IJARCCE

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 11, November 2021

DOI: 10.17148/IJARCCE.2021.101108

Smoking Cessation through Support Vector Regression in a Mobile Application

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Abstract: Smoking is the leading cause of early mortality in the world that may be prevented. However, there is a lack of evidence on the quality and efficacy of smartphone apps for smoking cessation. Mobile phone health interventions have made therapy more accessible than ever before thanks to the ubiquity of smartphones. Tobacco kills one person every six seconds. The use of machine learning techniques in the study assisted in reaching a conclusion on the cessation of tobacco consumption. Moreover, it provided a solid framework for dealing with cognitive dissonance via the use of a mobile application, among other things. This research article examines the relationship between the adoption of HCI and Support Vector Regression (SVR). Also, it makes use of K-means clustering to target specific groups of chain smokers. Furthermore, this study article delineates a comparison of the replacements that are now accessible in the application sector.

Keywords: HCI, Cognitive dissonance, Smoking cessation, Support vector regression, K-means clustering, application's efficiency

1. INTRODUCTION

1.1 Human Computer Interaction

In the field of human-computer interaction (HCI), researchers work at the nexus of psychology and social sciences on the one hand, and computer science and technology on the other, to understand how people interact with computers. The field of human-computer interaction (HCI) has gradually combined its scientific concerns with the engineering objective of enhancing the usability of computer systems and applications, resulting in an extensive body of technical knowledge and methods.

It is utilized because both psychology and anthropology research how the human mind and human behaviours operate, which is significant when developing interaction between humans and computers since both disciplines help UI designers to build an interface that is enjoyable or simple for the Client to use or follow. It is the goal of HCI to fully comprehend the role of intellectual, visual, and motor components in the interaction that a person experiences when working with smart devices on a moment-to-moment basis (computers, Mobiles, etc.).

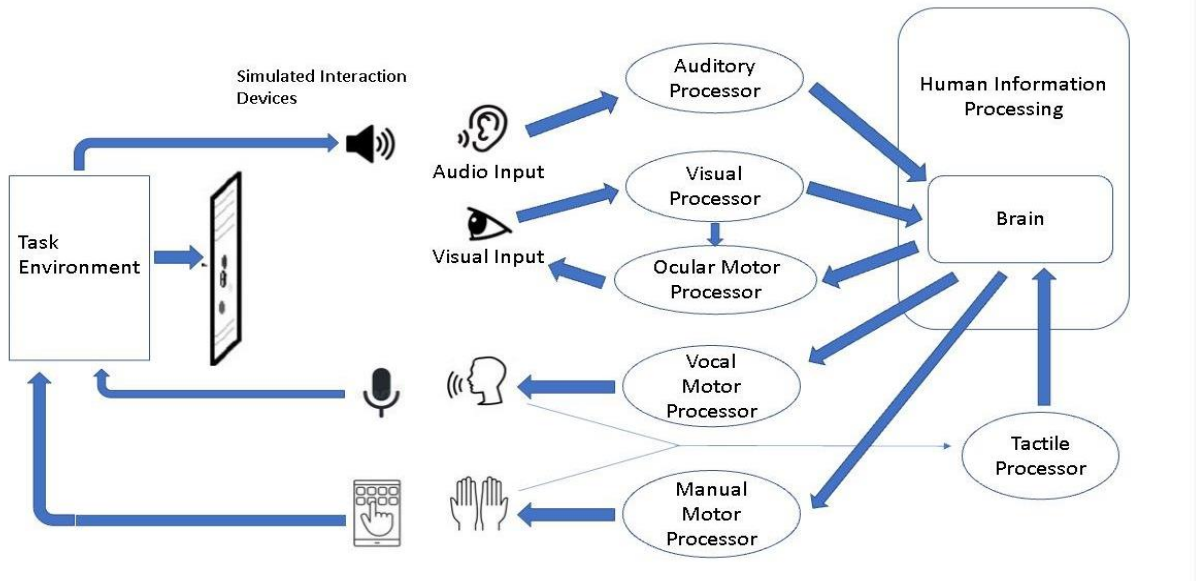

Figure 1.1 People's interaction with mobile application

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Human-computer interaction (HCI) involves both humans and machines working in parallel, building a user interface needs expertise on both the human and mechanical sides. One side of the equation requires knowledge of communication theory, graphic disciplines, sociology, cognitive psychology, and so on; the other side necessitates knowledge of computer graphics methods, operating systems, programming languages, and so on [1].

1.1.1 Interaction design

Interaction design is a word that is used by individuals from a variety of different backgrounds. The phrase is used to define a variety of actions involved in the design and creation of various artifacts, such as artistic works, websites, PC software, GPS systems, and other similar items. It was described as "creating interactive devices that assist the way people communicate and engage in their daily and professional lives" by Sharp et al [2].

- Interaction designers must approach their designs from the point of view of the customer; in other words, they must include consumers in the design process from the beginning.
- Products that engage with the user should be valuable to the user in his or her everyday activities.
- In the process of developing goods, it is critical to consider the needs of the end-user first.The distinction between interface design and interaction design is clearly defined by this concept. However, although interface design is a component of the development process of interaction design, interaction design is comprised of a number of other processes in addition to interface design. Jones and Marsden define interaction design as the discipline that is responsible for designing the functionality of goods and systems in response to their users [3]. When designing interactions, interaction designers place a strong focus on the objectives and experience of the user, and they assess designs in terms of usability and emotive effect [2].

Good interaction design is user-centric; its goal is to reduce frustration and increase user productivity and satisfaction.

1.2 Cognitive dissonance

Cognitive dissonance occurs when there are inconsistencies in one's beliefs about oneself, one's actions, or one's surroundings [4]. In psychology, cognitive dissonance is defined as a state of mind in which one's beliefs, attitudes, and actions are contradictory with one another [5]. Individuals are motivated to alleviate their psychological distress as a result of this discrepancy [6]. Individuals who have experienced dissonance as unpleasant will be driven to eliminate the dissonance and attain consistency in their disparate ideas, attitudes, and actions [7].
Cigarette addiction has long been recognised as a behaviour that may be one of the causes contributing to the growth of cancer. According to statistical findings, more individuals die as a consequence of cigarette and tobacco usage than as a result of AIDS, alcohol abuse, drug misuse, vehicle accidents, and homicide combined [8]. According to the results of a logistic regression study, heavier smokers (those who smoked more than or equal to 20 cigarettes per day) were more likely than lighter smokers to experience cognitive dissonance about smoking-related health beliefs [9].
According to the findings of research done in 2004 in Kelantan, Malaysia, smokers do explain their behaviour as not harmful by holding to certain popular ideas that there are safer methods to smoke that do not cause damage to their health. Smokers who are aware that smoking is harmful to their health might have their dissonance reduced by instilling illogical ideas in them [10]. Some viewpoints on smokers' psychological reliance on the cigarette, such as considering smoking as a stress-relieving pastime or as a regular habit, can be observed [11]. The most direct manner of influencing smokers' choice to smoke is via their living environment, notably their family and work environment [12]. In addition to external psychological elements, internal psychological aspects have a role in decision making. These variables influence smoking behaviour, which in turn influences the amount of cognitive dissonance experienced by the smoker. Participants have been experiencing cognitive dissonance from the day they decided or tried to stop smoking, and this has been evident since the beginning of the study. When dealing with cognitive dissonance, smokers use a variety of defensive strategies. Denial is the most widely used defensive strategy in the reduction of cognitive dissonance in the context of tobacco use. Smokers' egos and self-concept were instinctively shielded by this defensive mechanism, preventing them from being imprisoned in the pain that followed contradictions.

2. METHODOLOGY

2.1 Build of a ML model
2.1.1 Dataset

Choosing the dataset was one of the most crucial aspects of the research, which would provide insights for application development. The dataset used was provided by the American centre for disease control and prevention (CDC) [13].

International Journal of Advanced Research in Computer and Communication Engineering
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It includes 12 features with one dependent variable vector, which is the total per capita. The matrix of features thus can be listed by years, location, population, domestic/imports of tobacco-related consumables, types of consumables, and per capita utilizations. The machine learning model incorporated the intrinsic features like the years, population, all the per capita elements to determine the trend in consumption of tobacco. The accumulation of data took place from 2000 till present. This indeed delineated a sturdy base for CHANTIX's development.

2.1.2 Use of support vector regression

The trend seen in the dataset is a non-linear polynomial function and therefore the use of support vector regression justifies the insights developed. First, the dataset was cleaned and split into a matrix of features and dependent variable vector (total per capita). Simple imputation from scikit learn was applied to fill the missing places with the average arithmetic mean of the respective column's feature.
The columns containing string values were categorized by the use of one-hot encoding followed by the splitting of the dataset into a training set and a test set. This was achieved by model_selection's train_test_split function. Feature scaling was applied to both sets by standardization, having two distinct scalars.
A model was trained by the use of SVR from scikit learn' s SVM package by plugging in a gaussian radial basis kernel ('rbf'). The mathematics backend of SVR is depicted in the figure below [14].

$$y = f(x) = \langle w, x \rangle + b = \sum_{j=1}^{M} w_j x_j + b,\ y, b \in \mathbb{R}, x, w \in \mathbb{R}^M \tag{4-1}$$

$$f(x) = \begin{bmatrix} w \\ b \end{bmatrix}^T \begin{bmatrix} x \\ 1 \end{bmatrix} = w^T x + b \quad x, w \in \mathbb{R}^{M+1} \tag{4-2}$$

$$\min_w \frac{1}{2} \|w\|^2 . \tag{4-3}$$

With the aid of this formula, the SVR model plots an epsilon insensitive tube minimizing the errors by embedding data

$$L_\varepsilon(y, f(x,w)) = \begin{cases} 0 & |y - f(x,w)| \le \varepsilon; \\ |y - f(x,w)| - \varepsilon & \textit{otherwise}, \end{cases} \tag{4-4}$$

$$L_\varepsilon(y, f(x,w)) = \begin{cases} 0 & |y - f(x,w)| \le \varepsilon; \\ (|y - f(x,w)| - \varepsilon)^2 & \textit{otherwise}, \end{cases} \tag{4-5}$$

$$L(y, f(x,w)) = \begin{cases} c|y - f(x,w)| - \frac{c^2}{2} & |y - f(x,w)| > c \\ \frac{1}{2}|y - f(x,w)|^2 & |y - f(x,w)| \le c \end{cases} \tag{4-6}$$

points within the tube. Meanwhile, the intensity of the weights can be visualized by the measure of flatness [14].

$$f(x, w) = \sum_{i=1}^{M} w_i x^i, x \in \mathbb{R}, w \in \mathbb{R}^M .$$

2.1.3 Results

The model thus has an accuracy of 92.356% and an R2 score of 0.92356, which is better performing. By considering a test size of 20% and a random state of 45, these results are approachable. The predictions of the dependent variable vector to a greater extent parallel to that of the test set. This implies the use of SVR with a Gaussian radial kernel.

2.1.4 Graphical comprehension

The graphs below are derived from an SVR model by comparing a feature to the prediction vector (total per capita). Figure 1.2 shows a gradual plummeting trend in the consumption of tobacco in the United States over the years as provided by the predictions made. Meanwhile, many sectors in the country have their per capita consumption as low as 0. Thus, this representation turns out to be linear with a negative slope.

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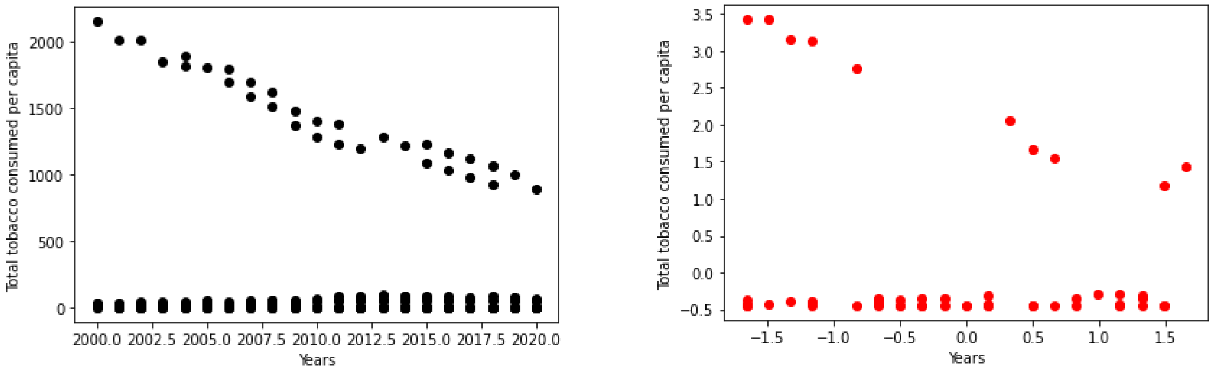

Figure 1.2

Nevertheless, a reverse pattern can be observed while comparing population with per capita consumption. As seen in figure 1.3 the consumption of tobacco tends to increase with the population rise. The growth is ceaseless. While some regions show a downward shift from a population point of 1.3 million. (Training and test set)

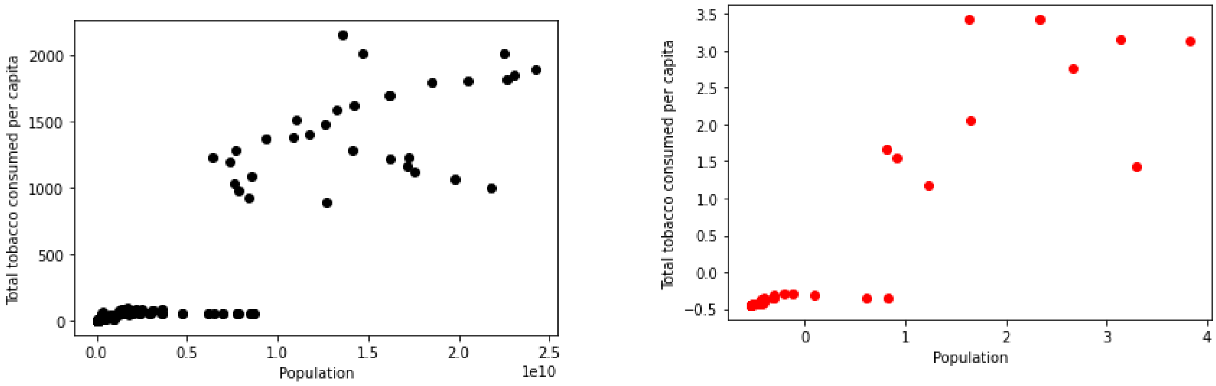

Figure 1.3

This concludes that American citizens are inclined towards smoking cessation and are willing to quit. Thus, applications will play a crucial role in boosting the process substantially.

2.2 Usage of K-means clustering

K-means clustering was used to identify the trend in the category distribution across the United States, considering population and consumption of tobacco. An optimal number of clusters was found by the use of the k-means++ algorithm and plotting WCSS values for N clusters. This method involved the use of an elbow-joint graph as depicted below.

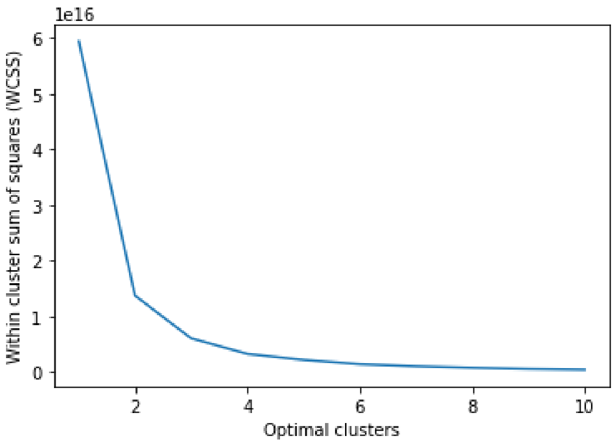

Figure 1.4

IJARCCE

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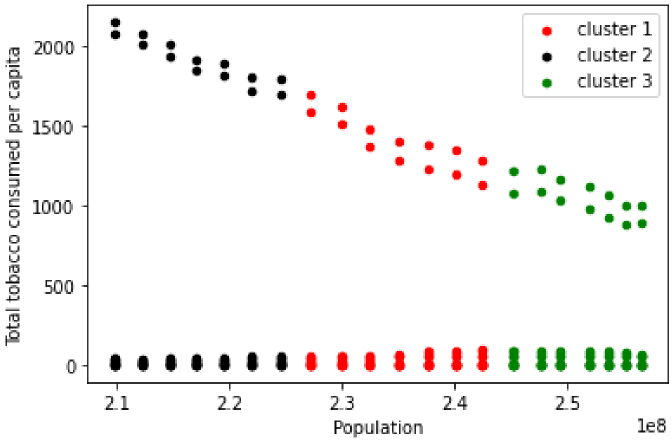
The optimal number of clusters was 3, thus splitting the dataset into 3 sections. This can be inferred the figure 1.5.

Figure 1.5



Administrative bodies can target the groups with the highest consumption. In this case, cluster number 2 requires smoking cessation products to be marketed (e.g., medicines, yoga, exercises, health care). Henceforth all the cities falling in category 2 should be targeted. Thus, applications like CHANTIX play a vital role.

3. Analysis of chemical compositions

The composition of three different noxious chemicals can be corroborated by the formulas.

3.1 Nicotine

N_t = Total nicotine in body
N_i = No. of cigarettes smoked in a week
n = 7 (days in a week)

$$N_t = (\sum_{i=1}^{n} N_i * 1.1)/7.0$$
$$if,$$
$$N_t <= 35;$$
$$Nicotine\ is\ optimal$$
$$N_t > 35;$$
$$Nicotine\ level\ exceeded$$

3.2 Carbon Monoxide CO

CO_t = Total CO in body
CO_i = No. of cigarettes
n = 7 (days in a week)
We took a reference of 3.2 ppm Co present per cigarette.

$$CO_t = (\sum_{i=1}^{n} CO_i * 1.1) * 3.2\ ppm$$

3.3 Tar

T_t = Total tar in body
T_i = Number of cigarettes smoked in a week
n = 7 (days in a week)
We took a reference of 12.5 mg Tar present per cigarette

$$T_t = (\sum_{i=1}^{n} T_i * 1.1) * 12.5\ mg$$
$$if,$$
$$T_t <= 240;$$
$$Tar\ is\ optimal$$
$$N_t > 240;$$
$$Tar\ level\ exceeded$$

4. MOBILE APPLICATIONS

A previous review suggests mobile phone technology has enormous potential for behaviour change [15]. Smartphone applications (apps) are well accepted among mobile phone users. More than 3 billion mobile health (mHealth) apps are estimated to be downloaded worldwide in 2015 [16]. A large number of people may get personalized text messages and

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information at a minimal cost via the use of mobile apps that are simple to download and use. The usage of mobile phones and the number of people who own them is increasing at an alarming rate throughout the globe.

4.1 Effects

Smokers are encouraged to quit smoking by the application's content, which includes knowledge repositories, information on the advantages of quitting, and preparing for the cessation attempt. It is necessary to plan ahead, keep track of progress, visualize outcomes, and master various behaviour modification approaches, such as auditory and visual messaging, throughout this process. Studies that focused only on this strategy found a statistically significant improvement in knowledge, attitude, and self-efficacy in terms of quitting smoking. Some mobile apps make an effort to involve smokers within the content of the application. Techniques included establishing a quitting date, sending push notifications, keeping quit diaries, sharing features, email reminders, prescribing theory-based activities aimed to decrease cravings, and developing a quit plan. Other techniques included constructing a quit plan [17][18][19].

Certain applications instil a fear factor, which in turn assists the user to hasten the smoking cessation process. One such application that has taken such an initiative is the app called 'CHANTIX', which is an anti-smoking application that displays the life lost by the users from past to current years using the pack year formula. This keeps the users informed of their health issues and insinuates how much effort they should put in order to successfully quit smoking. This not only benefits the users but also benefits the doctors in utilising that data for treatments since it is more precise compared to the one's they obtain from patients at the time of examination. As doctors ask for the average value of cigarettes smoked to compute pack year, apps like 'CHANTIX' calculate it accurately as they have the exact data of cigarettes smoked by a patient in a day. This, in general, assists both doctors and the users.

4.2 Market statistics

The market analysis shows the expansion of a wide range of diverse applications that are now accessible. Some of them are accessible in both application stores, but others are exclusively available in one or the other. All of the programmes mentioned below have received an average rating of more than 4, and the majority of them are completely free. This demonstrates that there is significant potential in the use of smoking cessation apps.

Apps	Apple Store	Google Store	iPhone Rating	Android Rating	Price	Download
QuitNow!	✓	✓	4.7★	4.5★	Free with in-app purchases	1M+
Smoke-Free	✓	✓	4.7★	4.7★	Free with in-app purchases	1M+
Chantix	✗	✓	-	4.9★	Free	1K+
Quit Tracker	✗	✓	-	4.8★	Free with in-app purchases	1M+
EasyQuit	✗	✓	-	4.7★	Free	1M+
Quit Genius	✓	✗	4.5★	-	Free with in-app purchases	100K+
My QuitBuddy	✓	✗	4.4★	-	Free	100K+

Table 1.1

CHANTIX's developer console study shows that smoking apps are more widespread in the United States than they are in other nations, based on the results of the analysis. As the application was promoted in India, a marginal increase was seen when compared to the United States.

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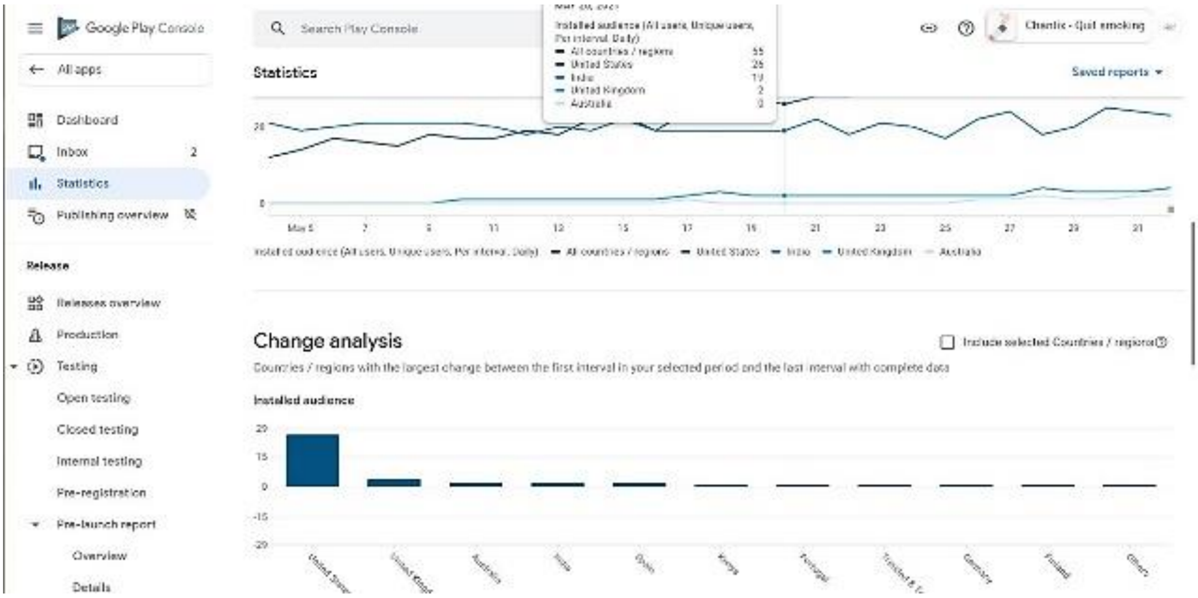

Figure 1.6

5. CONCLUSION

According to the conclusions of the study, nations with a greater degree of globalization have more potential in terms of utilizing smoking apps for smoking cessation. Interaction design is important in capturing users' attention and assisting them in their efforts to stop smoking. Thus, smoking cessation has grown in popularity over the years, and smoking apps that use machine learning models, such as SVR, are playing an increasingly important role by integrating HCI and dealing with cognitive dissonance.

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