SOCIAL REFERRAL MECHANISM FOR CONTEXT-AWARE MOBILE ADVERTISING[1]

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ABSTRACT

The prevalence of mobile devices has significantly increased in recent years, becoming an integral part of our daily lives. This shift has created promising opportunities for mobile advertising, with industry leaders like Apple and Google already integrating it into their services. However, effective mobile advertising still grapples with challenges such as precise customer targeting and adaptability in an ever-changing landscape. To address these issues, we propose an innovative mobile advertising recommender system that employs "context-fitness" and "social referral" techniques. Experiments provide compelling evidence that context-aware information significantly enhances accuracy in predicting users' evolving needs. With our system, we can identify the most suitable ads for targeted users in a changing environment and enhance ad effectiveness by considering friends' influence.

Keywords: Mobile advertising; Context-aware; Social Referral; Machine Learning; Recommender systems

1. Introduction

The extensive adoption of mobile devices, such as smartphones and tablets, has transformed them into indispensable tools for everyday living. Users can now easily access social media platforms, check emails, search for information, and make purchases with just a few taps on their mobile devices. Based on the findings from report (Diana, 2023), titled " The Complete Guide to Mobile Advertising", it can be inferred that mobile usage has become an indispensable aspect of people's daily routines. The report reveals that individuals spend an average of five hours a day on their mobile devices, primarily using apps. Additionally, 98% of Gen Z use their mobiles as their primary internet source, while 60% of millennials check their phones first thing in the morning. It's also noteworthy that most people tend to check their phones up to 63 times a day.

As mobile devices have become the go-to source for online queries, shopping, and entertainment, it's not surprising that mobile advertising has seen a tremendous surge. The report predicts that mobile advertising will continue to dominate the advertising industry, with a projected budget of 446 billion dollars in 2023. Many mobile advertising platforms are now available to vendors, such as Google's AdMob, which delivering over 40 billion text ads and mobile banner monthly, spanning a diverse array of mobile websites and applications.

Despite this growing trend, the effective use of mobile advertising to create value for businesses remains a challenge. According to 2023 Goran Dautovic's report, titled "The 45 Most Important Advertising Statistics of 2023," it was found that a staggering three-quarters of marketers do not leverage behavioral data to enhance online ad targeting strategies. 70%-80% of users ignore sponsored search results. Not only do most users ignore sponsored search results but they're also more likely to distrust the brand that's advertising itself in that way. Moreover, "effective cost per mille" (eCPMs) remains significantly lower on mobile devices compared to desktops, with a difference of five times. Additionally, the average revenue per user (ARPU) on mobiles is trailing behind. Therefore, there is still room for improvement and innovation in the mobile advertising industry. Consumers don't inherently despise all advertisements; many simply desire the ability to filter out the ones they find irrelevant rather than blocking them entirely. The real issue lies in intrusive and poorly executed ads that negatively impact the user experience. This underscores the growing importance of employing a thoughtful approach when designing and implementing ads.

Location-based advertising (LBA) has been a traditional solution for improving mobile user targeting effectiveness. However, existing LBA approaches that rely solely on current location information are not always effective in providing relevant ads to users (Kim et al., 2011). Previous findings indicate that increasing distance

[1] **Cite**: Lin, L. F., (2024, May) Social Referral Mechanism for Context-Aware Mobile Advertising, *Journal of Electronic Commerce Research, 25*(2).

between households and stores reduces consumers' store preferences due to travel costs (Li et al., 2018, Lian et al., 2019). Store distance significantly influence consumers' mobile search behavior for offline retailers to better understand locations specific consumer demands and improve their mobile in-app targeting (Molitor et al., 2023). Delivering ads solely based on users' geo-information may not always be the most appropriate approach. For instance, consider a scenario where an individual happens to be near a Starbucks location due to their residential proximity. However, it is important to acknowledge that they may not be in the mood for coffee at that particular moment.

Apart from the location, the context surrounding users also impacts their decision-making process (Zhu et al., 2018, Sojahrood & Taleai, 2022). Context refers to "any information that can be used to characterize the situation of entities" (Dey, Abowd, & Salber, 2001). Taking the environmental context into account can enhance the precision of ad targeting. Nevertheless, within a mobile setting, the context may change frequently, leading to changes in a user's needs. To address this issue, mobile advertising with context awareness can be used to improve ad-targeting accuracy. This approach not only allows ad sponsors to reach consumers wherever they are but also enables them to gain an understanding of their surroundings. By incorporating context-awareness, mobile advertisers can provide highly effective and relevant ads to users, improving the overall effectiveness of mobile advertising.

In addition to the above, the study of social diffusion and social advertising, finding out the influential people is always a key factor to influence users to purchase the advertised products, significantly improving the acceptance and effectiveness of ads (Niu et al., 2020; Ryu & Park, 2020). However, in mobile advertising, social influence feature is always missing (Qiu, et al., 2020). Even Facebook, the world's famous social networking platform, has not fully use the power of social influence in its mobile version. In our daily lives, cell phones serve as a primary means of communication with family and friends. Surprisingly, this aspect is often overlooked in traditional online social advertising. In the era of mobile commerce, the influence of offline human networks on social interactions is a crucial factor that cannot be overlooked in the mobile advertising market. As a result, we extract social influence from mobile contacts and integrate it into the analysis of social referrals within our proposed mechanism. Additionally, we employ store categorization to establish user preference profiles and utilize a distance-based similarity computing approach to evaluate the appropriateness of matching advertisements for each user.

To sum up the above, in the era of social media and mobile business, it is crucial to harness the potential of context awareness and social influence in the mobile advertising market. In this study, our primary emphasis is on pioneering a cutting-edge approach to mobile advertising that harnesses the influence of social dynamics and contextual awareness. The key objectives we seek to address include:

(1) How can the contextual information be utilized to accurately anticipate users' evolving needs?

Various types of recommendation systems have been developed to precisely discern users' preferences and provide tailored suggestions for the most suitable products or services. Nevertheless, traditional recommender systems encounter difficulties in accurately predicting users' dynamic needs due to the inherent mobility and ever-changing contexts they operate in (Li et al., 2019). The objective of this study is to analyze and effectively utilize temporal, spatial, and weather context information in order to extract and understand users' present needs. Based these context information, a store's contextual popularity (which denotes the number of customers who have visited the store within a specific context) and contextual quality degree (which represents the average rating or evaluation provided by customers for the store within that context) can be derived to understand how well the store aligns with users' needs and preferences within specific contexts.

(2) In what ways can the power of social influence be harnessed to amplify users' acceptance of mobile ads?

It is widely recognized that individuals are influenced by their close friends when making decisions. However, the potential impact of leveraging social influence to improve the effectiveness of mobile advertising has not been fully explored. While social media marketing has successfully utilized this approach, it has yet to be applied to mobile advertising. This study will examine the role of social influence in mobile advertising and how it can be used to enhance users' acceptance of ads.

(3) How can stores that align with users' evolving preferences be accurately identified?

A successful advertising greatly relies on its alignment with the needs and preferences of users. Thus, enhancing the compatibility between advertising content and users is vital for maximizing profits for advertisers and vendors. By integrating context awareness and social referral analyses, it is possible to determine the most appropriate stores for users. However, the main challenge lies in effectively combining these techniques to achieve optimal results.

Our study utilizes contextual fitness analysis, social referral analysis, and devise a groundbreaking mechanism for contextual mobile advertising recommendations. Through our rigorous experimentation conducted on participants' smartphones, we have unequivocally established that this mechanism substantially amplifies the precision of user targeting and the efficacy of ad recommendations compared to other benchmark advertising methods.

The paper is structured in the following manner: Section 2 offers a comprehensive overview of the pertinent concepts, and literature pertaining to our work. Section 3 presents the proposed mechanism in detail, which utilizes contextual fitness analysis, social referral analysis, and devise a groundbreaking mechanism for contextual mobile advertising recommendations. Section 4 delineates the experimental setup employed to evaluate the efficacy of the proposed mechanism. Section 5 presents the results of the conducted experiments, providing a comprehensive evaluation of their effectiveness. Finally, Section 6 concludes the study and offers suggestions for future research.

2. Related Works

2.1. Mobile Advertising

Due to the widespread use of smart mobile devices, the demand for mobile commerce applications and services has significantly increased. In this context, mobile advertising plays a pivotal role by offering advertisers a new channel to effectively reach and engage with mobile users. Compared to traditional online advertising, mobile advertising offers unique advantages such as accessibility, personalization, and location-awareness (Yunos et al., 2003). Location-based advertising (LBA) is an increasingly popular application of mobile commerce that leverages the capabilities of customers' mobile devices to track their real-time location. By utilizing this information, LBA enables advertisers to deliver targeted advertisements tailored to the specific location of mobile users, enhancing the relevance and effectiveness of their ad campaigns (Rory & Aimee al., 2020; Niu et al., 2020). Successful companies like Yelp.com have leveraged LBA to improve their services.

Numerous studies have examined the effectiveness of mobile advertising, with empirical evidence indicating that it can lead to significant sales growth (Merisavo et al., 2006). However, overexposure to mobile ads can negatively impact their value (Niu et al., 2020, Singaraju et al., 2022). Empirical research has shown that fit-revelation may enhance the effect of advertising (Deng et al., 2023). The distance to stores is also central in the literature on spatial competition and store choice. Previous findings indicate that increasing distance between households and stores reduces consumers’ store preferences due to travel costs (Li et al., 2018, Lian et al., 2019). Store distance significantly influence consumers’ mobile search behavior for offline retailers to better understand locations specific consumer demands and improve their mobile in-app targeting (Molitor et al., 2023). While mobile advertising offers numerous benefits, it continues to encounter obstacles, including user acceptance (Tsang et al., 2004, Dong et al., 2022), privacy concerns (Cleff, 2007), and technical challenges (Gao et al., 2008). However, by combining mobile advertising with brands and products, it has the potential to attract consumers and drive engagement in online-to-offline commerce (Amal & Barakat, 2020; Rory & Aimee, 2020).

To overcome the issues related to user acceptance and effectiveness, this study introduces a novel contextually-based social referral mobile advertising mechanism. This mechanism aims to leverage contextual information and social referrals to enhance the relevance and impact of mobile advertisements.

2.2. Context-Aware Computing

Context-aware computing is a fundamental aspect of mobile computing that capitalizes on contextual information to facilitate informed decision-making (Arndt et al., 2016). The concept of context has been extensively explored and defined in numerous studies. For instance, Schilit et al. (1994) conceptualized context as a fusion of computing context, user context, and physical context, emphasizing the integration of these elements. Schmidt et al. (1998) viewed context as the circumstances and environment encompassing a device or user, while Dey and Abowd (1999) defined "context" as any data that contributes to depicting the situation of an entity. Schilke et al. (2004) introduced a personalization model that incorporates three dimensions of user context: their interests, location, and visiting time. This comprehensive framework allows for a more nuanced understanding of user preferences and behaviors. Context-aware refers to the ability of a system or application to gather and utilize information about its environment or situation in order to provide a more relevant and personalized experience. Furthermore, Noguera et al. (2012) presented a mobile recommender system specifically designed for tourists, integrating distinctive features such as a 3D map-based interface and real-time location-sensitive recommendations. This tailored system aims to enhance the tourist experience by providing relevant and timely suggestions based on their specific context.

As smartphones continue to advance at a rapid pace, an ever-growing cohort of researchers (Ball and Newmean, 2013; Arndt et al., 2016; Sohn, 2017) and companies are increasingly acknowledging the significance of incorporating context to attain enhanced precision in user targeting.

Contemporary smartphones are outfitted with a myriad of sensors capable of accurately capturing diverse contextual factors, including but not limited to location, time, weather conditions, and light intensity. However, previous research on context-awareness has primarily relied on manually defined rules to determine application responses in different contexts. These static rules lack flexibility in a dynamic mobile environment and struggle to adapt to individual preferences (Block & Grund, 2014). Additionally, they cannot accurately predict users' preferences in unfamiliar situations.

To tackle this challenge, utilizing probabilistic reasoning methods, researchers have leveraged studies such as Maslow (1943) & Kim et al. (2011) to predict and quantify the uncertainty associated with human behavior. For example, Kim et al. (2011) devised a prediction model that takes into account sequential visit patterns, incorporating both temporal and spatial relevance of ads for mobile users. Likewise, Li et al. (2017) employed a relational Markov network to deduce user activity from GPS traces. While these methods effectively tackle the challenges associated with dynamic contexts, they are often constrained to specific use cases and lack generalizability to other contexts.

Context-aware models have been employed in several studies, including the work of Dao et al. (2012), to dynamically predict users' preferences. The fundamental concept underlying this research is to harness context-similarity features and collaborative filtering techniques. While general preferences may exhibit some stability, the demand for an item can be influenced by additional and variable factors. Thus, when a user seeks a recommendation, it is important to compare their present context with a similar context from the past and evaluate the choices made by others in that context.

Social context, also referred to as the social environment, encompasses the immediate physical and social surroundings in which individuals reside (Barnett & Casper, 2001). People who share the same social environment often foster a sense of social solidarity. leading to similar thought processes and behavioral patterns (source: http://en.wikipedia.org/wiki/Social_environment). By considering the choices made by friends in similar contexts, we can effectively cater to users' needs within a specific context. Incorporating context-aware information enables users to not only connect with nearby individuals regardless of their location but also gain a deeper understanding of their surroundings. In this study, our objective is to anticipate and predict the ever-changing needs and preferences of users not only based on their individual context but also by analyzing their social context, leveraging their friends' choices and decisions. By employing this approach, we anticipate achieving heightened precision in advertising recommendations.

2.3. Social Recommendation

The rapid growth of the internet has presented a significant challenge in efficiently extracting valuable information from the vast amount of online data. As a result, efficient information filtering mechanisms have become necessary. Collaborative filtering (CF) (Su & Khoshgoftaar, 2009) is one of the techniques used to address this issue. E-commerce recommendation systems widely use CF to provide customers with personalized recommendations.

The fundamental concept behind Collaborative Filtering (CF) is that individuals often receive the most suitable recommendations from others who share similar preferences (Bobadilla et al., 2012g). Many CF studies concentrate on identifying users with similar preferences and suggesting items that have been approved by those users. However, this technique is vulnerable to abuse and malicious behavior (Niu et al., 2020).

Social media platforms such as Facebook, Instagram, and Twitter have become essential components of individuals' daily lives in recent years. Social influence refers to the process through which individuals or groups affect the attitudes, beliefs, behaviors, or decisions of others. This influence can manifest in various forms, such as direct communication, observation, or exposure to information or opinions from peers, family, friends, or broader social networks. The social impact theory asserts that individuals are inclined to adhere to normative social influence, positing that the extent of social influence is contingent on the strength, immediacy, and number of sources or targets exerting influence (Latané, 1981; Latané, 1996). Research on social influence indicates that individuals' attitudes and judgments often align with those prevalent in the majority (Nemeth, 1986). Conformity may arise from either external social pressure or an individual's belief in the likely correctness of the majority (Deutch & Gerard, 1955). When a substantial portion of a reference group shares a specific attitude, there is a likelihood that individuals will adopt the same perspective. In today's digital era, where individuals spend increasing amounts of time connecting with friends and family, sharing information, and organizing social gatherings, social influence has emerged as a potent tool for advertisers to counter advertising avoidance (Kelly et al., 2010; Li et al., 2021). Social referral typically refers to the practice of obtaining recommendations or referrals for products, services, or opportunities via social networks or platforms. It involves leveraging personal connections and relationships within online communities to gather information or make decisions about various aspects of life, such as job opportunities, business partnerships, consumer products, and more. By harnessing social influence, advertisers can shape a user's decision-making process by appealing to their personal connections. According to a 2012 social media industry report conducted by Stelzner, 93% of companies utilized social media as a marketing tool, with half of all marketers having over a year's experience in leveraging social media for marketing purposes. Social advertising, which capitalizes on the power of social influence and word-of-mouth, proves to be an exceptionally effective approach to marketing through social media platforms (Kempe et al., 2003).

Numerous researchers have dedicated their efforts to enhancing collaborative filtering, the cornerstone of social recommendation systems, by incorporating a social factor such as "trust" (Dell'Amico & Capra, 2008; Fujimoto, 2013). Dell'Amico & Capra (2008) devised a social filtering approach that assigns greater weight to recommendations from trusted users who possess both competence and good intentions. Recent studies (Lai et al., 2017; Zhao et al., 2019) have introduced trust-aware systems where only trusted neighbors participate in the filtering process to identify the most relevant items. Consumers typically rely on recommendations from trusted individuals in their social circle, such as friends and family members (Lai et al., 2017; Li et al., 2019, Li et al., 2021). Suh & Han's (2002) research revealed that trust plays a pivotal role in predicting users' acceptance of online banking. Additionally, Dinev & Hart (2006) established a positive correlation between a higher level of internet trust and a greater willingness to share personal information and engage in transactions online. The user's trust expectations vary with the type of information systems that a user intends to adopt (Siljc et al., 2018). In the context of online systems, particularly in e-commerce, trust emerges as a critical factor. Studies, such as the one conducted by McKnight et al. (2002), emphasize that trust is instrumental in making consumers feel at ease when sharing personal information and conducting transactions online. Consequently, the influence of social connections is often considered a significant factor in the decision-making processes related to information systems. Since social influence is based on trust (Li et al., 2019). Social interaction may stimulate trust and perceived trustworthiness (Zheng et al., 2010). ZMontaner claims that trust should be derived from user similarity (Lin et al., 2015), and that since trust is the basis of social interaction, it would be reasonable to measure trust value by using similarity and interaction. Inspired by the above studies, this paper will follow a similar formulation and propose social similarity and social interaction as the replacement of trust value. Nonetheless, traditional collaborative filtering techniques based solely on a user-item matrix have limitations in accurately capturing users' evolving preferences and changing needs.

In this paper, we integrate social referral analysis by taking into account ratings from two distinct groups: individuals who have a close interaction relationship (i.e., Social Affinity) with the target user, and those who have similar tastes (i.e., Social Similarity) to the target user. By valuing referrals from these two types of people, a more comprehensive assessment of store preferences and recommendations can be achieved.

2.4. Machine Learning

Machine learning, a branch of computer science, enables computer systems to learn and improve from experience, mirroring the learning process of humans (Lee & Shih, 2009). Machine learning can be divided into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Recently, machine learning technology has developed very rapidly and is mainly used to deal with prediction, classification and clustering. Prediction, classification, and clustering issues have been recognized as the common applications of machine learning, such as predicting the advertising responses from customers, and predicting future bank failure, and dealing the consumer selection problem for determining profitable clients (Lee & Shih, 2009; Zahavi & Levin, 1997).

With the growth of machine learning, some widely used models and algorithms, include linear regression, logistic regression, support vector machine (SVM) algorithm, naive bayes algorithm, decision tree, random forest algorithm, neural network, convolution neural network, dimensionality reduction algorithms, recurrent neural network, gradient boosting algorithms and adaBoosting algorithms. These models or algorithms have been used in different application domains, such as image recognition, financial market predication, and nature language processing. Inferring consumers' preferences provides a better understanding of their purchase behavior (Cheng et al., 2023), which is very important for business success, e.g., recommendation systems and targeted advertising. An explainable machine learning approach, namely Multi-view Latent Dirichlet Allocation (MVLDA) (Zhou et.al, 2023), to infer and interpret consumer preferences.

In this study, we employed machine learning algorithm proposed by Zhou et.al 2023 to improve the accuracy of users' dynamic preference of the classification of commercial categories based on user posts and check-ins.

2.5. Multi-criteria decision-making (MCDM)

Multi-criteria decision-making (MCDM) theory, one of the branches under the field of operations research, was established to solve complex problems which include multiple conflicted criteria. The MCDM problem can be found not only in professional settings but also in our daily lives (Zhao et al., 2011). The objective of multi-criteria decision analysis is to assist a decision maker in choosing the best alternative when multiple criteria conflict and compete with each other. Most commonly used decision aiding methods, such as the analytical hierarchy process (AHP), are based on multi-criteria aggregation procedures (Froot & Scharfstein, 1992, Lin & Li, 2017). Similarly, in marketing research literature, buying a product also can be regarded as a multi-criteria decision problem (Liu & Shih, 2005). The conjoint model is most commonly used technique for solving multi-criteria problems in this field (Green et al, 2001). This model determines the importance weights of product attributes and the values of the attributes. The customers' preference for the product then can be calculated as a linear combination of weights and values. Multi-criteria information is also used in certain electronic market mechanisms, such as multi-attribute auctions (Bichler, 2000). Multi-attribute auctions are typically used in procurement settings and enable auction participants to negotiate not only on price, but also on other attributes of a deal (e.g., quality level, style, delivery date). It has been demonstrated that multi-attribute auctions have several advantages over their single-attribute (i.e., price-only) counterparts, including the improvements in the overall utility and suitability for various application domains (Bichler, 2000). Recently, multi-criteria rating problems have started receiving attention in recommender systems research and are regarded as one of the important issues for the next generation of recommender systems (Adomavicius & Kwon, 2007). Analytic network process (ANP), one of the powerful MCDM methods, is a generalization of the analytic hierarchy process (AHP) proposed. Because the significance of the criteria not only determines the importance of the alternatives, as in a hierarchy, but also, conversely, the importance of the alternatives themselves determines the significance of the criteria, many decision problems cannot be structured hierarchically. ANP uses a network model which can take the interactions between elements into consideration. ANP is widely used in decision-making in various aspects, such as R&D project selection and management (Meade & Presley, 2002), logistic partner selection (Jharkharia & Shankar, 2007), supply chain management (Meade & Sarkis, 1998), and even financial-crisis forecasting or bank ranking (Doumpos & Zopounidis, 2010).

In this study, in order to deal with the issue of store priority ranking and the selection of the most fitting store, based on multiple evaluation criteria that are interrelated with each other, ANP is utilized in our proposed mechanism (Saaty, 2004).

3. The System Framework

The effectiveness of a recommendation greatly depends on delivering it to the intended user at the opportune moment and within the suitable context (Ramaswamy et al., 2009). However, predicting a user's current needs requires understanding their contextual surroundings. People who share the same social environment often exhibit similar decision-making patterns in specific situations, and close friends tend to have similar tastes and can influence an individual's choices significantly. Therefore, this study proposes a new advertising mechanism that considers personal contextual information and friends' actions to make mobile ad recommendations in a given situation. The proposed framework includes three primary modules: users and stores data construction module, an advertising store discovery module, and a store ranking module. Figure 1 illustrates the system framework of the proposed mobile advertising mechanism, which incorporates contextual information and employs a social referral approach.

The three modules can be characterized by the following main features:

1. Users and Stores Data Construction module: this module focuses on gathering pertinent data to build the dataset necessary for our experiments. We use web crawler programs to collect both users' personal information and store information from Instagram. Additionally, we utilize Amazon's data to construct a commercial category tree, which we will use for our user-store similarity analysis.
2. Advertising stores discovery module: this module is divided into three sub-modules: preference similarity analysis, context characteristic analysis, and social referral analysis. Based on the individual's personal preference and the unique characteristics of a store, the measure of preference similarity determines the extent of similarity between the two, enabling predictions regarding the suitability of the store for the target user. The context fitness analysis analyzes stores' characteristics and evaluate their relevance to users in a given context. The social referral analysis evaluates users' similarity in preferences to identify individuals with comparable tastes.
3. Store Ranking module: this module consists of two key processes: the generation of personal criteria weights and the evaluation of priority scores. Through a series of pairwise comparisons, the personal criteria weight for each individual user is determined. Once the criteria weight is established, then utilizes the Analytic Network Process (ANP) method to calculate the priority score. Subsequently, the system identifies and selects stores with the highest scores, presenting them to users as relevant and fitting recommendations.

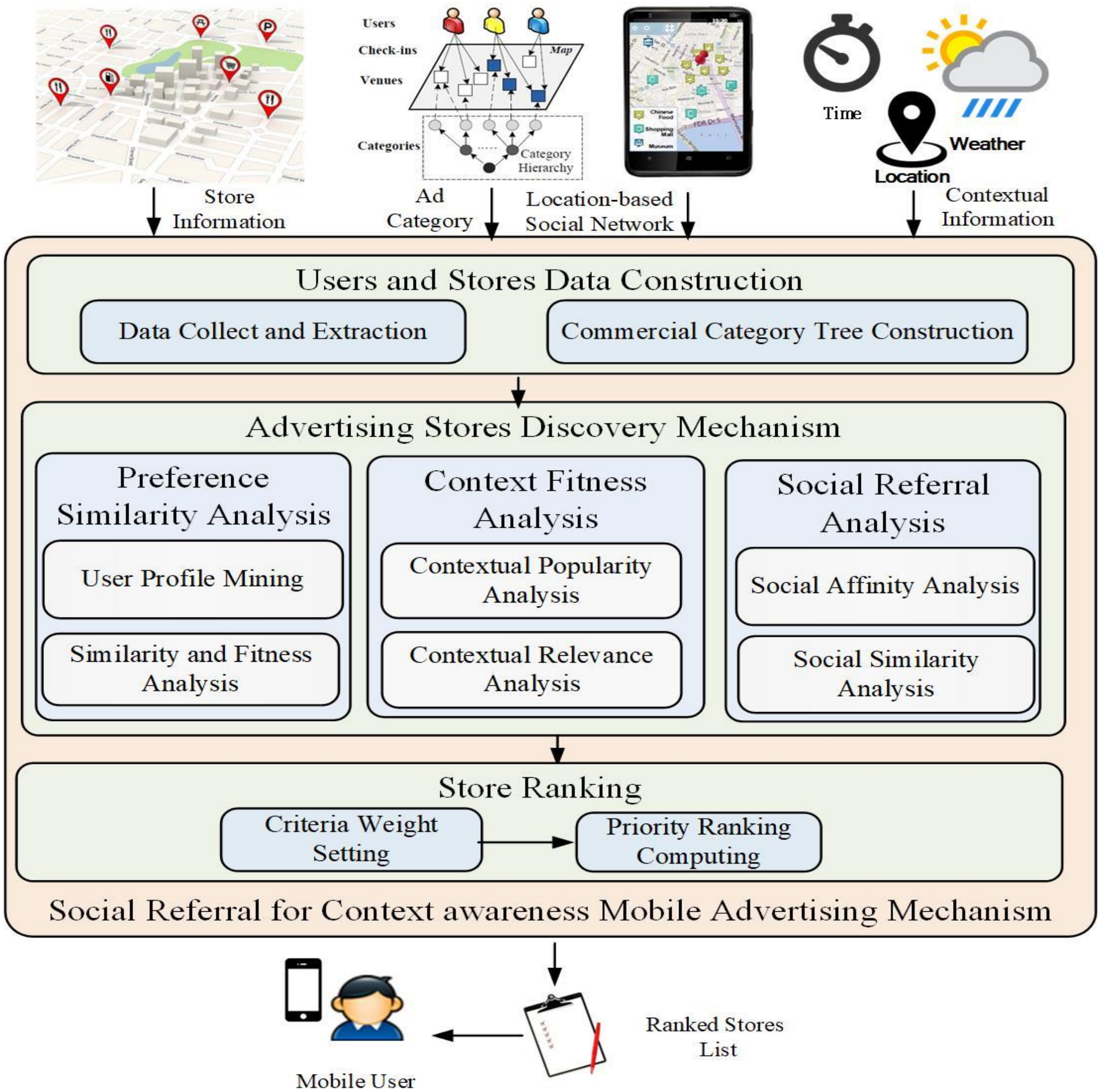

Figure 1: A Context-Aware Social Referral Mobile Advertising Mechanism

3.1. Users and Stores Data Construction

Within this module, we undertake two primary steps to facilitate subsequent analysis. Firstly, we employ crawler methods to gather data from Instagram. Secondly, we analyze user preferences and store information sourced from the official website and Instagram platform of the respective stores. In order to conduct user-store similarity analysis, we establish a commercial category tree by referencing the product or service categories found on the renowned e-commerce platform Amazon. The information collected from Amazon is utilized to construct a category tree encompassing three overarching categories: Entertain & Living, Consumer Products, and Computer, Communication & Consumer Electronics.

3.2. Advertising stores discovery Analysis

The store discovery mechanism evaluates the level of compatibility between users' preferences and the advertising service type. It achieves this by assessing the similarity between the categories of users' preferences and the categories of the provided services. This analysis enables the mechanism to identify target stores that are highly likely to pique the users' interest.

3.2.1. Preference Similarity Analysis

While people's preferences generally remain constant, they can also be influenced by dynamic contexts. In this module, we employ text mining techniques to extract and predict a user's preferences based on various sources of information such as their personal profile, activity history (including their likes, searches, and discussions), and other relevant data. Moreover, the user's historical check-in data is utilized to further understand and characterize their personal preferences, represented as a vector of interests across specific commercial categories.

3.2.1.1 User Profile Analysis

The primary objective of this module is to analyze and categorize user preferences effectively. To accomplish this, we leverage advanced text mining techniques to extract and predict preferences based on various sources such as personal profiles, activities, and discussions. The ultimate aim is to identify relevant keywords that encapsulate the main characteristics and tendencies of users in order to gain valuable insights into their preferences.

Static Preference Identification. The users' profile data plays a crucial role in identifying their stable preferences, which remain relatively unchanged over time. By leveraging the previously developed commercial category tree, we can map the users' profile information to the relevant product or service terms within the tree. This mapping process enables us to establish a connection between users' profile data and the corresponding categories, facilitating a comprehensive understanding of their preferences within the given commercial context. The static preference set of an user $u_i$can be denoted as $\Phi sCat(u_i)$.

Dynamic Preference Identification. Users' dynamic preference tendencies are identified by analyzing their recent activities. By examining what they have been discussing and posting about, we can detect their new focus on products or services. Using natural language processing (NLP) technology and the commercial tree structure, we extract users' recent activities (such as likes, posts, check-ins, and searches) to identify the dynamic preference set $\Phi dCat(u_i)$. In this study, we also use deep learning algorithms to improve the accuracy of the classification of commercial categories based on user posts and check-ins. Finally, we combine the static and dynamic preference sets to obtain the complete product or service commercial set of a user's preference:

$\Phi Cat(u_i) = \{\Phi sCat(u_i)\} \cup \{\Phi dCat(u_i)\}$.

3.2.1.2. Similarity and Fitness Analysis

When it comes to user interest, the concept of similarity plays a crucial role. Similarity refers to the degree to which two or more things are alike or resemble each other in certain aspects. Similarity measures are used to understand the preferences of a user based on their interactions with the system. For example, in a movie recommendation system, if a user frequently watches action movies, the system infers that the user is interested in action films. User feedback, such as ratings or explicit feedback on recommended items, can be used to refine similarity measures. If a user consistently rates items with similar attributes highly, the system will learn to emphasize those similarities in future recommendations.

In summary, the relationship between similarity and user interest in a recommendation system is fundamental. It enables the system to learn from user behavior, understand preferences, and suggest items that align with those preferences. By effectively leveraging similarity measures, recommendation systems can provide personalized and relevant suggestions, ultimately enhancing the user experience. In various contexts, understanding and leveraging similarity can significantly impact user engagement and satisfaction.

The interests of users are linked to specific commercial categories, which are assigned to corresponding category nodes within the commercial category tree. To assess the similarity between a user's interests and the services offered by a store, we employ the concept of graph distance. By calculating the distance between the first mutual category node that both the user and store are assigned to, we can determine the level of similarity between their interests. This approach enables us to gauge the relevance and alignment between a user's preferences and the offerings of a particular store. For example, let user *u* be assigned to category S_1 ($\Phi Cate(u) = S_1$), and store *c* be assigned to category S_2 ($\Phi Cat(c) = S_2$). Let S_m represent the first mutual node of S_1 and S_2. In order to determine the commercial similarity between them using the commercial category tree, we consider the distances between S_1 and S_2, as well as S_2 and S_m. We denote the distance from node from nodes S_1 to node S_m, the distance from node S_1 to node S_m as d_2. Furthermore, we define h as the length of the path from the root node to S_m in the commercial category tree as *h* (as depicted in Fig. 2). The preference similarity score, which indicates the level of match between a user's interest and a store's service, can be calculated using the following equation:

$$Sim(S_1, S_2) = e^{-\alpha d} \times \frac{e^{\beta h} - e^{-\beta h}}{e^{\beta h} + e^{-\beta h}},$$

where α and β are parameters that scale the computation of the shortest path length and depth, respectively. The shortest path length between nodes S_1 and S_2 is represented as *d* (i.e., d_1+d_2). Additionally, the length of the path from the root node to S_m in the commercial category tree is represented as h (refer to Fig. 2). Since a user may have interests in multiple stores, we further assess the average level of compatibility using the following formula:

$$Fit(u,c) = \frac{1}{|\Phi Cate(u)|} \sum_{S_u \in \Phi Cate(u)} Sim(S_u,\ \Phi Cate(c))$$

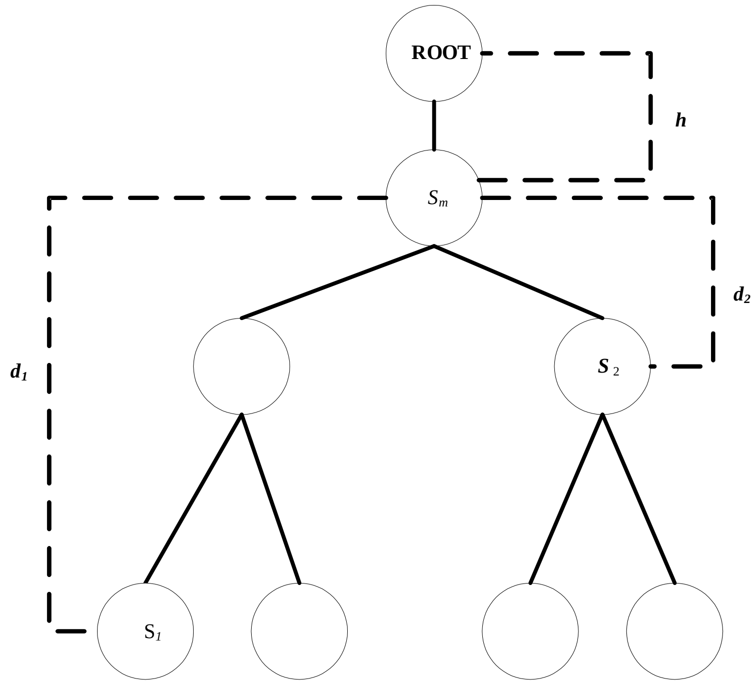

Figure 2: The Concept of Similarity within the Commercial Category Tree

3.2.2. Context Fitness Analysis

3.2.2.1. Contextual Popularity Analysis

The popularity of a store within a specific context can serve as an indicator of its ability to fulfill users' needs. To capture the essence of users' requirements, we incorporate the notion of contextual popularity as a contributing factor. In this study, we employ two features to model a store's contextual popularity: contextual popularity degree (which denotes the number of customers who have visited the store within a specific context) and contextual quality degree (which represents the average rating or evaluation provided by customers for the store within that context). By conducting an analysis of customers' consumption history data, which encompasses contextual information and users' ratings, we can accurately assess and characterize a store's contextual popularity. This comprehensive analysis allows us to understand how well the store aligns with users' needs and preferences within specific contexts.

In this study, we define and characterize a store's context based on three variables: temporal, spatial, and weather. These context dimensions provide valuable insights into the specific conditions surrounding a store's operations. The domain values of these context dimensions are outlined in Table 1, as shown below.

Table 1: The Domain Values Associated with Each Context Dimension

Type	Context	Value
Temporal	*Season*	Spring, Summer, Fall, Winter
	day	Weekday, Weekend
	time	Moring, Lunch, Afternoon, Dinner, Night, Midnight
Spatial	*distance*	<200 m, 200-500 m, 500-1000 m, 1000-1500 m, >1500 m
Weather	*weather*	Sunny, Cloudy, Windy, Rainy, stormy

Contextual Popular Degree (CPD). The level of popularity that a store achieves within a given context is determined by the frequency of customer visits. A higher frequency of visits indicates a higher degree of popularity for the store in that particular context. A period of high visit frequency indicates a "popular" for the store in that context. The contextual popularity degree (*cpd*) of a store is defined as:

$$popular(s_i, c_j) = Total\ number\ of\ users'\ visit\ records\ \ of\ \ store\ \ s_i\ in\ \ context\ c_j. \tag{1}$$

The popular score then normalized using min-max normalization, shown in equation (2):

$$cpd(s_i, c_j) = \frac{popular(c_j, s_i) - popular(c_j)_{min}}{popular(c_j)_{max} - cpopular(c_j)_{min}}, \tag{2}$$

where $cpd(c_j)_{min}$ and $cpd(c_j)_{max}$ represent the minimum and maximum values of the popularity scores among all stores within the given context c_j.

Contextual Quality Degree (CQD). Undoubtedly, individuals typically tend to prefer stores that offer higher quality, as evident from the feedback provided by users who have visited those stores. Hence, Hence, we analyze the rating scores provided by users to evaluate the contextual quality degree (*cqd*) of a store. The contextual quality degree of a store s_i within a given context $c_j$is represented as:

$$quality(s_i, c_j) = Average\ rating\ score\ of\ store\ s_i\ in\ context\ c_j. \quad (3)$$

Similarly, the normalized value of contextual quality is formulated as:

$$cqd(s_i, c_j) = \frac{quality(s_i,c_j) - qualtiy(c_j)_{min}}{quality(c_j)_{max} - quality(c_j)_{min}}, \quad (4)$$

where $quality(c_j)_{min}$ and $quality(c_j)_{max}$refer to the lowest and highest quality scores among all the stores in the context c_j.

3.2.2.2 Contextual Relevance Analysis

This module examines the relevance of stores to users' needs/preferences by evaluating their contextual popularity through three indicators: temporal relevance, spatial relevance, and weather relevance. If a store is in close proximity to users (spatial relevance) or if the products offered by the store are likely to be consumed by users in the near future (temporal relevance) and the current weather conditions align with the services provided by the store (weather relevance), the advertisement has a higher probability of attracting users.

Temporal Relevance Degree (TRD). This module quantifies the level of temporal relevance between a user's current contextual profile and the contextual characteristics of a store. It identifies stores that not only possess excellent quality features but also align with the user's preferences based on their popularity. For an active user, the temporal relevance is assessed by comparing the user's current temporal context $c_j = \Theta_c(u)$ and a store s_i is defined in equation (5):

$$trd(u, s_i) = cpd(\Theta_c(u), s_i) \times cqd(\Theta_c(u), s_i). \quad (5)$$

Spatial Relevance Degree (SRD). Generally, customers prefer using a service that is conveniently located and easily accessible. Therefore, transportation convenience plays a crucial role in influencing customers' decision to visit or make a purchase. Even if smartphone users receive an appealing advertisement for a service, if the distance between them and the service is too great, they may not be able to reach the destination to avail of the service. In our proposed mechanism, we specifically target locations within a 1500-meter radius of the four landmarks selected for our experiments to ensure that the store is not too far from potential customers, thus positively impacting their likelihood of visiting. Research findings indicate that individuals generally exhibit a preference for businesses situated in close proximity to their present location (Ramaswamy et al., 2009). Consequently, proximity assumes a crucial role in location-based advertising, as users are more inclined to accept recommendations about stores that are nearby. Leveraging GPS technology, a user's current location can be accurately determined (Ashbrook and Starner, 2003). The spatial relevance degree (*SRD*) of a store (s_i) to a specific user (u) is modeled as an exponential function, where the value decreases exponentially as the distance between the store and the user's current location increases.:

$$srd(u, s_i) = e^{-dist(loc(u), loc(s_i))}, \quad (6)$$

where $loc(s_i)$ represents the location of store s_i, $loc(u)$ denotes the geographical location of the target user u, and $dist(a, b)$ represents a function used to measure the distance between *a* and *b*.

Weather Relevance Degree (WRD). Research has shown that climate change has a significant relationship with consumers' purchases and retail sales (Lian et al., 2019). Therefore, weather holds considerable importance in various aspects of decision-making within the retail sector. The weather relevance degree (*wrd*) of a store s_i to a specific target user u is formulated using the following equation (7):

$$wrd(u, s_i) = \begin{cases} 1 & if\ weather(u) = weather(s_i) \\ 0 & otherwise \end{cases}, \quad (7)$$

Lastly, in order to compute the contextual relevance score (*CR*) of user u with the store s_i, the temporal relevance score, spatial relevance score, and weather relevance score are combined using the following formula:

$$CR(u, s_i) = trd(\Theta_c(u), s_i) \times srd(u, s_i) \times wrd(u, s_i). \quad (8)$$

A store with a higher contextual relevance score demonstrates a stronger alignment with the target user in terms of the current temporal and spatial contexts, signifying a better match between the user and the store.

3.2.3. Social Referral Analysis

Predicting dynamic user preferences can be challenging, as their needs frequently change with their context. Determining the most suitable store for a user's present requirements is a complex task. Despite the advancements in mobile devices and their capabilities, fully tracking users' life logs while respecting privacy concerns remains infeasible. However, it is well-known that individuals are often influenced by the choices and recommendations of close friends or those who share similar interests (Forgas & Bower, 1988; Song et al., 2007; Agarwal & Liu, 2018). Hence, in this paper, we integrate social referral analysis by taking into account ratings from two distinct groups: individuals who have a close relationship (i.e., Social Affinity) with the target user, and those who have similar tastes (i.e., Social Similarity) to the target user. By valuing referrals from these two types of people, a more comprehensive assessment of store preferences and recommendations can be achieved.

3.2.3.1. Social Affinity Analysis

We frequently exhibit comparable behavior patterns and thought processes to those of our friends, particularly those with whom we have frequent interactions. The primary objective of social affinity analysis is to assign higher rating scores to recommendations received from close and active friends who are likely to exhibit similar behavior patterns and have a significant influence on the target user in a given context. Essentially, users hold a higher referral value in predicting the target user's preferences. Upon consumption of an item or service by an active user, the information or advertisements associated with that item or service have a greater likelihood of reaching the target user. As a result, the social affinity analysis module consists of two components: a closeness degree analysis and an activeness degree analysis.

Closeness Degree (CD). To measure the closeness degree between two users, we examine their interaction data by analyzing various forms of human interactions. In this paper, we specifically concentrate on users' check-ins, and Instagram interactions, which encompass messages they respond to and forward. The degree of proximity between user u and user v can be evaluated by calculating their interaction ratios, as illustrated in the following equation:

$$cd(u,v) = \frac{|\phi c_u \cap \phi c_v|}{|\phi c_u \cup \phi c_v|} + \frac{|\phi r_u \cap \phi r_v|}{|\phi r_u \cup \phi r_v|} + \frac{|\phi f_u \cap \phi f_v|}{|\phi f_u \cup \phi f_v|}, \quad (8)$$

where ϕc_u (ϕs_u,ϕr_u,ϕf_u) represent the set of interactions (check-ins, messages responded to, messages forwarded) made by user u. Similarly, $\phi c_u \cap \phi c_v$ ($r_u \cap \phi r_v$,$\phi f_u \cap \phi f_v$) represent the set of interactions (check-ins, messages responded to, messages forwarded) that both user *u* and user *v* engaged in together. On the other hand, $\phi c_u \cup \phi c_v$ ($\phi r_u \cup \phi r_v$,$\phi f_u \cup \phi f_v$) represents the combined set of interactions (check-ins, messages responded to, messages forwarded) made by either user *u* or user *v*.

Activeness Degree (AD). The level of user activity can serve as an indicator of their ability to effectively deliver messages to the intended recipient. To measure user u's activeness degree, we use the equation:

$$ad(u) = \sum_t^T act(t)/T, \quad (9)$$

where $act(t)$ represents the count of user engagement (check-ins, posts) within a given time period *t;* it is then aggregated across all time periods *t* and divided by the total number of time periods T, as depicted in the equation (9). A user with higher activity levels is expected to engage in interactions more frequently, thereby increasing their potential to influence the target user. Furthermore, the social influence of user *v* on user *u* is assessed by multiplying the degree of closeness (*cd*) and the degree of activeness (*ad*), as shown in the equation (10):

$$SI(u,v) = ad(u) \times cd(u,v). \quad (10)$$

where *cd* (*u*, *v*) represents the degree of closeness between user *u* and user *v*, while *ad*(*u*) signifies the level of activity or activeness of user *v*. The higher the social influence score, the more likely the recommendations from user *u* will be accepted by user v.

3.2.3.2. Social Similarity Analysis

Users who are considered trustworthy have a higher likelihood of influencing others through their recommendations. These trusted users are characterized by being both intentional and competent, as observed in previous studies (Lam et al., 2006; Dell'Amico and Capra, 2008). Intentional users typically maintain a closer and more active relationship with the target user, while competent users are capable of providing insightful and informative advice. When the preferences of a trusted user align with those of the target user, their shared experience is more likely to be beneficial, ultimately leading to a higher referral value for the trusted user.

Similarity Degree (SD). The conventional approach of asking users to reveal their preferences directly is often seen as bothersome. Alternatively, numerous researchers are shifting their focus towards examining users' online behavior, particularly their social media posts, through semantic analysis methods to extract their preferences. Nevertheless, the utilization of efficient semantic analysis methods can be intricate, demanding in terms of resources, and may raise concerns related to privacy. Recently, some researchers have proposed alternative methods of social filtering that rely on the principle that people with similar tastes can provide better recommendations. Rather than directly identifying users' preferences, these methods rely on recommendations from individuals who share similar tastes to make personalized suggestions.

In today's landscape, there is a proliferation of local review platforms such as Yelp.com that offer convenient access to public ratings for local stores. Leveraging the analysis of ratings provided by users who have similar preferences to a target user, we can facilitate more streamlined recommendations of suitable stores to them. To quantify the similarity between two users based on their past ratings, this approach utilizes the Pearson correlation coefficient. The Pearson correlation coefficient is computed as the covariance of two variables divided by the product of their standard deviations. The degree of similarity (*sd*) between user *u* and user *v* can be represented as:

$$sd(u,v) = \frac{\sum_{s_i \in S_{uv}} (r_{u,s_i} - \overline{r_u})(r_{v,s_i} - \overline{r_v})}{\sqrt{\sum_{s_i \in S_{uv}} (r_{u,s_i} - \overline{r_u})^2 \sum_{s_i \in S_{uv}} (r_{v,s_i} - \overline{r_v})^2}}, \tag{11}$$

where S_{uv} represents the set of stores that both user u and user v have rated, $r_{u,s_i}$and r_{v,s_i} correspond to the ratings given by user *u* and user *v* for store s_i, respectively, and $\overline{r_u}$and $\overline{r_v}$ denote the average ratings of user *u* and user *v* respectively. Furthermore, the similarity degree obtained from the Pearson correlation coefficient serves as a weight in the store recommendation process.

Social Referral Rating (SRR). To forecast the referral rating score of a store for a user within a specific context, we integrate the static preference similarity value with the social affinity value. The formulation for the predictive referral rating score (*rrs*) of user *u* for an unrated store s_i in a given context $c_j$is formulated as:

$$SRR(u, s_i, c_j) = \overline{r_u} + k \sum_{v \in VS_i} \left(R_{v,s_i,c_j} - \overline{r_v}\right) \cdot \left(1 + SI(u,v)\right) \cdot sd(u,v), \tag{12}$$

where VS_i represents the set of users who have rated store i , R_{u,s_i,c_j}represents the rating given by user *v* for store s_i in the specific context c_j, and *k* is a normalizing factor used in the equation:

$$k = \frac{1}{\sum_{v=1}^{n} |(1+SI(u,v)) \times sd(u,v)|}. \tag{13}$$

3.3. Store Ranking

3.3.1. Criteria Weight Setting

To choose the most suitable store considering multiple criteria, we employ the analytic network process (ANP), which is a widely used approach in multi-criteria decision-making (MCDM). ANP allows us to analyze and compute the purchasing strength of a user across various stores. Unlike the analytic hierarchy process (AHP), ANP takes into account the interactions between criteria and does not require independence among them. This feature makes ANP a more appropriate approach for computing in this particular scenario. In order to establish the relative importance of the weights, we ask users to assess the significance of preference similarity, contextual influence, and social influence. The initial step is to construct a matrix called M_{PCS}, which facilitates the determination of pairwise weight ratios. The matrix is presented below.

$$M_{PCS} = \begin{bmatrix} 1 & C_{PC} & C_{PS} \\ \frac{1}{C_{PC}} & 1 & C_{CS} \\ \frac{1}{C_{PS}} & \frac{1}{C_{CS}} & 1 \end{bmatrix} \tag{39}$$

In M_{PCS}, *P* implies preference similarity, *C* refers to contextual influence and *S* represents social influence. Each element C_{ij} in the matrix represents the relative weight between criterion *i* and criterion *j*. Specifically, C_{pc} denotes the relative weight between preference similarity and contextual influence, C_{ps} refer to the relative weight between preference similarity and social influence, and C_{cs} represents the relative weight between contextual influence and social influence.

To calculate the criteria weights for the matrix MPCS, we utilize the following equation.

$$W_i = \frac{1}{n} \sum_{j=1}^{n} \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}}$$

The variable W_i represents the relative value of criteria i, where $\alpha = w_1$, $\beta = w_2$, $\gamma = w_3$ and n denotes the number of criteria. By utilizing the ANP method to calculate the weights of the factors, we can determine the elements that users prioritize to a greater extent. These values are then employed in our experiments to evaluate the proposed mechanism. Please note that in the absence of explicit weight preferences from users for each criterion, the default weight distribution will be evenly allocated among them.

3.3.2. Priority Score Computing

In this study, we try to construct a contextual-based social referral advertising mechanism according to preference similarity, contextual influence, and social influence to provide a store recommendation list for users. The Priority Ranking Score (The Priority Ranking Score (PRS) module examines a user's current context profile along with contextual characteristics of stores in order to identify the most suitable stores for the user. To accomplish this, the module computes a score for each store s_i in a given context c_j by incorporating factors such as preference fitness (*fit*), contextual relevence (*cr*) and social referral rating (*srr*)factors. Specifically, when considering a target user *u*, the score for store s_i in context c_j is calculated using the following equation:

$$PRS(u, s_i, c_j) = \alpha \times Fit(u, s_i, c_j) + \beta \times CR(u, s_i, c_j) + \gamma \times SRR\,(u, s_i, c_j). \tag{14}$$

where $\alpha = w_1$, $\beta = w_2$, $\gamma = w_3$. The weighting of parameters be determined by AHP approach discussed in section of criteria weight setting. The top N stores with the highest scores can be recommended or presented to the target user.

Algorithm 1 illustrates our proposed *social referral mechanism for context-aware mobile advertising procedure* in detail. ANP approach uses matrix to solve the weight of evaluated-criteria. The time complexity of matrix solving is O (n^3). However, the number of factors considered in our approach is very small (in this study the number of factors is 3). Hence, the high computation time problem does not occur even the time complexity is O (n^3). After the weight is determined, the computation of priority ranking approach is a linear combination of the three criteria; the complexity of each criterion is O (n). Therefore, the time complexity of priority ranking approach is O (n).

Algorithm 1. Social referral mechanism for context-aware mobile advertising

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Input: Give a number *k*, a landmark L with *n* commercial categories, and a terms library for each commercial category location of mobile user *u*, and current context of user $\Theta_c(u)$, *stores set s*

Output: The *k* fitness context-relevant stores

/* *Step 1*: *Detects users' current context $\Theta_c(u)$, including their current location, date, time, and weather, Similarity analysis, Fitness analysis*

**Step 2: Preference Similarity Analysis, Context Fitness Analysis, Social Referral Analysis*

Analyze *Preference Similarity Analysis*;

Compute $Fit(u,c) = \frac{1}{|\Phi Cate(u)|} \sum_{S_u \in \Phi Cate(u)} Sim(S_u,\ \Phi Cate(c))$

Analyze *Context Fitness Analysis*;

Compute $trd(u, s_i) = cpd(\Theta_c(u), s_i) \times cqd(\Theta_c(u), s_i)$;

Compute $srd(u, s_i) = e^{-dist(loc(u), loc(s_i))}$;

Compute $CR(u, s_i) = trd(\Theta_c(u), s_i) \times srd(u, s_i) \times wrd(u, s_i)$;

Analyze *Social Referral Analysis*;

Compute $SRR(u, s_i, c_j) = \overline{r_u} + k \sum_{v \in VS_i} \left(R_{v,s_i,c_j} - \overline{r_v}\right) \cdot \left(1 + SI(u,v)\right) \cdot sd(u,v)$**;**

/* *Step 3: Store Ranking ANP*

Compute Inharmonious 3x3 super-matrix;

Compute Harmonious 3x3 super-matrix;

Compute Limited 3x3 super-matrix;

Extracting Priorities and Weights (α, β, γ) *;*

Compute $PRS(u, s_i, c_j) = \alpha \times Fit(u, s_i, c_j) + \beta \times CF(u, s_i, c_j) + \gamma \times SRR\,(u, s_i, c_j)$.

return top-k ranked stores.

---

4. Experiments

We have developed a mobile advertising mechanism, which is tailored to function on mobile devices. This mechanism has been implemented on the Android platform through the creation of an app called "PCS" (Preference and Contextual-based Social Referral ad Recommender). Our app has the ability to automatically detect users' current context, such as their location, time, date, and weather, and it analyzes their social relationships and ratings data to generate personalized ad recommendations. To assess the performance of our mechanism, we conducted a comparative analysis against other benchmark approaches. The following sections describe our data collection process and experimental procedures.

4.1. Data collection and Pre-processing

For our experiments, we collected and analyzed two types of data: contextual rating data and users' social data.

Contextual rating data. To establish the contextual characteristics of stores and users' preferences, the collection of contextual data is essential, which includes temporal and spatial context data, along with rating data. However, widely-used review sites like ipeen.com and Google Map do not offer this specific type of contextual rating data. Furthermore, with the growing concerns around privacy, it has become increasingly challenging to automatically track users' life logs using their cellphone data. As an alternative approach, we conducted experiments to collect the necessary data, focusing on four popular landmarks in Kaohsiung City, Taiwan: Dream Mall, E Sky Land, Feds, and Hanshin Arena Shopping Plaza as our target locations because these landmarks sell more types of products of the representativeness and the richness of data in respective categories. These locations hold valuable data pertaining to the commercial categories targeted by our proposed model. During the data collection phase, participants were requested to recollect and report all the stores they had visited in the past 12 months, along with the accompanying context of their visits. We gathered information including the store's name, the date, time, and weather during the visit, the user's satisfaction level (rated on a scale of 1 to 5 stars), and any additional comments provided by the user.

Subsequently, we carefully chose 703 stores that possessed more than five significant rating records from nearby establishments, resulting in a cumulative total of 8,453 ratings. Comprehensive details regarding the stores, including their location and business hours, were acquired from prominent review platforms in Taiwan, such as Google Maps and ipeen.com. The stores were categorized based on Amazon product categories (Lin et.al., 2015) and classified into three general categories: Entertainment & Living, Consumer Product, and Computer, Communication & Consumer Electronics. These three types can almost cover most of check ins, rating data and the relative store type or user preferences. Please refer to Table 1 for further details.

Table 1: Components of the category tree (Lin et.al., 2015)

	Category					
	Entertainment & Living		**Consumer Products**		**Computer, Communication, & Consumer Electronics**	
	Sports & Outdoor	*Movies, Reading, & Music*	*Health & Beauty*	*Apparel, Shoes, & Accessories*	*Electronics*	*Computers*
Element	Extreme Sports	Books & Magazines	Cosmetics	Clothing	Cameras	Office Products & Supplies
	Exercise	Music	Food	Shoes	Cell Phones & Apps	Software & Support Services
	Travel	Films & TV	Grocery	Jewelry	Mobile Electronics	Computers & Accessories

Users' social data. The data is gathered from two distinct sources: mobile phone contact logs and users' activities on Instagram. For collecting mobile phone contact data, we created an Android app dedicated to capturing contact logs. We analyzed the frequency of calls and text messages exchanged between users to derive insights from the data. To collect data from social network sites, we utilized the Instagram API to extract publicly available posts that users have engaged with on their Instagram accounts. The participants in this research experiment were all volunteers who were invited to participate, and as of May 2023, 215 users have taken part. Due to the privacy constraint, we can only collect the social information from those users who are willing to authorize us to do that. Snowball sampling (Ahn et al., 2007) has been proved to be a feasible method to study the issue of social networks. Handcock and Gile (Handcock and Gile, 2010) indicated that sampled networks are not "biased" but can be representative if analyzed correctly. Exponential random graph model (EGRM) has been demonstrated to be capable of capturing some of the key structural of networks such as the degree of clustering, the degree of distribution, and feature of network connectively (Snijders et al, 2006). To obtain a more accurate assessment of the contextual popularity of stores as a representation of users' dynamic needs, participants were required to have resided in Kaohsiung City for a minimum of 6 months. Additionally, the gender distribution of participants is provided, with 43% being male and 57% being female. Their age distribution is showed below in Figure 3. The age distribution of the users spans from 20 to 50 years old. Specifically, 72% of users are aged between 20 and 30 years old, which aligns with the main population rate of Instagram users. Additionally, 17% fall within the 30 to 40 age bracket, and 11% are between 40 and 50 years old.

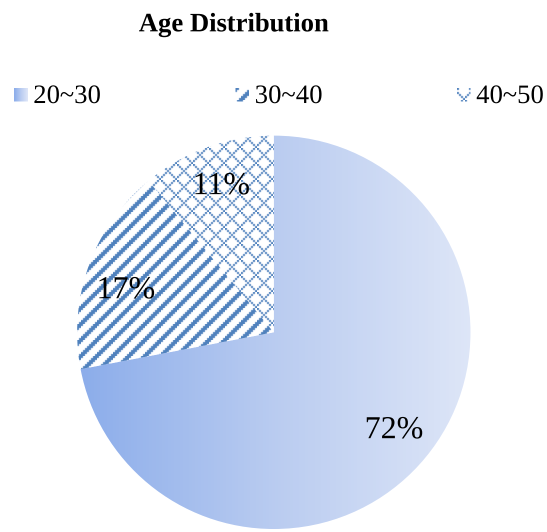

Figure 3
Figure 3: Distribution of Users' Ages

4.2. Advertising Strategy

In order to assess the performance of our proposed mechanism, we conducted a comparative analysis between the PCS method and five other distinct advertising strategies as the benchmarks. These benchmarks are:

1. Preference and Contextual social referral approach (PCS): this approach is rooted in our proposed mechanism.
2. Preference similarity approach (Preference): in this advertising strategy, considers only preference similarity between users and stores, ignoring context and social influence
3. Context fitness approach (Context): in this advertising strategy, considers only context fitness between users and stores, ignoring social influence.
4. Social referral approach (Social): in this advertising strategy, social similarity and social affinity between users are taken into account, while preference and context factors are excluded.
5. Collaborative filtering approach (CF): in this advertising strategy, the predictive score for a store is determined by employing the conventional collaborative filtering method.
6. Random selection approach: In this advertising strategy, the recommended store is selected through a randomized approach.

In order to ensure that users are not overwhelmed with advertisements, each participant only receives five recommendations, each generated using one of the five advertising strategies. The participants are not aware of which advertising strategy generated which ad, and the advertising strategies are applied in a random sequence.

The feedback from users is recorded for further evaluation. By comparing the feedback received from the different advertising strategies, the researchers can determine which strategy is the most effective in terms of generating positive user feedback. The use of a randomized sequence and limiting the number of recommendations helps to ensure that the feedback received is unbiased and reflective of users' actual preferences.

4.3. Experimental Procedures

To conduct the experiment, the following procedure is followed:

1. The first step of the experiment involves asking participants to install the research team's Android app on their mobile devices. When a user requests a recommendation, the system detects their current context, including their current location, date, time, and weather, before proceeding.
2. Step 2: The system uses each of the five advertising strategies to calculate fitness ratings for stores. Subsequently, the stores with the highest fitness rating score are selected based on each strategy. The system presents the top five recommendations, one from each strategy, to the target user.
3. Step 3: After receiving the recommendations, active users are asked to provide feedback by answering three questions.:

Q1: To what extent did the recommended store align with your present requirements?

The fitness levels are graded on a scale of one to five stars, where five stars indicate a highly precise prediction, and one star represents a completely inaccurate prediction.

Q2: On a scale of satisfaction, how pleased are you with the advertisement for the recommended store?

The satisfaction levels are likewise evaluated on a scale ranging from one to five.

Q3: To what extent are you inclined to consider shopping at the suggested store?

The willingness to make a purchase is assessed using a five-point scale, where one point indicates a lack of desire to make a purchase, while five points indicate a strong inclination to make a purchase.

The mobile advertising application interface consists of three essential components, as depicted in Figure 4. The first component is contextual information, which presents various details about the recommended store, such as its name, location, business hours, and distance from the user's current location. The second component is social influence information, which exhibits ratings and comments provided by the user's friends regarding the recommended store. The third component is the system menu, which grants users the ability to request a new recommendation in response to changes in their context and provide feedback on the recommendation. The feedback received, comprising three questions, is utilized to evaluate the accuracy of predictions and gauge the acceptance of the advertising recipients.

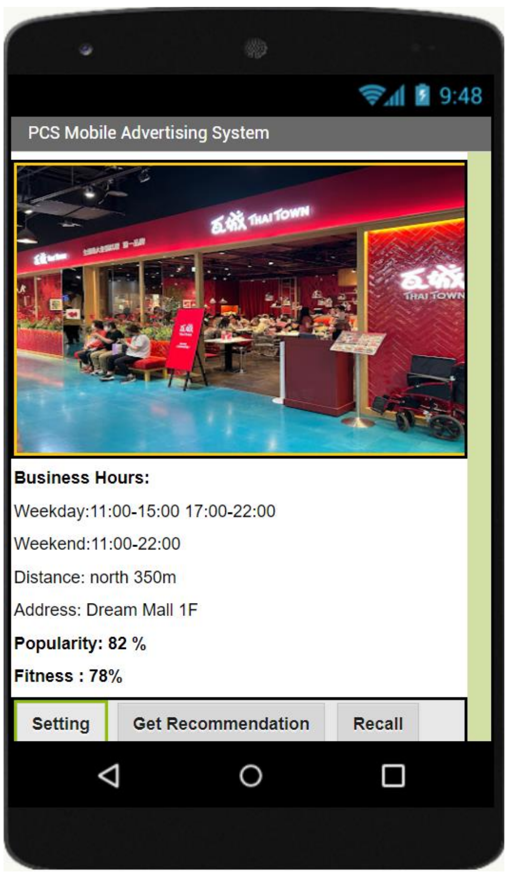

Figure 4: The User Interface of the PCS Mobile Advertising Application

5. Results and Evaluation

In this section, we will present and discuss the results of our experiments. We will evaluate the effectiveness of the proposed mechanism using three criteria: (1) the accuracy of predicting the user's needs; (2) the satisfaction level with the recommended advertisements; and (3) the willingness to make purchases at the suggested stores.

5.1. Accuracy in Predicting User's Current Needs

We employ this metric to evaluate the efficacy of our proposed approach in accurately predicting the evolving needs of users. By assessing the performance based on this criterion, we can determine the effectiveness of our approach in meeting users' dynamic requirements. To evaluate the performance, we conducted a comparative analysis between our PCS mobile advertising mechanism and five benchmark approaches. We gathered user feedback on various recommendations and calculated the average accuracy scores for different advertising strategies. These results are presented in Figure 5, providing insights into the effectiveness of our approach compared to the benchmarks.

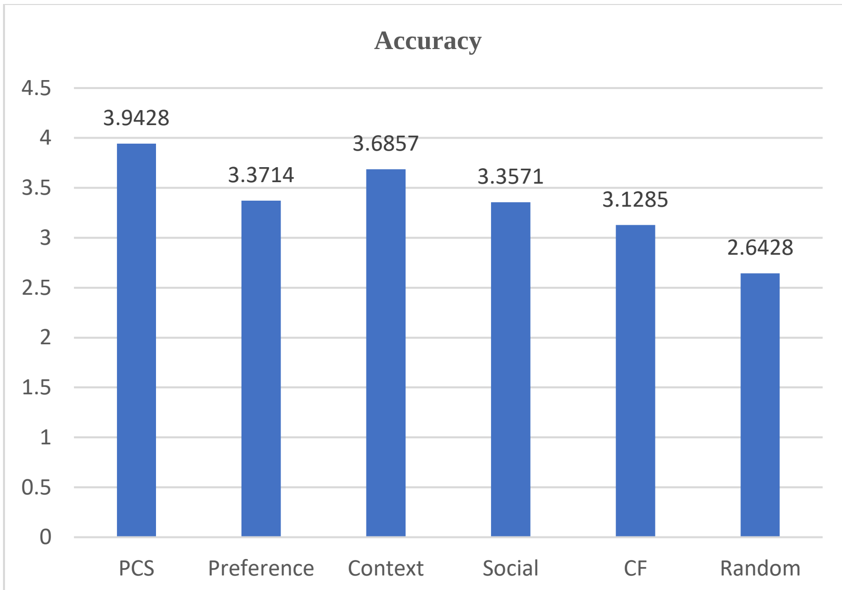

Figure 5: The Accuracy Scores of Dynamic Need Prediction

Upon analyzing the data, we can conclude that the proposed PCS method exhibits higher accuracy in predicting users' needs compared to the other benchmark methods. The results clearly demonstrate the superior performance of our approach in accurately anticipating and catering to users' evolving requirements. The accuracy score of PCS is 3.9428, which surpasses the scores obtained by the Preference (3.3714), Context (3.6857), Social (3.3571), CF (3.1285), and random (2.6428) strategies. These results highlight the superior performance of the PCS method in accurately predicting users' needs compared to the alternative strategies. This indicates that incorporating the contextual factor is beneficial for enhancing the accuracy of predictions. The improved performance of the PCS method, compared to other strategies, suggests that considering the contextual information plays a significant role in making more accurate predictions. Although the good performance of our proposed mechanism in dynamic need prediction, we want to further understand the difference of each model is whether significant or not. To verify the statistical significance of the discrepancy between the PCS method and the other benchmark methods, we conducted a paired t-test. If a p-value reported from a t test is less than 0.05, then that result is said to be statistically significant. If a p-value is greater than 0.05, then the result is insignificant. The results are presented in Table 2, revealing that all p-values for the paired comparisons are smaller than 0.05. This suggests that the variations in accuracy between the PCS method and the other methods are statistically significant. Hence, the findings provide strong evidence that the PCS method is a statistically superior approach for accurately predicting users' needs in mobile advertising applications.

Table 2: The Paired Samples Test of PCS with Other Five Strategies (Recommendation Accuracy)

Paired Group		Mean	Std. Deviation	Std. Error Mean	T	Sig. (2-tailed)
PCS	Preference	0.571	0.950	0.113	5.070	.000
	Context	0.257	0.787	0.093	2.753	.008
	Social	0.586	0.643	0.076	7.670	.000
	CF	0.814	1.100	0.130	6.242	.000
	Random	1.300	1.033	0.123	10.604	.000

5.2. Evaluation of advertisement satisfaction rates

Although we can identify user needs, low satisfaction with the ad or reluctance to accept the recommendation of the store may still result in users not clicking on the ad. Hence, enhancing ad satisfaction plays a pivotal role in boosting the click-through rate and revenue for advertisers. In order to assess the satisfaction levels of users with ads recommended through various advertising strategies, we conducted an analysis of user feedback. The findings of this analysis are depicted in Figure 6. Out of all the methods examined, the PCS method exhibited the highest level of satisfaction, achieving an impressive score of 3.9271. Additionally, the results indicate that social influence has a greater impact than contextual factors in enhancing the impression created by ads.

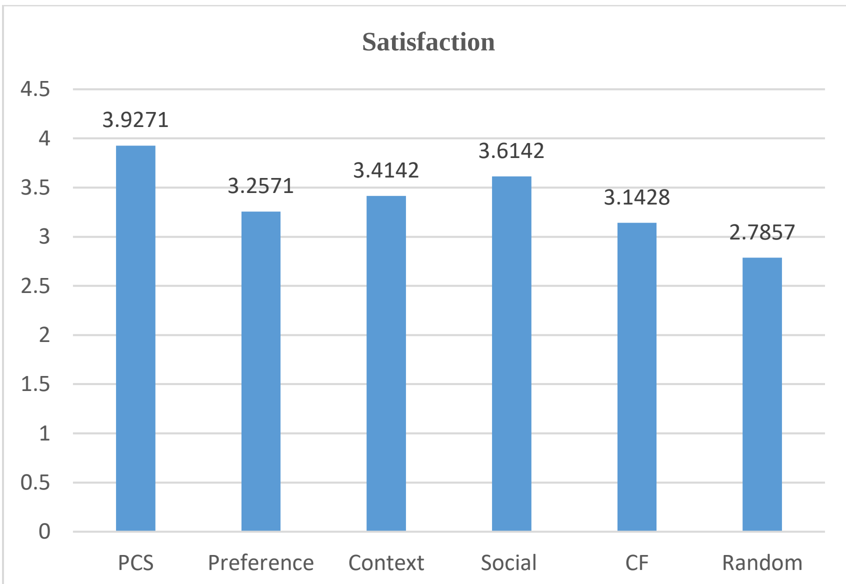

Figure 6: The Satisfaction with Each Recommendation Strategy

The results presented in Table 3 support the conclusion that satisfaction levels with ads recommended by the PCS method are statistically higher than those recommended by other benchmark methods. The paired t-test confirms that the difference in satisfaction levels is significant at a predetermined level of significance. Therefore, our study suggests that the PCS method can effectively increase users' satisfaction with recommended ads, which can ultimately improve click-through rates and revenue for advertisers.

Table 3: Paired Samples Test for PCS and Other Five Strategies (Ad Satisfaction)

Paired Group		Mean	Std. Deviation	Std. Error Mean	T	Sig. (2-tailed)
PCS	Preference	.671	1.038	.123	5.450	.000
	Context	.514	.982	.116	4.413	.000
	Social	.314	.919	.1093	2.882	.005
	CF	.771	1.031	.1223	6.307	.000
	Random	1.143	1.032	.1225	9.330	.000

5.3. Willingness Evaluation to make purchase

Figure 7 showcases the evaluation results for the willingness to make purchases at the recommended stores. The findings clearly demonstrate that our proposed PCS method surpasses all other methods employed in the experiments, achieving a remarkable score of 3.9142, indicating that customers are more willing to purchase from stores recommended by the PCS strategy. Furthermore, the results reveal that the willingness to purchase score for the Context strategy slightly trails behind at 3.5142, when compared to the Social strategy. These findings indicate that social influence has a greater impact than contextual factors on customers' willingness to purchase at the recommended stores.

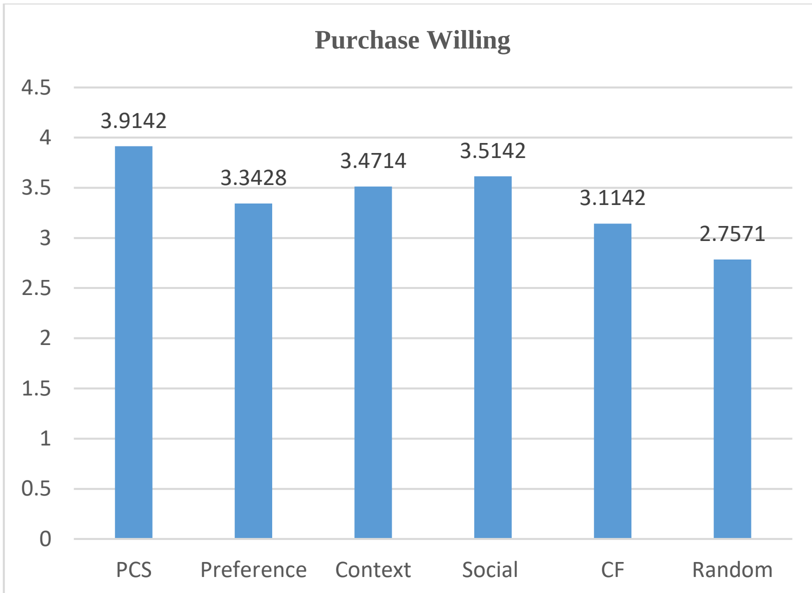

Figure 7: The Willingness Score to Make a Purchase for Each Recommendation Approach

Table 4 presents the results of a two-paired sample t-test, highlighting that the willingness to make a purchase, as induced by our proposed PCS method, is significantly higher than that induced by the other four advertising methods, with a 95% confidence level. Based on these findings, it can be inferred that the PCS method is more effective in motivating customers to make product purchases when compared to the other advertising methods.

Table 4: Paired Samples Test of PCS with Other Five Strategies (Willingness to Make a Purchase)

Paired Group		Mean	Std. Deviation	Std. Error Mean	T	Sig. (2-tailed)
PCS	Preference	0.571	1.089	0.129	4.418	0.000
	Context	0.400	1.100	0.130	3.062	0.003
	Social	0.357	1.191	0.141	2.517	0.014
	CF	0.785	1.274	0.151	5.193	0.000
	Random	1.100	1.123	0.133	8.253	0.000

6. Discussion and Conclusion

The growing population of smartphone users has positioned mobile devices as one of the most promising platforms for advertisers to effectively deliver their ads. Because of its great opportunities for targeting user, mobile advertising has attracted more and more venders' and advertisers' attention. However, current mobile advertising approaches suffer from a lack of effective advertising mechanisms, resulting in suboptimal performance. Consequently, there arises a necessity for innovative mechanisms to enhance the effectiveness of mobile ad recommendations which can precisely respond the trend of the time. In response to this demand, we apply the social influence and context-aware concept, which are the core features of social commerce and mobile computing, to the proposed mobile advertising mechanism.

Our proposed mechanism takes the fact that a user's need changing with context into consideration by adopting the concept of context-fitness into social filtering method, which could increase the targeting accuracy. To increase the acceptance of ads, the recommendations with the social influential messages and contextual messages generated by the system can automatically gain a more positive users' acceptance and feedback. Furthermore, we employ store categorization to create user preference profiles and utilize a distance-based similarity computing approach to assess the suitability of matching advertisements for each user. To evaluate the performance of our propose mechanism, we conduct a series of experiments which demonstrated that our proposed PCS mobile advertising mechanism outperforms other benchmark methods, providing a more accurate and efficient approach for mobile ad recommendations. As the number of smartphone users continues to rise, our proposed mechanism offers significant potential for improving the effectiveness of mobile advertising and targeting users more effectively.

A successful advertising greatly relies on its alignment with the needs and preferences of users. Thus, enhancing the compatibility between advertising content and users is vital for maximizing profits for advertisers and vendors. By integrating context awareness and social referral analyses, it is possible to determine the most appropriate stores for users. However, the main challenge lies in effectively combining these techniques to achieve optimal results.

Our study utilizes contextual fitness analysis, social referral analysis, and devise a groundbreaking mechanism for contextual mobile advertising recommendations. Through our rigorous experimentation conducted on participants' smartphones, we have unequivocally established that this mechanism substantially amplifies the precision of user targeting and the efficacy of ad recommendations compared to other benchmark advertising methods.

The preference targeting, context relevance and social referral features allows us to not only decrease the negative impression on the advertisement received. For the efficiency aspect, the proposed mechanism can deliver ads to targeted users with a higher accuracy rate. This makes the proposed advertising meet the goal of adverting and brings benefits to marketers. For the effectiveness aspect, the proposed mechanism can gain more positive feedback from users. The positive reactions from users prevent the advertising disturbance and ensure that information of advertisements would be delivered to the audiences with satisfaction. This research contributes efforts to mobile commerce and applications which applied on social media from the perspectives of customer, vendor, and a mobile commerce platform.

6.1. Research Contributions

Our research makes several noteworthy contributions. Firstly, from the system development perspective, in this work, we have developed an effective PCS mobile advertising application which has significantly enhanced the precision of users targeting and increased the purchase willingness of the recommended stores, as demonstrated by experimental results. Secondly, from the methodological perspective, we believe that social influence and context are crucial factors in a mobile environment, and advertisers should account for them. Additionally, we employ store categorization to establish user preference profiles and utilize a distance-based similarity computing approach to evaluate the appropriateness of matching advertisements for each user. Thirdly, from the practical perspective, this work introduces an innovative approach to utilizing contextual rating data to characterize stores and identify potential user needs, our approach highlights the importance of context-aware recommendations. This contribution has the potential to inspire the review platforms and advertisers to recognize the value of incorporating contextual information in their recommendation strategies. Lastly, from the empirical perspective, the experiments provide compelling evidence that context-aware information can significantly enhance the accuracy on predicting the users' evolving needs. Furthermore, the inclusion of a social referral mechanism has been observed to alleviate negative sentiment towards ad recommendations. Methodologically, our work highlights the importance of integrating social context factors into mobile advertising mechanisms.

6.2. Research Limitations

Despite the significant contributions of this study, several limitations should be acknowledged. First, due to the privacy issue, it is difficult to extract online personal data (e.g., social information). Therefore, we invite participants to join in the experiments. If there are more users recruited and engaged, the accuracy of the proposed mechanisms will be more improved. Secondly, due to the lack of contextual rating data for local stores on existing review websites, we had to rely on self-reported data from our experimental participants. As a result, it is important to note that the number of stores included in the study and the availability of contextual rating data used for modeling store characteristics were limited, which may have impacted the effectiveness of the system. Thirdly, while we incorporated visiting day, time, and weather, other contextual factors, such as temperature and emotion, could also impact users' decision-making and satisfaction. Lastly, location-based group-recommendation is also a new area for advertising. With the help of GPS, why can we find a set of friends who are near to each other to recommend them to do what they like or to eat what they prefer to together.

6.3. Future Work

Further exploration and investigation are warranted in several interrelated areas. Firstly, to collect a larger amount of social information from a user’s social network, developers could incorporate an incentive mechanism into the system to encourage the disclosure of information. Secondly, although we utilized many things from social networks for this study, there are also some social interactions that we did not use, like poke, share, events, etc. In the future, we can utilize more types of social interactions to evaluate social knowledge and experts. Secondly, besides relying solely on contextual rating data, other indicators, such as the duration of store visits (which can be automatically collected from mobile device logs), could be explored to enhance the accuracy of mobile ad recommendations. Besides, the contextual data can be analyzed based on the time slots and weather types. Time context is obtained from the timestamp of the posts and the weather data of a time slot is achieved by referring the Weather Underground website, utilizing JSON API. Thirdly, high-level context factors, including personal emotions and user profiles (such as job, income, and age), have a significant impact on users' decision-making processes, and this area could be further investigated. Lastly, the use of location-based group recommendations presents a promising area for advertising. GPS and social media can be utilized to identify a group of friends nearby and recommend activities they may enjoy together. Future research should explore the potential benefits and challenges of this approach.

Acknowledgment

This research was supported by the National Science and Technology Council of Taiwan (Republic of China) under the grant NSTC 112-2410-H-992 -025.

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