Brand Management Using Data Mining Techniques

AFZAL AHMED

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Supervisor: Dr. Tamim A. Khan

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ABSTRACT

As people spend more time on their mobile devices equipped with advanced features such as GPS, the Internet etc. It has attracted E-marketing companies to market their brands on mobile in as sense shift from E-marketing to M-marketing. Higher level enterprises have successfully captured huge marketplace using mobile advertising. But small and medium enterprises are still using the social media promotions without knowing customers location and any other contextual information. In this study, a context-aware Location Based Advertisement system (LBA system) is being proposed. LBA system uses the contextual information of the users to extract from a bunch of ads the most relevant ads. To validate the result field experiment is being conducted on ninety-five participants and eighteen thousand response on one hundred and ninety-three different ads uploaded by eighteen vendors of Mirpur city Azad Kashmir. Experiments show that location congruent advertisements are more relevant and attractive to the users then location in-congruent advertisements. A comparison with other techniques is being performed and the statistics suggest that the model proposed in this study is better in getting a positive response from users in sense of relevancy.

DEDICATION

To my family for their love and support

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

INTRODUCTION

Advertisement is necessary for any brand to be successful in the market. The capability of sales and using dashboards for marketing explicitly contribute to the performance of firm [1]. As information technology (IT) grow up and becomes an essential part of firm’s operations, its role in traditional business decisions needs to be reconsidered. This role is especially relevant for an offline business while optimizing advertising expenditure. This study contributes by suggesting optimization of advertisement strategies to target relevant customers in any specific area.

1.1 Motivation

Marketing Strategies have been modified in past two decades as there is a rapid growth in technology related to information and communication [4]. In the current era, advertisements sights such as billboards are seen everywhere [5]. With the advent of internet and its allied services, internet has become an effective tool for marketing [38, 39]. The same eagerness could be seen these days in adopting the available social media. Another development is the introduction and the use of smart phones where users can access internet from anywhere allowing marketers to design new strategies for marketing (i.e. e-commerce) [4].

One of the major benefits of the smartphones for the user is that they are constantly connected to the social networking sites like Facebook, twitter etc. This combination of both the social network and smartphone has attracted billions of users to stay connected to their friends, relatives and loved ones, and to share pictures, posts, videos and location information etc. to express their feelings.

Service based on location is defined as offering value added and interesting service or information to the user, considering user location coordinates [6]. Rapid increase in smartphones fitted with the GPS device gives the way for this new technology [7]. The techniques of services based on locations has broadened the opportunities to know about the users' location. It also could help to mine location-based data to extract the behaviour towards visiting places and daily routines [8]. The digital footprints which the users left help in providing the analysis of the network, detection of community and targeted Marketing [9, 10].

The analysis of the difficulties faced by the SMEs in digital marketing [12,13] motivated to study and propose a context-aware advertisement system using Data mining techniques on the location and the social media data. Which on the basis of the user preferences and the location history advertises the brands near the persons' location. The advertisement expenses are sometimes unavoidable [26]. The spending for an SME over the advertisements does only a little bit of the benefit to the company. This in turns helps SMEs to efficiently utilize their resources to advertise their product.

We need to study how we can we make use of internet access, applications such as location knowledge of the users and the commercial hubs, users likes and dislikes and related historical information. We also need to study how we can make use of data processing methods to infer which types of advertisements are expected to attract users based on their travel history and the location of the commercial hubs.

1.2 Problem Definition

After going through the literature it is observed that the smartphones are ubiquitously present in our society [14] and their numerous uses have attracted the brands to utilize their information to market their brands [15]. Although the problem of effectiveness of the advertisement is still questioned [17]. The studies conducted in similar perspective have limitations of using only location as the context for advertisement which brings us back to the question that whether to show an advertisement to a particular person or not?

It is observed that the conversion rates associated with the advertising campaigns are usually quite low due to the low quality of the datasets and impropriate predictive model. It is also observed that everyone is not interested in each type of advertisement. Although the interest of the people can be favorably shaped through effective advertisement but still people have their own preferences in buying a product [20]. Facebook, a social network, has become the point of attraction among the people irrespective of the age factor. People share their preferences about how they feel about things [23]. People share their activities over these type of sites to let others know what they are up to. This type of data is sparse but if it is mined correctly it can be very useful to collect the preferences of an individual which later on helps to improve the advertising strategy.

Sometimes gender is not considered to be the influencing factor in the online advertisement as most of the advertiser remove this factor and make a more general advertisement but a significant difference in the beliefs has been observed. While advertising belief and ethnicity and culture should be considered as the factor affecting the success of the advertisement [22].

Leveraging data about customers either geographical, temporal or emotional in scale and sometimes in the real time has led to a new concept known as programmatic-commerce [26]. It is noticed in the literature that the people are more interested in the brands with easily accessible locations [16] and interest of people is increasing toward social networks based on locations [24]. People react to an advertisement differently depending upon the distance between the customer and the purchase point [19]. Hence the problem for the companies is that these companies are spending their money on the advertisement which does not cover the proper audience.

On the other hand, it is observed that if some attribution is performed over the targeted audience the advertiser gets more profit as compared to the profit got from common attribution for all [21]. The above-mentioned attributes i.e. an individual’s location history, preferences obtained from the social networking sites and, mining and matching these record could help in the improving the Brands advertisement strategies. Also, the use of smartphones and communication technology has been increasing day by day for the past two decades. This growth in usage opens the door for the SME companies, launching their products and want to advertise their products, to efficiently utilize the information available and increase their profit without wasting much of their resources over inappropriate audiences.

The literature analysis suggests that there are several studies conducted on the Location Based Advertisement (LBA) but the studies conducted only took into account the current location as context to advertise. There is a need to conduct a study that utilizes more than the current location as context. Hence this research study combined the geographical, personal and social information to implement the model using data mining techniques to answer following questions.

- Are the location congruent advertisements better than location in-congruent advertisements?
- Is the location only context the Advertisement system keep itself aware of for better relevancy?
- What is the effect of advertising for each location user visit on user's behaviour towards advertisement system?
- Does the contextual information (i.e. time location, gender, and interests) have a positive effect on predicting the relevance of advertisement?

1.3 Purpose

The objective of this research work is two folded. Firstly, it focuses on the customer who is the targeted audience for many brands. Secondly, the brand which is wasting the resources over the inappropriate audiences in terms of advertisement. In the first part, the geographical, personal and social data of the person is collected to identify the behaviour of the customers toward the nearby available brands. In the second part brand companies' geographical and business type data is collected so that the customers' choice and type of product a company is selling could be matched.

All the participants shall be given an application to be installed on their android device with GPS activated, to get the personal information, Facebook information to the extent user permits while the user signs up as a customer for the application, after sign up the coordinates of the user after every minute are taken and stored in a cloud (firebase.com).

If the user signs up as the service provider the exact location of that person is asked and the type of business that company is acquired and then on the basis of the data collected from customer using data mining algorithm the clusters are made and then those clusters along with the persons Facebook preferences and the service providers coordinates along with the type of brands that company is selling are compared. The matched data is then saved in the file for the service provider. The service provider on the basis of the budget to afford advertisement shall choose the number of audiences. The audiences available to the service provider are only the persons who are interested in such type of brands and also near to these SMEs.

Although the point of consideration while advertising is a customer but the proposed model not only going to help customers but also to the companies. Advertising brands to only those relevant to the advertised brand will decrease the cost in terms of money and effort exerted while advertising these brands to irrelevant audiences.

When it comes to the shopping there are many factors that affect the behaviour of the customer. We have divided the factors into two main states 1) individual state 2) external/environmental state. The first state is the description of individual activity state focusing on the age group, daily routine, occupation, emotional state and income level etc. while the second state is description of the external factors affecting the individual's life in which we shall be focusing on the society, friends circle, and travel patterns etc.

Let us consider the scenario of Rawalpindi-Islamabad Metro Bus System in Pakistan. This rapid transport system has a total length of 22 kilometers with 24 stations. An average 0:1million passengers per day use this transport. Suppose, a student of Bahria University Islamabad named as Usama has a residence at 6th-Road Satellite Town Rawalpindi. Often, he enters the 6th-Road station between 8: 30 am to 9: 00 am and checkout at Kechahri station between 8: 50 am to 9: 20 am. Similarly, Usama enters Kechari station at 5: 00 pm to 5: 30 pm and leaves at 5: 20 pm to 5: 50 pm. On weekend and in holidays, Usama visits Saddar and 7th-Avenue as well. Depending upon this information we can send him relevant ads. Let's say Subway has a branch in F-8 and Usama moves in that direction from the nearest station Kechahri. Then, the advertisement of the Subway will be appropriate for Usama. Similarly, if Usama provides feedback that the Subway advertisement is not relevant to him then, other ads according to his interest should be sent. Also, Cabinet Computer at 6th-Road announces a discount on laptops. So, this advertisement should also be sent to Usama.

After the successful implementation outcomes of this research study are

- A modeled system for brand management.
- Validation of the system through implementation of the system.

1.4 Background

As information technology (IT) grow up and becomes an essential part of firm's operations, its role in traditional business decisions needs to be reconsidered. This role is especially relevant for an offline business when they are deciding on the optimal advertising expenditure. In this article, we study to optimize the advertisement strategies to target the relevant customers in a specific area. The idea is to target the customers often visiting the area of a specific brand. Information and communication technologies (ICTs), such as mobile phones and the Internet, have become increasingly pervasive in modern society and can be very helpful for the companies to advertise their brands.

The advancement in the technologies has made the user to have more choices about where to travel when to travel and how they should travel. The essential task of updating the policies for our tasks regarding our environment and to maintain bearable mobility along with the transportation [28], is to understand the ICTs influence in our society of mobile information [27]. Furthermore, sources of spatio-temporal data are made available in a wide range by the ICTs, which are considered very helpful in the discovery of geographic knowledge and perform data mining on these dynamics of geographic information, such as the behaviour regarding human travel and their patterns of mobility [29].

Although the data provided by many spatio temporal datasets (e.g. mobile georeferenced data) is incomplete, the resolution of the data is very low and there are only a few attributes [30], and it is necessary to determine how much extraction can be effectively performed and to what extent the knowledge extraction can be performed on these sparse data sets, along with that also deal with the vagueness in these sparse data sets but still the information extracted is considered very helpful in shaping the behaviour model of a person towards a specific company or brand [31].

Extensive mobile communication use made interest of many researchers towards conducting the studies [32, 33, and 34] related to acquiring geographical information from the mobile data being georeferenced to extract knowledge and then utilize the best of that knowledge for several purposes. For example, social positioning method (SPM) of Ahas help in combining the geographical data with social attributes of the user on the mobile phones to study in details the urban systems dynamics [35, 36]. Gonzalez, Hidalgo, et al. (2008) studied the trajectories of individuals from 100,000 users of mobile phones on the basis of tracking geographical data of six months and using that data provided and a new vision in understanding the basic law of motion for human [37].

However, the social network is way more expanded these days and almost everyone is connected to this network and the data extraction from social network can be quite helpful in determining the behaviour of the individual as well as a group of personnel travelling in a specific area and advertise the brands related to them.

On the other hand, there are a lot of Small Medium Enterprise (SME) business centers (e.g. restaurants, clothing, entertainment etc.) present in every corner of our cities. All of them have the vision to get customers and speed up their business growth. All they always look for is the idea that how they could acquire new customers and stay connected to the already existing customers for a longer period of time [9]. These days not only the brands promoters but the SMEs are also using the social networking sites (e.g. twitter accounts, Facebook pages etc.) to promote their businesses, offers information and coupons, and exhibit their information online [11].

An effective and more convincing, in terms of efficiency of coverage and resource utilization, system is required for the brand management of Small and Medium Enterprises (SMEs). There is a need for the customer as well as the company to model such system so the both the parties get benefit from it. The focus of this research is on the challenges faced by the SMEs and the customers in marketing. This research is going to focus on the benefit achieved through geographical information and the preferences of the individual customer in terms of Product success as well as customer satisfaction

1.5 Thesis Outline

This section presents the overview of contents described in this dissertation.

Chapter 2 provides a comprehensive literature review of the topic under discussion. Section 2.1 contains the elaboration of the data mining techniques used for different fields of life for extraction of useful information. Section 2.2 explains the concepts related to the marketing strategies being used by the SMEs and improvement with time. Section 2.3 describes the importance of geographical information. Section 2.4 is about the people behaviour over social networking sites focusing on facebook especially. A detailed literature review smartphone influence in life is discussed in section 2.5. Section 2.6 summarize the whole chapter and briefly introduce to the model being developed for this research.

Chapter 3 introduces us to the designed system and the model in detail. Section 3.1 is about the abstract model description and the elements used. Section 3.2 describes the system design and methodology used for this purpose. All the algorithms are being explained in this section one by one along with all the modules of the proposed model.

Chapter 4 describes in details the results being collected from Experiment. Section 4.1 explains results of the first experiment. Section 4.2 explains the Location Based Advertisements results. Section 4.3 describes mining of users' location and other contextual information. Section 4.4 compares the results of three experiments. Section 4.5 contains a comparison between proposed and other available techniques in the literature.

Chapter 5 concludes the research being carried out. This chapter contains two sections section 5.1 is the brief conclusion and section 5.2 contains the future directions of the research.

Chapter 2

LITERATURE REVIEW

Improving the advertisement strategies for the SMEs has been the point of attention for marketers. Numerous studies have been conducted to improve online marketing methods for SMEs. We are all surrounded with SMEs in our cities and a proper advertisement methods for these shall be constructed so that the advertisement gets the optimal attention from the customers. Data mining techniques are considered very effective for the decision making in any field of life [51] and also effective in eradicating irrelevant parts of information from a bigger dataset [52]. Data mining techniques have the promising effect in quick decision making and efficiently examining the systems with interrelated and multidimensional data [53]. These techniques are also considered to be very optimal in fields of marketing [60].

2.1 Data Mining Techniques

Data mining is known to be the process of data digging from a large amount of data to get the important information for improving the efficiency of organizations [54]. The aim of the researchers is to recognize the role of the data mining techniques for marketing and designing strategies for a relationship with customers and inspire the customer to be loyal to them for a longer period and buy their products again [55]. Data mining offers some interesting approaches for extraction of predictive information from sparse data [56]. Its application to social media has been studied, especially for evaluating market trends from users' inputs this help defining the behaviour of a person in real life [57]. Such type of extracted data could help enterprises to make a decision how to advertise their brands such that they get maximum attention, profit and optimal utilization of the available resources.

Among the data mining techniques, the clustering of data is a considerably more significant method as it helps to capture of the natural structure of data [58]. The clustering algorithms have applications in almost every type of field with a huge amount of data with unknown relations present in it such as rapidly increasing data related to educational and marketing fields has led to a point that refining data needs more proficient clustering algorithms' set [59].

Majid, Abdul, et al. stated in their article that the pervasive use of digital cameras and sharing the photos on the social network such as flicker makes a lot of geo-tagged photos available to on the Web. On the basis of the geo-tagged photos and experienced shared over the social network they got the traveling preference of the user and proposed a new method to recommend user new tourism places relevant to them [40].

According to Yoon et al. it takes time for the travelers to digest and put together the collected information for use [41]. On May 10, 2016, Beijing Transit issued smart cards to traveling personnel to pay with it. They mined the data of the individual to reduce the involved complexity in travel pattern and make a cluster. A bayesian decision tree was used to extract the boarding changes in boarding volumes between two transactions conducted consecutively and evaluated this information combined with historical data of the speed profiles extracted using GPS to get the probability of the potential stop. Further Density based Spatial Clustering of application with noise (DBSCAN) was used to get the travel pattern of the individual in an efficient way [42].

According to chun et al. data mining methods based on the input from past data available for the prediction of the short-term movements of the important currencies, interest rates, or equities has been studied by the researcher to build a quantitative trading tool to improve the trading to make it efficient [43]. Banks have huge databases containing the transactions and other personal details which can be used for predictions but human resources are not enough for this so a data mining technique is necessary to detect the pattern of the customer and predict about the profile of the customer [44].

Lui et al. proposed a technique named Mining data Record (MDR) to mine the web pages data they extracted the HTML tags to build the tag tree and trained there system on the different domains like book, travel, auction, software and jobs and they also compared the results with other two techniques OMINI and IPEAD and when it came to prediction OMINI only detected 6 out of 46 pages correctly and IPEAD predicted 14 pages correctly while MDR predicted 44 correctly. In predicting patterns IPEAD does not work for the similar record but MDR is very good at detecting boundaries. [45].

Data mining is the respondent to the demands of acquiring useful and meaningful information from any type of sparse data if tackled smartly and elegantly [61]. Data mining techniques can be used for user profiling [69] which could help placing particular advertisements to appropriate audience at the right place.

2.2 Advertisement Strategies

“There is only one valid definition of business purpose: to create a customer…” [65].

There are several businesses who try to market their products on every available social network aiming to get maximum user traffic but the reality is that they are not getting any high engagement with the user rather their brands are less engaged with the users [62]. Social network marketing is important no doubt but there is another step to perform for online advertisement which is publishing brands own website [63]. The selection of the social media and the integration level shall be in line with the company’s culture and customer’s norms [70].

Other than the social network advertisement there are numerous ways to advertise the brand's short messaging service (SMS) is one of those. But the success of the SMS advertisement depends upon the content of the SMS i.e. the wording of the text, language being used and the overall presentation [64]. Although the SMS advertisement has gained popularity [65] but there are still some factors need to be addressed which are the permission of the user to get an SMS advertisement, people are more attracted towards offers and rewards and people get irritated when negatively insignificant advertisement are sent to the users [66].

According to a study, the medium of the advertisement does not matter so if the user is interested in the advertisement [67] and as per comScore local search usage study, 2013 suggest that 78% of people who search locally on their phone make a purchase. Grewal, et al. suggest that success of the advertisement campaign depends upon the stakeholder's nature as well as the factors related to the context of the environment, consumer preferences and technology [68].

According to Tseng et. al. the brand equity for a traveler behaviour is dependent on the following three points (1) frequent visits to that place, (2) time span spent there during visits and (3) recommendation frequency of the destination [46]. In a study Brand equity of a tourist place named Bali was measured in five measurement variables i.e. (1) knowledge about brand (2) image of the brand (3) associations of the brand (4) the observed quality of the brand and (5) loyalty to that brand. They concluded that by maintaining equity of the brand can help in getting the loyalty of the visitors, choosing the right area to be targeted and advantage over the competitors [47].

Keller's brand positioning, brand resonance, and brand value chain models, A study has been conducted in which impact of the brand management process fast paced advancement in technologies, digital development, and constraints related to environment and social activities have been discussed. They concluded their discussion suggesting that responsiveness according to user needs, innovation in the products and being responsible are crucial attributes in the management of brands equity. They also suggested that global macro changes demand to concentrate on specified brand equity for both the purposes to meet the expectations of the consumers evolving day by day and to be in the competitive state and achieve high performance in the market [48].

Krush et al. (2014) explored the connection available between marketing and resources of the sales (e.g. capability of sales and dashboards for marketing) and sensemaking, and the combinational effects on performance of the firm. The study explored that capability of sales and using dashboards for marketing explicitly contribute to the performance of the firm. In addition to this, sensemaking can affect both growth in firm and efficiency of the cost. For marketing scholars, sensemaking is important as it plays a vital role in knowledge capabilities of the firm and makes the firm more successful and sound in facing changes occurring in the market. These studies confirm how important it is for sale and marketing operations to integrate [49].

Zhao et al. (2015) discussed the preconditions for the success of first product launched in the market and the association to existing resources of the firm, and investigated about the strategy of positioning of the product that could mediate the effects of technical resources, marketing resources, and start-up expertise of the founding team on the success of the product. The authors claimed that impact of the founding teams with more prior experience was smaller than the founding team with less prior start-up experience [50].

Another research was conducted to get an appropriate advertisement for the user and the brand. They Google distance value between the keywords was computed to design a characteristics vector for the advertisement. Using the logistical regression for user profiling on the basis of reaction to the specific type of advertisements was designed. And finally by using the characteristics vector and the user profile generated appropriate advertisements were extracted from bundle of advertisements [71].

2.3 Geographical Location Influence

The importance of geographical data mining is growing with the increasing incidence and importance of large spatial datasets repositories of remote-sensing images, location-based mobile app data, satellite imagery, medical data and crime data with location information, three-dimensional maps, traffic data and much more [89]. There is a need for efficient as well as effective methods to extract the information hidden and somewhat unexpected from huge sized, very complex [90] and high dimensional data [91]. The fields of data mining on the spatial data and discovery of geographical knowledge have been developed to address the above-mentioned problems, the focus of the studies is on the methodology development, theory and practice to extract the meaningful information and knowledge discovery from this massive and highly complex data [92].

The geo-tagged embedded-photo on social media sites (e.g. Facebook, Twitter etc.) can provide information about that location likewise check-in to a specific place [93] using Facebook can tell about the presence of a person on the specific location and check in to a specific location frequently could describe the behaviour of the person. A recommendation system for tourism application which recommends interesting tourist location to the new tourist or traveler based on the previous collected geo-tag embedded photos. The context (i.e., time, date, weather) of location were also considered for efficient recommendation. Its user-generated content about the place in the photo made a high impact on that location. Mining User's geo-tagged location and referring those locations to other tourist were performed but he has not dealt with any location-based advertisement to the user [94]. People living in cities tend to visit less crowded locations and share their perspective about those places over social media and other mediums of communication the experience they had over their but for the daily life routines, they are totally dependent on their own cities so it the case with people living in less crowded areas.

Location of a person on the earth globe tells and influences its lifestyle very much. A study was conducted in which the phone calls timing were observed for detection of their behaviour. The results indicated that the call timings were dependent on the longitude of the people [95].In another study conducted it is suggested that the settlement location of people has a key influence on the lifestyle of the individual, it suggested that people from the same region have the same attitude towards things and the difference exists between different regions [96]. The overall behaviour of a person changes with a change in the location their lifestyle their routines merges with the locals of that region.

2.4 Social Media Influence

Apparently, there are 2.34 billion social media users, these numbers are increasing day by day and shall reach 2.95 billion in 2020 and solely Facebook has the 1.2 billion monthly active users [72]. This huge crowd over the network has brought this tool to the attention of several brands to perform marketing online as this tool provides more humanizing factor in this case because behind every brand there is actually a human communicating with customers actually [73].

The social media provide the way for the brands to collect the information of the user, to monitor the user views, and include the targeted viewer in a discussion related to services provided, products, or any other type of questions. The theories and concepts of social media can be defined as 1) the principle of marketing in which it reveals itself as among users using business profile in social media; 2) the interaction with user – social media can be considered as the having the impulsive and spontaneous connection with the user, technically inclusion of opportunity to comment, share available contents among others, also an interactivity with limited access when it comes to the users behaviours in utilizing technologies; 3) Concept of Groundswell which states that social media is less about the technologies and more about the personality [82].

The online available social media and immense of technology support have driven may researchers to collect the behaviour of social media user passively which seemed to be almost impossible a few years ago [74]. According to a survey people using the social media get social benefits which lead to the overall satisfaction in life [75]. And using the social media online or being social and interest of people are not gender based according to another survey people like to act same offline as well as online socially which shows a way that accurate observation about a user could be made by using the online data [76]. However, the behaviour of a person over social media is not the exact mapping of the offline life i.e. for any event to be shared over the social network is the result of the excitement interaction with the passion of the user [84].

As described earlier social media has opened a new path for the brand managers to market their brands. It is observed that images, posts, and videos on social media (i.e. Facebook) have more attractiveness and influence in the public than the articles which leads brands to choose social media to advertise their brands using that type of data [77].

The use of social media data for data mining to make decisions about the users is gaining popularity these days. Each brand wants to get the available information on the social media [78] and mine it to get the behaviour of the audience [79] and the trends going on in the society all these factors add a positive effect on the success of the brands [81]. As a result, each brand is connected to social media to get the better idea to make their product more successful. Several frameworks have been proposed in this regards [79, 80].

The social media does not only contribute to marketing but to the medical field too. The data from Weibo was being used to analyze the foodborne disease and this information was then utilized to recommend restaurants but the sparseness of data made the predictions less accurate [83].

Only big enterprises do not use social media data to promote their brands but it is the need of small and medium enterprises as well. For small and medium enterprises there is often a problem of the budget in start [85, 88] but to be successful in the market advertisements of the brand is to be performed [86]. In this case, the only solution is the social media advertisement, for example, the Facebook pages. But social media like Facebook pages usually contain noisy data along with meaningful information [87] so it is very important for any SME to interpret those pages to get the clear response of the users and after interpreting the response get the idea where, when and how should they launch their new product [88]. This type of extracted data can make enterprises resource utilization optimum and make a success of brand conducive.

2.5 Smartphone influence

The ubiquity of smartphones together with their ever-growing power of computation, ease of connecting through networks and ability of sensing has altered the landscape of people's daily life [97]. The suitability and the briskly increasing number of developed applications demonstrate that they have reached the place where it could be said that these devices are very dominant in the society [102]. Communication is the foremost usage of smartphones. However, through quick technological progression, there are other types of uses of these devices are also there like bill payments, audio and camera recordings, entertainment and internet browsing the most. These smartphones have been embraced by all age groups, young and old and are likely to become an addiction to both generations [101]. Computing, networking and sensing powers have been changing the landscape of people's daily life.

In a research conducted by 410 users of smartphone [98] to get the idea of drivers which lead to the acceptance of shopping on a mobile phone. The results implied that acceptance drivers to acceptance of this type of shopping differ with respect to the three mobile shopping physiognomies which were quoted as the sensitivity of location, degree of control and criticality of time. Empirical results demonstrate that several acceptance predictors are associated with ease of use and usefulness, which ultimately pose an impact over behavioural and intentional end result.

In another study [99] it is suggested that there is a need for every brand manager to exploit on these three deliberate advantages related to mobile marketing: 1) the fact that mobile devices for marketing are always in on state, connected through network 24/7 and make the consumer feel that you are always with them; 2) the ability of smartphones to generate location sensitive offer; 3) the ability to send only relevant personalized offers. Closeness with the customer can be very crucial for any market or brand to be successful and these factors lead towards the closeness. Smartphones these days have the ability to stay connected to everyone and can share locations which could benefit the enterprises in many ways to achieve customer satisfaction.

The literature enlightens that people keep on using Facebook and continue to perform their social activities over there why smartphone social network services (SNS) adopters continue to use Facebook for their social activities even after the perception that such type of services is insecure in sense of privacy protection. Trust factors affect the various type of activities on social media for example information sharing, look for an advice and then using it, spreading own opinion/word-of-mouth and behaviour toward the purchasing etc. and it could narrow it down. In succession, negative influencing factors (e.g., perceived risk) and positive factors (e.g. enjoyment of SNS activity and perceived value of smartphone SNS) could affect trust in travel advice acquired from a smartphone. The results of the conducted study indicate that when the influence of positive factors is greater than the negative influences, smartphone SNS users will keep using trustfully [100]. Immediacy works especially well with location-sensitive offers. As an example, marketers can contact consumers when they are within 5 miles of a branch location or when they are in a specific aisle of a store. Technologies like GPS, GSM (Global System for Mobile Communications), Bluetooth, and RFID enable marketers to identify the exact location of a specific mobile device at any point in time. Whereas geofencing technology works outside of a store, iBeacons enable marketers to target specific locations within a store. As a result of geofencing and iBeacons, retailers can use a simple Moball CMS (Content Management System) to drop pins on a map to generate a hot zone. These technologies enable retailers to send a mobile-based message to an app user as he/she enters the hot zone. Retailers can also set up a geofence around competitors' locations.

2.6 Proposed Model

After going through the literature it is observed that following factors highly influence person's lifestyle and behaviour towards purchases, the person location, social attribute of a person and way of communication the person is using. So this research study proposes a context-aware brand management system with techniques of data mining. For the proposed system an Android application was developed to collect data from the user. The proposed system collects geographical location data as the longitude and latitude of the user after every minute, temporal data as, time span and day, and Facebook data to get the interests of the person. The proposed system works on these type of data to improve the advertisement strategy for SMEs.

The advertisement strategies are studied in detail. Although the strategies like viral marketing, demonstration strategy, Empathy strategy etc, but these strategies work well for the high-level enterprises, however, for small and medium enterprises we need to focus more on the locality of the person, choices he/she makes and things a person like. Without these type of information designing an effective system is not possible. The proposed model comprises of tackling of these type of data mentioned above. In the proposed system the location changes are constantly monitored and decision is taken after exploring and mining this data.

The literature describes that smartphones are more popular and becoming more powerful with the passage of time [97]. The proposed system is an Android based application which collects the data, process on the data for instantaneous tasks and for the clustering purpose passes the data to the system. The system then processes data and passes it back to the application and that application uses processed data for the users to get appropriate and most relevant advertisements.

As described earlier in the literature that social aspect of the person is mostly like the person is in real life [76]. Facebook has the largest number of users as compared to the social networking sites. The proposed model extracts the Facebook data of the person with the extent of permissions they grant and find about the user activities over social network website. Although there are the possibilities of getting less information but our system tackles with that problem in a professional and efficient manner.

Chapter 3

RESEARCH DESIGN AND MODELS

The focus of this research is to design an effective model for small and medium enterprises (SMEs). The proposed model, Location and Interest Based Advertisement System (LBA system), establishes the efficient utilization of the resources for SMEs and effective way to get optimal coverage of audience. The conducted literature review describes that interest of people in any brand or business depends upon several factors the major categories of these are the technology used to promote [98], the value given to person's choices and behaviour towards brands [73] and the distance between brand and customer's location [46].

The Proposed model implements all the major factors affecting the advertisement of brands. The model is implemented as an Android and computer-based application which tells that the coverage of customers could be very high. It utilizes the facility of GPS to track user locations and make the system context aware. To know about the interest of the users their Facebook data is extracted with their permission. Three algorithms are implemented in this research study to perform user profiling over provided data. To perform user profiling Data mining clustering and classification techniques are used to get the meaningful information about the user and act upon that.

The proposed model does not only use the previous data of the people to perform effective promotions but it also takes into the account the responses of the individual users over the advertisements to make the profile of the user better. If someone likes an advertisement the type defined by the service provider gets priority in the customer profile and any advertisement that user does not like response over that advertisement is taken and according to that response user profile is modified. The response of the users can be categorized into following categories.

1. Did not like the product type.
2. Did not like the product company.
3. The product is expensive.
4. The place is not near.

3.1 Model Description

Figure 3.1 demonstrates the abstract model of the proposed system. The model suggests that application user is always connected to the GPS, a cloud-based service (firebase) used in our system and Facebook. All types of connections described for the users deal with data. The GPS provides the geographical location of the user which is used in determining the spatial value of the person. Connectivity with Facebook is to get some interests of the application users. The cloud service used in the system is to store and retrieve the information from a single place. The computer demonstrates the saved data on cloud shall be retrieved and processed for making clusters and then uploading that information back to the cloud so that user shall be able to see the advertisements. On the other hand businesses in the diagram are to illustrate that they also share the information over the cloud to promote their brands. Let's consider a scenario that a person is at a place where that person has never visited before and when the user enters at that place if the brands over there are the part of LBA system those brands can promote themselves to the visiting person. In this scenario, the person if interested in the brand shall be informed about the places of his/her interest. Suppose there are n brands at the visiting place p and the visitor is there for t time long and the LBA system has the interests I of that person then formally we can say

$$let\ pos_{visitor} \leftarrow position(visitor)$$

$$pos_{brand} \leftarrow position(brand)$$

$$Ad(i) \leftarrow advertisement(brand(i))$$

$$match\big(I, brand(i)\big) AND\ dist(pos_{visitor}, pos_{brand}) < epsilon$$
$$\rightarrow push\big(Ad(i)\big) \qquad \therefore\ i = 0,1,2,3 \ldots n.$$

Here $pos_{visitor}$ and pos_{brand} contain the longitude and latitude of the visitor and the brand, match function performs interest set of the person one by one with all the available brands. The dist function calculates the distance between the points passed to it. Haversine distance calculation technique is being used in LBA system. Epsilon is the minimum distance value which defines for the user to get the advertisement for specific brand or not.

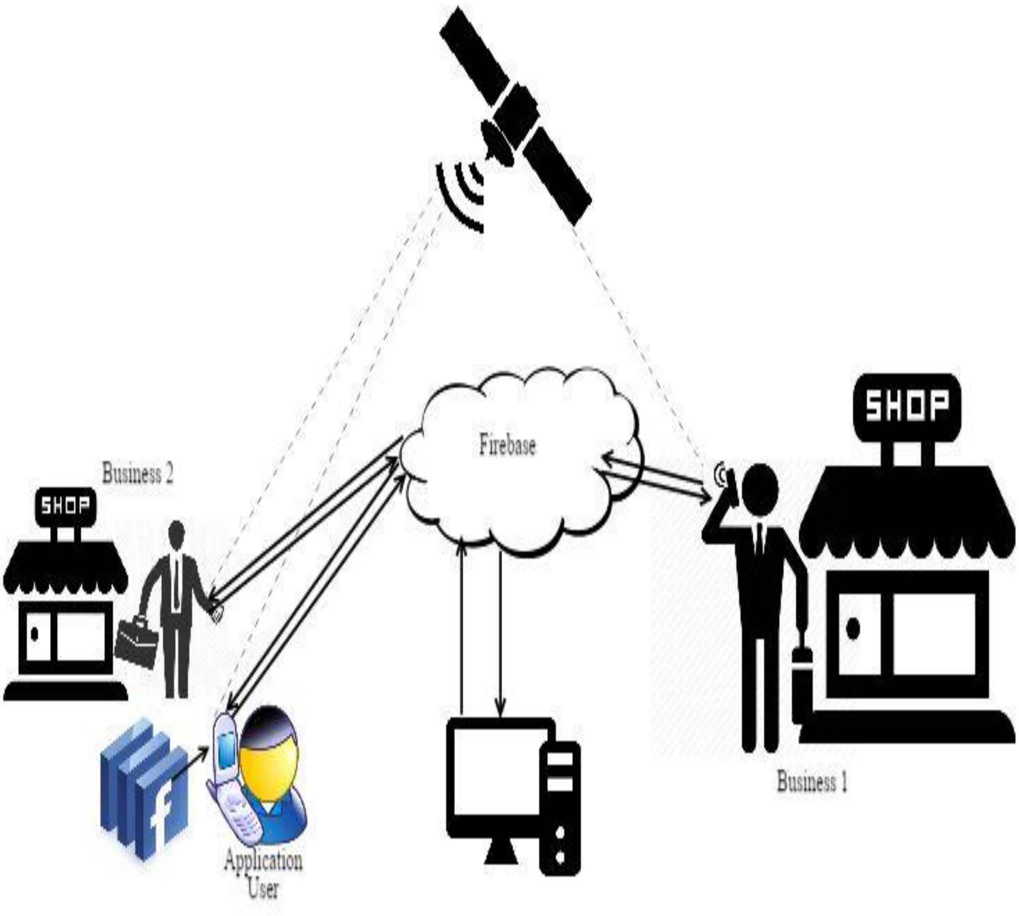

Figure 3.1 Abstract Model of proposed system

3.2 System Design and Methodology

In LBA system, the system entities include facbook.com for user interests' information, An Android application for the user who is to be served to get location coordinates data and to get the location of brand and information about the advertisement. This system works with three subsystem, namely an a) online Location Based Advertisement and b) Spatio-temporal clustering based advertisement c) response evaluator to update the user profile for improving accuracy and effectiveness of the system. The architecture framework of LBA system is presented in figure 3.2.

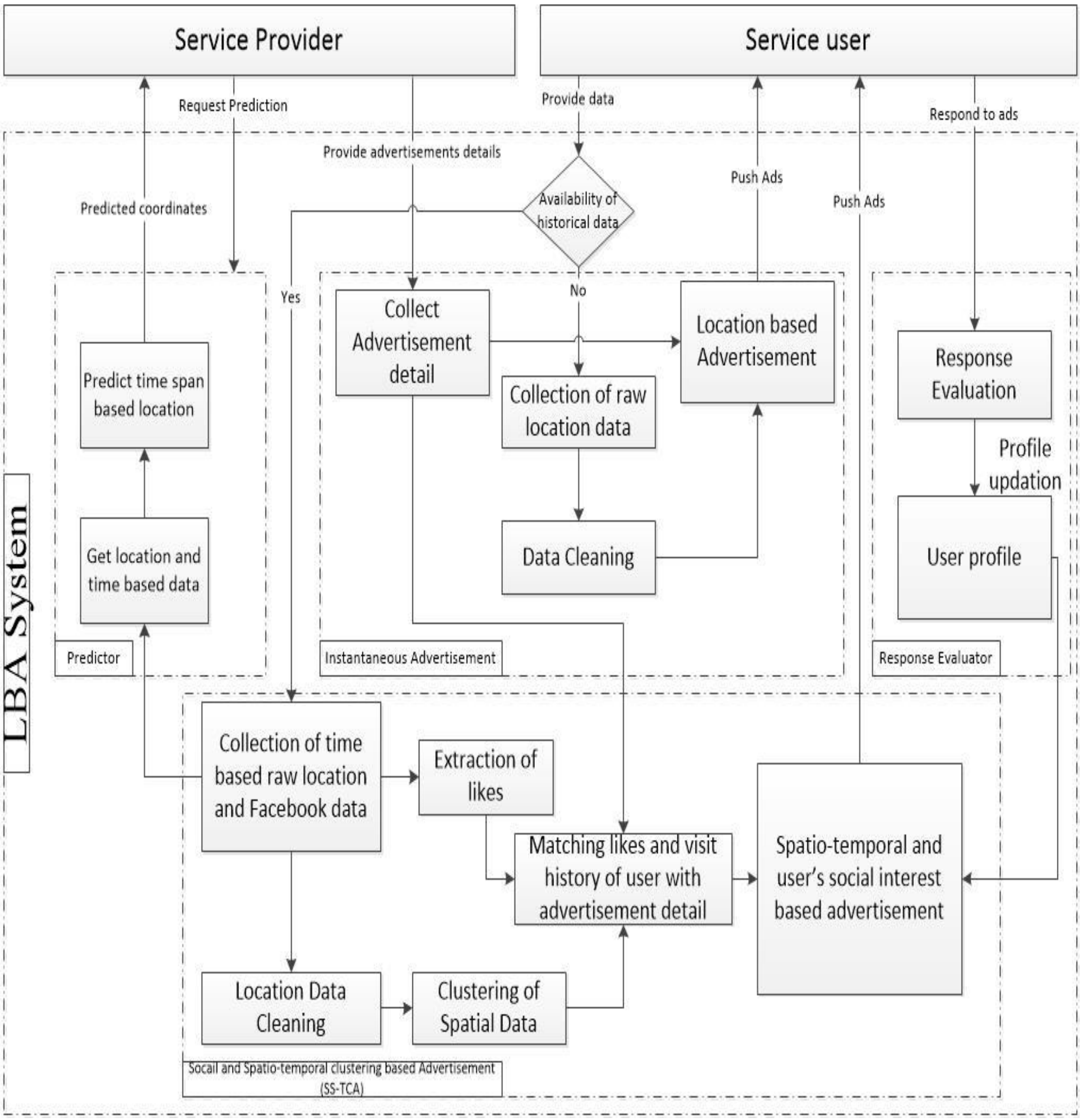

Figure 3.2 Architectural Framework of LBA system

3.2.1 Location Based Advertisement

Figure 3.3 describes the architectural framework of Location Based Advertisement.

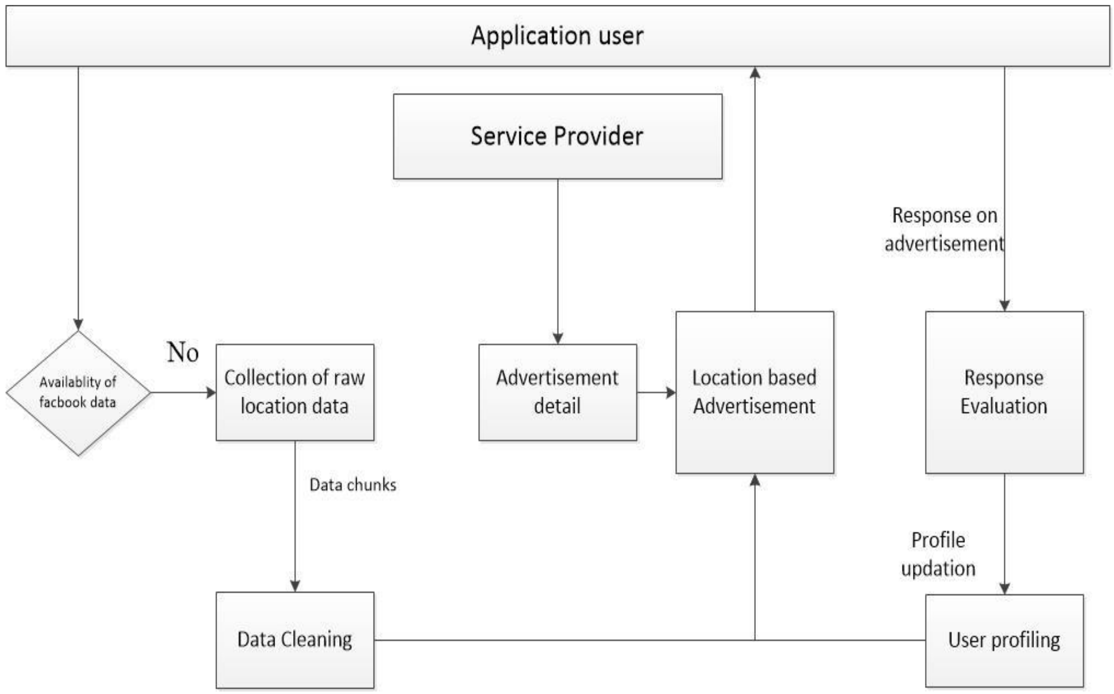

Figure 3.3 Architectural Framework of Location Based Advertisement algorithm

The role of online instant advertisement system is to send the location-based advertisement to the application user instantaneously when the user changes its geographical location. The geographical location information is obtained using GPS of the smartphone. The collected data is stored in pairs in a javascript object notation (JSON) format. Data cleaning is performed over the stored information of the application user such as a unique user id (Uid) assigned to the user is extracted from the data, Time and day for the location update (AU(dt)), user's geo-location coordinates (AU(loc)) and it is represented as twitter data (UDi), where 'i' represent the data count in the data set.

$$UD_i = \{U_{id}, (AU(\,dt, loc\,))\}$$

The AU(latitude, longitude) is shortly represented as AU(loc) which represent the latitude and longitude coordinates of the application user. After knowing the user location coordinates the next task is to push advertisement related to his/her current geographical presence. The advertisements are literally related to advertisement data or promotional offer messages broadcasted by the shop or brands (e.g. cafe, restaurant, salon, hotel) through the designed application. The brand data is represented by BD_i where I represent the count of data in the advertisement data set of that brand.

$$BD_i = \{B_{id}\ (loc, data)\ \}$$

The System posts the advertisement data to the application user (U_{id}) as a message. LBA system keeps the count of all the advertisement sent to the user. In LBA system's online Location Based Advertisement the system is set to one advertisement per thirty minutes per location update.

The algorithm for online Location Based Advertisement is as follows:

1. Start
2. $Get\ location\ data\ LD_i$
3. 2. $CleanData(UD_iChunks)$

   $$\#UD_i \leftarrow \left\{U_{id}\ , \left(AU\ (\ loc, dt)\right)\right\}$$
4. $Get\ the\ data\ about\ the\ brands\ vanue(BVD) with\ user\ location\ as\ the\ center\ point\ and\ defined\ radius$

   $$\#GetBrandVanueData\left(U_{id}\ \left(\ AU\ (loc)\right), r\ \right)$$
   $$\#BVD \leftarrow \{\ BV_{id}, (loc, data)\}$$
5. $If\ BVD == Null\ then$
6. $\quad \boldsymbol{return}\ Null$
7. $Else$
8. $\quad Push\ advertisement\ to\ the\ user\ U_{id}$

   $$\#Ad \leftarrow U_{id}\left(AU\left(UT(loc)\right)\right)$$
   $$\#PushAd\left(U_{id}(Ad)\right)$$
   $$GetResponse(Ad)$$
   $$Update\ AU_{id}\left(resp(U_{id})\right)$$
9. $END\ If$
10. End

On the start of the algorithm geographical location data about the user is taken from the GPS of the smartphone. Data is then cleaned to get only the longitude and latitude of the device's current position. The cleaned data with the unique id of the user is then saved as a first data set.

Data about the brand is then fetched from the online database. The fetched data contains the location of the venue as well as the advertisement details. First, the haversine distance between the venue and the user is measured. If venue of the brand is within the radius of the application user the person is chosen as the targeted audience and the audience set is updated. On the other hand, if there is no brand venue within the radius of the user's location then the venue data set for the user stays empty and no advertisement is pushed to the user.

On liking an advertisement the value attached to the advertisement is increased which defines the priority of the ads over the other ads. Upon disliking an advertisement user is asked about why it was disliked with giving the option to choose from. The options are 1) Not interested in such type of brands; 2) Price of the product is high; 3) Experience with this type of brands is not good. Each of the reason for negative response affects user interest differently. In first case the response defines for the user that brands with this type shall have low priority in users profile the second factor defines the price range for the user for that type of brand while the third response effects the user profile in a way that brands of this type shall not be in his/her advertisement vector.

3.2.2 Social and Spatio-temporal and interest based Advertisement (SS-TCA)

The online instant advertisement system has some limitations. It is found that most of the users are in mobility. That is, the users with smartphones use it on their go. As the user travels, the user's location is changed continuously. For example, when user starts his day to office from his home location (l_1) his location on the way to the office (l_2) changes and his next the person shall sty in the office area (l_3) and so on. Thus sending advertisement messages for each and every location of the user makes the user annoyed with this advertisement system and user might want to block the advertisement service.

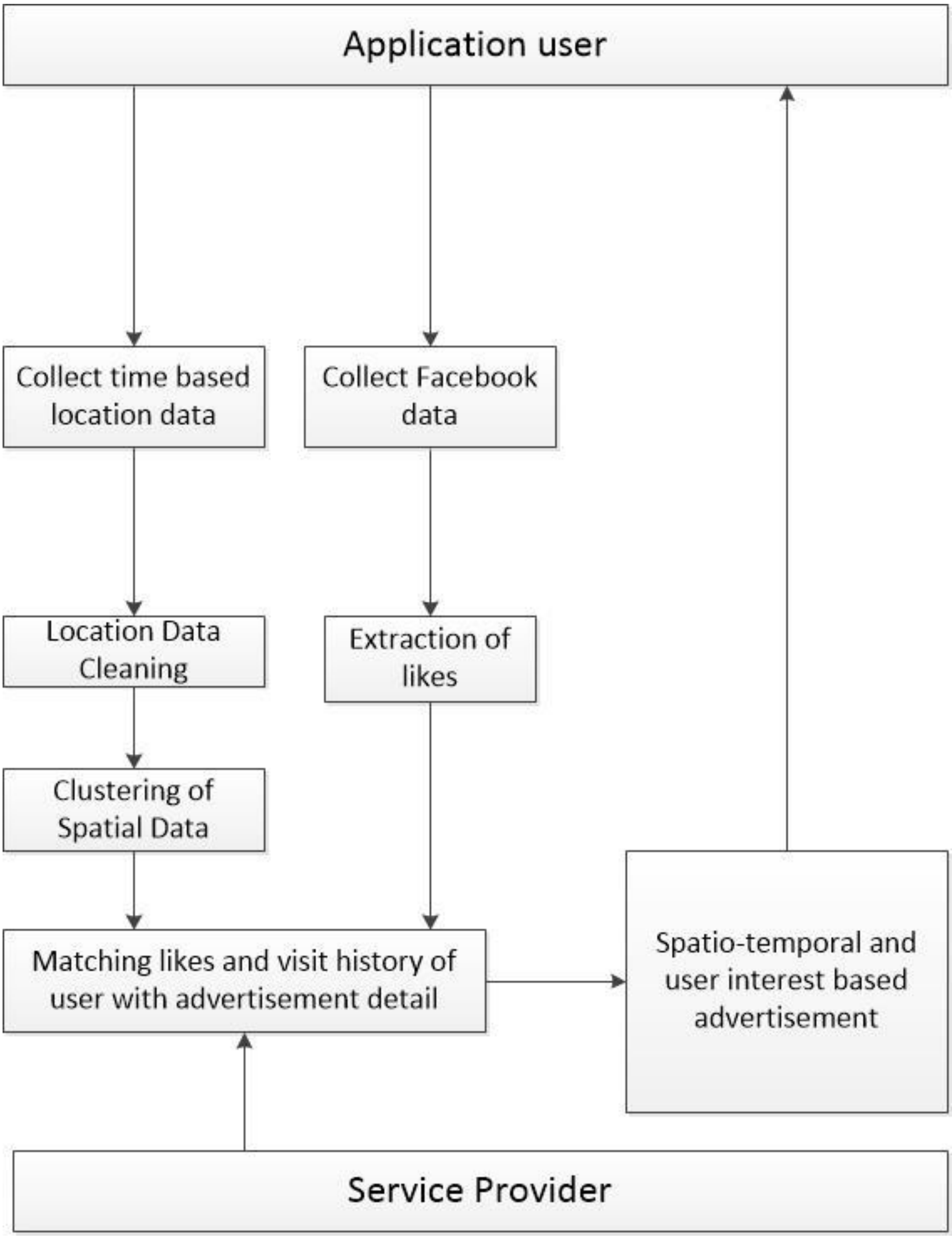

Figure 3.4 Architectural framework of Social and spatio-temporal based advertisement

Hence, a Saptio-temporal and interest based clustering algorithm is proposed to find out where the user resides for a long time and spatio-temporal clustering based advertisement is pushed based on his maximum geo-presence in a specified boundary of location. So when the user logs into the application on the basis of clusters formed on the person's historical data of places visited and the interests of the user he/she would be able to view those advertisements.

The interests are being fetched from Facebook. Although the fetched data does not fully define the interest of the person as people are normally not willing to share their information with the application. In that case, LBA system's response evaluation sub-model helps to determine the person's interest. Figure 3.4 describes the Architectural framework of the Social and Spatio-Temporal based Advertisement algorithm.

To perform clustering density-based spatial clustering of applications with noise (DBSCAN) algorithm is being used [61]. The purpose of using DBSCAN is that it creates the clusters with respect to the distance between point and number of points in that distance radius. As described earlier in the literature that people visiting a place most often are more likely to purchase from there so to find the maximum visiting place (MVP) DBSCAN provide excellent support but in DBSCAN all the points are compared with each other again and again which increases the time consumption by the algorithm for huge amount of data In our case the data was divided into chunks w.r.t. day and time span so DBSCAN provided effective results.

3.2.3 Algorithm and their Working

At the start of the algorithm the epsilon (eps) and minimum points (minPts) are being set. These two shall decide the size of the clusters to be made. Epsilon decides the minimum distance between any two points for these to be in a cluster while minimum points decides the number of minimum points which could form a cluster. After that brand venue data is loaded containing the location of the venue, type of brand, the price of the brand, the name of the enterprise and advertisements to be pushed for each brand. Next step is to load location history of the application user when location history is loaded along with the time to visit the place. That data is passed on to DBSCAN to be processed to get clusters. Facebook data and responses are then loaded and mined to get the interest of the person and prioritize the advertisements accordingly. Finally the distance to the SMEs are calculated from the average of the cluster and only SMEs in one Kilometre range and with less than three negative responses are chosen for that person. The implementation of the algorithm is as follows

1. $start$
2. $Input\ eps$
3. $Input\ minPts$
4. $Get\ brand\ venue\ data$

   $$BVD_{id}\{\} \leftarrow \big(\ location(BV_i) \cup data(advertisement)\big)$$
5. $Get\ Location\ history\ of\ user$

   $$\#X \leftarrow Coord(AU_{id})$$
   $$\#time_i \leftarrow TS(AU_{id}\ , loc_i)$$
6. $Extract\ the\ clusters\ for\ X$

   $$\#cluster\ \{\} \leftarrow DBSCAN(eps, minPts, X)$$
7. $Get\ Facebook\ Data\ of\ AU_{id}$

   $$\#fbdata \leftarrow data(Facebook, AU_{id})$$
   $$\#interest\{\} \leftarrow FBDataMining(AU_{id}, fbdata)$$
8. $UserInterest_{tempset}\{\} \leftarrow getAllAds(\ Type(advetisement) \in Interset)$
9. $UserInterest_{set}\{\} \leftarrow responseComparison(UserInterest_{tempset})$
10. $for\ each\ element\ in\ UserInterest_{set}$
11. do
12. $\quad for\ each\ (cluster(k)) \therefore k = 1,2, \dots num(cluster)$
13. $\quad do$
14. $\quad\quad \#dist_{all} \leftarrow haverSineDist(cluster(k), location(UserInterest_{set})\ )$
15. $\quad\quad \#Ad_{id} \leftarrow element_{id}$
16. $\quad\quad If\ dist \leq 1$
17. $\quad\quad\quad \#Push\ Advertisement\ \big(BVD_{id}(Ad_{id})\big)$
18. $\quad\quad\quad \#res \leftarrow GetResponse(Ad)$
19. $\quad\quad\quad Update\ AU_{id}\big(resp(U_{id}\ , res\ )\big)$
20. $\quad\quad Else$
21. $\quad\quad\quad return\ Null$
22. $\quad\quad end\ if$
23. $\quad End\ for$
24. $End\ for$
25. End

The sub-parts of the above algorithm are explained in as follows.

3.2.3.1 Implementation of DBSCAN

DBSCAN is takes three inputs epsilon, minimum points, and the coordinates set. Epsilon is the maximum distance between two points to be in a cluster while minimum points decides the minimum number of points requires to form a cluster. Distance here is calculated using Haversine. The implementation is as follows.

Procedure $DBSCAN(eps, minPts, X)$

```
Mark all thpoints in X as unvisited
#clu_id ← 1
for each unvisited point x in X
do
    #Z ← FindNeighbours(x, eps, X)
    if |Z| < minPts
        mark x as noise
    else
        mark x and each point of Z with clu_id
        #queu_list ← all unvisited points of Z
         until queue_list is empty
         do
            #y ← delete a point from queue_list
            #Z ← findNeighbors(y, eps, queue_list)
            if |Z| ≥ minPts
                for each point w in Z
                    Mark w with clu_id
                    if w is unvisited
                        #queue_list ← w ∪ queue_list
                    end if
                end for
            end if
            mark y as visited
         end until
    end if
    mark x as visited
    #clu_id ← clu_id + 1
end for
out put all the points in X with clu_id or noise
```

Procedure $findNeighbors(v, epsilon, dataSet)$

```
#distance ← haverSinDist(dataset, v)
for each element d with index l in distance
do
    if d < epsilon
        #neighbor_temp ← dataset( l )
        #neighbours ← [neighbor_temp; neighbors]
    end if
end for
return neighbors
```

3.2.3.2 Facebook data mining

The Facebook data is then loaded into the system and interests of a person are extracted. This task is accomplished using Facebook graphs in which all the data is stored in the form of edges and nodes. This algorithm helps in getting that edges details after comparing it with loaded edges set. The more the edges are present in data higher is the chance of getting that type of advertisement. The procedure for Facebook data extraction returns the set of interests in which edge name and number of occurrences of that edge in the dataset. The diagrammatic view of extraction of like is presented in figure 3.5. For only of the interests of the user in interests set advertisement are chosen to be displayed. The algorithm only chooses the advertisement which is of the type same as the interests of the interests set.

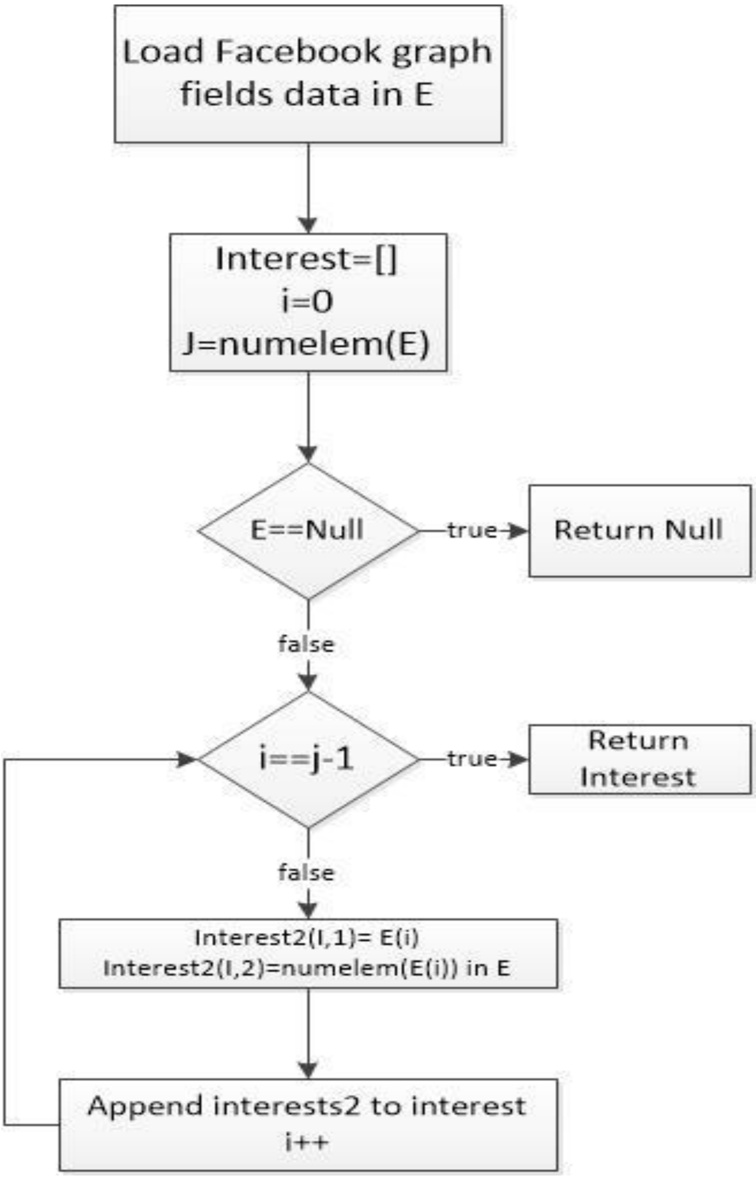

Figure 3.5 Diagrammatic view of Facebook data extraction

$\boldsymbol{Procedure}\ fbDataMining(AU_{id}, fbdata)$

1. $load\ all\ the\ fields\ of\ facebook\ graph\ in\ E$
2. $\#interest \leftarrow [\,]$
3. $if\ fbdata == Null$
4. $\quad return\ Null$
5. $else$
6. $\quad for\ each\ e\ in\ the\ E$
7. $\quad do$
8. $\qquad \#interest2[e, num] \leftarrow numOcc(e, fbdata)$
9. $\qquad \#interest \leftarrow [interest; interest2]$
10. $\quad end\ for$
11. $end\ if$
12. $return\ interest$

3.2.3.3 HaverSine Distance

For each advertisement chosen the distance for their venue to the clusters is measured using Haversine distance formula. Haversine distance formula helps to calculate the distance (in kilometers) of any two latitude and longitude values given. In this algorithm, Haversine function returns the set with all the distances measured from venue point to the all the points in the cluster and then minimum distance between that cluster is chosen as the decider for the advertisement to be pushed or not. The advertisement is pushed to the user if it is in one kilometer distance of the person.

$\boldsymbol{Procedure}\ haverSineDist(cluster, point)$

1. $for\ each\ point\ c\ in\ the\ cluster$
2. do
3. $\quad \#dist \leftarrow 2$
4. $\quad \#\varphi1 \leftarrow latitude(point)$
5. $\quad \#\varphi2 \leftarrow latitude(c)$
6. $\quad \#\Delta\varphi \leftarrow (\varphi1 - \varphi2)$
7. $\quad \#\Delta\lambda \leftarrow \left(logitude(point) - longitude(c)\right)$
8. $\quad \#a \leftarrow sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos\varphi1\,.\cos\varphi2\,.sin^2\left(\frac{\Delta\lambda}{2}\right)$
9. $\quad \#c \leftarrow 2\,.atan2\left(\sqrt{a}, \sqrt{1-a}\right)$
10. $\quad \#dist_{temp} \leftarrow R.c$
11. $\quad \#dist \leftarrow [dist;\ dist_{temp}]$
12. $end\ for$
13. $return\ dist$

3.2.3.4 Response Evaluation

In LBA system there are two types of response sets one with positive responses and one with the negative responses each element in the response set is assigned a value. At initialization these sets are empty. With each advertisement pushed to the user the value of response sets are updated.

The brand with higher positive response values gets the priority in advertising. Suppose if an advertisement is pushed to a person and the person likes it then in persons profile the values of that company, type of the brand and price range for that type of brands are incremented.

On the other hand, advertisement gets eliminated if the respective category of it is disliked in previous responses more than three times. In response to this, the LBA system's response evaluator asks for the reason of such response with prompting the user to choose from the options provided which are mentioned above in section **Error! Reference source not found.**. The selected response effects the respective f ield in the negative response vector. More than three negative response on one type results in elimination of that type of advertisement from user's list of advertisement. The algorithm for LBA system's response evaluator is as follows.

$\boldsymbol{Procedure}\ responseCcomparison\left(UserInterest_{tempinterest}\right)$

1. $Start$
2. $Get\ response\ R\ over\ advertiment\ Ad_{id} of\ product\ P$
3. $if\ R\ is\ positive$
4. $\quad increment\ company\ value\ by\ 1$
5. $\quad increment\ type\ value\ by\ 1$
6. $else$
7. $\quad if\ \ count\big(Value(R) == company\ (P, type)\big) > 3$
8. $\qquad eleminate$
9. $\quad end\ if$
10. $end\ if$
11. end

Figure 3.6 is the diagrammatic representation of the response evaluation and effects

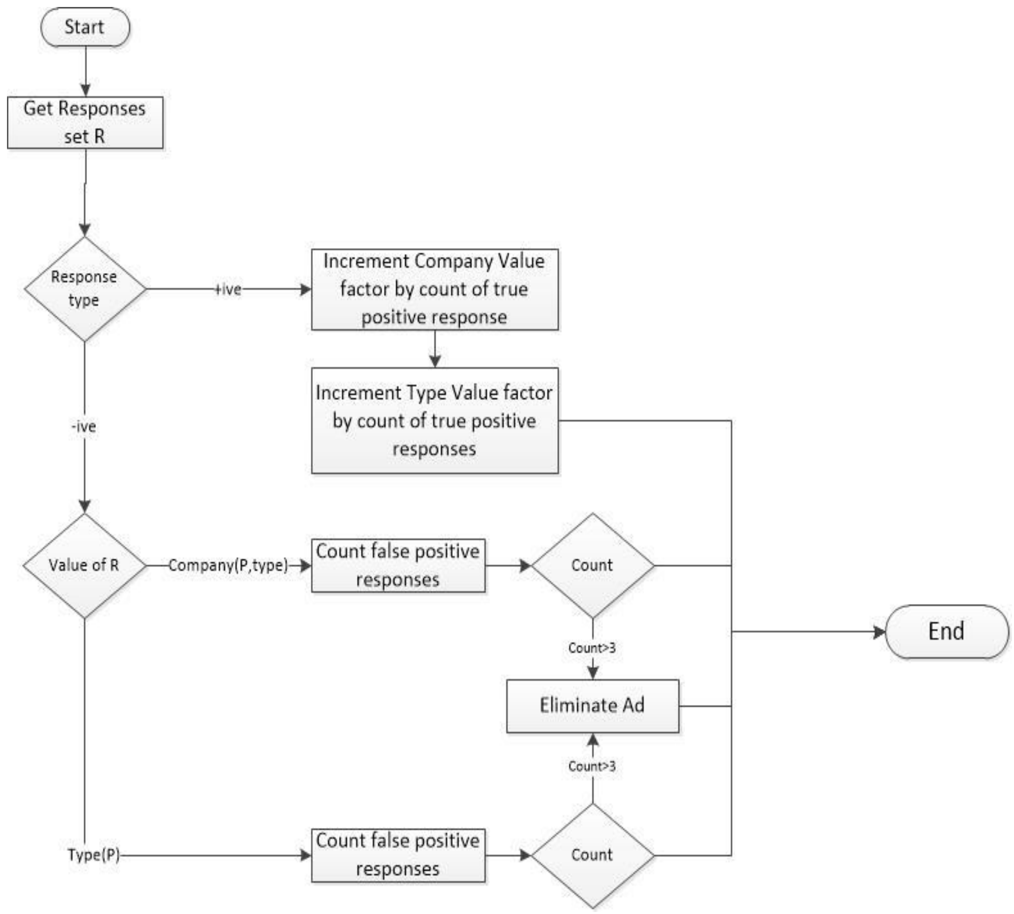

Figure 3.6 Diagrammatic representation of the LBA system's Response Evaluator

If there is no venue for that cluster and interest is found no advertisement shall be pushed and it is considered that person is not interested in that place and not advertisement shall be pushed to the user.

3.2.3.5 Notations used

There are several notations used in the algorithms which need to be described. The descriptions of the notations being used are described below

Eps/epsilon: *The minimum distance between two points to be in a cluster.*

minPts: *Minimum number of points to form a cluster.*

coord( ): *A function to get the coordinates from data.*

TS( ): *Time span of the day. The time span consists of 4 intervals shown in table 3.2.*

cluSize: *A vector of cluster sizes.*

Size ( ):	*A function to calculate the number of points in a cluster.*
mid( ):	*A function that finds the middle values from the vector.*
Dist:	*Distance vector.*
AU¬¬id:	*A unique application user*
Res:	*Response value of the user.*
X:	*Coordinates set of the user.*
X:	*A location point in X*
Cluid:	*An element from cluster set.*
Z:	*Set of neighbor location points.*
Y:	*A location point in the cluster to be used to expand the cluster.*
W:	*A location point from Z set*
V:	*Allocation point for which the neighbors are to be found.*
E:	*Set of Facebook the edges available*
E:	*An element from E set*
R:	*The radius of the earth.*

3.2.4 Prediction

The fourth sub-model of LBA system is the predictor. Using the historical data of the user the predictor predicts the location of the person. There are following parameters about the user which are to be considered for prediction.

1. The time span of the day for which the prediction is to be made.
2. Day of the week for which the prediction is to be made.
3. Person's historical data of visits.

Using these parameters the prediction of the person's location is carried out. Prediction is carried out for the scenario such as an event which is to be held on a specific place at the specific time and it needs appropriate audiences of its promotions. Prediction of LBA system is probability based. Higher is the probability of a specific visit point on a specific time higher is the chance for that person to visit that place at that time. The algorithm for the prediction is as follows.

1. $start$

$load\ location\ history\ LH\ of\ the\ each\ user\ AU_{id}$
$pridited_{location} \leftarrow \emptyset$
$for\ each\ user's\ location\ history\ lh_{id}\ from\ LH$
do
$\quad probability_{lh} \leftarrow \emptyset$
$\quad for\ each\ time\ span\ t\ from\ TS$
$\quad do$
$\quad\quad lh_{temp} \leftarrow unique_{LatLong}(lh_{id}, t)$
$\quad\quad probability_{ulh} \leftarrow \emptyset$
$\quad\quad for\ each\ element\ ulh_{temp}\ in\ lh_{temp}$
$\quad\quad do$
$\quad\quad\quad probability_{ulh}\{\} \leftarrow append\left(\frac{n(ulh)}{n(lh_{temp})}\right)$
$\quad\quad end\ for$
$\quad\quad probability_{lh} \leftarrow append(\max(probability_{ulh}))$
$\quad end\ for$
$\quad pridicted_{location} \leftarrow append(AU_{id}, probability_{lh})$
$end\ for$
end

3.2.5 LBA system's Architecture

LBA system is the combination of the four sub-systems described in above section. Each sub-system takes part in making the LBA system more effective. Such as a person may choose to view the advertisement at a new place where his location history does not show any record in that case the Location Based Advertisement could help the user to get the desired advertisement around that place.

When there is a long history of the user is available the system shall perform data mining using DBSCAN on that history and get the places with maximum visits. The results are in the form of clusters. These clusters along with the social record provided by the person shall be used to decide the type and venue of the brand to be advertised.

The above two sub-systems also interact with the third sub-system named as Response Evaluator to improve effectiveness with each advertisement pushed. On each advertisement pushed to the user, the response is collected about that advertisement. The response can be positive or negative. If the response is negative then the user is asked for the reason for that type of response with three choices given to the user which are mentioned in section 3.2.1.

Fourth subsystem of LBA system is the Predictor. As the name suggests it is for forecasting. In this research, the prediction is performed to get the users most expected visit point from historical data of the user. For prediction, the parameters such as day of the week and time span of the day are taken into the account. The time spans are divided into 4 sections and are shown in table 3.1. Prediction is performed for each of the time spans. The predictor provides the results to the service provider and if any event is expected in the future the service provider shall be able to know which people are expected to visit places around that venue.

Table 3.1 Time Spans defined

Time intervals	**Index assigned**
08:00 am - 11:00 am	1
11:00 am to 02:00 pm	2
02:00 pm to 05:00 pm	3
05:00 pm to 08:00 pm	4
08:00 pm to 08:00 am	5

Chapter 4

EXPERIMENTS AND RESULTS

The real-time GPS data is collected by using android application which is provided to the user as a beta version. The application was programmed to get the GPS location of the user after each five minutes. On each location update, current time and day are also fetched and saved this record in the online database. As the concern is about location based service the data was collected only within the specific area. The data has been collected across Mirpur city, Pakistan and a sample is visualized on the map as shown in Figure 4.1 with big circles indicating the SME while small ones indicating a sample of the users' data.

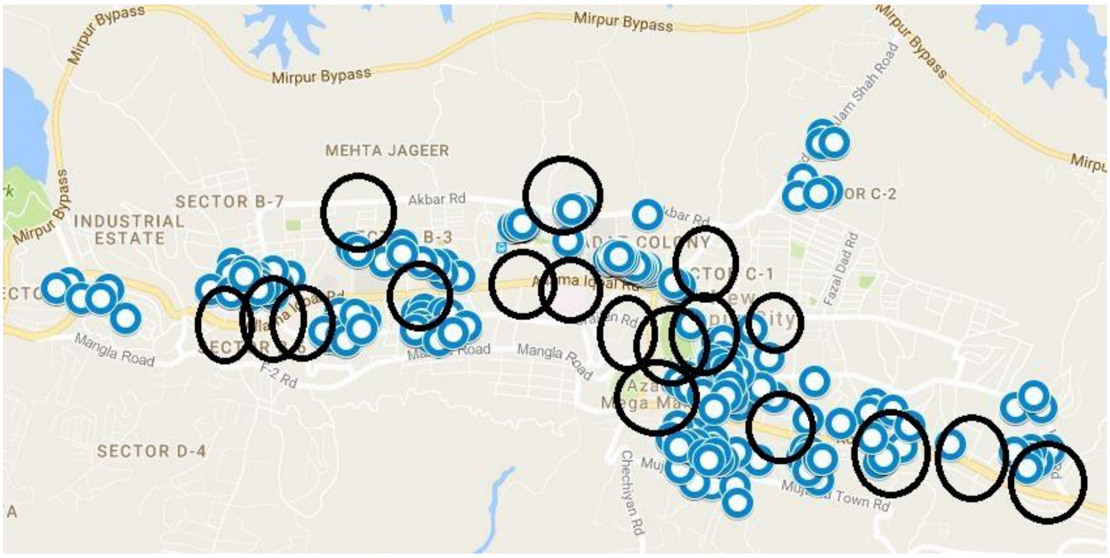

Figure 4.1 Visualizing the location of Users and SMEs

Nearly 1.8 lakh coordinate point of ninety-five users were collected for the purpose to conduct the experiment. Among these ninety five users there were twenty five girls and 70 boys. All the participants were students of Mipur University of Science and

Technology. The participants were chosen on the bases of snowball sampling approach. Each of the users when signed up to the application were provided with a unique ID by Firebase. That ID is then used to group the data of an individual.

18 venues have been used to advertise their brands using LBA system. These venues are chosen on the basis from different locations of the city as shown in figure 4.1. For each location update, the list of advertisement are updated. The advertisement list is based on the distance between the user location and location of the store. This is done by getting the advertisement data from the online database (i.e. Firebase). The vendors are given the same application with service provider privileges. The application allows a vendor to upload advertisements with following details. a) Company name, b) product type and tags c) Product price and d) coordinates of the store. There were five types of advertisements i.e. male clothing, female clothing, male accessories, female accessories, health and care, food and mobile phones.

There were 193 different ads uploaded by all the vendors. Upon each of the advertisement displayed response was collected as if the user likes it the location, company and type of the product in the advertisement gets one plus point. While in the case of negative response a questionnaire asking for the reason to dislike an advertisement is prompted to the user. Because of the limited screen size of the phones, the survey questions were kept short. From 195 advertisement there were 57 ads those were offers and discounts. Others were a simple advertisement about new arrivals and available stock.

The Experiment was conducted in three phases. In first phase all the 120 LBA system users were exposed to the advertisement randomly with only preferences that an advertisement already pitched to them shall not be displayed again, only one advertisement of one store shall be displayed to avoid biasing towards any store and in a day a user can only view 6 advertisements so that the factor of irritation does not come into the play. The response over each of the advertisement was collected. This phase lasted for 10 days. And in this phase, 25 users stopped using the application.

In second phase responses were collected on the Location Based Advertisements. On each location update, the users' location was compared to get the congruency with registered SMEs in LBA system. In this phase, the users were on average 100 responses per user were collected. This phase lasted for three days.

In the third phase, the 95 Users were pitched a maximum of 60 ads per person based on the location clusters and the interest of the users obtained from Facebook data (i.e. linked pages). This phase also lasted for 10 days. In this Phase, the response evaluation module of LBA system was also activated. Based on the responses of each person the new ads were filtered for each user and then these filtered ads were pitched to the users. The response to these advertisements was observed for conclusions.

4.1 First experiment

In first Experiment, there were 120 users at the start but 25 users left without completing the first phase so responses of only 95 users were obtained. On the basis of 6300 responses, the observations were made.

Table 4.1 Results of responses with categories

<table>
<tr><th rowspan="2">Evaluation Type</th><th colspan="5">Responses</th></tr>
<tr><th>Likes</th><th colspan="4">Dislikes</th></tr>
<tr><td rowspan="3">Count</td><td rowspan="3">1,887</td><td colspan="4">4,413</td></tr>
<tr><td>Product Price</td><td>Product Type</td><td>Company</td><td>Location</td></tr>
<tr><td>896</td><td>2563</td><td>1057</td><td>2297</td></tr>
<tr><td rowspan="2">Percentage</td><td rowspan="2">29.95%</td><td>14.22%</td><td>40.68%</td><td>16.68%</td><td>36.46%</td></tr>
<tr><td colspan="4">70.05%</td></tr>
</table>

These results show that the liking of any advertisement depends on a lot on the contextual information about the user such as location, gender, and interests of the person. The disliking is further discussed in details individually.

4.1.1 Product Type Based Negative Responses

40.68% disliking of the product because of type asks for a review. Disliking because of Product type when studied deeply it was observed that the most of the disliking was on the basis of gender. There were 70 males among the 95 LBA system users. The percentage of disliking the type of products are shown in figure 4.2.

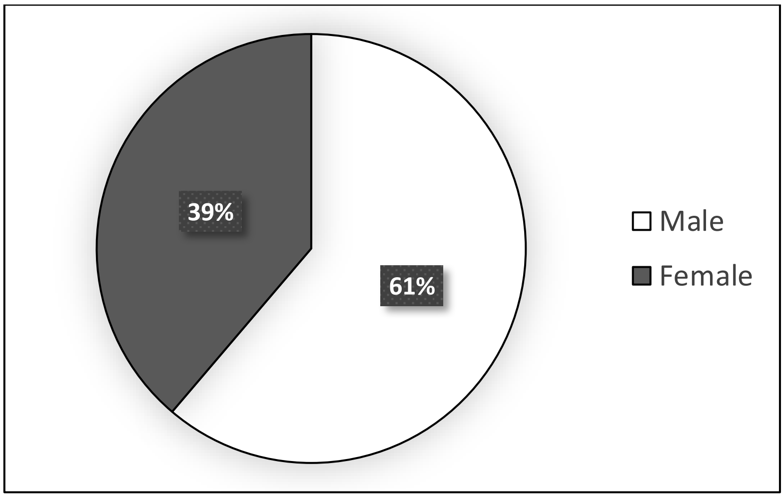

Figure 4.2 Types dislikes by gender

Further when the female "types dislike" were analyzed critically it was observed that the 66% of the types dislikes were on the male related advertisements. Figure 4.3 describes the detailed view of female "types dislikes" on the advertisements.

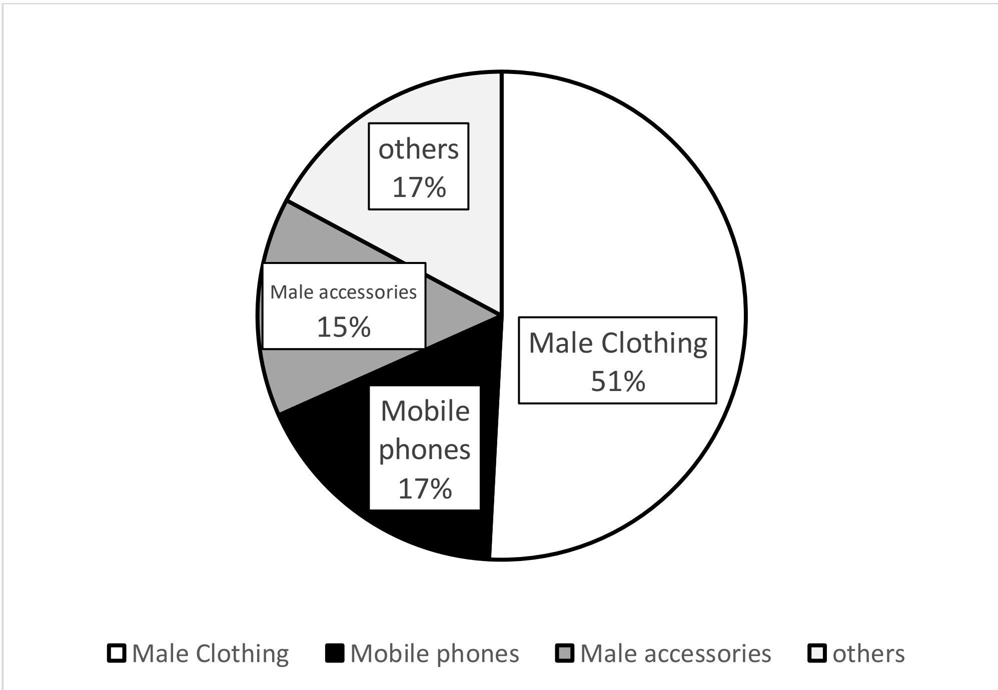

Figure 4.3 Female "Types Dislikes" distribution chart

Almost same type of results was obtained from the male users. Figure 4.4 shows the male "types dislikes" distribution.

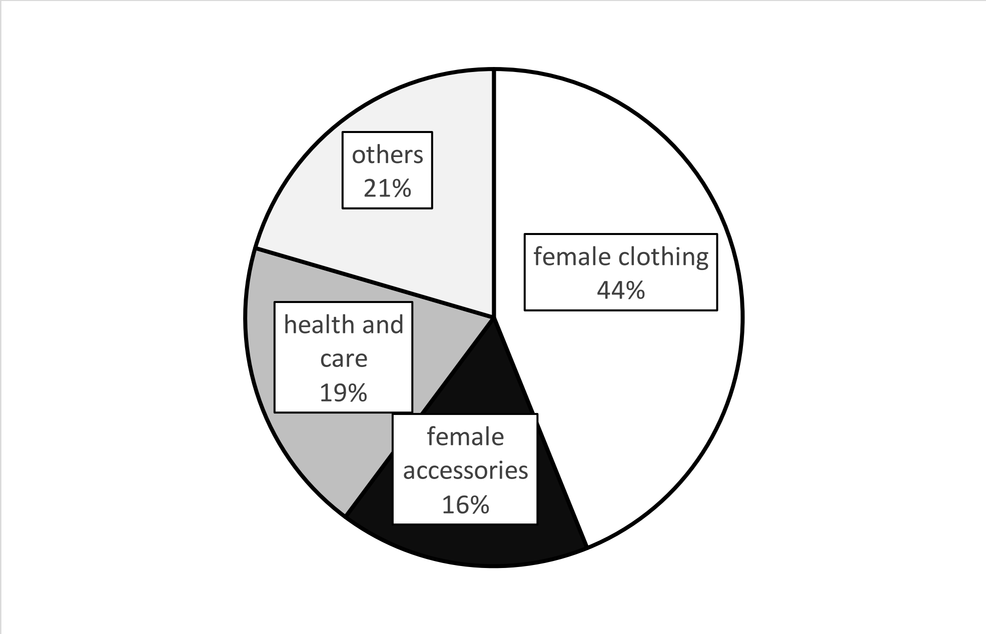

Figure 4.4 Male "types dislikes" distribution chart

A big reason identified for product type based negative responses was the advertisements' gender mismatch. Hence the type of product shall be considered in the gender context before advertising it to everyone.

4.1.2 Location Based Negative Responses

On location based disliking it was observed that mostly the location of that store is not in the 2 Km range of the user's place. The chart in figure 4.5 describes the disliking-distance relation observed in this study.

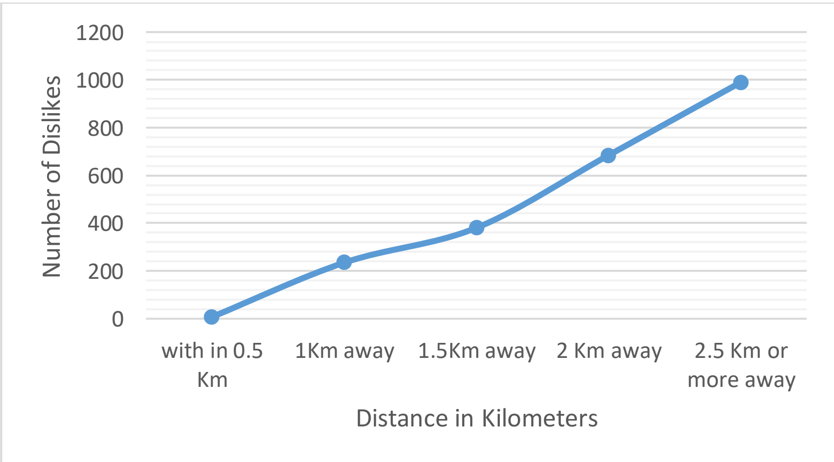

Figure 4.5 Dislikes with respect to the distance between the person and the SME's location

The observed statistics about the distance suggest that the distance between SME and person matters a lot. On every one Kilometer increase of distance from the person to SME's location the interest in that brand decreases by at least 10%.In a sense, the value of the brand decreases as the distance factor increases. In that case, the SMEs paying for the advertisement to such audiences is a waste of resources.

People consider such advertisement to be irrelevant to them. But when it comes to offers the response of the persons shows different behaviour. Results show that the percentage of disliking an advertisement containing offers is not exactly like the percentage of other dislikes with respect to location. Results suggest that people tend to like that advertisement if it contains an exciting offer or discount neglecting the factor of distance to some extent. Although there are some negative responses on the offers as well but there are some positive responses as well. Figure 4.6 describes the liking and disliking of the offers and disliking an offer based on the distance. This result is based on 1900 responses to 20 advertisements with discounts and offers.

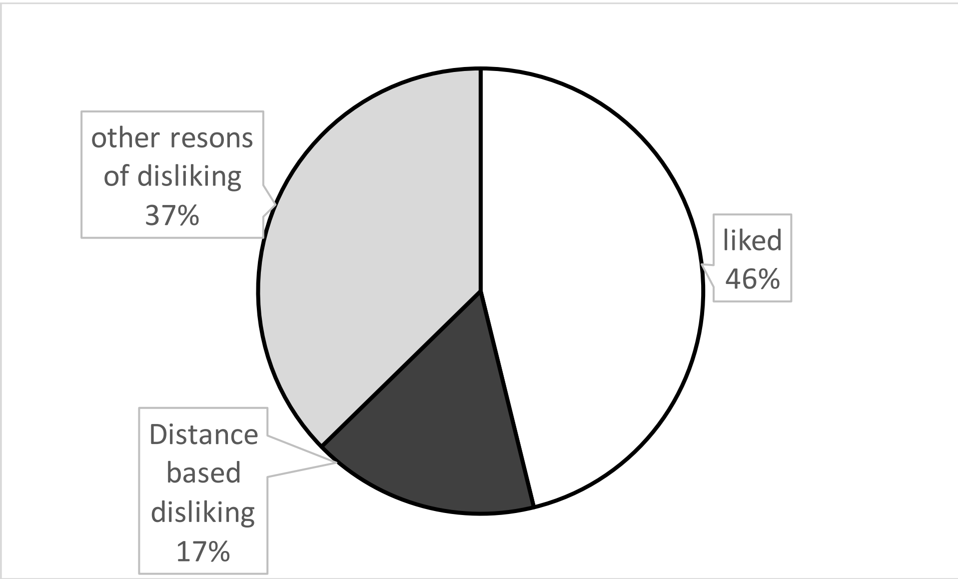

Figure 4.6 Response distribution w.r.t. offers related ads

Hence the effect of distance is not negligible. 17% of overall negative response on offers just because of distance brought the attention to the point to extract the distance of each disliked advertisement. The results showed that these offers' location were mostly farther than 2.5 Km from the persons' locations. The graph in figure 4.5 shows the graphical results of negative response to the offers related advertisements with respect to the distance between the place of the user and the SME's location.

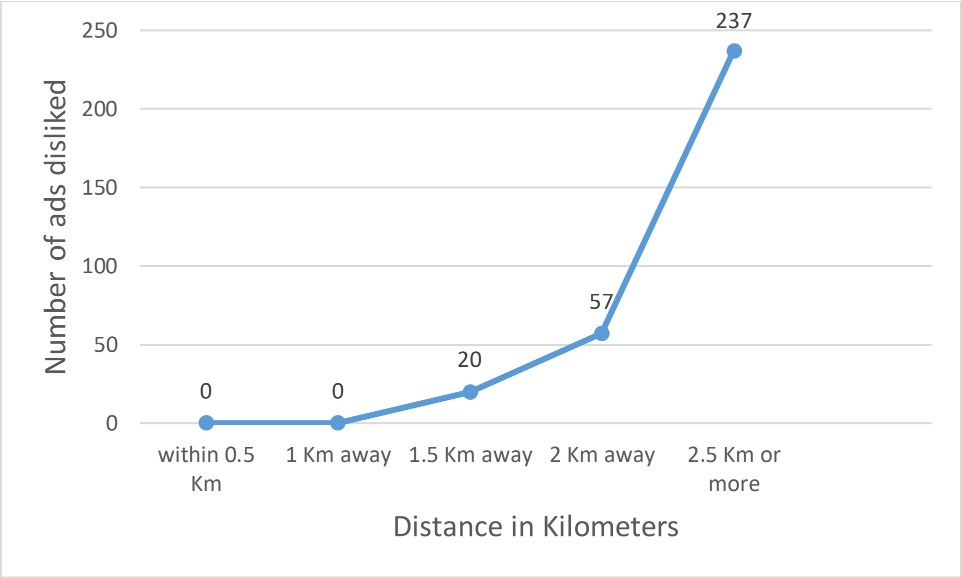

Figure 4.7 Graphical representation of the negative responses to the offers related Ads

As the graph suggest that the effect of irrelevancy was gradually increasing till 2 Km but it suddenly changed when the distance become 2.5 Km.

4.1.2.1 Overall v/s offer related ads negative responses

Overall distance based negative response was compared with responses on offers related advertisement. It was observed that offer related advertisements get more positive response for longer distance between user and SME than overall advertisements without offers.

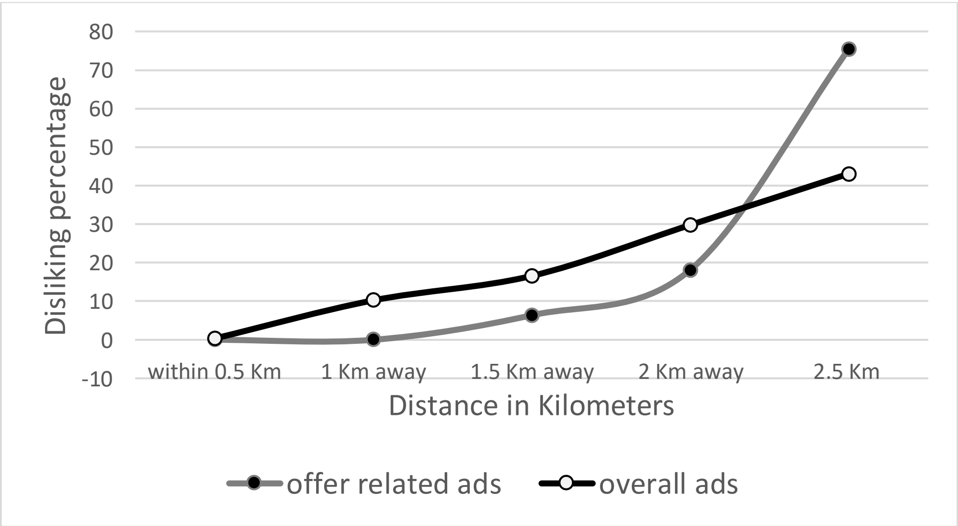

Figure 4.8 Comparison between negative responses on overall and offer related ads

The result of this experiment suggested that the offers become irrelevant to the customers if there are more than 2.5 Km away from the person's location. The graph in figure 4.8 shows the comparison between distance-based negative responses on overall with offers related ads.

4.1.3 Discussion on the First Experiment Results

The first experiment was conducted on the users and responses were collected till 10 days. The experiment showed results as expected that only 29.95% of the ads were being liked by the users and 70 percent of the ads were marked as disliked in different four different categories. These numbers revealed the wastage of resources by SMEs and the irritations faced by the people while looking for a good store to buy a product of their choice and at their ease.

The purpose of the experiment was two folded. The first side was to know about the users' behaviour towards location incongruent ads. The suggested that people certainly like an advertisement of those places which are close to them. As 36.46% of the total responses were marked as the negative based on the distance between the customer and the store. And these responses depicted that at each 0.5 Kilometre increase of distance the percentage of disliking is increased by 10%.

The second side of the experiment purpose was to get the contextual information about the users' interests. The results showed that contextual information plays a significant role in making an advertisement more suitable for a person. In the results obtained from the users it 40.68% of 6300 responses were marked as negative based on the type of product promoted to them. The study of the behaviour of such responses suggested that purpose of disliking these ads under this category was 65% based on the gender for females and 60% based on the gender for males.

These Results suggested that an advertisement system definitely needs the contextual information like gender, interest, and location of the person. LBA system used these responses to get the context of the user.

4.2 Location Based Advertisement

In this Experiment, the ads were displayed to users as they come in the range of an SME registered with LBA system. On each location update, the advertisements of the registered SMEs in 2 Km radius of the person were fetched and User is notified about the advertisement. This experiment lasted for only three days as the users felt irritated by the notifications on each location update. However, there were 6077 responses by the 95 LBA system users.

The responses were collected exactly like in the previous phase. The responses statistics are shown in the table 4.2.

Table 4.2 Response Statistics of Location Based Advertisement.

<table>
<tr><th rowspan="2">Evaluation Type</th><th colspan="5">Responses</th></tr>
<tr><th>Likes</th><th colspan="4">Dislikes</th></tr>
<tr><td rowspan="3">Count</td><td rowspan="3">2549</td><td colspan="4">3582</td></tr>
<tr><td>Product Price</td><td>Product Type</td><td>Company</td><td>Location</td></tr>
<tr><td>794</td><td>1782</td><td>863</td><td>613</td></tr>
<tr><td rowspan="2">Percentage</td><td rowspan="2">41.94%</td><td>13.06%</td><td>29.32%</td><td>14.20%</td><td>10.1%</td></tr>
<tr><td colspan="4">58.06%</td></tr>
</table>

The results of this methodology were clearly better than the previous one but this methodology was irritating for the users. The application provided shows a message after each notification “feeling irritated Switch to History Based Ads”. The level of irritation is described by a number of users leaving the Location Based Advertisement (LBA) Module in figure 4.9.

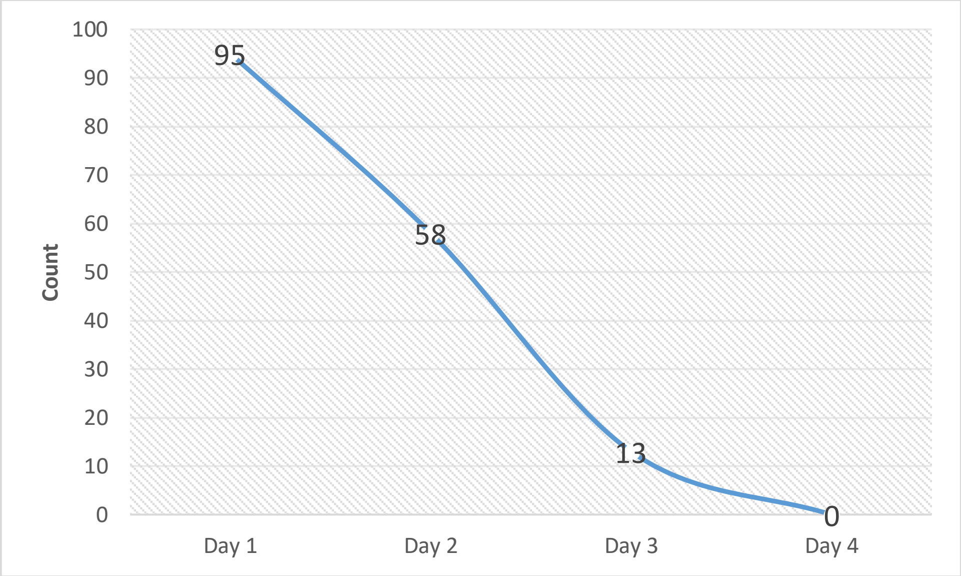

Figure 4.9 Number of users using Location Based Advertisement module by day

The graph shows that after first day 37 users chose to switch to history based ads. After 2nd day 45 more users left LBA module and after 3rd day there were no users of LBA module. The average of the advertisement views per person also decreased by days which suggests that the users started to ignore the application notification or stopped the application. Figure 4.10 show the average advertisement views per person on each day.

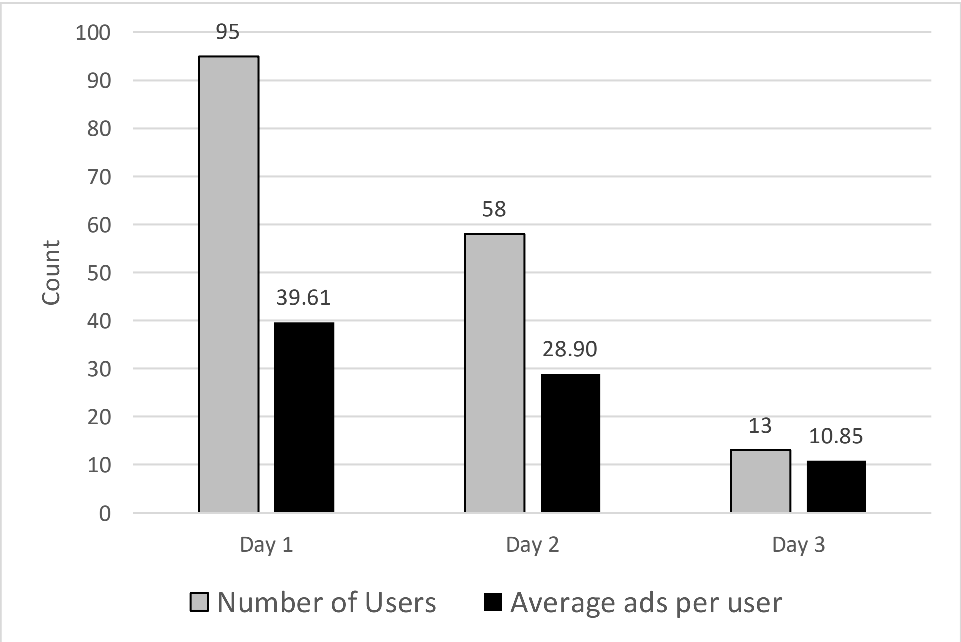

Figure 4.10 Ratio of number of users to number of ads responded upon

Coming to the contextual information about the users in LBA module there was location context available to the LBA system and results were certainly better in that context. Responses on the type of product in the advertisement are discussed in the subsection.

4.2.1 Product type based negative response

The observed results for the type of products were quite similar to the previous experiment. Most of the dislikes were because of users' conflict on gender-based advertisements. The pie chart in the figure 4.11 describes the percentage of dislikes based on gender in the category of products types.

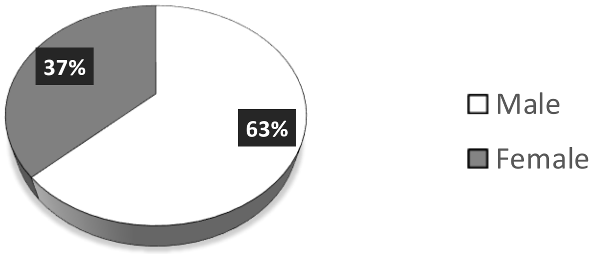

Figure 4.11 Gender-based negative responses in category of product type

When gender-based negative responses to the product types were analyzed the results showed that factor of gender-related advertisement indeed affects the responses. The chart in figure 4.11 elaborates the factor of gender-based negative response in the category of the products types.

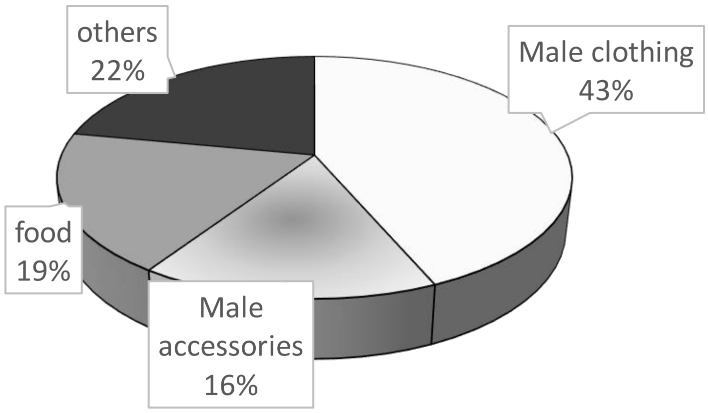

Figure 4.12 Females negative response distribution for type of product (LBA)

Figure 4.13 shows the negative responses got in LBA module in the category of product type by a male. This again was much similar to the previous experiment results for a male in this category.

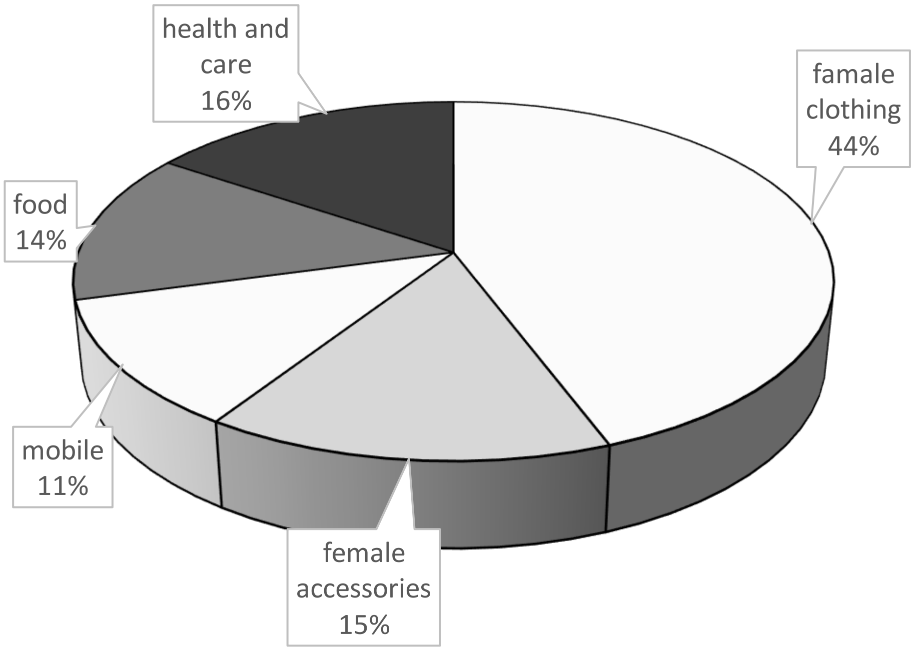

Figure 4.13 Male negative responses distribution of product type using LBA module

4.2.2 Discussion on 2nd Experiment results

The results are shown in table 4.2 clearly suggest that factor of location most definitely affect the percentage of the positive response to the advertisements. But the factor of irritation shall also be considered while showing the advertisements. Figure 4.9 evidently made a point that level of irritation is increased as the frequency of ads increases even if the advertising SMEs are close to the user. The irritation factor made all the users switch to another module within 3 days of time. This is quite disturbing for any system to get avoided within such short time.

Again in this experiment, it was observed that the contextual information of users is very important for any SME to advertise their products to the proper audience. 14% negative responses on food-related advertisements by male and 19% negative responses by female accumulate to 282 ads in 3 days of time. This number depicts that the time related contextual information about the user and SME is very important.

These numbers suggest that people want information about any product on a certain time of the day. A person sitting next to TV at home will not notice the advertisement about new store opened in the city [107]. As there were 3031 number of dislikes and among those more than 1700 were marked in the category of the product types. And in product type gender and time were considerable contexts with which the system shall keep itself aware.

4.3 SS-TCA

Previous two experiments have the following findings.

i) Advertising without any contextual information is not the right approach for any SME in a city.

ii) Advertising with respect to location congruency was definitely better but it was irritating for the customers as well as it requires more than just location context to improve the relevancy of advertisement.

Keeping in mind the above two findings third experiment was conducted using the response evaluation module. Response evaluation module used the responses obtained from previous experiments and filtered the ads accordingly.

To conduct this experiment users' location history was used. Using the smartphone GPS location data was collected for a minimum of one month. A months before the start of the first experiment the users were reached to 120 but as described earlier 25 users stopped using the application provided and the experiment was conducted on 95 users' data only.

In this experiment, following modules are used

a) Clustering of temporal data
b) Clustering of spatial data
c) Filtration of ads based on distance
d) Filtration of Ads based on previous responses
e) Prioritizing the Ads w.r.t to temporal and likes of the data.

4.3.1 Clustering Results

As described above there were two types of clustering used in this experiment Temporal based clustering and Spatial based clustering. Firstly the data was cleaned on the basis of day types (i.e. weekdays and off days) then for each of the two-day types coordinates were distributed w.r.t. time. The time span distribution is described in table 3.1 of the previous chapter. For each timespan of the day the coordinates were passed for clustering. This experiment was conducted only for the 12 hours of the day from 08:00 am to 08:00 pm.

After filtering the coordinates value w.r.t day and time these collected coordinates were passed to the DBSCAN to get the clusters from it. For this experiment, the minimum points required to form a cluster is being kept 70 and the value of epsilon is kept 0.1 Km for the cluster to be more concise. These clusters were obtained to know about the maximum presence of any user within a specific radius. The most visited places form clusters. The less frequently visited place coordinates are marked as noise. Figure 4.14 shows the results of DBSCAN on a person's data of weekday and time span 2.

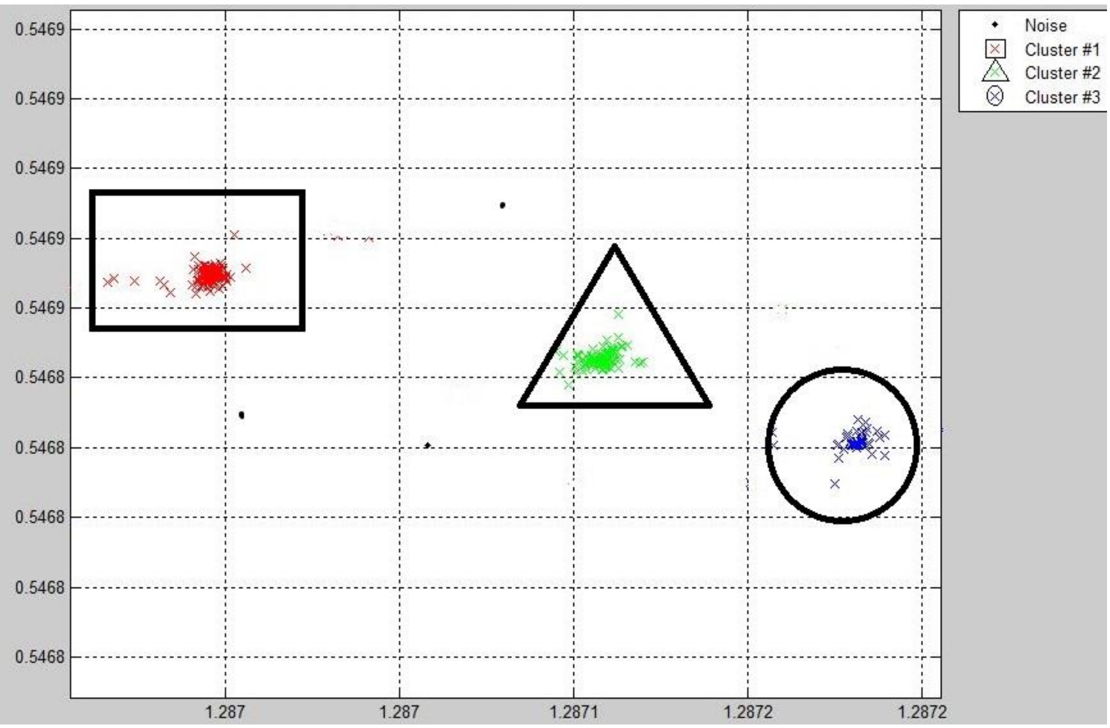

Figure 4.14 Clustering result of DBSCAN

4.3.1.1 Visualizing Users Presence

The users' geo presences are visualized based on their geo-tag information which arrives with the users' location update from the provided application. This visualization of the user presences helps to get information about the number of users available in that location with respect to day/time series calculation (Figure 4.15 through 4.18). This helps the LBA system to monitor people mobility or the crowd strength near to the business area of the vendor which in turns helps vendors to get the maximum benefit out of it.

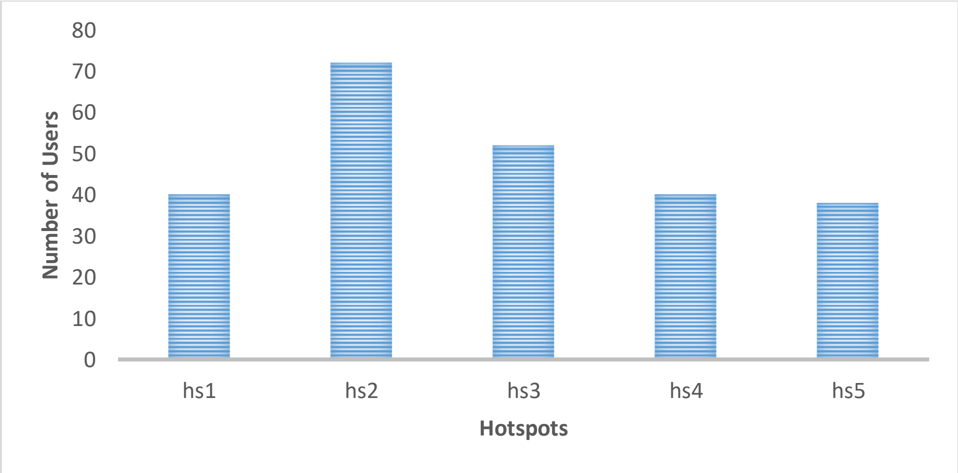

Figure 4.15 Number of applicaion User at each Hotspot on Weekday and Timespan 1

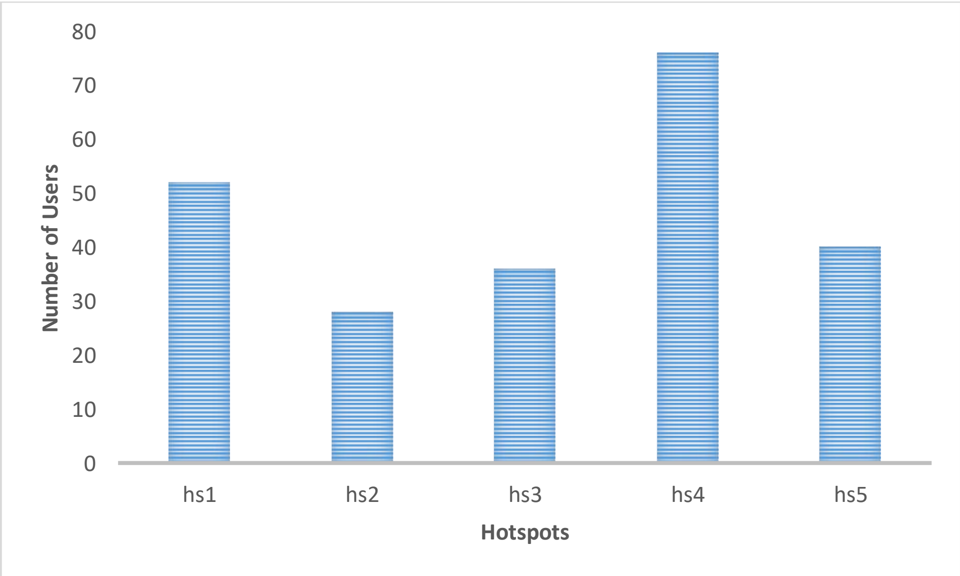

Figure 4.16 Number of Users at each Hotspot for Weekday and Time Span 2

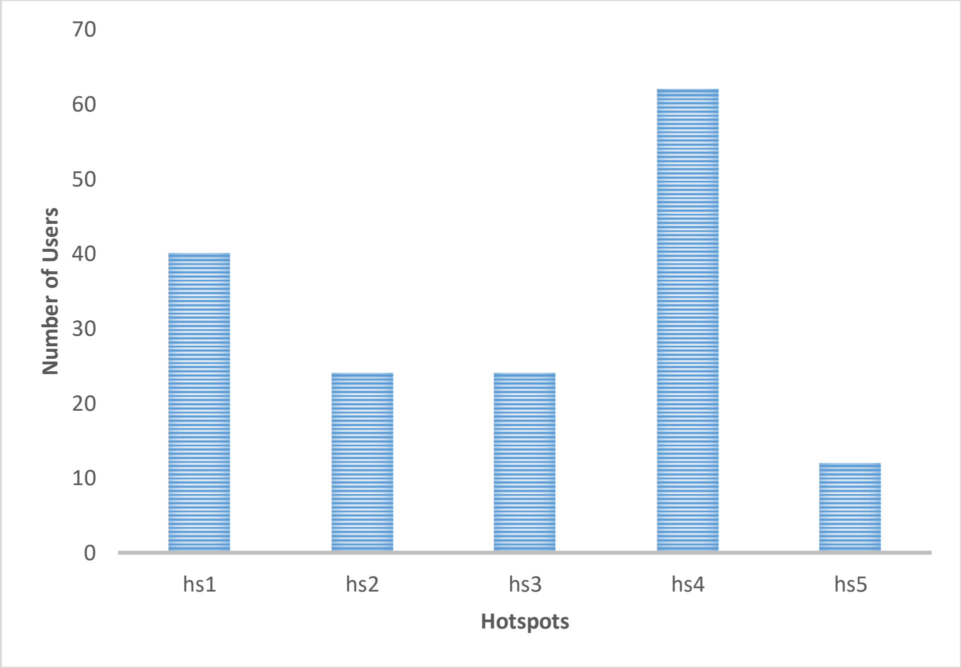

Figure 4.17 Number of Users at each hot spot for off days and timespan 1

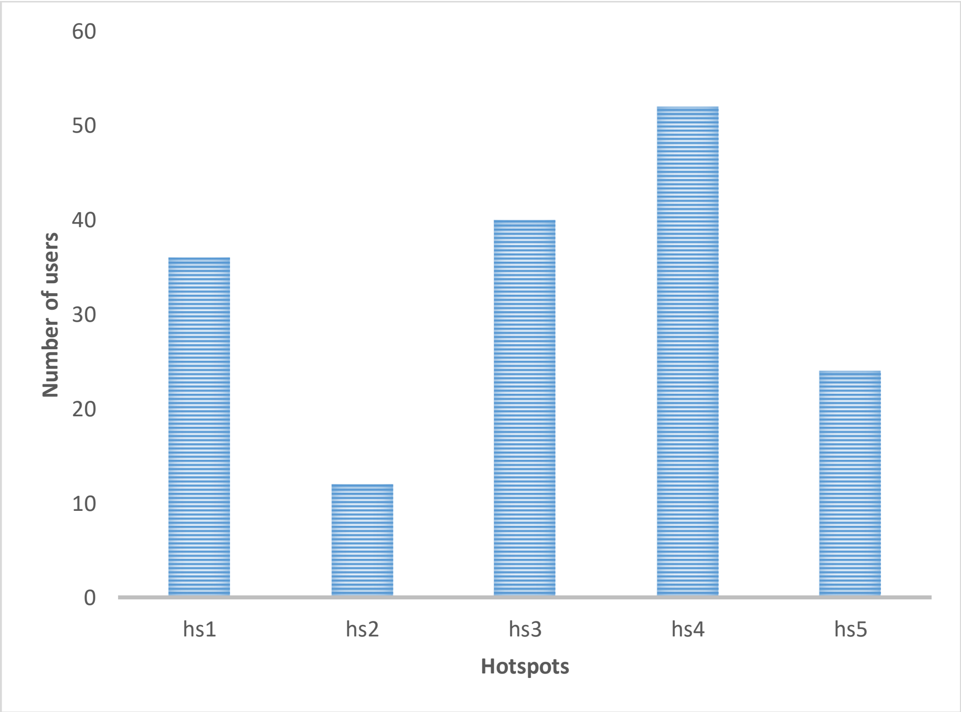

Figure 4.18 Number of LBA system user at each hotspot for off days and time span 2

A comparison between the hot spots (i.e. the most visited places by the LBA system users) of weekdays and off days is shown in figure 4.19.

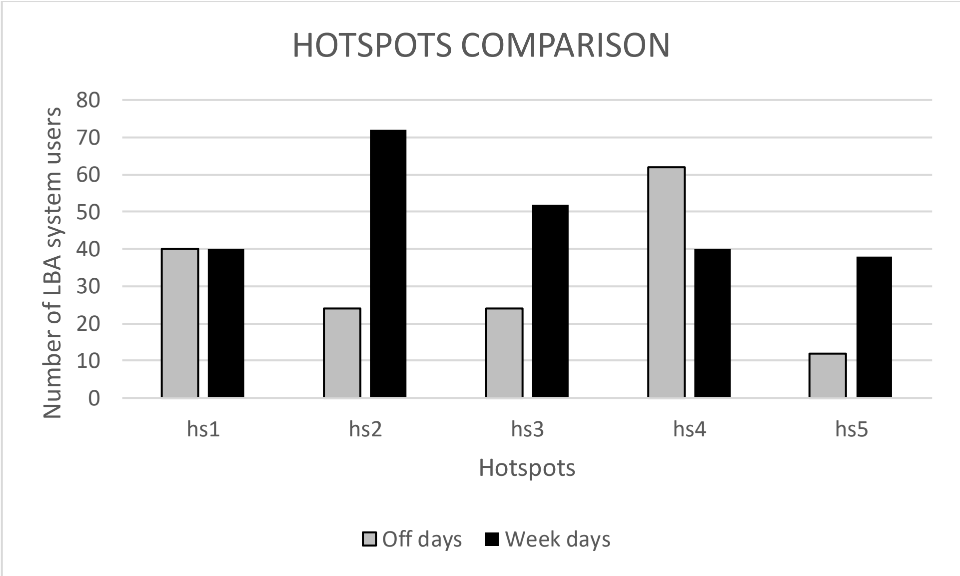

Figure 4.19 Comparison between number of users for week and off days

The results of comparison depict that people have different set of preferences for the weekdays and off days. This type of information made this study to divide the days into two categories i.e. off days and week days. This information is very helpful for any SME to be launched in future to decide the place for a successful business start. Any SME would want to choose the place where it can get maximum density of visiting people. Depending upon the type of SME and information shown in the graph the probability of successful business start at the hotspots is elevated.

4.3.2 Filtration of Ads based on distance

After forming the clusters a center point is generated for each cluster then the distance between that point and each SME's location is measured to add that advertisement to users vector w.r.t. distance. As observed in the previous experiments that people tend to dislike the ads of those SMEs which are more than 1 Km away from the users. So the maximum distance was kept 1 Km between the center point of the cluster and location of the SME.

Before filtration process, there were 120 ads for each of the participant but after filtration process, there were on average 73 different ads per person which mean there were 39% of the ads which were expected to get a negative response from participants as described in figure 4.20. In a sense, it increased the relevance by 39% in first filtration step.

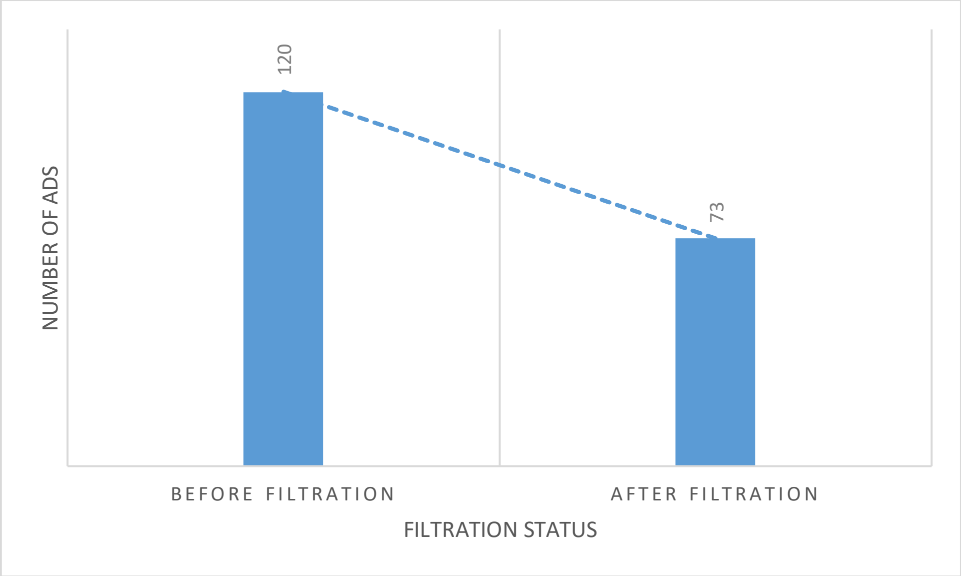

Figure 4.20 Filtration effect on the number of ads

4.3.3 Filtration of Ads based on Responses

The response evaluation was performed to filter the irrelevant ads other than the location congruence factor. In this phase, negative responses on the type and Stores/companies were used to eliminate such type of ads which are disliked by the user three times or more in previous experiments. If a person has disliked female clothing more than 3 times it would not be added to the participant's advertisements vector.

After this filtration, the filtered ads were prioritized on the basis of liked ads as described earlier in chapter 3. For each type of advertisement liked by the user the count was obtained and that count was placed as priority factor with respect to the type of filtered ads for the participant. The Same process was being followed for store prioritization.

Figure 4.21 describe the on average number of ads per user left for the each participant after whole filtration process.

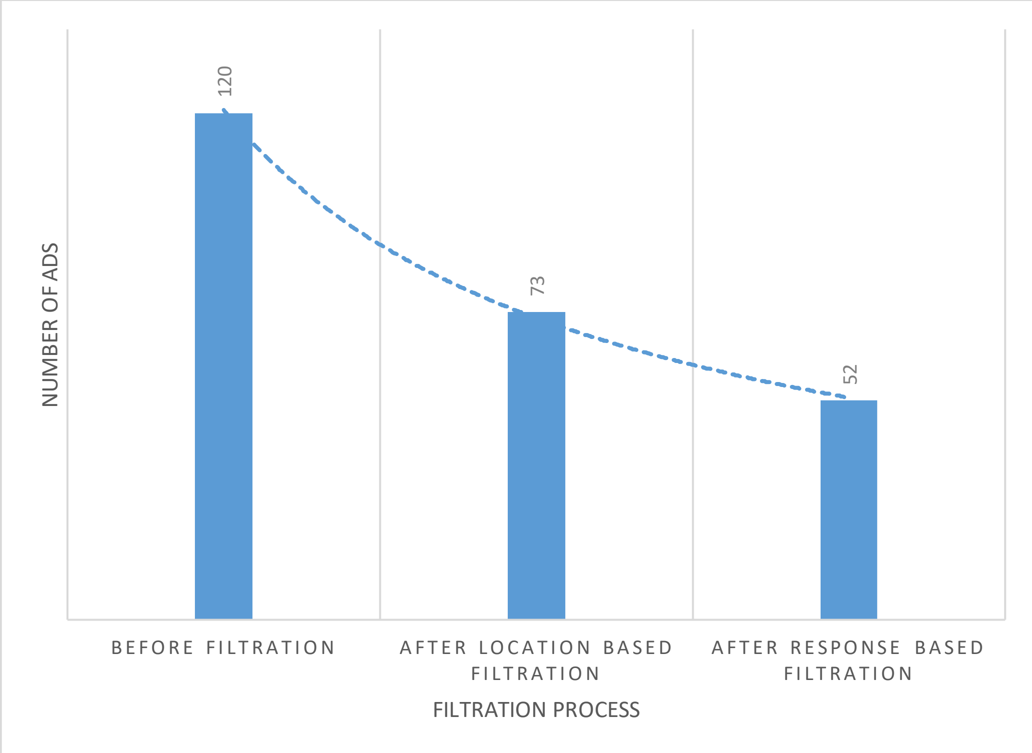

Figure 4.21 Effect of both filtration processes on number of ads

4.3.4 Responses to Filtered advertisements

5024 responses were collected over 4973 advertisements. These responses showed that the used technique is better than the other two techniques. The remarkable increase in the positive responses was observed. These results proved the previous two points that contextual information helps increasing the value perceived for that ads. Table 4.3 describes the responses distribution of the LBA system's SS-TCA

Table 4.3 Social and Spatio-Temporal Clustering based Advertisements

<table>
<tr><th rowspan="2">Evaluation Type</th><th colspan="5">Responses</th></tr>
<tr><th>Likes</th><th colspan="4">Dislikes</th></tr>
<tr><td rowspan="3">Count</td><td rowspan="3">3522</td><td colspan="4">1451</td></tr>
<tr><td>Product Price</td><td>Product Type</td><td>Company</td><td>Location</td></tr>
<tr><td>745</td><td>355</td><td>482</td><td>14</td></tr>
<tr><td rowspan="2">Percentage</td><td rowspan="2">70.82%</td><td>14.98%</td><td>7.13%</td><td>9.69%</td><td>0.2%</td></tr>
<tr><td colspan="4">29.178%</td></tr>
</table>

4.4 Comparison of Results

Results of all the three experiments conducted suggest that location congruency plays important role in the value of the advertisement perceived by users. Providing more contextual information to the system increases the relevancy of advertisements. The graph in figure 4.22 shows the overall positive and negative responses curves for the techniques used.

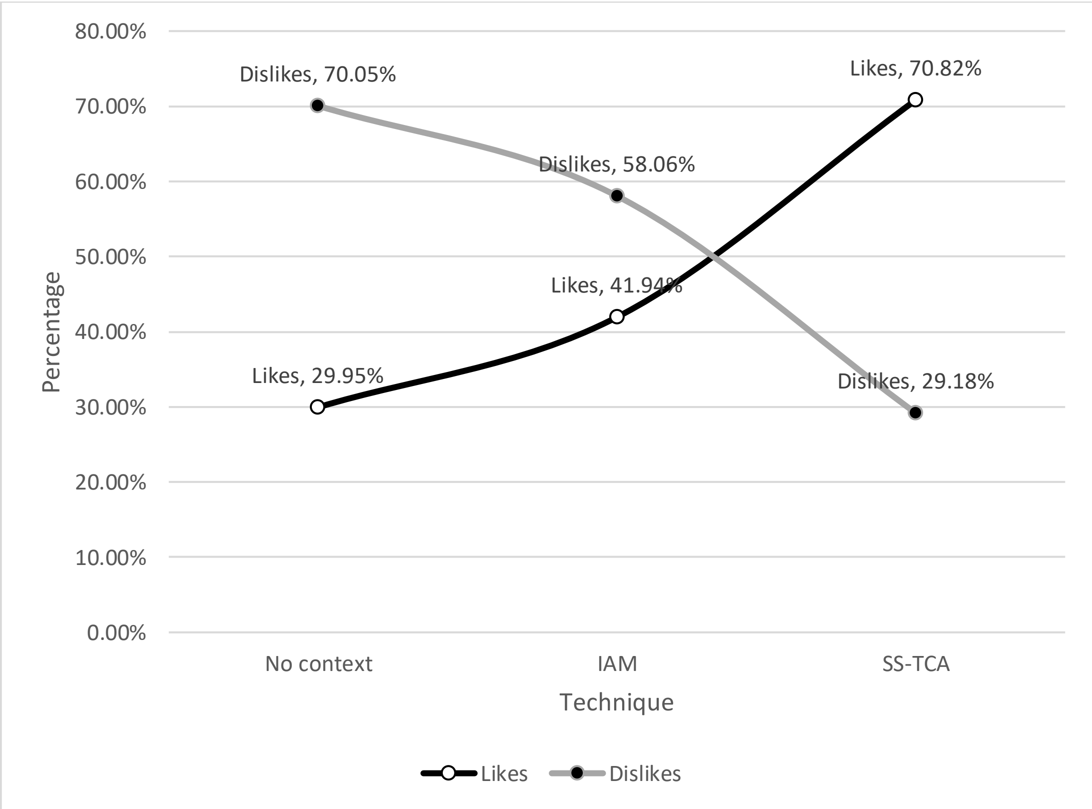

Figure 4.22 Graph of overall positive and negative responses

Table 4.4 show the comparison of positive and negative responses with categories on the advertisements pitched to the users.

Table 4.4 Comparison responses obtained from all three techniques

Response Type	1st Experiment	2nd Experiment	3rd Experiment	Best Technique
Like	29.95%	41.94%	70.82%	LBA system's SS-TCA
Price based disliking	14.22%	13.06%	14.98%	LBA system's LBA module
Type based disliking	40.68%	29.32%	7.13%	LBA system's SS-TCA
Company based disliking	16.68%	14.20%	9.69%	LBA system's SS-TCA
Location based disliking	36.46%	10.1%	0.2%	LBA system's SS-TCA

The graphical representation of the results of table 4.4 is described in figure 4.23

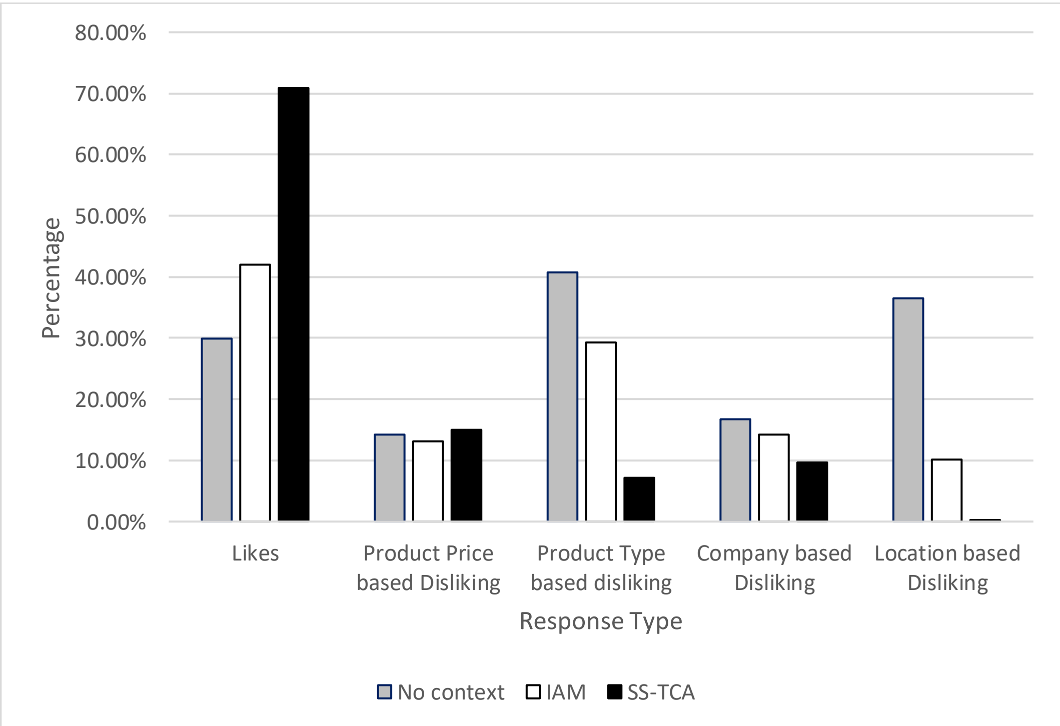

Figure 4.23 Graphical representation of responses in all three techniques

4.5 Comparison of LBA system with previous research

A comparison of technique is being conducted with other studies in the same domain. The table 4.5 shows the parameters used in other techniques and in this study.

Table 4.5 Comparison with similar techniques

Study	Advertisement Model	Field Experiment	GPS	Location-based Ads Treatment	Response Survey	Spatial Clustering	Sample Size	Study time duration	Product Types	Spatial Scope
Luo et al. 2014	Push	✓	✘	✓	✘	✘	12,265	3 days	1	4 movie theatre in 1 mall
Andrews et al. 2015	Push	✘	✘	✘	✘	✘	14,792	3 days	2	1 City
Danaher et al. 2015	Push	✘	✘	✘	✘	✘	143,958	21.5 months	4	38 stores in 1 mall
Fang et al. 2015	Push	✓	✘	✓	✘	✘	22,000	12 days	1	1 movie theatre in 1 mall
Fong et al. 2015	Push	✓	✘	✓	✘	✘	18,000	2 days	1	1 movie theatre in 1 mall
Gana et al. 2016	Push /pull	✘	✘	✘	✘	✘	6	1 day	n/s	1 City
Imran et al. 2016	Push	✘	✘	✓	✘	✓	500,000	n/s	n/s	1 City
This Study	Push /Pull	✓	✓	✓	✓	✓	18,688	3 months	7	17 stores in: 1 City

4.5.1 Comparison of results

The results when compared with Hühn et al’s results of value of the location congruent advertisements the SS-TCA outperforms the Location Based

Advertisement of hun’s et al’s technique. Despite the sample size used in this study was bigger than their but still SS-TCA managed to perform better. The table 4.6 shows the comparison of the results.

Table 4.6 Comparison of results for the perceived value

Factor	**Hun et al.**	**This Study**
Mean	5.41	0.8169
N	46	86
Standard Deviation	1.185	0.1220

The results of standard deviation clearly demonstrate that SS-TCA performed better than the other study. The standard deviation value suggests that SS-TCA performed equally well for all the individuals. Hence the Contextual information of individual is very important and mining that information properly makes the advertisement system perform better.

Chapter 5

CONCLUSION AND FUTURE WORK

It is a common belief that increased functionality offered by smartphones offers substantial potential for the development of mobile marketing and retailing [109]. In 2013, approximately $16.7 billion has been invested in the advertising industry and these numbers are expected to reach $62.8 billion by the end of 2017 [110]. This study proposed a model (LBA system) that focused on location-based advertising techniques to ensure optimum coverage of audiences. The model used other contexts to improve the relevance of the ads.

5.1 Conclusions

In this study effectiveness and relevancy of advertising for small and medium enterprises (SMEs) on smartphones was discussed. Most of the advertising in smartphone applications are occupied by the high-level enterprises and rarely by small and medium enterprises. This research work proposed a model (i.e. LBA system) for every SME to promote their business and publish a promotional advertisement to the users who most often stay close to their business area. An android application was developed to conduct the field experiment and to collect location history of the people as well as for the enterprises to upload their advertisement messages.

The scope of the experiment was limited to one city (i.e. Mirpur, A.K). The Experiment was conducted in three phases to validate the proposed model. In First phase, the users were exposed to the random ads with no relevance. The results showed that in random ads people tend to dislike the advertisement if that SME is distant from their location. It was also noticed that some contextual information such as gender and time is definitely required for effective and more relevant advertising as people showed more than 70% negative response.

In the second phase the location congruent advertisements were pushed to the user on each location update. The purpose of the experiment was to get the response from users over the advertisements of SMEs congruent to their location. The results showed that people respond positively to such advertisements as the percentage of negative responses were decreased to 58.06%. Along with that, another behaviour of people was observed that the frequency of pushing advertisement annoy users in such a way that people stop using that application.

In third experiment 1.8 lac coordinates of users were utilized to get location congruency. And responses collected from previous experiments other than related to the location were mined to increase the relevancy of advertisement through this contextual information. The results showed that the relevancy of the ads was improved and the percentage of negative response was decreased to less than 30%.

Based on eighteen thousand responses in all three experiments it is suggested that contextual information such as location, time and gender etc. improve the relevancy of advertisements. Results also determine that enterprises waste their resources while advertising without any contextual information.

5.2 Limitations and Future Work

There were some limitation of this study as it was conducted on ninety-five users, eighteen vendors, and one city. There is need to test LBA system on more participants. Also, there is need to view the behaviour of the model when the number of vendors is increased and the scope of the research shall be expanded to more than one city. The prioritization performed on the basis of Facebook data was only done on the basis of liked pages there is also need to apply some linguistic techniques on other posted contents to more effectively detect the behaviour of the person.

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APPENDICES

Appendix-A

Participants sample data

The table 1 below shows the spatio-temporal data sample of the participants.

Table 1 Sample of Users' Spatio-Temporal data

User ID	Latitude	Longitude	time	day
8mPcKoSOQvSWoMyJPfaGCdsogFi1	33.14982449	73.72204373	5	5
lb9AgL3MxpgmOH04CkIfV6x26YA3	32.83800667	74.33680333	4	7
9T1yssvauWQk5es8V3666eVLcAH2	33.14889409	73.72243375	5	4
6yAyZkbqFbOg9Rb2DFWXbib5rmv2	33.15226497	73.73820423	3	6
kb0Sobewhoe66HaUchFyVMhO25t2	33.15073484	73.7457184	1	6
EtOGFZxkZ9WOOp3MqJPSjT0xLSS2	33.15328944	73.74282211	11	7
uSe8ggPTqAUuQTbMHQYuak3Xcdp2	33.15258281	73.73948687	1	2
lVHlrcfaGUQJulnAnk3z40x57u03	33.15253557	73.73947219	11	3
PLTvco1bQ7eZpFbWtSQdZTsCBIH2	33.15080055	73.74591465	3	7
PLTvco1bQ7eZpFbWtSQdZTsCBIH2	33.15253074	73.7394576	2	1
fjd2DzlKRVSsxfLFTjHLrNwMTLY2	33.15038878	73.73453637	13	2
9T1yssvauWQk5es8V3666eVLcAH2	33.14907292	73.72315641	9	3
ZNzLV0Tqp8cCVwl2YqH48nqlFrF3	33.15069963	73.74586614	6	4
Uc6KVAIGfAW9EdMj14gSk6NtBQ72	33.15057116	73.7461962	2	3
Nkn4zQFSnOY1eGOCTHk4Bti73553	33.15209758	73.73855787	2	6
F6NWiJvWzdeDvZ18BnLXHl0syC23	33.15067223	73.74561695	10	1
adt1VkYFkUZxFcqU5gE92BPi7s53	32.83798167	74.33685667	7	2
Uc6KVAIGfAW9EdMj14gSk6NtBQ72	33.15241805	73.74598797	5	3
KQqKFvvnz7fwu06u4bxeFDPKVD12	33.15260588	73.73944506	4	2
eEMfR7aKOcY4xY7BRUmKB91Cnf53	33.15091833	73.74618667	2	6
PLTvco1bQ7eZpFbWtSQdZTsCBIH2	33.15258247	73.73949728	11	4
KPR68kuAKCbsLsAXEzV7eqsxEvE3	32.83797	74.33677667	3	1
lb9AgL3MxpgmOH04CkIfV6x26YA3	33.15069878	73.74588173	4	4
9T1yssvauWQk5es8V3666eVLcAH2	33.14988934	73.72210212	10	4
lb9AgL3MxpgmOH04CkIfV6x26YA3	32.837875	74.33680167	5	5
AzZVprgTqyYSquhsGOKKeWNt0QZ2	33.15261192	73.73946433	11	6
wev46En8zwPQdT4T7gYS6ZsP1B82	33.15072694	73.74567822	2	7
MPuso7k1Y8fVhtzgMhxyVPHMgFs1	32.83793	74.33687167	10	5
9T1yssvauWQk5es8V3666eVLcAH2	33.14973936	73.7223728	7	1
8mPcKoSOQvSWoMyJPfaGCdsogFi1	32.83785667	74.33689667	7	6
Uc6KVAIGfAW9EdMj14gSk6NtBQ72	33.15255999	73.73919943	3	5
AzZVprgTqyYSquhsGOKKeWNt0QZ2	33.14919126	73.74994701	6	4

Advertisements' sample data

The table 5.2 below shows the sample data of the advertisements being used during the study.

Table 2 Sample of Advertisement data

Ad ID	Company ID	Price	Ad type and tags
3189	5UbV2sCPLNSyUMIQATCuxK5b7U53	40000	Samsung galaxy s7 edge (mobile)
3243	qWPxkrdhWQgzLdGQd4AXScI2eMf1	1700	pants (male clothing)
3336	HXrK5qR86wSi0z0VVxdIqmUOLBo2	2499	wrist watch (men's accessories)
3393	i4NzTNZGsbQ9H5kvM5HRW8vOoYI3	1875	sandals(female clothing)
3378	HrfcYQwWzEeM3cP7J4hmBP4lKO42	2100	Lakhani summer (female clothing)
3414	Rox6IYrg5URM75fJaJBvduGuhS62	4150	johra embroideries (female clothing)
3408	ySIfv3zsGtZtYqwMfEQT0DovWqE2	990	ultra slim plus(health and care)
3157	B4Bpqls0LhMqqxzh1eOcZqeFZNQ2	350	ice cream (food)
3357	FglicmcguadAYJUxa5rKRfuOdUG2	2799	Maria B Linen (female clothing)
3358	FglicmcguadAYJUxa5rKRfuOdUG2	6000	Gul Ahmed (female clothing)
3425	Rox6IYrg5URM75fJaJBvduGuhS62	4800	malhar(female clothing)
3279	BaA6kUsnZDYsf2VKdEHs6xEKFyA3	3990	mens shlwal kameez(male clothing)
3356	FglicmcguadAYJUxa5rKRfuOdUG2	2799	Maria Linen (female clothing)
3315	92d8mSVSX1Xs3rxYLHK8SEDAcSk1	3200	men's kurta (male clothing)
3352	FglicmcguadAYJUxa5rKRfuOdUG2	2899	anum lawn (female clothing)
3216	5UbV2sCPLNSyUMIQATCuxK5b7U53	40000	iPad air
3278	BaA6kUsnZDYsf2VKdEHs6xEKFyA3	1890	jeans (male clothing)
3313	92d8mSVSX1Xs3rxYLHK8SEDAcSk1	4590	ladies suits (female clothing)
3202	RocQRkamQmfMH0F8b5zniV3iy1w2	1500	charger (mobile accessories)
3369	Ya9ehBXRYjRQMttU21XV4G67Qwx1	170	whole wheat bread (food)
3191	qWPxkrdhWQgzLdGQd4AXScI2eMf1	15999	Samsung galaxy grand prime plus(mobile)

Responses' sample data

Sample of the responses being collected over advertisement is as follow.

Table 3 Sample of responses being collected on advertisements

AD model	User ID	Response type	Response	distance
Instanteneous Ads	lb9AgL3MxpgmOH04CkIf V6x26YA3	Likes	CompanyName	
Instanteneous Ads	9oXJCdzetcO2DbH5sq6l0 eNCws73	Dislikes	Type	
Random Ads	bKRpqm0KWfVtVk0GxsF UvLOBvx03	Dislikes	location	1.5
Instanteneous Ads	cG5srNoTeufv1gZlvWXG EHHocCc2	Likes	Type	
Instanteneous Ads	0zcMZMHSBPcEfRa6X2 L2W9wozPN2	Likes	CompanyName	
Instanteneous Ads	KPR68kuAKCbsLsAXEz V7eqsxEvE3	Likes	CompanyName	
Random Ads	Uc6KVAIGfAW9EdMj14 gSk6NtBQ72	Dislikes	Type	
Random Ads	bKRpqm0KWfVtVk0GxsF UvLOBvx03	Likes	CompanyName	
Random Ads	MA9KnA0jQnVCkLt3e56 s45jPfTk1	Likes	CompanyName	
Random Ads	f4OHmgo9gBebWW71FU SsfPgmI5E2	Likes	location	1.5
Instanteneous Ads	WItVlIUPuEQTmY0Q2rfv NSiRrRx1	Dislikes	price	
Random Ads	jDIOEF94o6OfZwZpijXG GhjKS7Q2	Likes	location	1.5
Random Ads	F0K70ZxWstWybuWgKdi XhjpJ3Y02	Likes	Type	
Instanteneous Ads	4CfNgWW8T4hcyHjGozX F70kdOvX2	Dislikes	Type	
Instanteneous Ads	0zcMZMHSBPcEfRa6X2 L2W9wozPN2	Likes	Type	
Random Ads	b60Gll6keve2Gu84pCny6f WR6UV2	Dislikes	Type	
Instanteneous Ads	adt1VkYFkUZxFcqU5gE9 2BPi7s53	Dislikes	Location	0.5
Random Ads	OvT4A4QROnaEpkZM9 WV96VuJqDW2	Dislikes	Location	2
Random Ads	pkzdbG0O8xXilNsG4G8o yf1A7Jj1	Likes	Type	
Instanteneous Ads	xKZWuPPX3sOlFvvCqff mUvceLIr2	Dislikes	price	

Instanteneous Ads	wev46En8zwPQdT4T7gYS6ZsP1B82	Likes	location	1
Instanteneous Ads	f4OHmgo9gBebWW71FUSsfPgmI5E2	Likes	Type	
Random Ads	lb9AgL3MxpgmOH04CkIfV6x26YA3	Likes	Type	
Instanteneous Ads	eEMfR7aKOcY4xY7BRUmKB91Cnf53	Dislikes	Type	
Instanteneous Ads	GD60J5cQNAYOHGbZnCEJJihmdAr1	Likes	location	1
Random Ads	wev46En8zwPQdT4T7gYS6ZsP1B82	Dislikes	Type	
Instanteneous Ads	oHnSRPP7xCOl2HgWaFglKC5OLNR2	Likes	Type	
Random Ads	0SAeWoc8sFYL1MtoSVjD8wlXrMr1	Dislikes	Type	
Random Ads	M6qR1VzdvmM0LiW2HA9B331oWP02	Likes	Type	
Instanteneous Ads	8mPcKoSOQvSWoMyJPfaGCdsogFi1	Likes	Type	
Instanteneous Ads	jDIOEF94o6OfZwZpijXGGhjKS7Q2	Likes	CompanyName	
Instanteneous Ads	27yuBvlP5Cehtrgi8iKZ5WsTN443	Likes	location	1
Random Ads	dHYVJprMxwgSSBmFvhBmqjel2Qk2	Dislikes	Type	
Instanteneous Ads	GD60J5cQNAYOHGbZnCEJJihmdAr1	Likes	CompanyName	
Instanteneous Ads	mRYLFYLN9zQmrTq7J31IzO4HYEi2	Likes	Type	
Random Ads	M6qR1VzdvmM0LiW2HA9B331oWP02	Likes	location	1.5
History based Ads	Uc6KVAIGfAW9EdMj14gSk6NtBQ72	Dislikes	Type	
Instanteneous Ads	AgayVl1MVaPcrUMrIVBiksKrRtu1	Likes	location	1
Instanteneous Ads	9oXJCdzetcO2DbH5sq6l0eNCws73	Likes	Type	
Instanteneous Ads	OvT4A4QROnaEpkZM9WV96VuJqDW2	Likes	location	1
Instanteneous Ads	MRUZhEHxJvaJNPSSz4dzBy1j6Ad2	Likes	Type	
Random Ads	xWZeQUoQMgOh1Wr2JCUXyTKMza93	Dislikes	Type	
Instanteneous Ads	fjd2DzlKRVSsxfLFTjHLrNwMTLY2	Dislikes	Type	
Instanteneous Ads	mGHRnTfu12a5Dr87hnqvLFTEC073	Likes	location	0.5

Appendix-B Application Screenshots

This section contains the screenshots of the application being used during this study. Figure 1 shows the login screen of the application.

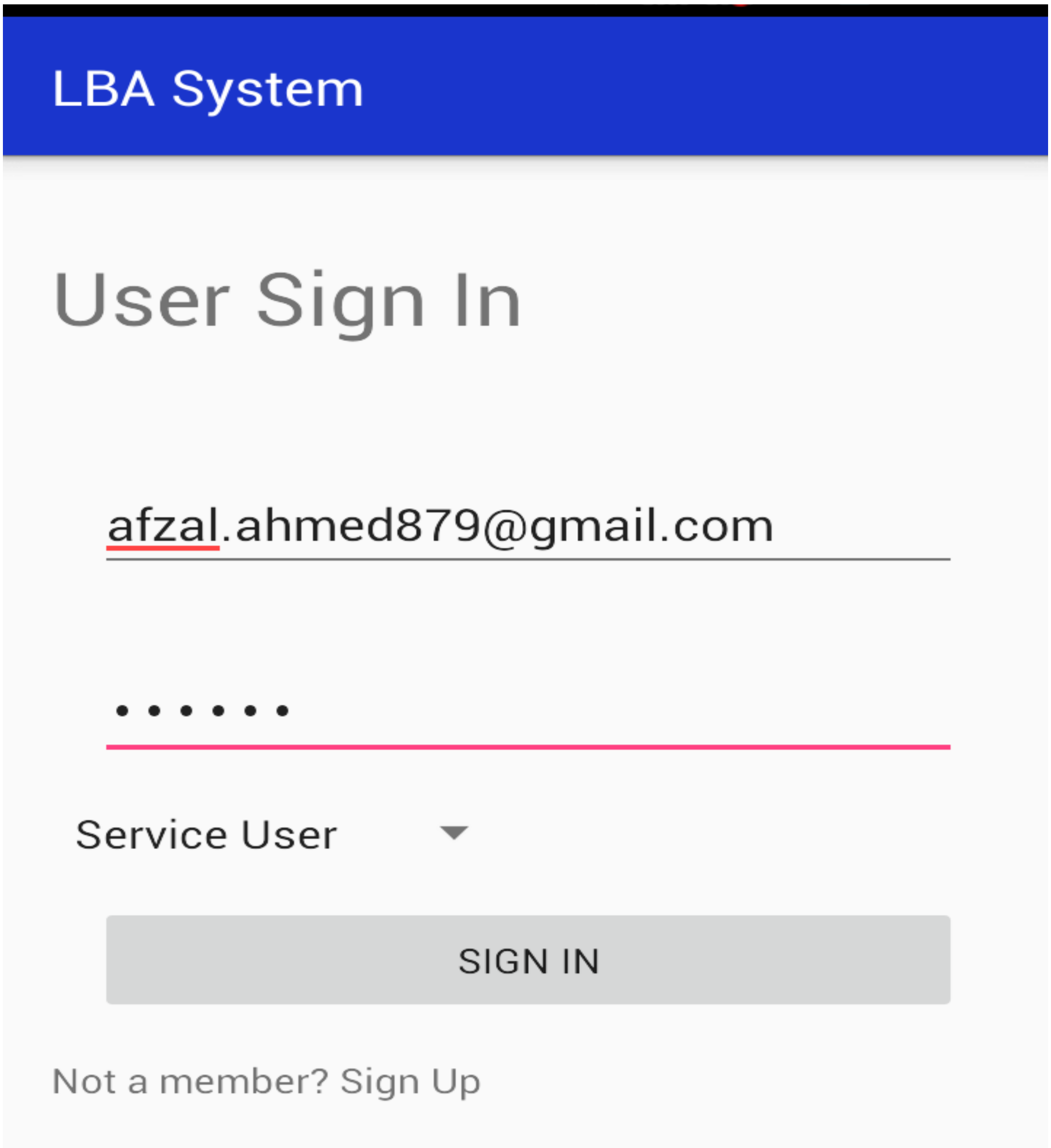

Figure-1 Sign in Screen

Figure 2 describes the prompted screen to turn on GPS when the application is launched.

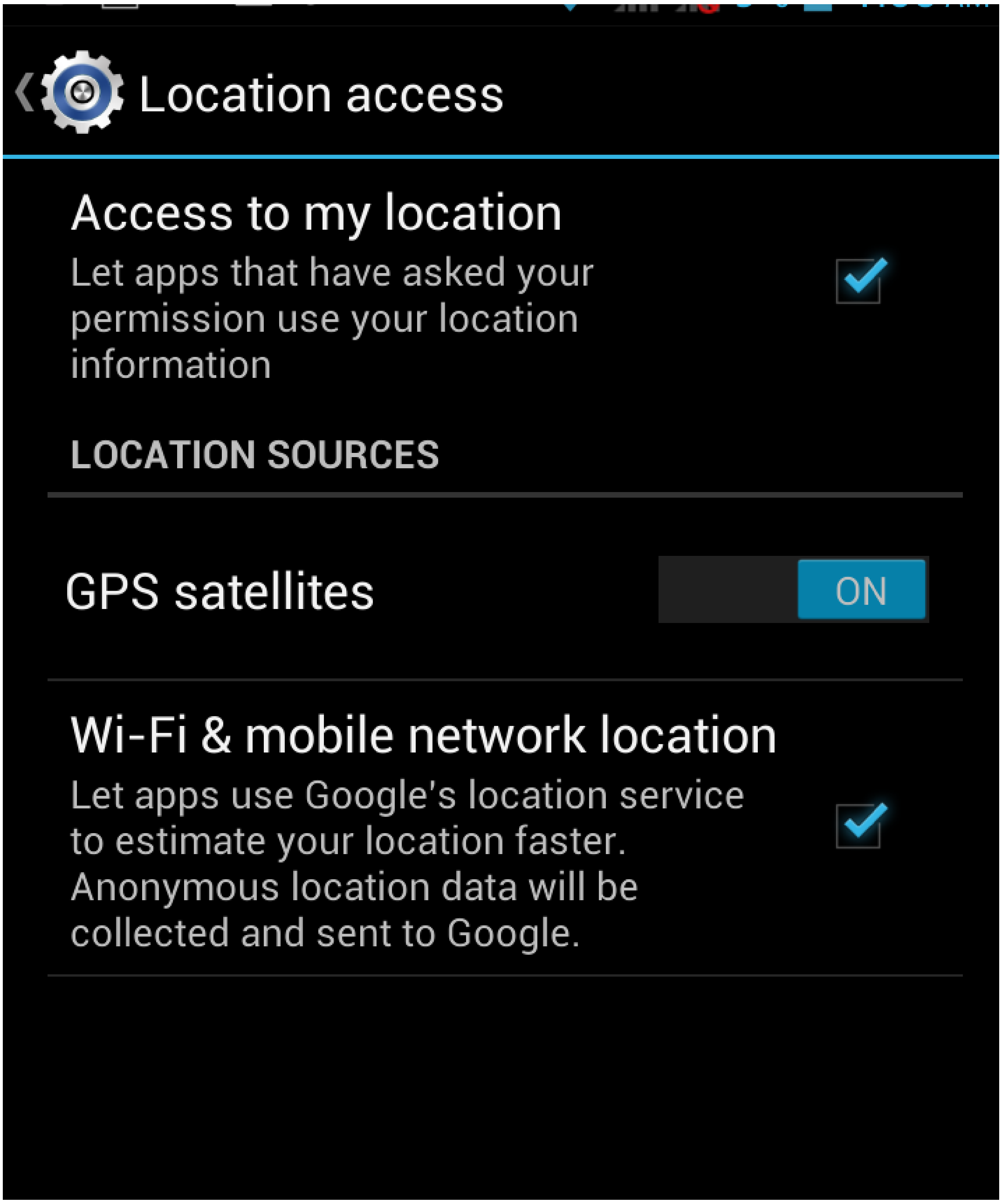

Figure-2 Screen to turn GPS on

Figure 3 show a random advertisement of food related SME which is more than 2.5 Km away from user.

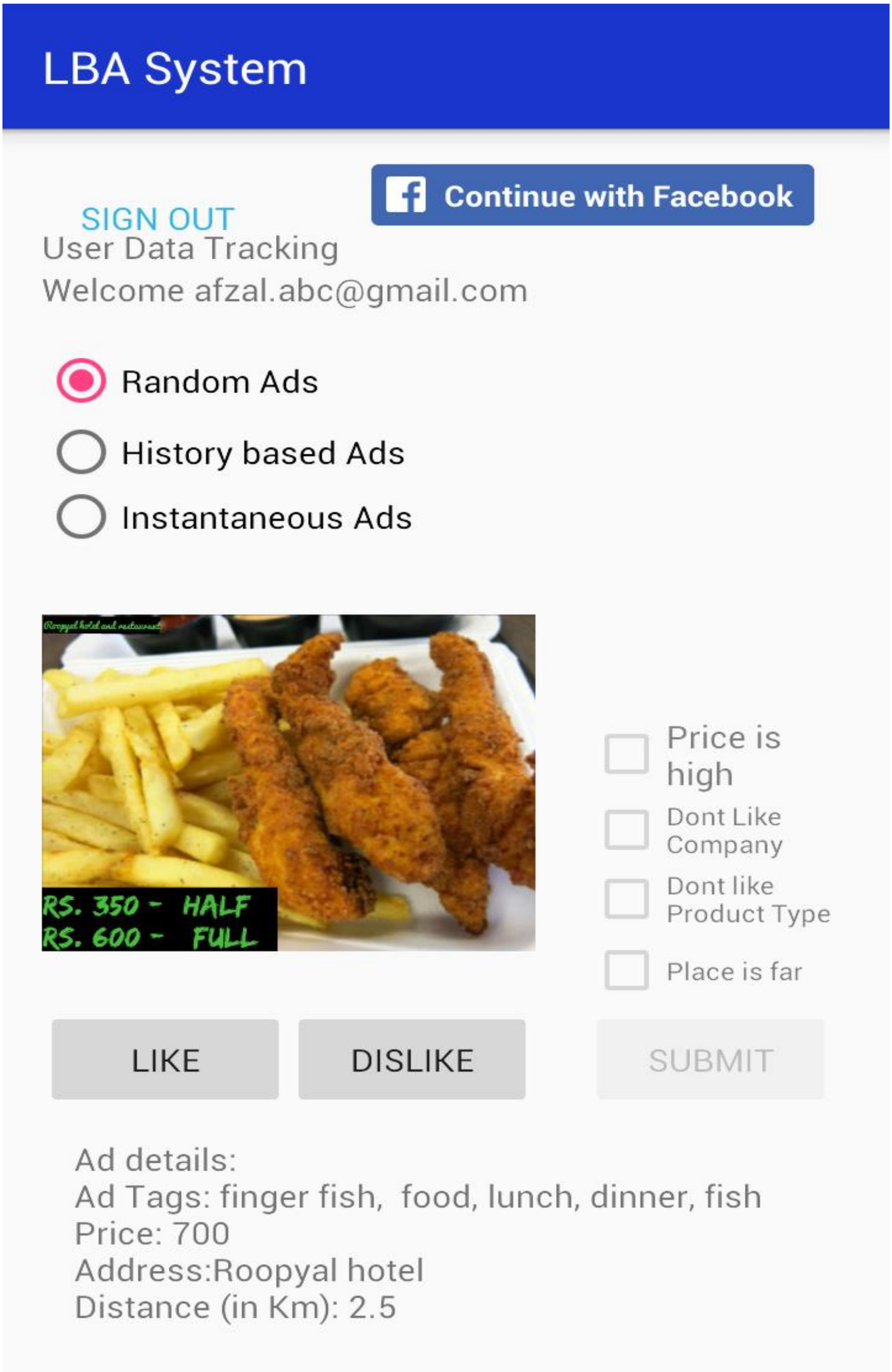

Figure-3 Screenshot of Random Advertisement

Figure 4 show the offer related advertisement at 2.5 Km distance or more.

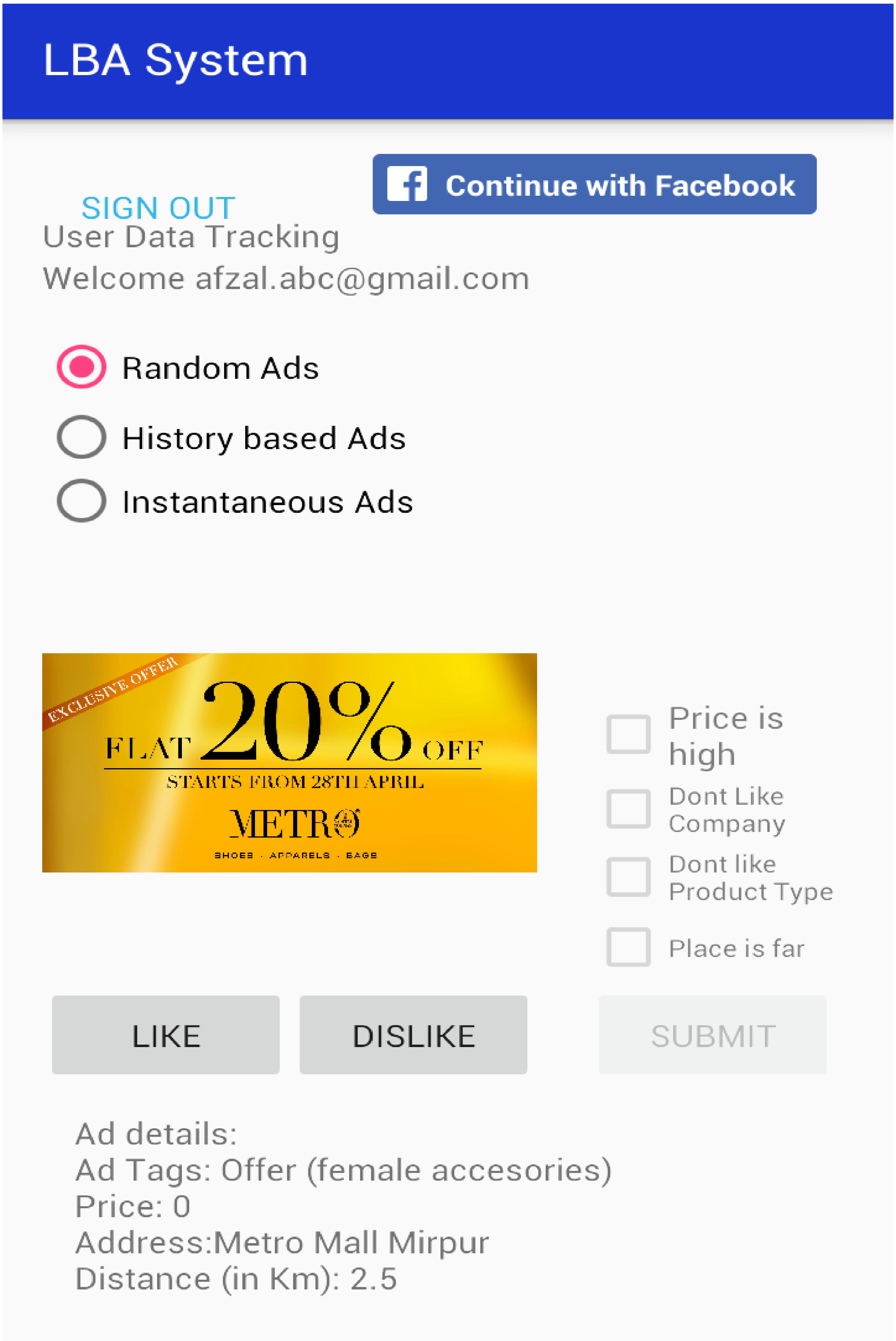

Figure 4 Offer related advertisement

Figure 5 describes the disliking of an advertisement and choosing a reason.

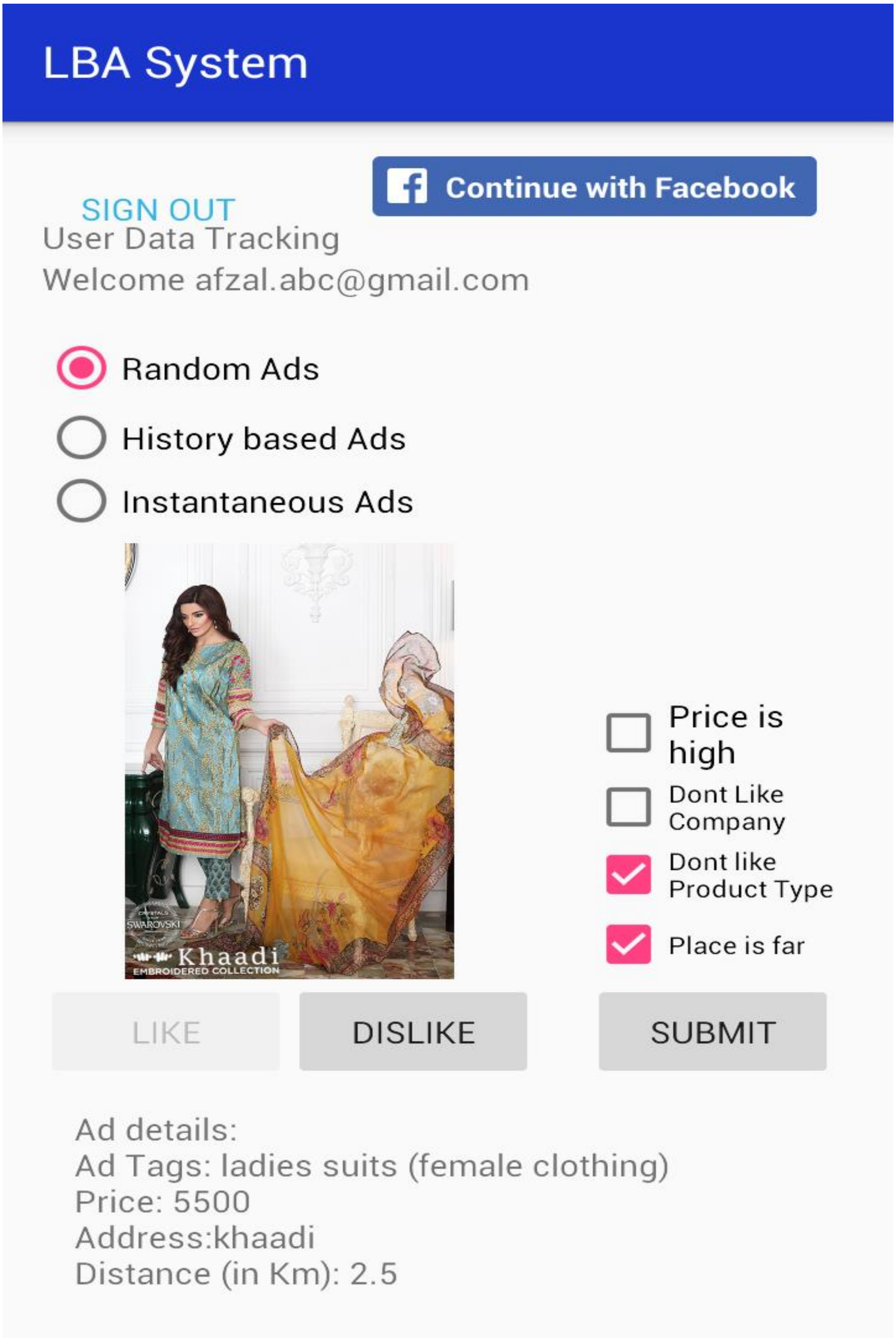

Figure 5 Random Advertisement while disliking

Figure 6 demonstrate the Location based Instantaneous advertisement of a 0.5 Km distant SME.

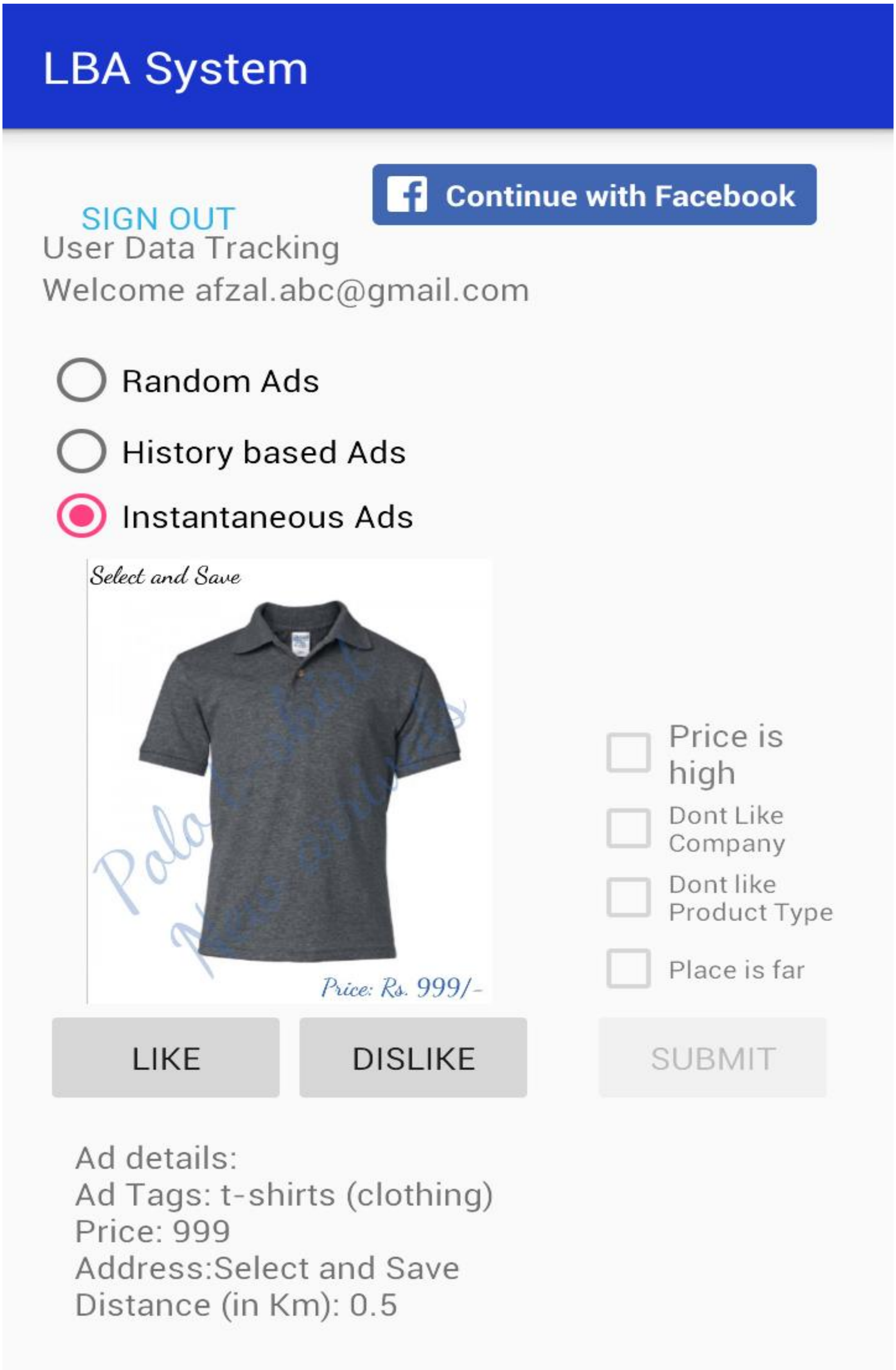

Figure 6 Location Based Instantaneous Ads

Figure 7 shows the message being displayed after Location based Instantaneous advertisement to switch to History based module if Location based advertisements are irritating.

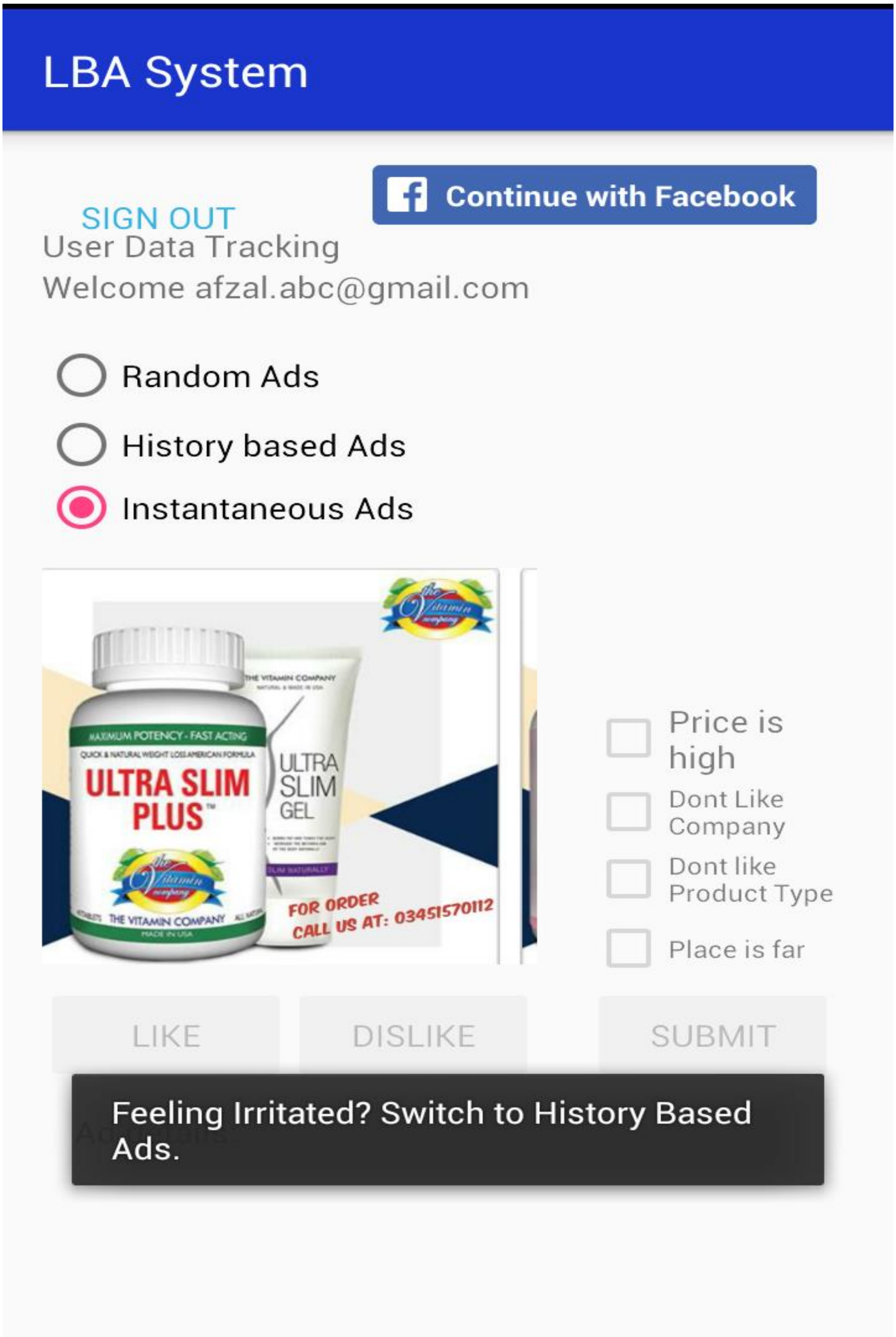

Figure-7 A message being displayed after each Location based Instantaneous Advertisement

When there are no advertisements for the day or time in history based advertisement a message is prompted to the user as shown in figure 8.

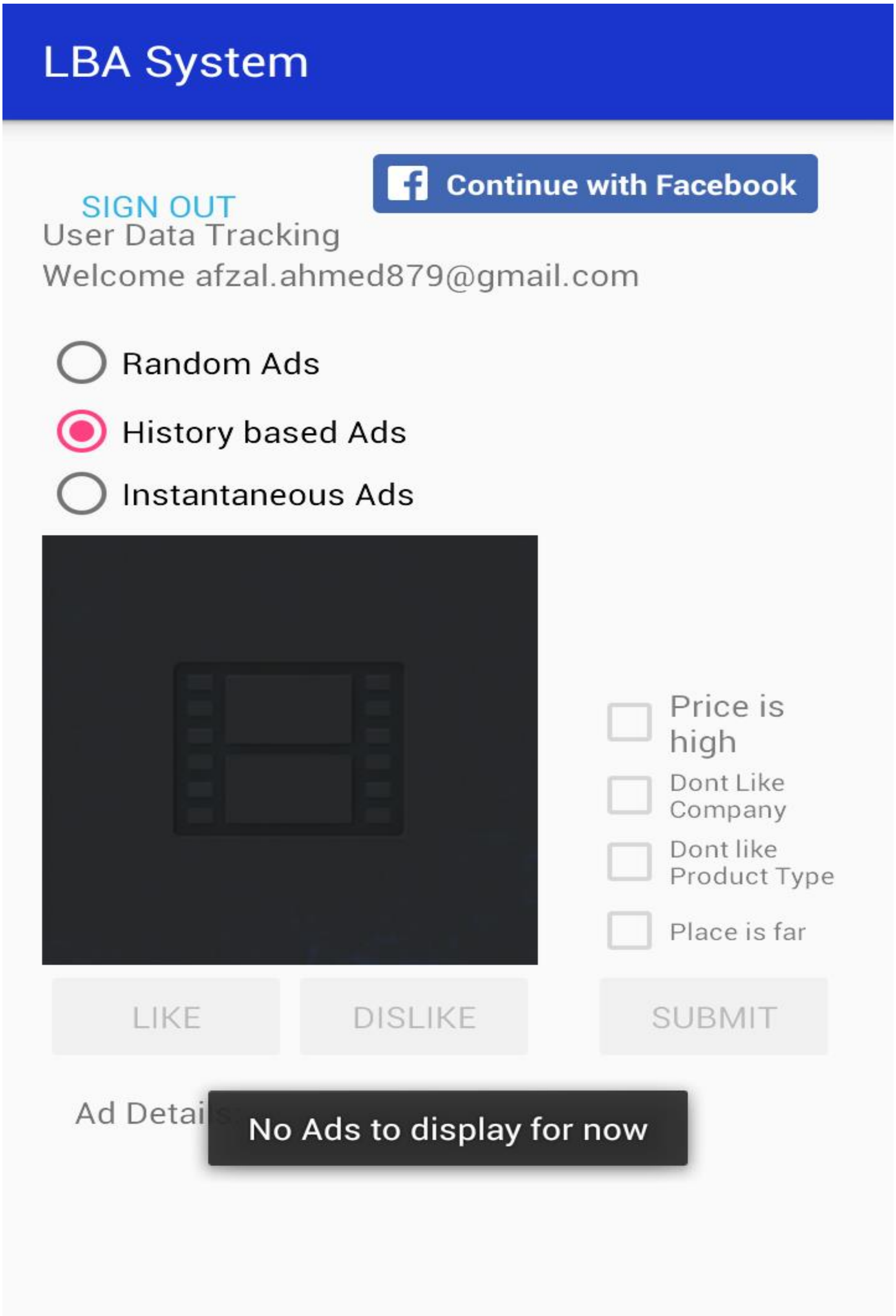

Figure-8 No Advertisement for a time and day

An advertisement with some priority value assigned in SS-TCA is being displayed in history based advertisement in figure 9.

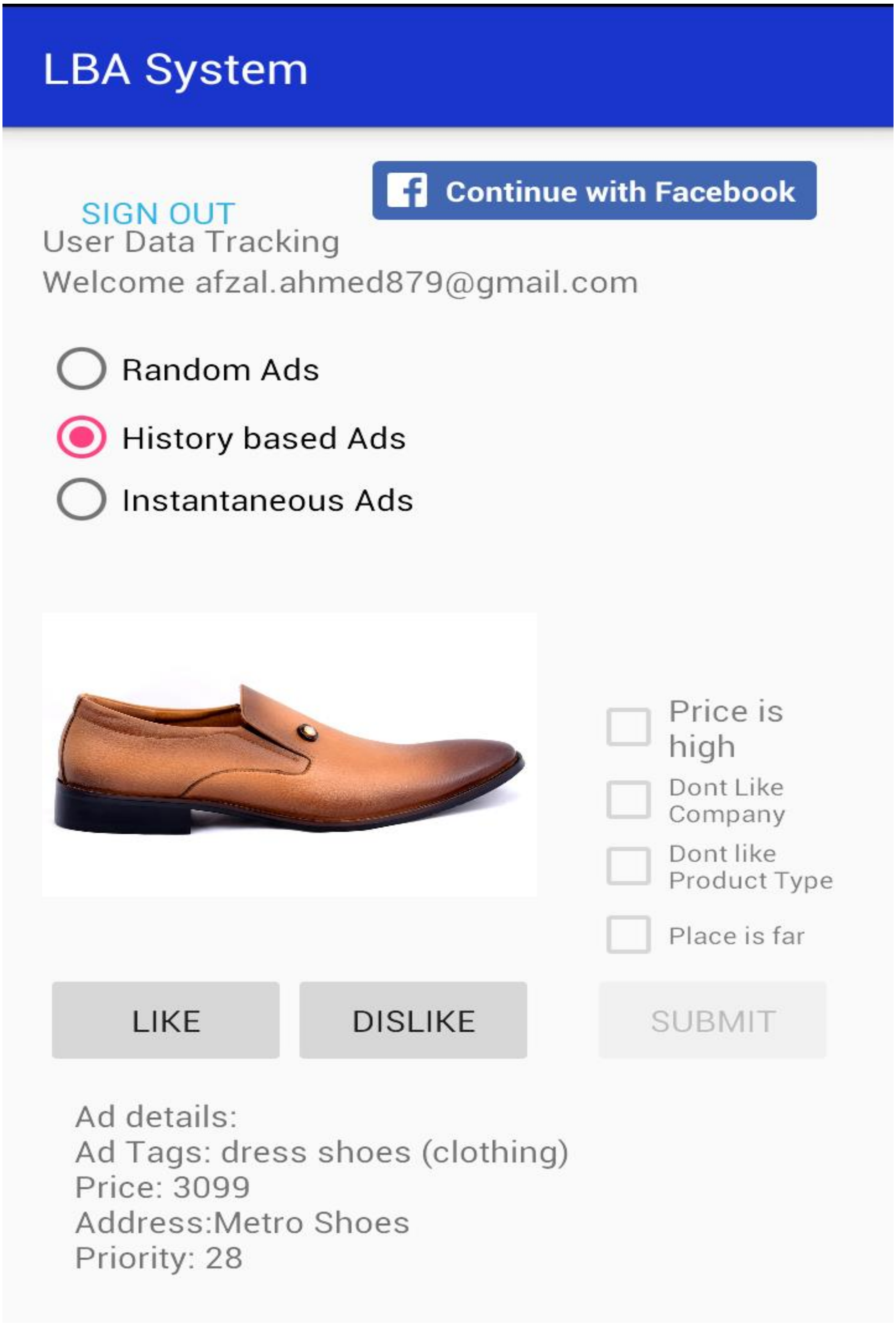

Figure-9 History based Advertisement with some priority value

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