPU.

Software proposed for consideration:

- Python, javascript, css
- Python packages listed in the requirements.
- Web browser (Google Chrome/Microsoft Edge)

Methods and Standards:

Procedures	Objective	Key Activities
Market research and needs	• Gathering market wants and needs. • Prioritizing key delivery of the project and application. • Choosing targeted market section.	1. Market research 2. Competitor research (existing application) 3. Define the target market 4. Define the application goal and scope
Technical workflow draft	• Overview end to end application workflow. • Define end in mind product. • Set up working platform	1. Flow chart of system behaviour based on market. 2. Construct acceptance testing 3. Set up GitHub project for integrated and parallel work
Frontend development (Web-app user interface)	• Define scope and evaluation method. • Developed application as per requirement	1. Plan for Acceptance Testing 2. Choose programming languages and packages 3. Development 4. Evaluate acceptance testing
Backend development (recommendation logic)	• Define needs and best algorithm. • Developed algorithm as per requirement	1. Plan for Acceptance Testing 2. Choose programming languages and packages 3. Development 4. Evaluate acceptance testing
Frontend and Backend integration	• Integrate front-end and back-end	1. Adding backend logic to the front end application 2. Testing features
Deployment (Beta)	• Package application in easier to start • Create user guide	1. Tidy up working environment in the project folder 2. Create step to step installation and user guide 3. Testing user guide

8.2. Appendix B: Functionalities & Intelligent Reasoning System Mapping

The AGR web application aims to utilize the topic introduced in the IRS (Intelligent Reasoning System). In this section every feature is mapped to topic studied under one of the category: Machine Reasoning (MR) , Reasoning System (RS) and Cognitive System (CS).

Section Number Section Title	IRS topics
3.1.1 Knowledge Acquisition	*Machine Reasoning* – Knowledge Discovery through data mining / Knowledge Elicitation using Knowledge Models / Knowledge Acquisition
3.1.2 Knowledge Representation	*Machine Reasoning* – Knowledge Representation
3.3.1 First user-exercise recommender	*Machine Reasoning* – Form of knowledge representation (rules) *Reasoning System* – Content based recommendation, Cosine similarity, Bag of words
3.3.2 Second & subsequent user-exercises recommender	*Reasoning System* – Matrix factorization for recommendation system
3.3.3 Group user-user recommender	*Machine Reasoning* – Analogical reasoning *Reasoning System* – KNN similarity by using Euclidean distance
3.4 Model and Database	*Machine Reasoning* – Database architecture and implementation / Knowledge Discovery through data mining
3.5 Front-end (UI interface)	*Cognitive System* – Cognitive System Architecture *Cognitive System* – Knowledge Representation and Reasoning

8.3. Appendix C: User Guide

8.3.1. Installation Guide

This section act as an installation guide for AGR in a new anaconda environment to ensure minimum installation problem by users. Pip install is used instead of conda install due to some packages require the instalment through pip. Although there is other way to install all the dependencies, we high encourage users to follow the guide below.

Prerequisite to have installed anaconda in local machine.

1. Download / clone this file into your directory.
2. Open **anaconda command prompt** and navigate into the downloaded/cloned directory. By default, the directory can be found in C:/<username>/Documents/GitHub/IRSPM
3. Run the following command line by line

Installation in windows 10	*Installation in unubtu Linux*
conda create --name myagr python=3.9.2 pip **conda activate myagr** **pip install -r pip_requirements.txt**	**conda create --name myagr python=3.9.2 pip** **conda activate myagr** **sudo apt-get install gcc** **pip install psycopg2-binary** **pip install -r pip_linux_requirements.txt**

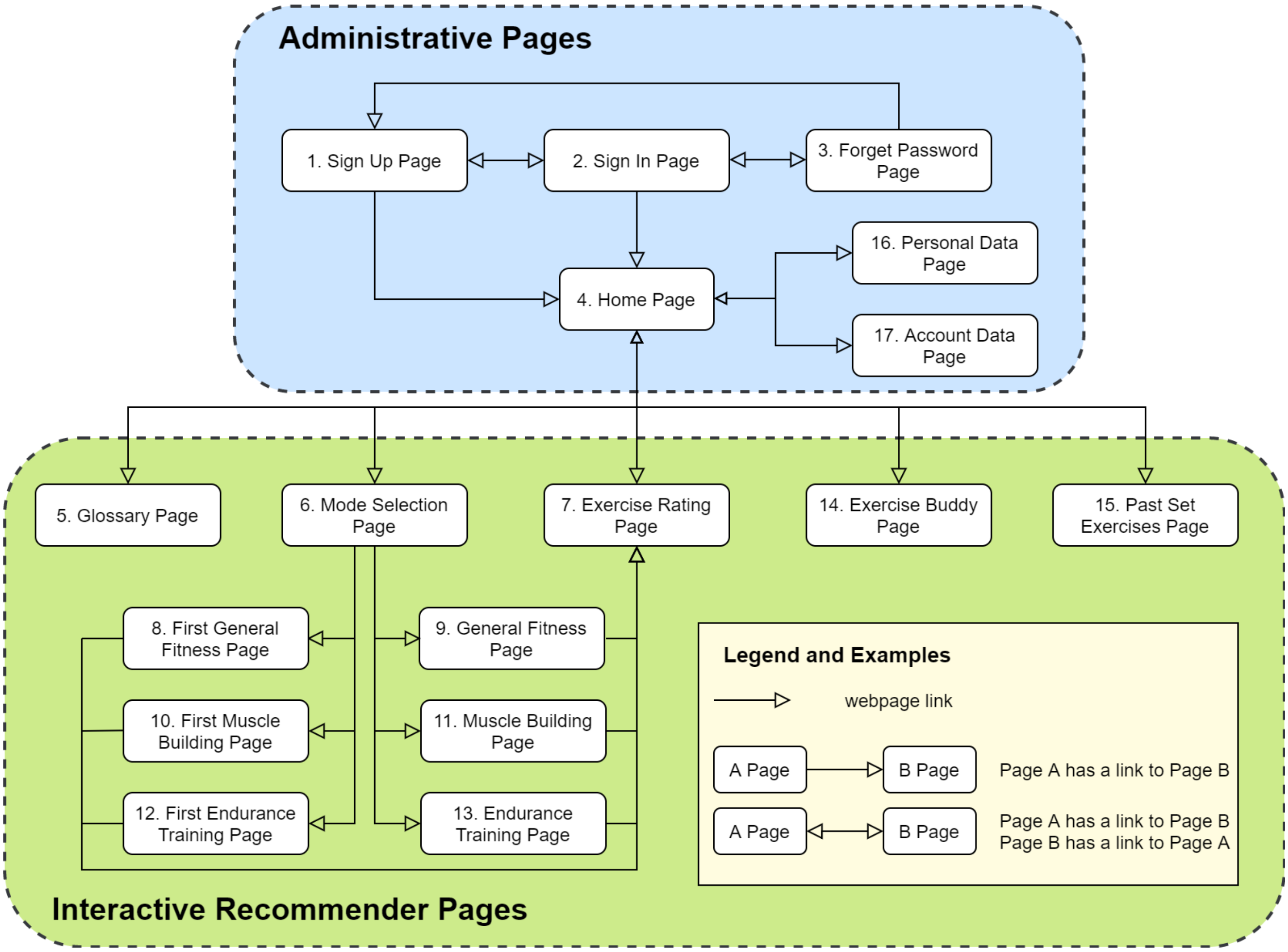
4. Navigate into *MyWebsite\AGR* folder
5. Run the line below to start the program running locally.

python manage.py runserver

6. Go to localhost:8000 from web browser, link: http://127.0.0.1:8000/

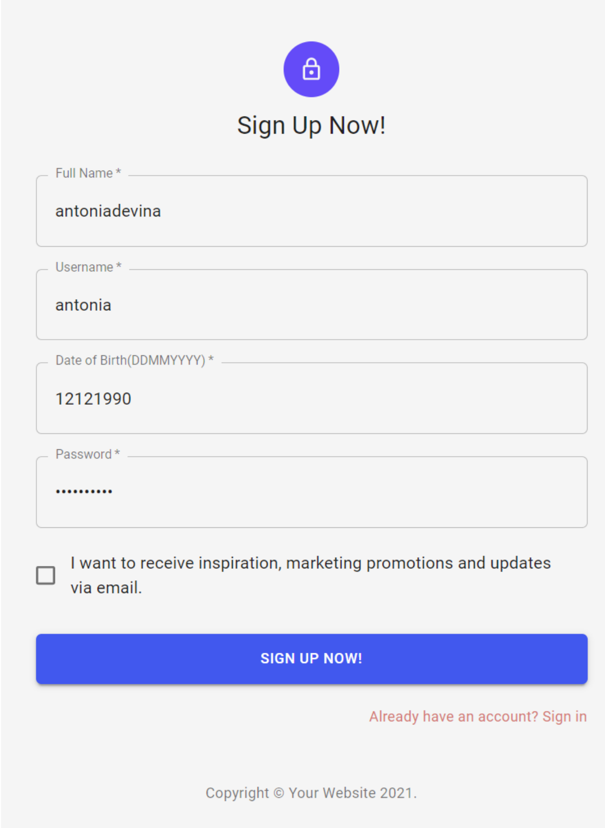
8.3.2. User Guide

The figure below is a replication of Figure 17 where the pages are numbered for easy reference in this section. The screen shots of each pages are shown under each heading with a short description about the page.



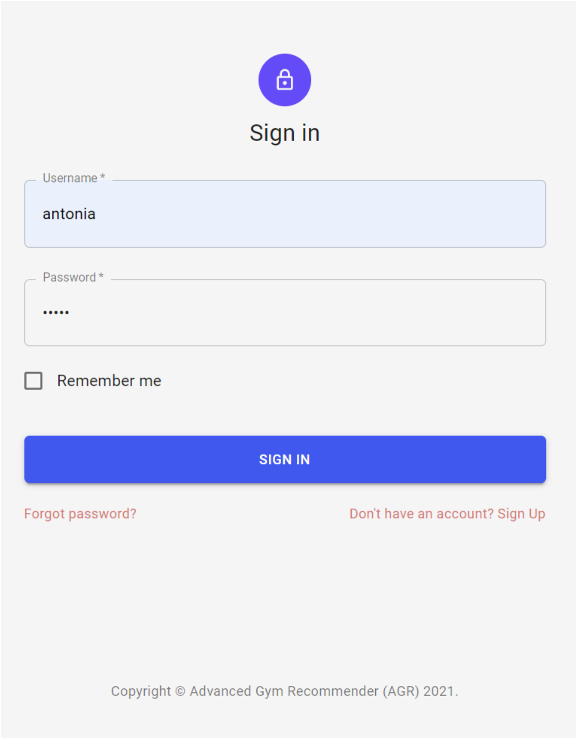
1. **Sign Up Page**

A page for a simple sign up to create a new user in AGR.

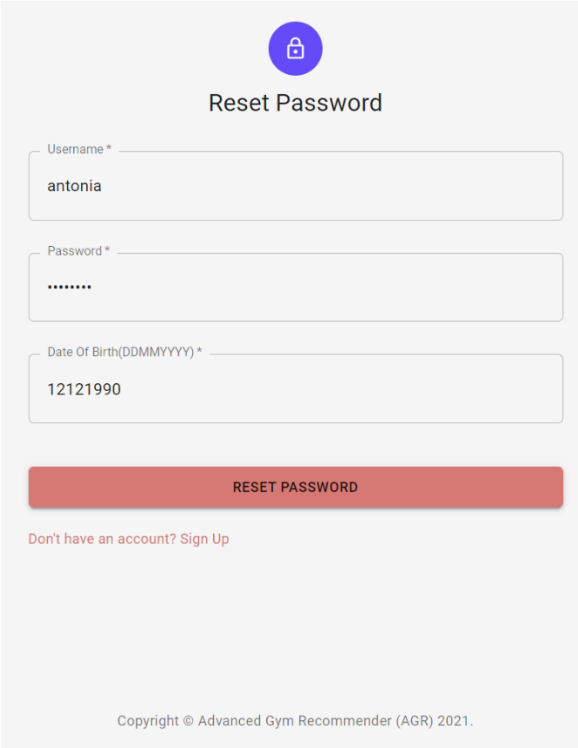


2. **Sign In Page**

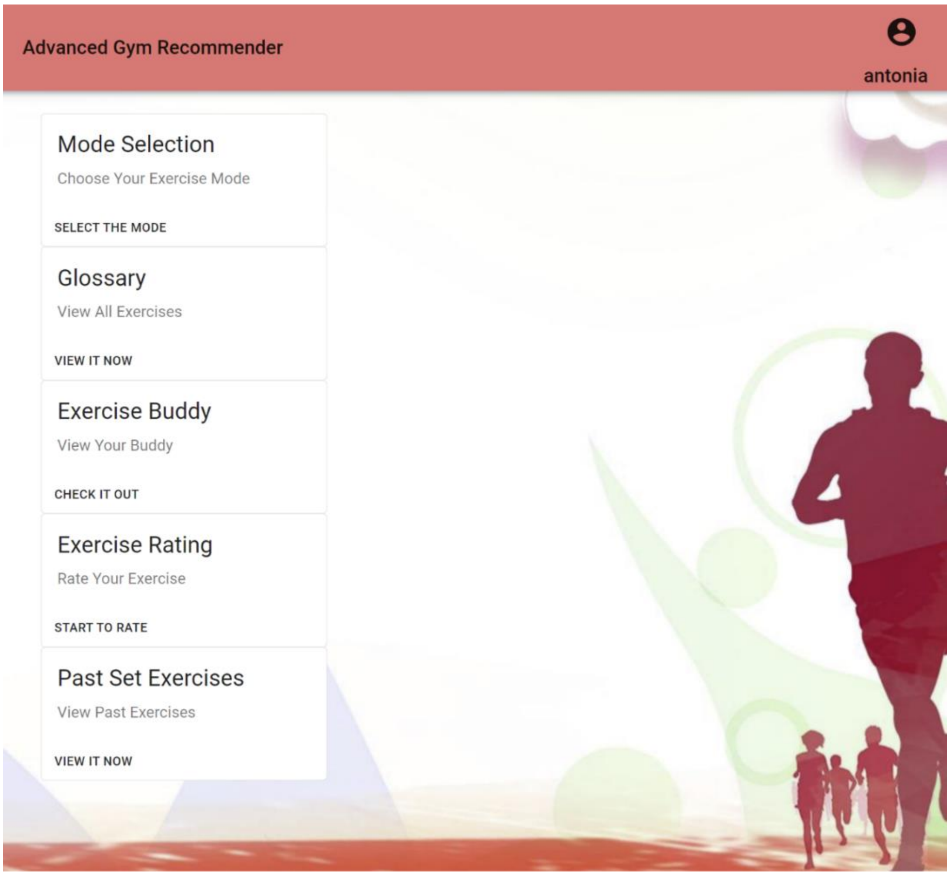
A simple administrative user verification to give access to the registered user. This page can also redirect user for the resetting the password and do a simple registration.



3. **Forget My Password**
Restarting forgotten password. System will validate based on the date of birth registered.

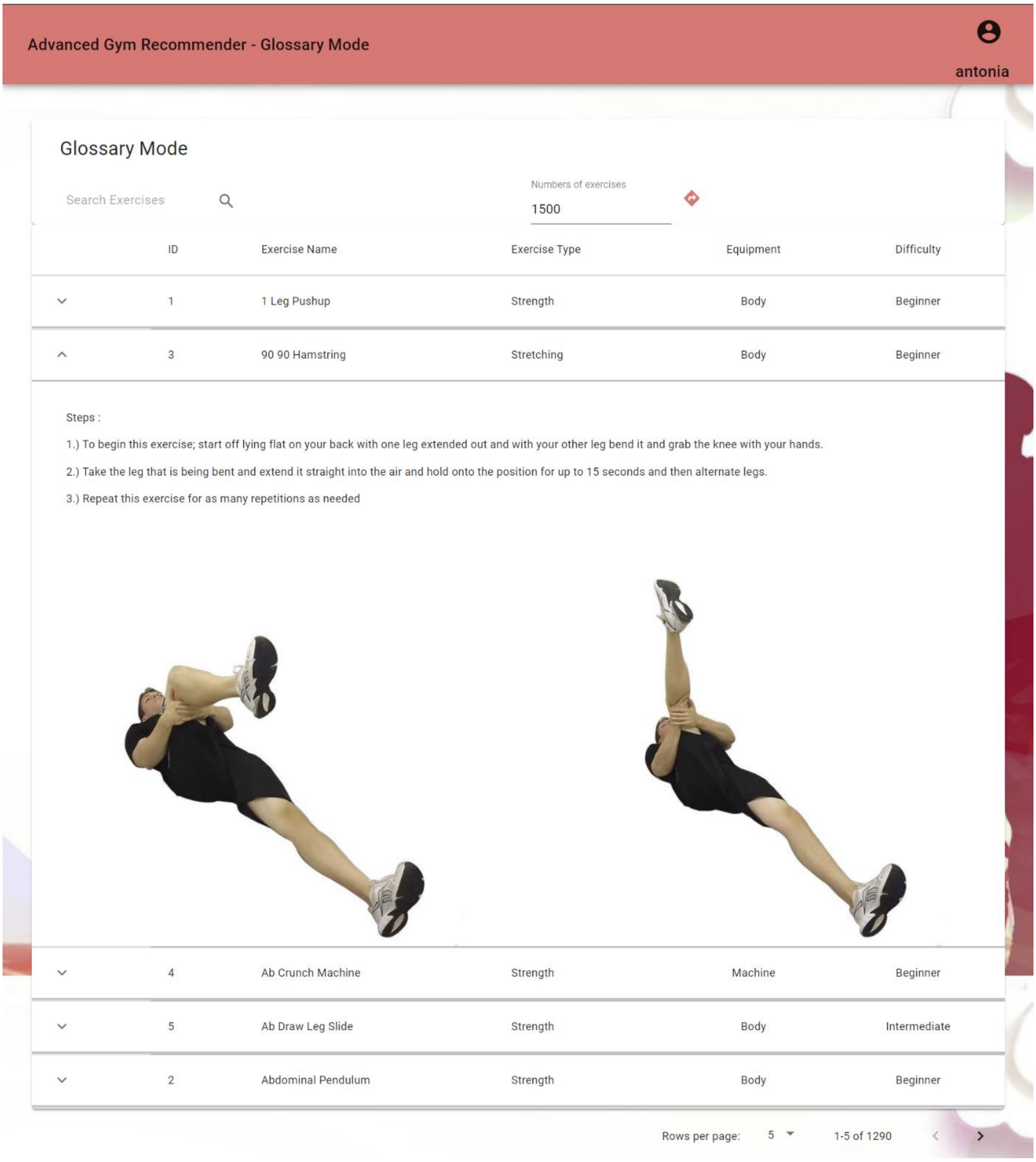


4. **Home Page**
The centre of the web-app showing all the application features. The homepage is simple and easy to navigate. This page can be routed back through the popup menu under the avatar icon of the app bar.



5. Glossary Page

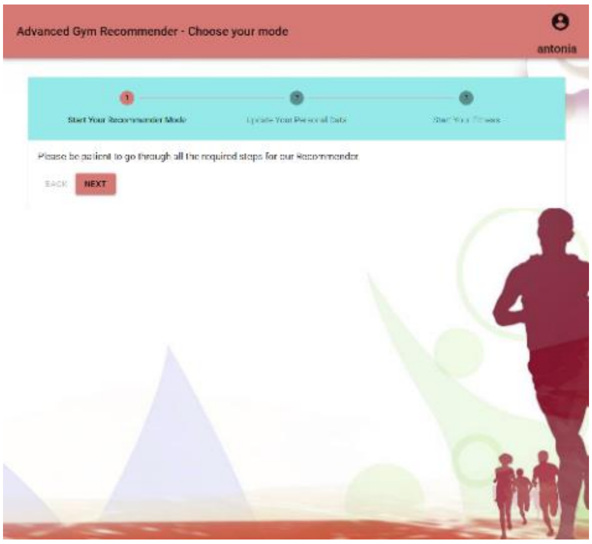
Glossary Page provided a AGR's search engine to browse through all the exercises under the system. It can filter all the exercises that contains the characters in the search bar. Due to the massive exercises data stored in our system, AGR limited the number of exercises shown on this page to avoid overflooded exercises data returned by the system. Users can also choose the total number of exercises to be browsed as well as the number of exercises per page so that the search engine can work more efficiently. Each exercise contains the relevant information to show the step-by-step instruction as well as reference picture under the collapsible container.



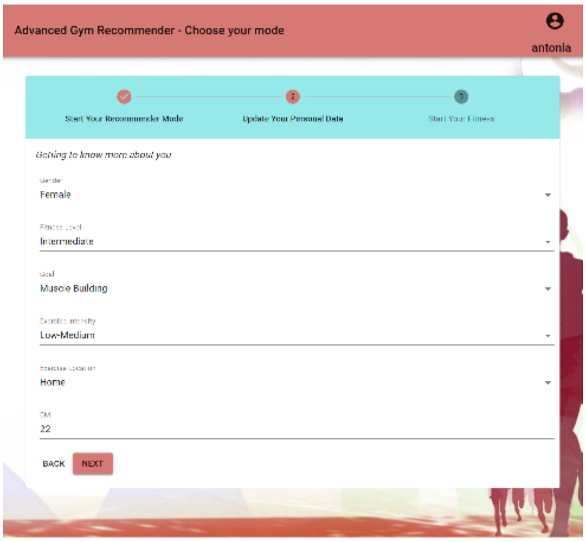
6. Mode Selection Page

Mode Selection Page will initiate the first recommendation for the user after the user has completed the registration. User can also access this page again from the Home page.

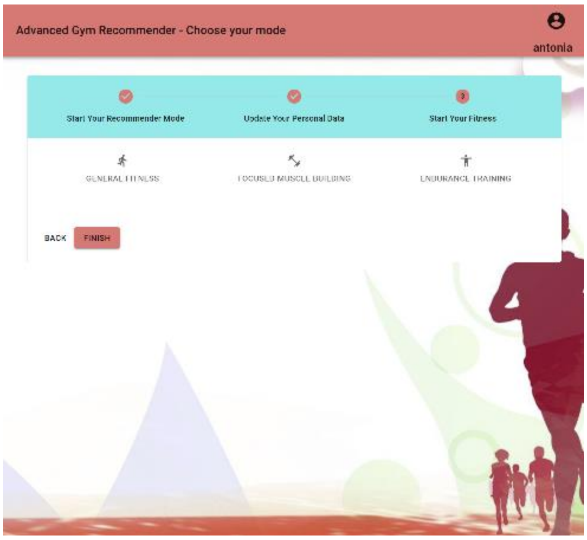
Mode Selection Page provides a smaller steps shown below:



1st page indicates the start of the mode selection page



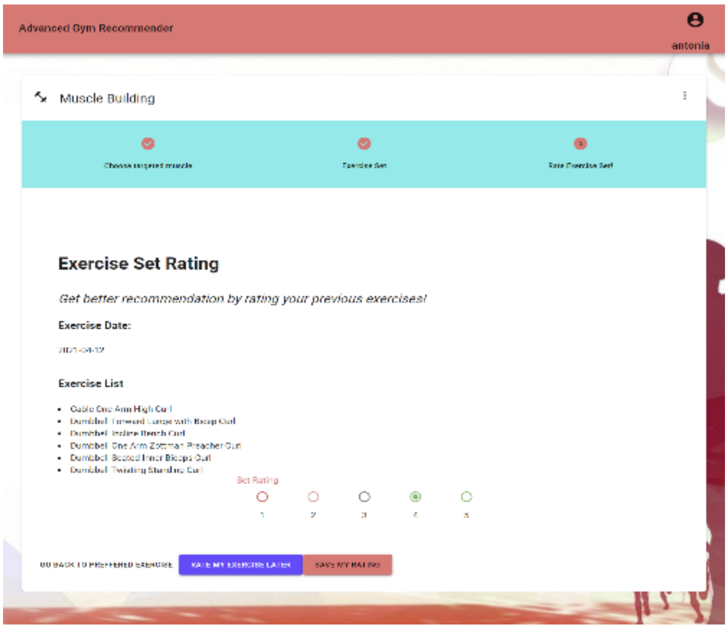
2nd page – update user details. If user have filled up user data before, the latest data will be shown



3rd Page – exercise mode selection where user able to choose type of exercises: general fitness, muscle building or endurance training.

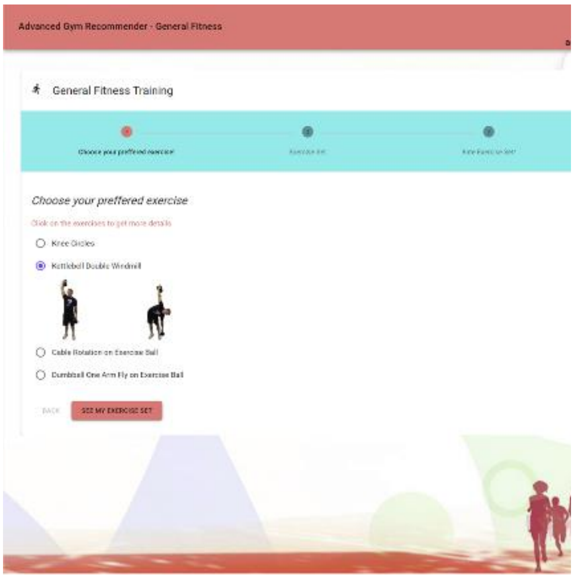
7. Exercise Rating Page

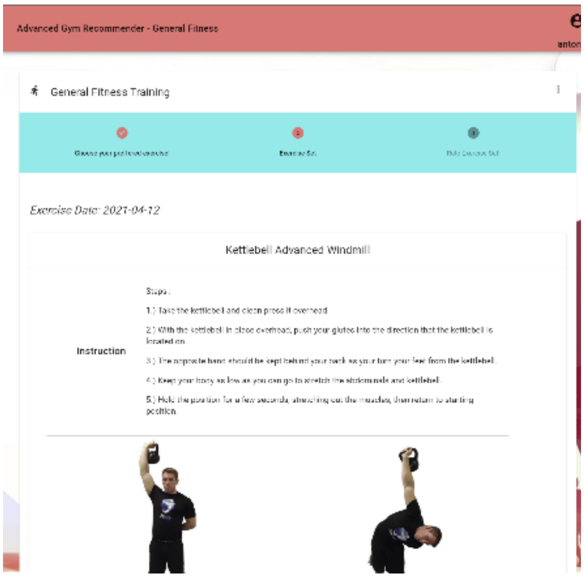
Exercise Rating page allows the user to rate the exercise set recommended to improve on the future predictions. This page will be shown at the end of every set of exercises recommended to encourage user to rate. If there are no more exercises can be rated, this page will redirect back to the home when user browses to this page.



8. First General Fitness Page

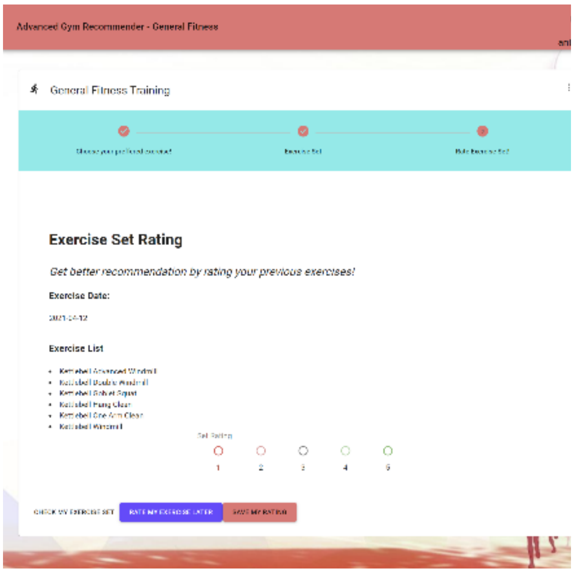
The AGR will introduce the user the first general fitness page when it is the first time for user to use the general fitness mode. The first general fitness page differs from general fitness page by the additional steps and information required from the users. The details are shown below.





1st page of general fitness exercise requires user to choose the exercise they like the best out of 4 random exercises. This is to get individual preference from the users.

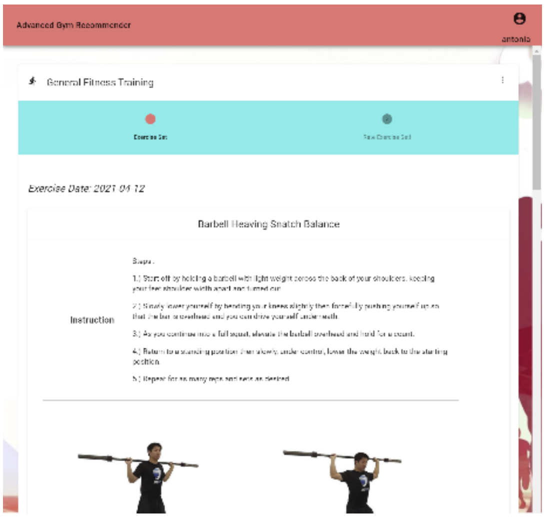
2nd page shows the 6 recommended exercises based on the preference chosen in page 1.

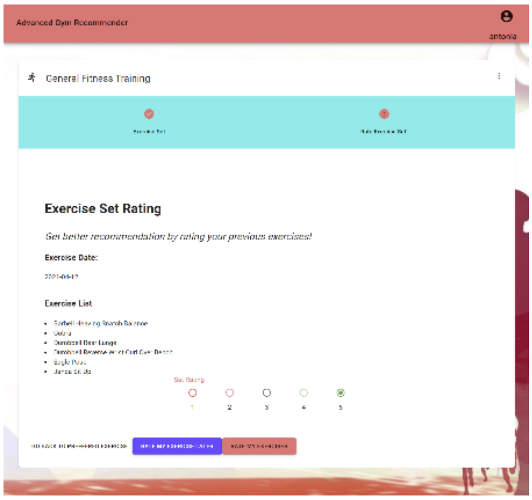


3rd page provides to rate the exercises recommended to improve future recommendation. User can skip the exercises recommended and rate it later.

9. General Fitness Page

General Fitness page mainly inherits all the steps from first general fitness page. Users must have rated at least one their previous exercises before they can access this page.





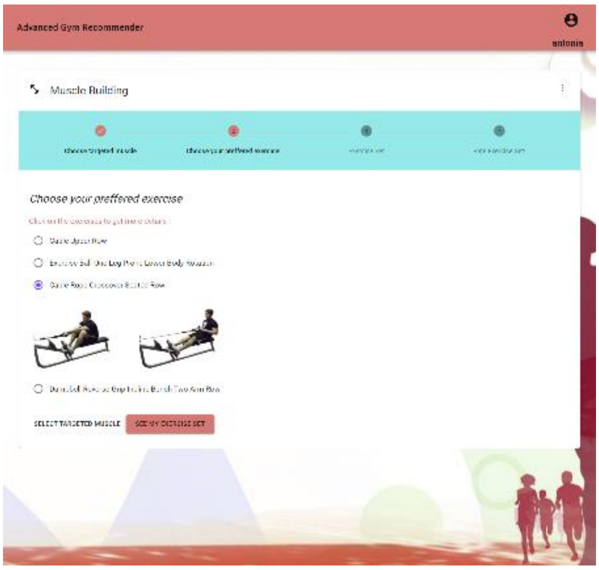
1st page is showing the 6 exercises recommended to the used based on the historical data.

2nd page is rating the exercises recommended to improve future recommendation.

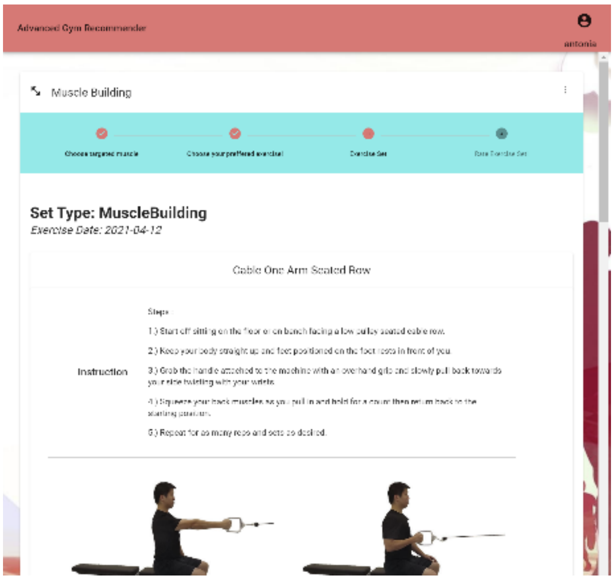
10. First Muscle Building Page

First General Fitness Page provides user different selections to choose a targeted muscle group to train but the steps in this page are similar to the General Fitness page. This page will only be shown to user if user never choose and rate any exercises under muscle building mode.

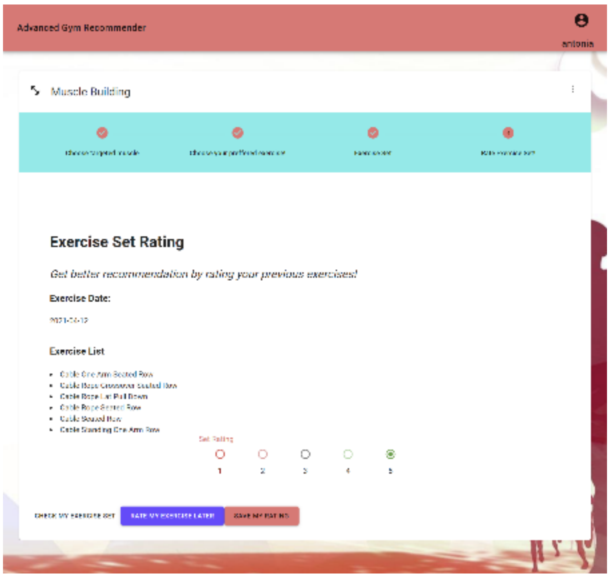
1st page is getting user's targeted muscle.



2nd page allows user to choose his preferred exercise which is the best out of 4 random targeted muscle exercises.



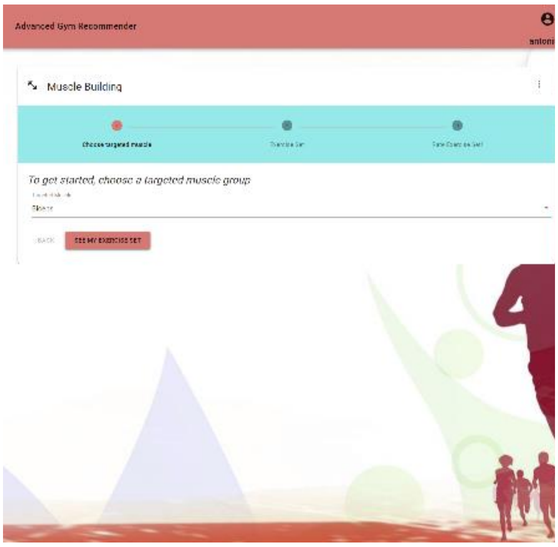
3rd page showing the 6 exercises recommended to the used based on the historical data.



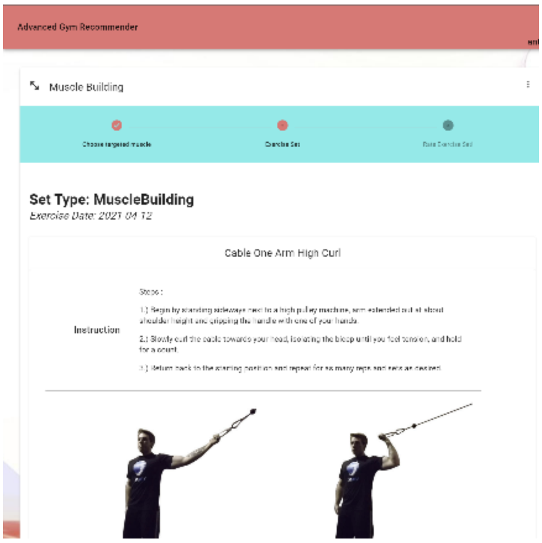
4th page is rating the exercises recommended to improve future recommendation.

11. Muscle Building Page

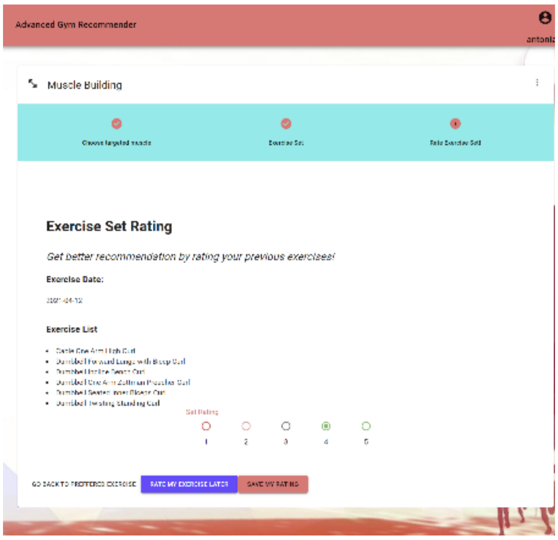
Similarly, the Muscle Building Page provides an additional step for user to select preferred muscle to train.



1st page is getting user targeted muscle.



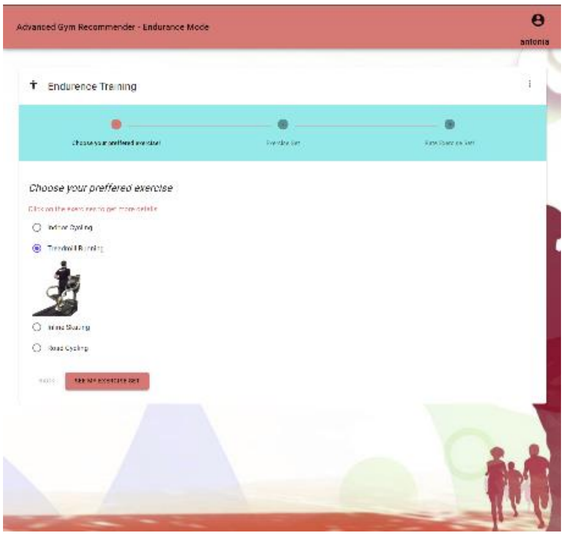
2nd page showing the 6 exercises recommended based on past exercises



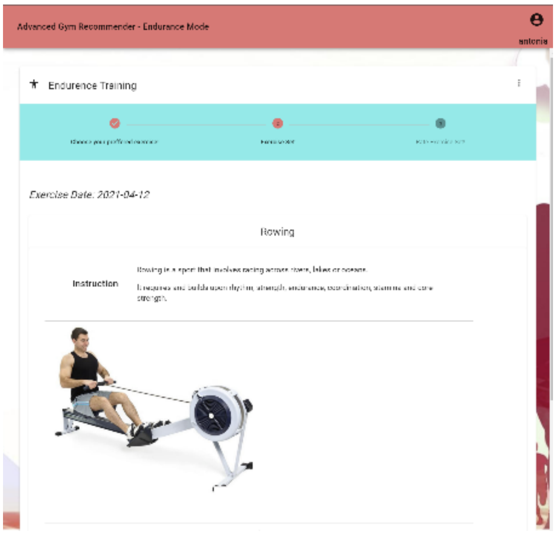
3rd page is rating the exercises recommended to improve future recommendation.

12. First Endurance Training Page

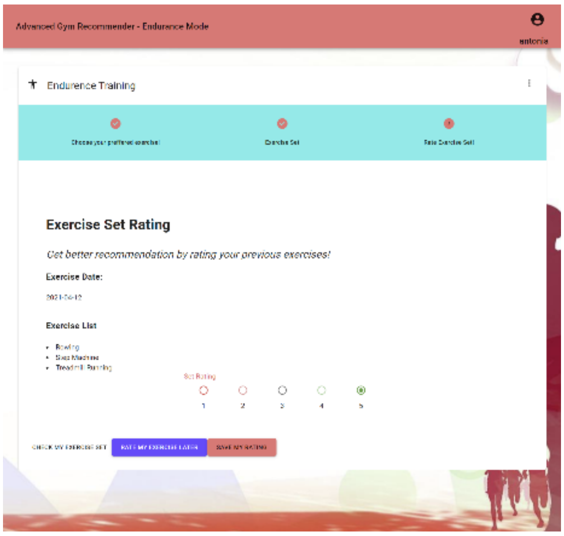
The structure of the First Endurance Training Page replicates the First General Fitness Training Page for user familiarity and the ease of use. The page is divided into 3 parts.



1st page of general fitness exercise require user to choose the exercise they like the best out of 4 random exercises. This is to get individual preferences from the users.



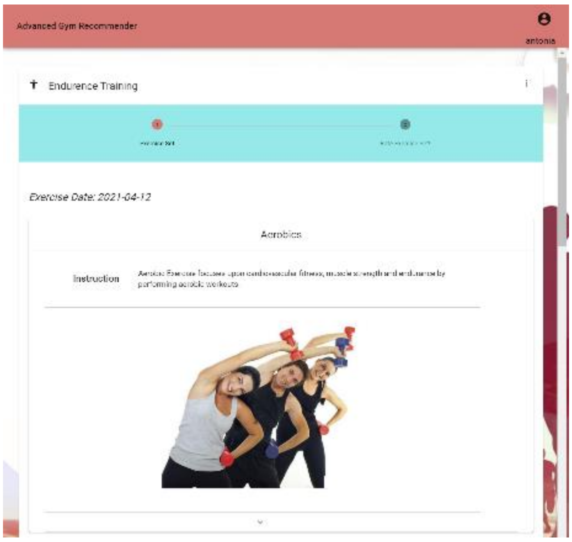
2nd page is showing the 3 exercises recommended to the used based on the chosen exercises in page 1.

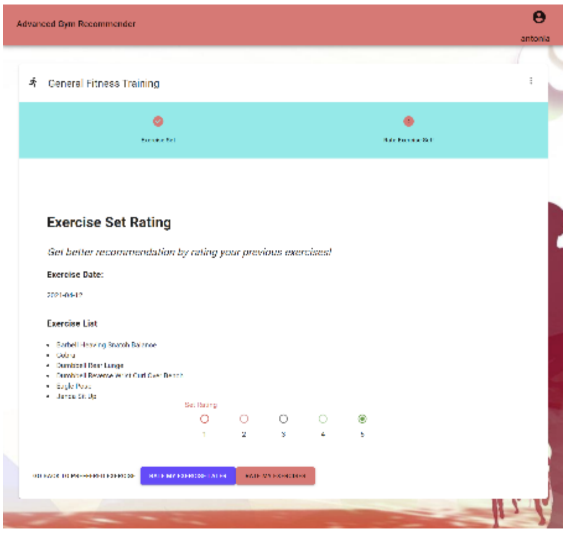


3rd page is rating the exercises recommended to improve future recommendation.

13. Endurance Training Page

The Endurance Training Page is similar to the General fitness page. It only inherits the second and third steps from the First Endurance Training Page.



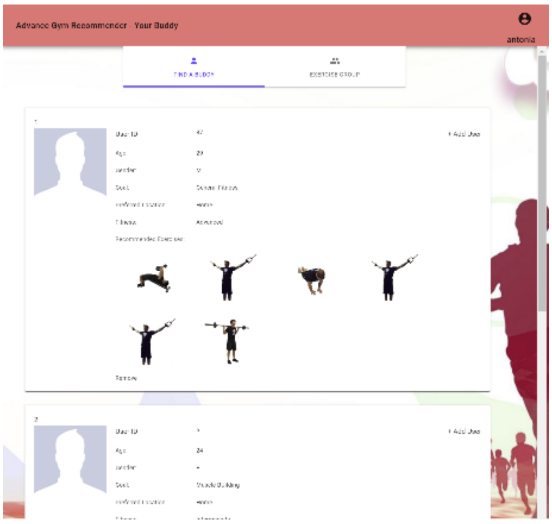


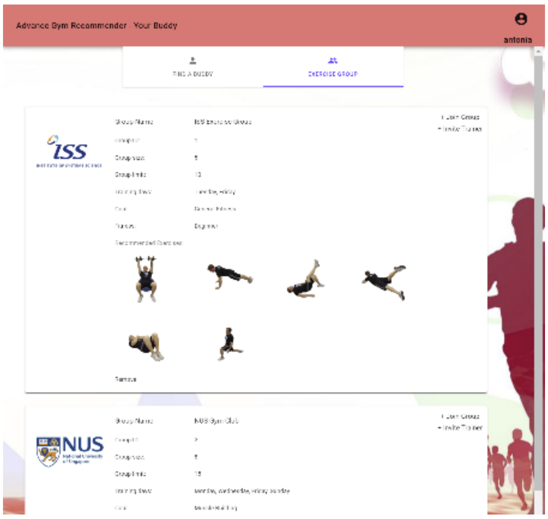
1st page is showing the 3 exercises recommended to the used based on the historical data.

2nd page is rating the exercises recommended to improve future recommendation.

14. Exercise Buddy Page

The Exercise Buddy Page is used to find other user / exercise group with similar training profile, interest as well as exercises preferences. The platform is meant to connect with other users and encourage users to work out together to keep the momentum going.



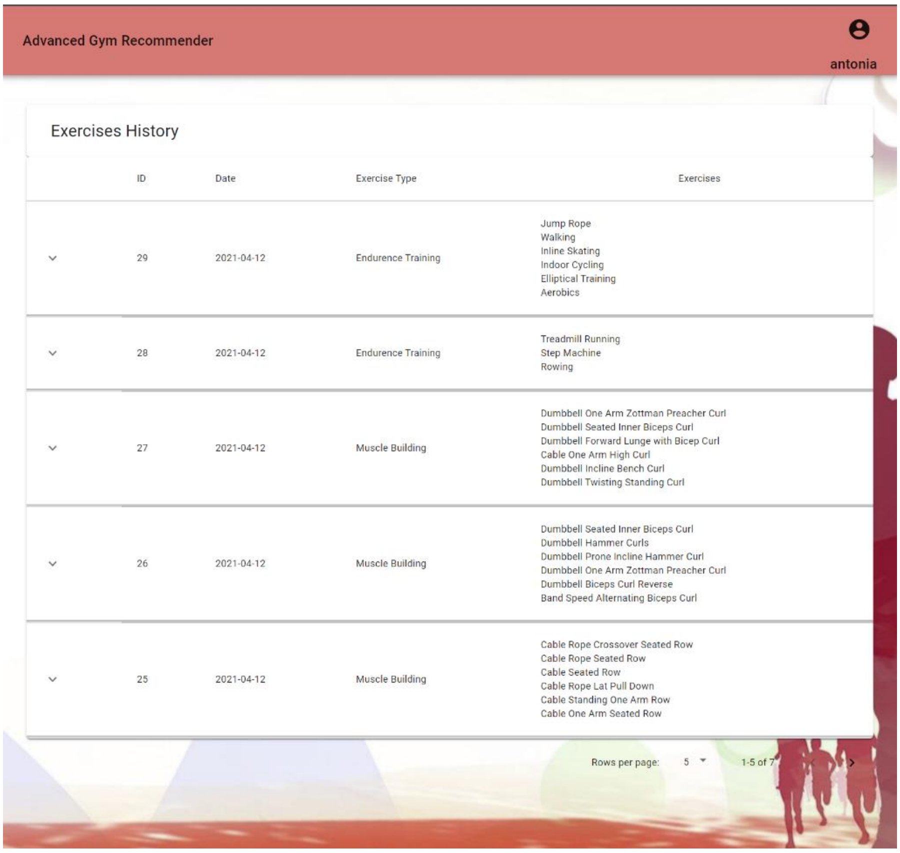


1st page shows other users with similar profile.

2nd page shows exercises group

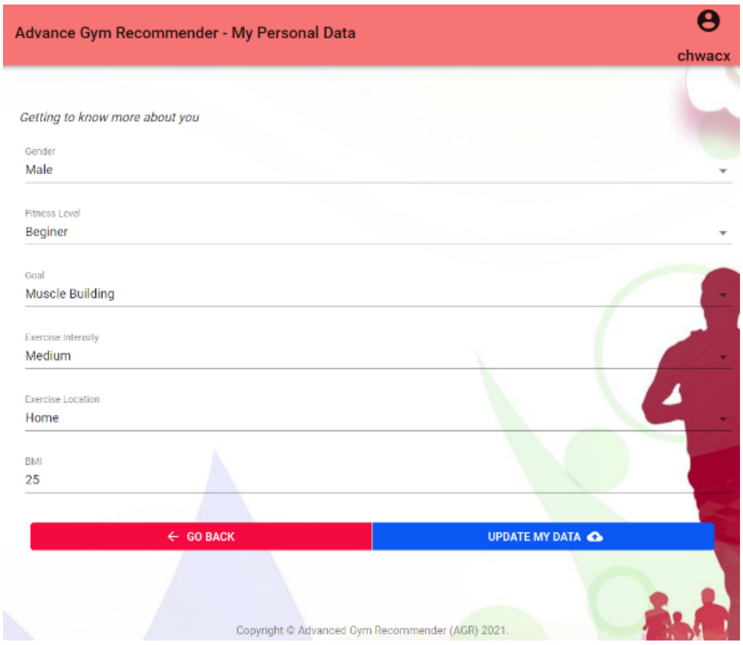
15. Past Set Exercises Page

Browse through all the past exercises set that was recommended for reference to the users for easy recall. The exercises sets are expendable showing the exercises notes and pictures for more details.



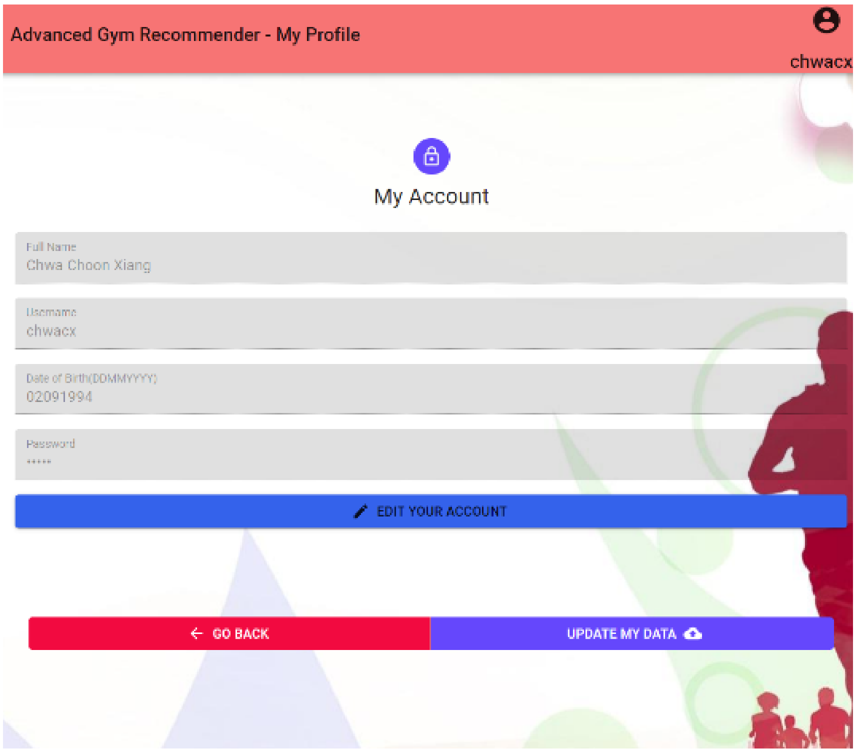
16. Personal Data Page

This page provides an auxiliary function to update his personal data anytime. If user has skipped to update his personal data after he just signs up the page, user can access to this page by clicking the popup menu shown under the avatar icon in the app bar.



17. Account Data Page

This page provides an auxiliary function to update his account data anytime. User can access to this page by clicking the popup menu shown under the avatar icon in the app bar to change the account data, e.g. username, date of birth and password.



8.4. Appendix D: Individual Project report

Individual Project Report

Your Name:	Benjamin Quek
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

For the Intelligent Reasoning Systems Practice module, I lead the development of the solution architecture via Knowledge Modelling and Acquisition to design the overall flow of our Advanced Gym Recommender. The design of the solution architecture involved linking what data we could obtain via our various means (online, interview, YouTube videos) to what our solution can feasibly do with our limited time and finally how the solution would be presented to our potential customers. From the raw data we have, I reviewed the relevant data columns and feedback them to our backend team and contribute towards the design of the backend database framework. These columns were important as they will serve as inputs to the recommendation algorithms that were to be developed at the later stage. I had to put on the hat of different groups of gym-goers to be able to determine the different recommendation modes that our solution was to offer to capture as much potential customers as we can. From there, I developed the formal logic rules to guide the flow of our solution based on the categorical data. Finally, I placed all the information together in a knowledge model in the form of a flowchart so that the team can have an aligned overview of our solution and can work on the individual parts of the project.

I was also tasked to design the recommender algorithm for first time users. This was an interesting problem as we would have very little or only basic information on new users signing up for our app and yet we had to be able to provide them a usable recommendation or risk losing potential customers. To develop this solution, I investigated recommender apps from other sectors for information. Article recommender apps such as Blinkist and Flipboard will show new users a random group of articles for them to select and based on the selected article the app will recommend a list of articles to get started. From here I realized that a similar methodology would work for our project and what we learnt in class is directly applicable. As we would not have much user data on the new customer, I opted to go for a content-based recommendation approach. Based on the learnings from the state of art research and what was taught in class, I decided to use Cosine similarity as the similarity metric using a bag-of-words of the various description of the exercises based on the categorical data we decided to use.

2. What you have learnt from the project.

Through this project I learnt about how to design a simple recommender solution to target potential users, in the overall design of the Knowledge Model as well as Knowledge Acquisition and Representation of the exercise data and associated expert rules.

I learnt how to translate expert rules learnt from Knowledge Acquisition to Python, building the rule-based engine for the recommender. I also learnt how to code in Python a recommender algorithm using NLP methods such as using count vectorizer to generate a bag-of-words of the descriptions of selected categorical data of the exercises to use as input for Cosine Similarity recommendation systems.

Although I am not the main contributor in these, I also learnt more about Django as a Python backend framework and using SQL for our database of exercises through working with my teammates and am thankful for that.

3. How you can apply this in future work-related projects.

The knowledge I learnt in terms of knowledge modelling and representation is extremely useful in framing work-related data science projects and planning it in a way that management can understand and support. The knowledge acquisition portion is also useful to identify potential sources of data within the company for the potential projects.

With the new skills in coding similarity-based recommender systems, I can foresee that this would be very applicable for defect descriptions in manufacturing. The various written defect description by inspectors can be run through NLP and similarity can be extracted to perform grouping of the defect episodes. This grouping can be further analyzed using other machine learning methods which we will learn in the subsequent courses to yield higher fidelity insights.

Your Name:	Chwa Choon Xiang
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

For the Intelligent Reasoning Systems Practice module, I am mainly responsible on the system architecture design of the web application solution. As a career background of system integrator and the experience on development of simple web application in my hobby project by using reactJs, I volunteered to design the system architecture and researched for the suitable framework so that all the team members can do own task independently. A suitable and efficient framework is the crucial key to succeed in this Practice Module as we must complete the full development by optimizing the time spared from all the working adults in the team. After some effort on investigation and self-learning on online tutorial, I purposed to use the Django, a well-known framework for rapid development and clean, pragmatic design and maintain the versioning control by using Github. Django provided a convenient environment to allow the backend developer to fit the Knowledge Modelling and Acquisition with the backend web API so that the full solution architecture can run smoothly. The Git versioning also kept our team in sync with everyone so that every team member is up to date with what they need to be working on.

For the development of the application, I am responsible for the full single page application design and teamed up with Antonia for the front-end development. I am focusing on the web administration, overall design for user interaction and the implementation of the Material UI components on each page. Antonia and I also discussed together about the overall user interaction and resolved many bugs encountered in the reactjs Material UI framework. We maintain a good habit to keep our work in sync so that we may not create any conflict in the code written. Lastly, we discussed together for the scene for the promotion video and it was a great team effort for completing the preparation of the two videos. I also took initiative to update the content of our github repository so that our github repository and video link in the Youtube are ready for submission.

2. What you have learnt from the project.

At the very beginning stage, I do not have sufficient knowledge on the intelligent system and cannot understand clearly about the previous practice module given. However, we do not stay idle and started to discuss some points from the knowledge modeling from the example given and were opened to any idea proposed. We recorded down the business idea and the idea shared which benefited me to have better understanding on the information shared on class. I have learnt from my teammates about the knowledge modeling and acquisition proposed and brainstormed about the method to fit the modeling with the user interface. After many informative and knowledgeable classes, I managed to know about the solution architecture and recommendation algorithm developed by our teammates and related it with the content delivered by the professor. Nevertheless, I also sharpened my skillset on the web development from many mistakes and bugs faced and learnt more efficient time management. When the full recommender system is successfully implemented, the outcome of knowledge modeling and behavior of the web application is amazing. It was really a great team effort to complete whole practice module.

3. How you can apply this in future work-related projects.

By using Collaborative Filtering and Matrix Factorization learnt, the data stored in the production can be analyzed to define the product similarity. Excessive or duplicate product definition or unused product can be easily detected. If the description of the recipe is given, we can apply the content-based filtering to retrieve the reasoning of the recipe and apply it to get the favorable recipe of the product. The characteristic of Collaborative Filtering on recommendation system is impactful on the understanding and relationship among all the useful data.

Your Name:	Antonia Devina
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

The project flow can be divided into three general sections. Project research, project execution and project report and videos. Together with my three team members, I contributed to brainstorming of possible project ideas and market research. Upon the chosen topic, gym exercises recommender system, I took initiative to create web scraping codes in order to get all the available information from publicly available web sites. The data are then combined into a table, which become the 1300 exercises dataset. Following my initial work, my main task in project execution is to create, maintain and connect the database to the backend/frontend application based on the specification. In this task I ensure all data are saved as intended with minimum data repetition for easily scalable project. I weigh the pro and cons of using unstructured database vs structured database. Although at first unstructured database appeal more to me for the flexibility that it offers and minimum repetition from the dataset, the data would require processing to be translated into arrays format to supply all the needed information to the back-end recommender algorithm. Thus, I decided to pick structured database for the ease of useability in this project. The data are broken down into many smaller tables to prevent repeated data storage for one-to-many relationship. Furthermore, I have also taken the responsibility to develop the front-end webpage lead by Choon Xiang. My primary task is to developed interface for the recommender systems, ensuring the right query and render of the back-end data. One such task is to ensure the system able to correctly call the appropriate recommender function (first/second) without the users specifying which they would like to call. During the implementation, I have also created utility functions which are universally used to simplify the parsing of information from the back-end into a json format that can be easily be transferred to the front-end system. For the final part of the project, the team consolidated and summarized the project in one report. I ensure the relevant information and require topics are included in the project report. I took the initiative to provide the installation guide for our AGR web application so that it will be replicable in the examiners local machine.

2. What you have learnt from the project.

Being involved in front-end designing and back-end logic without any prior experience in web application, I have learnt substantial amount in how information flow from the webpage to the core of the program logic and vice versa. Although the scale of the project is relatively small, it still managed to give me a holistic view of application design and development. Taking the point in creating the system database allow me to explore database structure and designs on how to reduce repeated data in the database without compromising on the easy access SQL provides as well as deepening my understanding in the pro and cons of different database management systems. On a more fundamental routine, since the project uses GitHub to manage the collaboration, I have learnt the correct procedure in creating a branch to work with, how to fetch and create pull request to ensure minimum conflict between working codes.

3. How you can apply this in future work-related projects.

At work, I have developed backed solutions to reoccurring problems, however the solutions are not user friendly as I did not build a user interface for the backend solution due to limited knowledge. With the knowledge I have learnt in this project, I will be able to create a simple web application to allow non coder users to be able to access my solution. Furthermore, the organization provide us with Bitbucket as collaborative platform which is like GitHub. My experience with GitHub in this project is directly applicable in my work.

Your Name:	Gerard Ong Zi Quan
Certificate:	Graduate Certificate in Intelligent Reasoning Systems

1. Your personal contribution to the project.

In this project, my contribution started with idea conceptualization and project scope development, which I shared and discussed with my group members. The chosen topic of AGR was accepted and I generated a business case for our project, by conducting in-depth market research and analysis of existing products/solutions. I gathered information from a wide range of sources such as journal articles, market reviews, statistical data, domain knowledge blogs and product descriptions & reviews. Following that, I consolidated and analysed the data to identify key features to include in our project scope, and outlined the business case narrative in our written report.

Next, I focused on the backend algorithm solution for our recommender system. At the initial stages, I researched on different recommender algorithms from their documentation, which could be applied to our project. Working closely with Benjamin, we developed a hybrid-reasoning system to cater to different functions and utilities of our entire product. I worked on the data-driven explicit recommendation using user ratings of the exercises, to narrow down the exercises the user might like from a database over 1,300 different exercises. Due to the hidden nature of latent factorisation, I conducted generation and test runs of user data to understand the algorithm performance and whether it provides a suitable recommendation to the users. By analysing the output user feature matrices, I further extended my work to establish user to user recommendations using analogical similarity, and generation of shared-interest exercises by exploring how I could maximise the use of the algorithm outputs, to create added features to our product. This would help to address the challenges of the market and distinguish our product among others.

With the added feature in mind, I worked on the integration of this feature on the frontend. Being relatively new to frontend development, I learnt from online tutorials and consulted my experienced teammates Choon Xiang and Antonia. I successfully managed to create the desired webpage, buddy/group recommender, which linked the backend algorithm outputs and database information to the frontend display. As part of the final deliverable submission, I contributed to the video content development with my teammates and did the video editing for the promotional video. In the report, I also showcased the project implementation through a case study, providing a detailed walkthrough of the system features, and application of our reasoning output to value-add to our users.

2. What you have learnt from the project.

Having worked on the backend and frontend development, this practice module project has given me a better understanding of how an intelligent cognitive system is developed. In addition to the new coding and development skills I have picked up, I have also learnt how different reasoning techniques apply in various scenarios in order to provide a complete solution to our users. While the reasoning methods/algorithms are central to an intelligent system, it also encompasses development of other key aspects such the database (memory) and frontend user interface, which provides data exchange and interaction with the 'real world' users. Hence, there are several new considerations to take into account, for example the scalability, real-time processing, memory space and practicality of our proposed system. At a product level, the user experience and reception to our proposed solution is important to retain our clients, and should also be designed to allow us to implicitly and explicitly gather as much data as possible to drive our reasoning algorithms more accurately.

While I was conducting the market review and business case development, I learnt that our ideas should have a differentiating factor over other products, and provide a value-added service to our clients. As the reasoning and recommender algorithms may not be new, the usage/analysis of the collected data and translation to meaningful outcomes becomes very important to create a demand for our product. This requires proper understanding of our target audience and specific challenges in the domain or local context where we want to implement our solution.

3. How you can apply this in future work-related projects.

Having integrated various system components and completed the project successfully, the knowledge and experience gained will help me in designing future intelligent cognitive systems for my company. This involves proposing and developing full stack solutions that takes into account how the user will interact with the product, and how the company specific domain knowledge may be used to conduct the reasoning process. This project has also expanded my viewpoint on AI beyond the classical “machine learning”, and I could propose alternative or hybrid reasoning solutions to my company, depending on the problem statement and data/knowledge available. The various tools/platforms that we have utilized in the coursework and project will also provide a good foundation for me to further deepen my skills in the future, to assist in building more robust and industry ready solutions for my company.

8.5. Appendix E: Abbreviations

List of abbreviations used are summarised below:

AGR	Advanced Gym Recommender
AGC	Active Gym Coaching
BMI	Body Mass Index
CF	Collaborative Filtering
CAGR	Compound annual growth rate
MR	Machine Reasoning
RS	Reasoning System
CS	Cognitive System