Nojaded App: Paper Printing and Recycling Mobile App using Recommender System

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Abstract*- Paper Recycling has always been a major issue and according to the Food and Agricultural Organization of the United Nations (FAO), the total global paper use is still steadily increasing. We argue that, among many factors, Homeowners' failure to divide up waste is one of the causes. The objective of this research is to design the Nojaded app, a mobile application that uses recommendation techniques to ease the paper recycling operations by facilitating communication between the recycling organizations and the paper donors and also facilitating the paper printing operations for users by creating a platform for which they can easily use to print or purchase papers and receive them from their house step. The recommendation engine in this research uses a combination of Collaborative Filtering (CF) and Content-Based Filtering. CF is used to perform data filtering based on the similarities of user characteristics, which will help us identify patterns that choose the appropriate parameters dealing with users, whether it is for paper donation or paper purchasing. Content-Based Filtering is used to enhance the personalization experience of the user in the paper printing side of the app. The used datasets have features that benefit the recommender system and help build a model for the user. These features are obtained from the printing centers and the users. Each operation has a rating. The filtering methods are measured for accuracy using Mean Absolute Error (MAE) with a most significant MAE of 2.27.

Keywords-- Recommender System, Collaborative Filtering, Content-Based Filtering, Paper Recycling, Paper Printing.

I. Introduction

Wastepaper collection is economically and environmentally inevitable. And with population growth and technological developments, the paper consumption rate is rapidly increasing. Collecting paper waste in third world countries does not always work as intended due to various reasons. One of these reasons is the appearance of valuable material in the composition of other municipal waste, also referred to as dirty gold [1].

Many factors can affect paper recycling. One of these factors is the citizen's recycling habits. Controlling these habits in metropolitan areas is an arduous task since people who live there have different cultural and social backgrounds.

Much of the effort has already made use of mobile applications to engage users to improve recycling. Most of these apps are by Municipalities. However, these apps lack features that keep the user from uninstalling the application after using it once. Also, users do not benefit from using these apps, which leads to rare adoption.

To know the advantages and disadvantages of the applications developed to supports recycling and paper printing in Egypt and to know what is lacking in these solutions, we performed a market survey of the currently existing recycling mobile apps. We found only four applications that are in the domain of paper printing or recycling in general. Two of the surveyed apps are in the recycling domain the others are in the printing domain. For simplification purposes, we will only report the main highlights and problems in these applications.

After making the market survey, we found that the number of reviews and app downloads is pretty low. This sentence is true for all the surveyed applications except for one app managed by collaboration with the Egyptian Ministry of Environment and GIZ Egypt. This app has a rating of 4.3 and more than 10 thousand downloads. The idea of this application is to take a photo with your mobile phone of the street garbage, the photo will be sent to the authorized waste collection company, and they will send you back a photo of the location after they have removed the street garbage from it. The initiative is creative and clever. However, users complain about the shallow coverage of areas, and as we have mentioned, this will not fix the "dirty gold problem" since they collect the garbage with different types of wastes.

The other recycling application has recently changed its theme from collecting street garbage to residential services, increasing its rating from 2.2 to 3.7. This app intended to reward users by giving them money for calling the service and letting them clean the area, but it ended up making users pay more for transportation services and the effort spent on cleaning, leading users to put the app down and stop using it. After changing its theme, the number of app downloads has increased from one thousand to ten thousand.

In the printing field in Egypt, most of the applications are for connecting your mobile phone to your printer, which is not useful at all for users who do not have a printer. Only two apps take care of printing and delivering your prints One of them asks you to upload your document file and then sends that file to the printing center who in turn prints it and delivers it to you using your location, while the other takes care of 3D prints only. The app concerned with paper printing is dedicated to only one printing center. That means that the service coverage area will be very shallow. And the number of users will be limited. This in turn explains why there are few downloads and no app reviews for that app.

Our approach to solving these problems is to create a mobile application that will ease the paper recycling process by motivating users to divide up waste and hand the paper waste to the municipality in exchange for points. We aim to create a platform that brings together the bulkiest number of people who frequently involve in paperwork in one place to track their paper purchases and offer them the easiest and the handiest way to recycle these papers. For this purpose, we created a platform that uses recommending techniques for which users can print, purchase, or customize their softcopy documents and receive them as hardcopy ones from their house steps with the intended quality and format by partnering with paper stores and printing centers. Recommendation techniques are utilized to remove the overload of selecting the appropriate paper shop or printing center from the user's shoulder. And it is also used to offer the proper services to the users based on the users' profiles. Doing so gives the user more reasons to keep the app and use it more frequently. Different types of recommendation techniques are used.

In this work, we will be presenting the initial design steps of the Nojaded app, a paper printing and recycling cross-platform mobile app.

II. Related Work

Few studies directly address recycling problems using a mobile application. Each of them addresses the issue with different techniques. For example, the authors of [2] proposed a design of a recommendation engine for a waste recycling application that uses a combination of Collaborative Filtering (CF) and Location-Based Service (LBS) to connect waste donors with users who need these wastes having in mind the distance and the type of the waste. Recommendation technology finds a matching type of waste for your needs using your Android device's geolocation and waste description. Meanwhile, the authors of [3] presented an application to support waste recycling for smart cities based on user-centered design principles to solve the problem of low adoption rate. The authors showed that involving the users in the design process can increasingly help create a better and more adoptable recycling application. To increase adoptability, gamification was introduced to influence an individual's desire to recycle their waste. The authors of [4] showed that gamification techniques have a significant influence on making the user recognize the functionality of the app with less pressure and to adopt the application overall.

In Nojaded App, in the recycling field, we focused our efforts on paper recycling only. Our Contribution is creating a platform with services that can attract users who frequently involve in the paperwork. That gives us the ability to follow them and offer them the handiest ways for recycling their wastepaper independently and without it being composed of other types of wastes. Doing so helps in the dirty gold problem. To do this, we used machine learning techniques to facilitate the processes of the application for the user and gamification techniques to encourage users to change their recycling habits for the better.

III. Proposed System

A. The need for the app

For the proposed system we studied the advantages and disadvantages of the currently running apps in the recycling and paper printing domains in Egypt to know their limitations and to obtain the requirements and the features of the Nojaded mobile app. The final output is summarized in the following:

- A combination of paper printing and recycling services should be available in the app.
- The partnered paper printing centers shall be distributed in different locations and available for service.
- Choosing the printing center for the user shall be an automated task using recommendation techniques.
- The system shall capture the user's location on every new order.
- The system will use a combination of different recommender techniques to enhance the personalization experience.
- The user shall give a rating for every completed purchase operation.
- The system shall use gamification techniques to encourage the recycling behaviors of the users.
- The system shall use machine learning techniques to predict the active and the non-active users, to target the active ones.

To further facilitate the recycling habits of users, a schedule is set up for users based on their location in the city. Each site has a specific day of the week on which municipal staff come to collect wastepaper from the users who have submitted a request for a donation.

B. The design of the proposed system

Committing to the previously discussed features and requirements, we came up with building The Nojaded App, a cross-platform mobile app that consists of two parts and is concerned about two things, the app aims to help the environment on the recycling side by providing a platform for paper recycling. This section of the app is a platform for paper donors and for people or organizations who could potentially be interested in these papers. The donors will get points when donating. These points can give donors offers or can be converted into cash.

The app also aims to ease the process of paper printing for students and people who frequently involve in paperwork by making a delivery system that delivers their softcopy papers as hardcopy ones by partnering with paper shops. It is like having a printer inside your mobile phone device. You will need to upload the intended paper in a supported format and our system will do the rest. In the end, you will receive your file from your doorstep as a hard copy with the expected quantity, style, and shape.

After using these papers, you will have the option to give them back to a recycling organization in exchange for points. In that way, users and paper recycling organizations will benefit from the app.

As of now, we are proposing to build the minimum viable product (MVP). The design is open for further improvements.

The application is split into two main services. The first services for paper printing, while the second one is for paper recycling.

1. Paper printing Service

According to our goals, we wanted to create a platform where users can perform tasks such as printing a particular document, purchasing a specified amount of paper of a certain type, or purchasing a template filled with specific information (ex: a business card with a user information)

An app that performs many functions may be complex for many users. Functionality and good appearance are essential for creating a relationship with the customers. Although the user interface is not everything, a good user interface gives more chances for the users to use the application and increases customer loyalty [5]. With that in mind, we had to create an eye-catching, easy-to-use, and self-explanatory user interface. To make it less challenging for the user, we had to separate the main operations on different screens to make them easier to access and distinguish (Fig. 2). Also, we gave the multi-choice

Fig. 1. The full app cycle.

features a unique UI so that users can be assured of what option to choose (Fig. 3).

For the operation of printing a particular document, the user should upload the file in WORD, PDF, TXT, or any valid format. When the file upload is completed, the user will walk through the subsequent steps. The user will need to answer all the questions to complete his/her order. An example of the questions is the paper type, number of copies, the packaging method and whether the user wants it color printed or not. When the user completes the order, the system will send the order details to a printing center with the help of recommendation techniques. The user can check the status of his/her order for the duration of the process (Fig. 3). If the user's order gets rejected by multiple printing centers, the application will send a notification message to the user explaining the cause of the problem and asks him to try again.

For the operation of purchasing a particular template, a set of templates will appear to the user based on his/her past purchases using recommender filtering techniques. If the user does not have a purchase history, templates will appear based on the user interests or profile details. User interests are recorded the first time the user logs in by answering some questions and his/her interests are updated by clicking on products or the viewed products by the user.

2. Paper recycling Service

This section has two views, one for the users and the other is for the recycling organizations and municipalities. For the users' view, users can make a donation request by taking a photo of the wastes and specifying its type, whether it's white office paper, newspaper, colored office paper, cardboard, white computer paper, magazines, catalogues, and phone books, etc. He/she also states the paper condition and quantity if possible and then posts the request. As mentioned in the requirements, the user will know what time the municipality staff will come and collect the wastepaper through a schedule set up for users based on their location in the city. So, the user can be ready to submit his/her wastepaper donations. For the recycling organization's view, organizations can view donations posts to collect them efficiently.

Users will be motivated to recycle their waste regularly through a gamification strategy. Gamification is when you use a video games element in a non-game application [6].

Fig. 2. Paper Printing services.

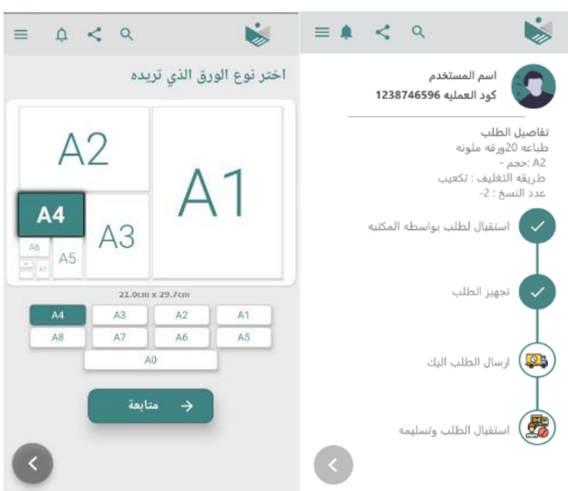

Fig. 3. Dimension of the A series paper sizes to choose from, as defined by the ISO 216 standard and the Order Status screen.

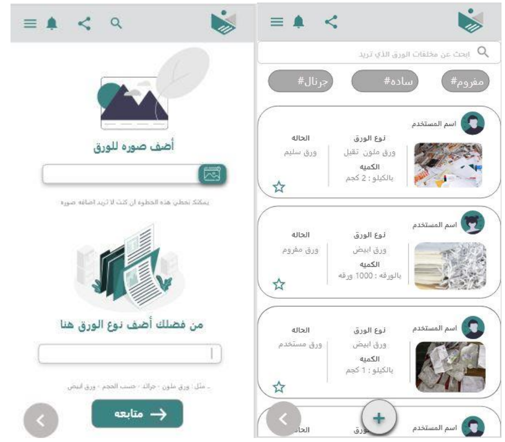

Fig. 4. The user's view adding the paper waste data and the look of the users' donations request posts.

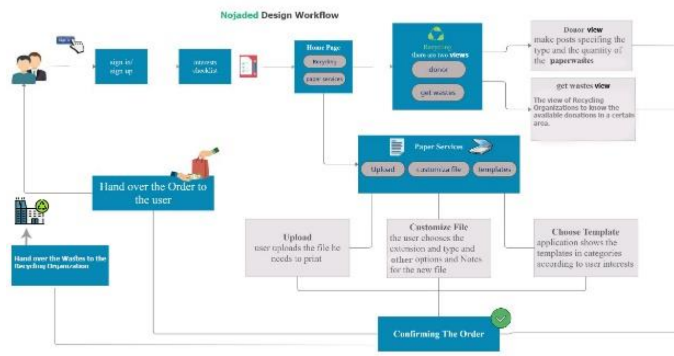

Fig. 5. The Nojaded App Workflow.

A gamification strategy can change personal attitudes based on the literature "How to Encourage Recycling Behavior? The Case of WasteApp: A Gamified Mobile Application" that worked on a gamified mobile application to encourage recycling behavior [4].

Users who made donations will earn points. These points can be increased or decreased based on the user's regularity to donate and the details of the donation request post.

IV. Designing And Applying Features

At first, back-end was extremely important to the project as it satisfies the requirements of the machine learning section. Our Recommender system will be dealing with many features and different requests from users. So, we were dedicated to build a database that can hold suitable data about all our entities that can provide an accurate recommendation as much as we can and handle the requests for data by the users fast without breaking down the system.

We were careful to brainstorm all the important features that will guarantee a perfect experience with our app and to make an effective recommender system that enhances both the printing and recycling services. As shown in fig 6, we classified the main entities participating in the printing and recycling services, we drew a complete ERD that determines both the features and relationships for all our entities that we will need for the recommender system. As shown in table 1,2. We had a description of our entities for their role in both printing and recycling processes and the most important features from their data that help us make a practical recommender system.

A. Paper Printing Service

When the user first logs in, s/he will not have any purchase history. This leads to the cold start problem; it is difficult to give recommendations to new users as the profile is almost empty, and the user has not rated any items yet, so his/her taste is unknown to the system [7]. We approached to solve this problem by using the user's profile as a starting point for the recommender system. For example, we can use the user's job or study, also the years s/he is practicing this job, or the studying year; this information will give different suggestions for the templates s/he may need. As we pass this problem, the recommender system will depend on or give more weight to different features like the number of views, clicks, requests, or purchases that user did from templates. When it comes to choosing the best printing center to deliver the user's order, we chose certain features such as the distance between the printing center and the user. We calculated the shortest path using the geolocation technology that measures the distance between the user and the printing center, but not as a straight line as it will produce a misleading output for the real distance between them, and we keep all the results and sort them to find the shortest distance. Number of printers in the printing center is important as it indicates both the number of requests the printing center can handle simultaneously and the time taken by the library to accept and finish the task. It is called "delay time" as not all the libraries take the same amount of time. The library which has the less delay time gets the priority. We use this feature to indicate whether the library will be available when the user makes an order request or not. If the user wants the package to be color printed, we recommend printing centers that can print colored papers. As for the templates, we depend on some features that give priority to a certain template, like ratings, price, the availability of the template, or some styles in it like the number of letters, number of papers, color, decorations, or views. All that makes the recommender system calculate and produce an output that is the best template the user is looking for and the best and nearest printing center to deliver the user's package. We also let the user make a review of the package and give a rating to the template and the printing center once the package was delivered. All of these features are stored in our database and are being updated continuously. We also make datasets that become bigger by time and give more accurate results.

B. Paper Recycling Service

We made it easier to link the donors with the receivers, as the donors are our users on the app who have paper wastes and want to get rid of, and the receivers can be organizations like a recycling factory who is interested in gathering these wastes. The process is as follow; the donor makes a donation request, and then, gives a brief description of the waste like its weight range, type of paper, and the location. The receiver (organization) makes a schedule for each location in which the receiver can send the employees to collect wastes from the donor and give points as a reward. These points can be exchanges with offers or discounts. The points of those regular users are always multiplied every time the user makes this process. That put a gamification layer to our service to make the users willing to donate. We recommend donors according to what suits the organizations and also according to the shortest route to the donor. To determine the shortest path, we will use the same technique as in the printing service.

Technically, to handle all these obstacles we chose Nodejs as we need to make lots of connections between many sources, it was the best choice because it supports the handling of many connections concurrently. We chose the MySQL server as using a relational database will make it easier to store and retrieve the features we are using in our recommender system.

There are some common entities between printing services and recycling like areas: It's the cities and regions in this city, it helps in finding the nearest printing center for the user and nearest delivery man as in the printing service, or for scheduling the donor's locations to collect the wastes as in the recycling service. And also the delivery men: It's the personal details for the delivery men on the app who are going to deliver packages from the printing centers to the users. There is a common feature between jobs and area which is the user will be allowed to enter the data by one term to prevent any conflictions. The last entity is paper: It contains all paper types that could be in the printing centers it's used as a reference to know what type of papers or paper sizes that a printing centers have at the time.

TABLE I
PRINTING SERVICE ENTITIES

Entity	Description
User	This collects data from the user to find him the nearest center and best services and according to the user's job and interests or the user's recent activities we could recommend the templates.
Printing	It has all the details about printing centers including their locations and the type of paper they print (type of paper has

center	many features like the size and the coloring) and the number of printers they have and also consider its efficiency
Templates	The templates features like the category, price, number of papers, design and rating
package	It has all the details about package that is delivered from the center to the user like: price, date of delivering, weight, and description of the order
Purchased package	Details about successive delivered packages which contains more descriptions like state of the package, rating of the delivery process and review on the package itself.

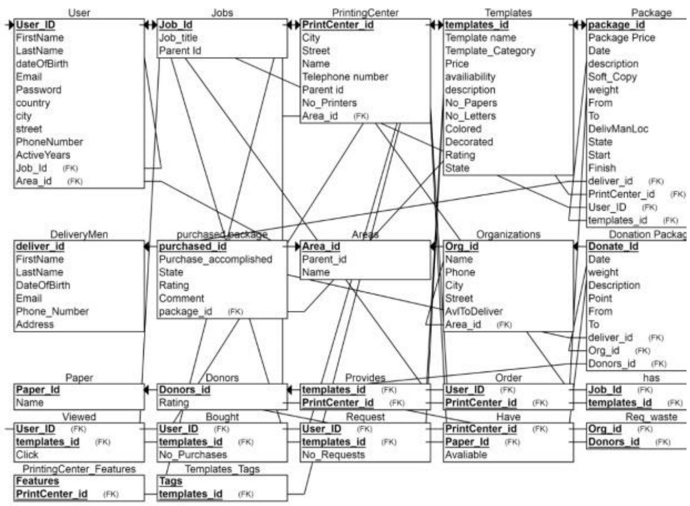

Fig. 6. Relational model.

TABLE II
RECYCLING SERVICE ENTITIES

Entity	Description
Donor	It has the same features as the user entity but with different name because the subject changed, it has one more feature which is the donor's rating (they are points achieved after every donation)
Organizations	It has all the details about the receivers of the donations and their locations and availability of delivering.
Donation package	Has all the details about the donated package which delivered from the donor to the receiver like date, weight, description of package content and points given to the donor.

V. Recommernder Process

A. Recommender System

The recommendation is a prediction system designed to predict what item the user will choose, so we use it to make our system more effective and to save the user time. So, in the templates recommendation part, we will use Collaborative Filtering (CF) which works by searching in all users in the system and finding a small group of users who have similar properties to a particular user and make a group of items they liked and a ranked list of suggestions. This technique is divided into two parts the first part is User-Based. This part works by searching the neighborhood of users who are similar to the user. And the second part is Item-Based which works by having item the user chose before and search by it in all items in the same category and make a list of similar items of it and prepare these items for suggestions by getting into some steps that will be discussed later, as shown in fig 7.

In our system we will use the two parts of CF, we will use the User-Based part for the first time for the user in our application. Because we don't know what items will the users like, we look for similar users with common interests and recommend items they chose before. The recommender system will see some information for this user like (job and number of years of experience) and search based on them in all users and select users that have the same job and the same number of years of experience and recommend to him items which have high ratings that are given by similar users like him. Item-Based will be used after the first time. When the user chooses an item or more, we will take the last item and search by it in all items to get an item that has similarity with it. Then we recommend the item with the highest similarity and rating. To ensure that our recommender model works well, we try to apply our recommender on a dataset for amazon with the same concept to ours to make sure that our model recommends the right items [8].

B. How to choose library

In this phase, we will use hybrid techniques on the recommendation process, a combination of two techniques, Collaborative Filtering and Content-Based Filtering. We will use both in our model to get the advantages of both. In our system, we will use these two techniques to make the process of recommendation more effective. We have already discussed the Collaborative-Filtering part previously, so we will go into discussing the Content-Based Filtering. Content-Based Filtering is a technique that uses item features to recommend other items similar to what the user likes based on their previous actions, as shown in fig 8.

For the first time a user uses our app, when a user requests a service, the first step is to take that service to filter the libraries based on that service, so that we get all the libraries that can provide the requested service. Secondly, to choose the desired library we have some priorities, the first priority is the distance, we choose the closest library in distance to the user.

If multiple libraries have the same distance to the user, we go to the second priority which is the library rating in the desired service. The third priority depends on delay time to make the process more effective to the user, the less delay the better of a chance the library will get to be chosen, this process will be recursive until we find a library that the user gives a good rating to it. If the user has previously used our services, we will go through the next steps. Firstly if the user orders another service, we look for the highest-rated library in that service, this part is the use of Content-Based on our recommender system, the input for the Content-Based method is the output of the collaborative, in Content-Based we have the features of the library the user likes based on his first use, secondly, we choose for him based on both the features we have and what user likes. These are the steps the recommender system goes through to choose the most suitable library for the user based on the intended service.

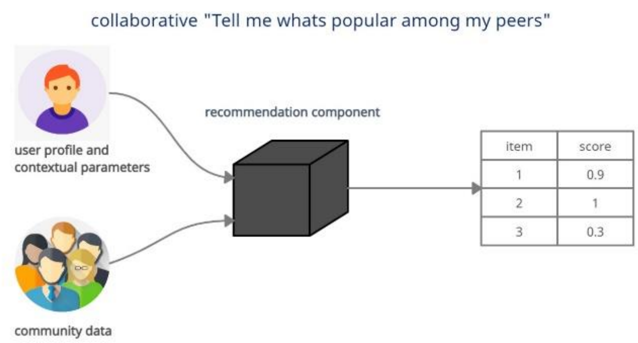

Fig. 7. Collaborative Filtering Process

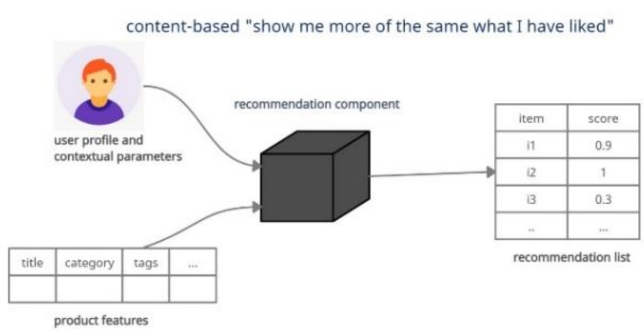

Fig. 8. Content-based Filtering Process

C. Performance measure

We use performance measures to make accurate decisions because the cost of errors or wrong decisions can be huge, but optimizing performance measures mitigates that cost, So for this process, we use MAE (mean absolute error). It is the sum of the average of the absolute difference between the predicted and actual values. With MAE we can get an idea of how wrong the predictions were. Equation symbols are 'n' which is the number of data, 'i' is the number of iterations, ‘Y’ which is the actual data, ‘Y^’ is the predicted data and '∑' which is the summation symbol. We will use this performance function to calculate accuracy for both recommenders.

$$MAE = 1/n \sum_{i=1}^{n} |Y - \hat{Y}|. \quad (1)$$

VI. Machine Learning for Predicting Active Users

One of the biggest problems with the mobile apps for recycling that exists today is the rare adoption issue. Users often use the app for a short time before they stop using it. This problem is a consequence of a poor UI and a limited services problem. Although we tried to fix these problems by enhancing the UI and improving the services, we still know that this won't solve the problem completely. A way for predicting the active and the non-active users is needed to differentiate between them so we can focus our efforts more on the active ones, which could lead to better user engagement. To do so, we adopted a machine-learning technique, which is logistic regression. Logistic regression is a classification algorithm that is used to predict the outcomes in a binary format. it is used when the output variable is categorical. In our case, the output will be whether the user will be an active or a non-active one. We can say that an inactive user is a user who has uninstalled the application or is simply not worth focusing on.

A. Building Model

To build the machine learning model, we need to create the dataset that we will use to train the model. First, we need to choose the features that can determine the output. The chosen features are the user's daily time spent on app, age, average rating of the past operations, Number Of operations, city, gender and job. We choose these features as it best indicates the willingness of the user to make an order and shows the user's need for the service. The average rating and number of operations are self-explanatory features and it's obvious why we choose to use them, while the others are a little ambiguous. The city feature is crucial to know since there could be some places where the service is not appropriately covering.

Knowing that the user is located in one of these locations can indicate a future non-active user. Also, a job that needs lots of paperwork signals a long-term customer. Gender is also a feature that can help to predict the output. For the gender, we can say 1 for a male and 0 for a female.

The second step is to fill the dataset with data. That could be a pretty heavy task since we need a consistent and large amount of data. An inconsistent dataset can lead to accuracy problems. Besides, we still don't have active users on our database to use their data. An alternative for filling the data is to get an already populated real dataset from the internet to test our algorithm [9]. The real dataset has a goal similar to ours. Ultimately, they want to know if the user will click on an ad or not. The sample size of the data is one thousand. So, we can safely say that it will be a good test for our model. We started by visualizing the data to understand it more, and then we started the preprocessing part where we get rid of the unwanted features and remove the null values. Logistic regression doesn't support the use of categorical data in the training process. So, we need to convert these data into numerical by encoding them.

Before training the model, we need to split the data into a training and testing set. We use the training set to train the model and the testing set to evaluate the model's performance. The split is usually performed randomly.

B. Explaining the output of the model using Explainable AI

Machine learning is a black box. Even if we knew that the model has good accuracy, can we depend on its decision? AI, in general, has lots of applications. You can build a model in a financial or security context. If you were to take responsibility for the machine's decision in such contexts, would you blindly trust its decision? Probably the answer is no. It is doubtful to find a person who would trust a machine in an ethical, serious, or life-changing situation without understanding the decision-making steps of the system [10]. That is when the Explainable AI (XAI) comes in handy. XAI supports the machine decision with a human-understandable explanation. You can then analyze the explanation to see if it is based on logical arguments and does not conflict with reasoning. If this is true, you can trust its decision.

To understand the decision-making route for the logistic regression output and how features affect the decision. We adopted an explainable AI technique called Local Interpretable Model-agnostic Explanations (LIME). Simply put, LIME works as if you have a black box in which you can insert input and get the output as many times as you want. Your goal is to figure out the relation between the inputs and the output and understand why the machine made a certain decision [11]. We used the LIME technique to explain the output of the logistic regression model to back it up.

TABLE III
ENCODED FEATURES FOR ACTIVE USER PREDICTION

i	Daily Time Spent on App	Age	Average Rating of Five	Number of Operations	City	Male	Job	Active
0	8.04	35	4.5	*14*	*19*	*0*	*3*	1
1	1.62	31	4.0	*2*	*4*	*1*	*14*	1
2	0.1	35	*2.0*	*1*	*9*	*1*	*22*	0

TABLE IV
ENCODED FEATURES FOR CLICK ON ADS PREDICTION

i	Daily Time Spent on Site	Age	Area Income	Daily Internet Usage	City	Male	Country	Clicked on add
0	22.35	38	6183	*259.3*	*82*	*0*	*3*	1
1	34.23	35	6844	*121.2*	*23*	*1*	*211*	1
2	55.47	26	5000	*412.6*	*75*	*0*	*88*	0

VII. RESULTS

A. Recommender Process

For training our model, we choose flat contract as an example, so our model starts to classify all items and get only the ones that are in the legal contract category, and our model finds out that the highest rated item in the legal contract is marriage contracts, and that what will be the first item to be recommended followed by divorce contracts, For hybrid technique which is a combination between Collaborative Filtering and Content-Based Filtering we will Look for an item that the user chose, then we search for the highest library in rating for this item. After that, we will compare the characteristics of the highest-rated libraries and the library that the user dealt with before to try to get the best library with the characteristics that the user likes most. The Item-Based CF method gets an MAE value of ***2.27.***

B. Machine learning for predicting active users.

We populated our dataset with 1000 users' data. The User's activeness prediction test using the logistic regression model has shown an accuracy of 97%. The testing was with a sample size of 200. These results are demonstrated with a confusion matrix (Fig. 9). This is related to the user adoption problem. The user activeness prediction helps with this problem as it gives us an indication of whom to target and where to put our efforts.

C. Local Interpretable Model-agnostic Explanations (LIME)

LIME was used to support and explain the decision of the machine. The result of LIME shows how each of the features has affected the decision and by how much. A negative number means that this feature in this certain status affects the decision negatively, while a positive number shows the opposite. As shown in fig 10 and table V, an average rating of less than or equal to four negatively affects the activeness of users. It means that a rating of four doesn't always mean a satisfied long-term user. A 0, which means a female, negatively affect the output by 0.03. In the dataset, we got thirty different jobs. When encoded, they change into numbers from 0 to 29. the results show that three jobs negatively impact the output by 0.02. A user who works in one of these jobs is an indicator of a non-active user. It also shows that five cities affect the output negatively and the ages from 30 to 34 does the same. On the other hand, the daily time spent on the app positively impacts the output of the prediction model by 0.08. Users who use 5 minutes of their daily time to use the app are active long-term users. And a number of operations of more than 2 also positively impacts the prediction by 0.02. Users who made two or more operations are likely to be active long-term ones.

When we used the model on the real dataset for predicting if the users will click on an ad or not [9], we tried to choose features that are similar to ours. The result showed negative outcomes for the daily internet usage time and daily time spent on the app (Fig. 11), which means that users who tend to use the internet or the app for more time usually avoid clicking on any ads. The Age feature from 10 to 16 and the gender feature when the user is a male has the same negative impact of 0.04. The only positive impact is for the area income when it is more than 243.75 dollars. It means that users that have more income tend to click on ads more, these ads could be product ads or e-commerce websites ads. Of course, the system can behave differently based on the ad type.

Fig. 9. A confusion matrix of the user activeness prediction.

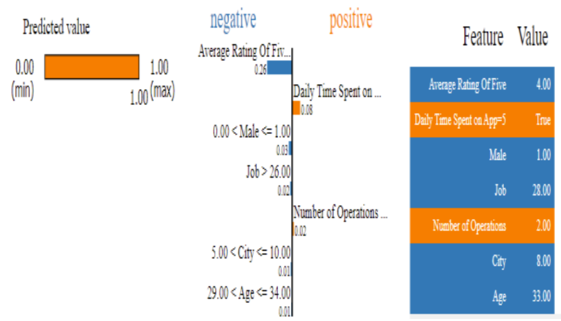

Fig. 10. The explanation of user activeness model prediction result using LIME.

TABLE V
EVALUATING THE MODEL BASED ON PRECISION, RECALL AND FI-SCORE.

	precision	recall	f1-score	support
Non-Active	1.00	0.83	0.91	30
Active	0.97	1.00	0.99	170
Accuracy			0.97	200
Macro avg	0.99	0.92	0.95	200
Weighted avg	0.98	0.97	0.97	200

TABLE VI
THE EFFECT OF EACH FEATURE ON THE DECISION FOR USER ACTIVENESS DATASET

Feature	Effect on decision
Average Rating of Five <= 4.0	-0.25605062534269346
Daily Time Spent on App=5	0.08191300244441065
0.00 < Male <= 1.00	-0.03412678477794724
Job > 26.00	-0.019490772989767348
Number of Operations <= 2.0	0.016674509317738805
5.00 < City <= 10.00	-0.014128766182051536
29.00 < Age <= 34.00	-0.008324613130111373

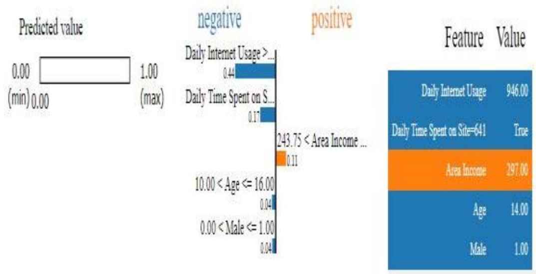

Fig. 11. The explanation of the prediction of user click on ad result using LIME.

VIII. Discussion

A. Recommender Process

In the first phase which is recommending in the template part, we create a dataset that contains some information needed in the recommendation process like user id, template name, template category, rating given by the user, user years of experience and user current job. We use these data to train our model to get accurate recommendations. The training dataset contains two categories, the first one is law contracts which contain flat, marriage, and divorce contracts. The second one has cv templates. Our model gives recommendations by making a table that contains each user and items that the user rated. That helps to get correlations between these items by getting other users who rated items similar to the user choice and in the same category. Marriage contracts are better than divorce contracts because the value of the average rating of the marriage is close to the value of the average rating of the divorce, but it has been rated more times than divorce, so it is better than it. For the hybrid technique part, we made a dataset with library id, library services and the rating for each service.

Taking black and white paper printing as an example for an item users choose to try to apply our model on these data and get results using the hybrid technique. Firstly, we get libraries that provide the intended service. And now comes the Content-Based part, we read the data that will be used in this part, which consists of library id and characteristics about each library. These characteristics will help to recommend a suitable library to the user based on what he likes. We took a library that holds id 10 as an example as the user chose it before, then we search in all the libraries we have about a library that has the same characteristics as the one we have. Finally, we merge the output of the collaborative technique that contains the highest-rated libraries with the libraries which have similarities with the desired library. Then we search for any duplicate library and take them. And by them, our model will give a recommendation.

B. Local Interpretable Model-agnostic Explanations (LIME)

The LIME output for the user activeness prediction dataset showed that users who spend 5 minutes per day had a positive impact on the prediction with a 0.08, but what about users who spend more time? The explanation showed that users who spent 6 minute had negative impact and others who spent 7 minutes have also negative impact. This result here does not make sense. Unless 5 is a magical number, the explanation should have stated that users who spend more than 5 minutes daily positively affects the prediction, not those who use the app for precisely 5 minutes. The dataset seems to randomly show that most users who spend exactly 5 minutes are active users. That is an excellent example of when we should not blindly depend on a machine's decision since some of the explanations were not rational. Such error was anticipated because the dataset was somewhat random and is not programmatically build from real users' data. On the other hand, the data set to predict whether a user will click on an ad or not has real data and gives a justified output. Thus, we can rely on the results of predictions that came when using this dataset [9].

A timestamp of each user's operation can improve the prediction of the users' activeness results because there is a difference between a user who performed ten operations in the past year and another who performed the same amount of operations but in the past week.

Conclusion And Future Work

In this paper, we presented the initial design and implementation of a paper printing and recycling mobile app. We used gamification and machine learning techniques to solve the most faced problems in the paper printing and recycling domains to facilitate the use of our services. Printing service will be easier for the users, as we use our recommender system to suggest templates, choosing the best and nearest printing center that fulfils the user's order description. Recycling services would be more painless and more motivational for users as the recommender system will link them with organizations that need the wastes they want to get rid of. Also, users will get rewarded using gamification techniques.

The primary taken steps are promising and motivated us to further improve our application. We are planning to perform a user study to get the user's impression of the app and test the UI and UX with the users involved. Paper printing centers showed support of the idea and are willing to accept offers from our app. We are also planning to add different payment methods and a volunteering feature in the recycling part of the app, where volunteers can collect wastes to help the environment.

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