# Phone-based Data Collection for Consumer Behavior Research

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ABSTRACT
An important question in consumer behavior research is how to systematically and quantitatively determine patterns in consumer behaviors that can facilitate understanding of where, when, and how consumers purchase products and services at (non-online) retail shops. Collecting naturalistic data on real consumers who shop at retail stores is often one of the most critical, challenging, and expensive parts of consumer behavior studies. This paper introduces phone-based data collection to consumer behavior research, specifically targeting local residences shopping at their neighborhood convenience stores. We have developed a phone-based data collection system (called ConvenienceProbe) and deployed and tested the system by collecting real customer flow data to neighborhood convenience stores. Results shows that consumer flow data collected from the ConvenienceProbe system is comparable to that from a traditional face-to-face interview method.

**Keywords** Phone sensing, data collection and analysis, consumer behavior and marketing research

# 1. INTRODUCTION

Mobile phones have become indispensable part of our everyday lives, as they go with us everywhere. New mobile phones are equipped with sophisticated sensing, computing, and communication capabilities. For example, new smart phones have a variety of sensors including GPS, accelerometer, digital compass, Wi-Fi, and cell-ID sensors that can detect users' locations and movements. By taking advantages of phones' ubiquitous presence with their users and phones' sensory capability to observe their users everywhere, it is possible to leverage and organize these phones (which are user-owned and –maintained) and to build *naturalistic* and low-cost data collection systems that capture spatially relevant information of human behavior at *large scales*. Such data collection of human behavior enables geographical and quantitative analysis of where, when and how people conduct their everyday activities *invisibly* and *non-intrusively*, i.e., without disruption to human natural behaviors.

This study introduces this phone-based data collection approach to the field of marketing research, focusing specifically on determining spatial patterns in customer behaviors and understanding where, when, and how urban consumers visit their neighborhood convenient stores (CVS). For examples, where do a CVS outlet's customers come from? Where are the gaps and overlaps in the market coverage of nearby and competing CVS outlets? What is the cannibalization effect of nearby CVS outlets that compete for the same customer base in the same area?

**Marketing research and retail trade area analysis**
Since CVS outlets sell similar items, in-depth marketing research and retail trade area analysis play particularly vital roles in determining their business success. Marketing research is a systematically approach of identifying, collecting and analyzing data relevant to marketing products and services. Consumer research is a part of marketing research that analyzes how changing marketing factors affect customer behavior. This study targets consumer research and provides a phone-based data collection system to gather spatial data about customers' CVS visits, which include customer inbound/outbound paths to CVS stores. Retail trade area analysis [8], which is one kind of marketing research, is defined as a methodology or technique that provides a basis for understanding, quantifying and visualizing customer flow and moving direction in the area around a store. In other words, a store's retail trade area maps a geographical area where most of a store's customers come from. Such information is critical for making business decisions, such as selecting the optimal store location, identifying competing stores, and placing outdoor advertisements. Since consumer flow and direction may change due to newly opening or closing of nearby stores and changing composition of local residence, there is a need to regularly perform retail trade area analysis to track a store's current trade area and customer flow.

**Opportunities for phone-based data collection**

We believe that phones provide opportunities to *outsource* the process of collecting customer flow data to any local residence who owns and/or carries a mobile phone and is also a customer of neighborhood CVS stores. Outsourcing data collection to consumers can significantly reduce the cost for consumer behavior researchers to run quantitative marketing studies. Furthermore, phones provide opportunities to *automate* the data collection process by embedding smart sensing, detecting, and logging of customers' CVS trips in the phones. Automating data collection does not only enable gathering of consumer behavior naturally without interrupting users' activities, but also reduces underreporting and recall errors found in the traditional self-reporting, face-to-face interview, and surveying methods.

Traditional data collection methods for analyzing consumer behaviors [2] are labor-intensive. Researchers recruit human observers to watch customers entering and leaving a store. Those who are regular customers are asked to fill out a questionnaire about their inbound/outbound paths to the store and shopping behavior. Another commonly used human metering method is by shadowing customers and observing their behavior over time. Since human labor does not scale, data collection often becomes an expensive part in consumer behavior research. To reduce the cost of collecting consumer data, this study proposes the ConvenienceProbe system, which organizes phones as mobile sensors and gathers customer flow data from phones and their owners who shop at neighborhood CVS outlets.

The ConvenienceProbe system works by enabling consumer behavior researchers to recruit qualified residence, who live or work in an area of interest, to *participate* in the data collection process. Participants first download an application to their phones, in which the phone application embeds automated sensing to detect trips to CVS outlets and also logs CVS patronage data in their phones. The phone application runs in the background and does not disturb participants' normal phone's usage. Periodically, participants upload data from their phones to a data repository on a server. For security and privacy purpose, the phone application must ask and obtain user permission prior to any data uploading. At the end of uploading data, participants can optionally help in correcting any mistake made by automated sensing and/or label meta-data description (e.g., purchased items, purchased amount, etc.) about their CVS visits. Then, the server processes data stored in the data repository, while summarizing and visualizing customer flow behavior to the consumer behavior researchers. To encourage participation in data collection, consumer behavior researchers can set incentive policies that reward micropayments to participants based on the quality and quantity of their uploaded data.

The contributions of this paper are two-fold:

- We introduce a phone-based data collection system that can significantly reduce the cost of data collection for consumer behavior researchers. This system enables outsource and automation of the consumer data collection to everyday customers and by organizing and embedding automated sensing into their phones.
- We have designed and implemented this phone-based data collection system called ConvenienceProbe. We have also deployed and tested the ConvenienceProbe system by collecting real customer flow data to CVS outlets within an area of interest. Results shows that consumer flow data collected from the ConvenienceProbe system is comparable to that from a traditional face-to-face interview method.

The remainder of this paper is organized as follows. Section 2 presents the design and implementation of the ConvenienceProbe system. Section 3 details a comparison user study that uses both the ConvenienceProbe system and the traditional face-to-face interview method to collects real customer flow data to CVS stores, and presents findings from this comparison study. Section 4 discusses pros and cons associated with the ConvenienceProbe system and the traditional face-to-face interview method. Section 5 reviews related work. Finally, Section 6 draws conclusion and outlines directions for future work.

# 2. SYSTEM ARCHITECTURE AND DESIGN

The ConvenienceProbe system is based on the client-server architecture shown in Fig. 1. Phones carried by participants run the client-side phone application that senses participants' consumer behavior. Periodically, phones transmit consumer behavior data to a backend server through the phones' wireless networks. The ConvenienceProbe system operates according to the following steps. (1) Participants download the phone application to their phones and run it in the background. Participants carry their phones while performing normal daily routines including trips to neighborhood CVS outlets. (2) The phone application implements automated sensing that analyzes data from the phone's location & movement sensors and detect visits to CVS outlets. The phone application also logs CVS trip data in the phone. (3) Periodically, participants upload CVS trip data to a data repository in the backend server. To motivate participants to contribute their consumer data, consumer behavior

researchers can set reward policies that determine how much money participants earn given the quality and quantity of data uploaded from their phones to the server. (4) Optionally, participants can earn extra money by correcting any mistake made by the phone's automated sensing and/or by labeling additional details about their store visits (e.g., the purchase amount, purchased items, etc.). (5) Consumer behavior researchers view data collection progress made by each and/or all participant(s), and then optionally consider dropping any non-productive participant not contributing data. (6) The server implements data visualization tools such that consumer behavior researchers can view spatial patterns in customer flow behaviors from data currently stored in the server's data repository.
The following subsections explain the details of the phone application and the backend server.

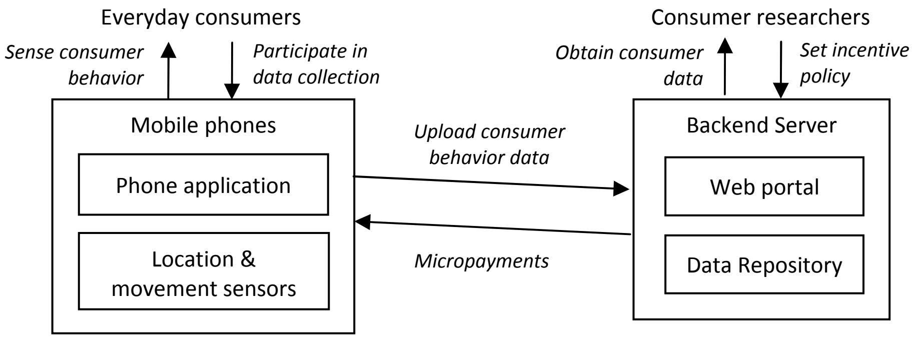



**Figure 1. Client-server architecture of the ConvenienceProbe system.**

## 2.1 Phone Application

Figure 2 shows the design of the phone application that includes the following two modules: (1) phone user interface and (2) automated CVS trip detection with battery-efficient sensor selection. Participants use *phone user interface* to upload any collected data to a server and/or to label meta-data description about their CVS visits. The mobile phone implements *automated CVS trip detection* and logs any spatial data associated with these detected CVS trips. The data collection software performs *optimal sensor selection* to conserve the phone's battery and to scale down its energy consumption when a participant is not within the target area and/or not visiting any neighborhood CVS stores. For additional battery saving, a mobile phone offloads processing of inbound/outbound customer path reconstruction to the back-end server. Currently, the phone application supports HTC Android smartphone series, including HTC Magic, Hero, Legend, and Desire models. The following subsections explain each phone application module in details.

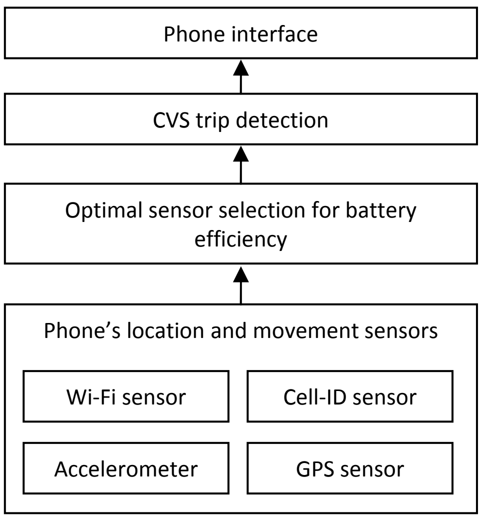



**Figure 2. Design of the phone application**

**Phone user interface**

We designed simple phone user interface that allows participants to perform data uploading and to insert meta-data descriptions with only a few button clicks. The user interface serves two main functions: (1) to take a photograph of the CVS purchase receipt as evidence of a store visit, and (2) to upload CVS trip data logged in a phone to a server. To correct any mistake made by the phone's automated CVS trip detection, a participant matches each receipt photograph to a list of phone-detected CVS visits (Fig. 5(b)). Any receipt photograph without a matching phone-detected CVS visit (i.e., a false negative in which the phone did not detect a CVS visit but in fact there was a visit) and any phone-detected CVS visit without a matching receipt photograph (i.e., a false positive in which the phone detected a CVS visit but in fact there was no visit) counts as an error in the automated detection algorithm. The user interface provides two uploading methods to transfer CVS visit data from a phone to the server. The first uploading method uses a direct wireless Internet connection on a phone to transfer data to the server. In the absence of a direct wireless Internet connection on a phone, the second uploading method uses a USB connection to a PC, in which the PC first retrieves data from the phone and then transfers data to the server.


(a) The main interface (b) The labeling interface

**Figure 3. Phone's main and labeling interfaces. The main interface (Fig. 3(a)) shows a photo receipt capturing button, a data uploading button, and an exit button. The labeling interface (Fig. 3(b)) shows a list of phone-detected store visits from which a participant matches each receipt photo to.**

**Automated CVS trip detection with battery-efficient sensor selection**

Running data collection software consumes a phone's limited battery. As participants need to use their phones' battery for normal day-to-day communications, a key issue is battery management on the phone. In particular, participants would complain and/or refuse to participate in the data collection process if the data collection software consumed significant battery but did not collect useful data that earned rewards. In other words, the data collection software ought to *scale down* its battery consumption during times of zero/low probability of collecting useful data. To achieve this scaling-down goal, we developed the battery-efficient sensor selection algorithm by taking into account sensors' accuracy-energy tradeoff, i.e., accuracy represents a sensor's positional accuracy and energy represents the sensor's energy consumption. For examples, the GPS sensor gives accurate location but consumes large energy, whereas the cell-ID sensor provides coarse location but draws little energy. When a phone is outside the area of interest, the probability of collecting useful data is almost zero. Hence, the sensor selection algorithm turns on only the low-power cell-ID sensor that outputs coarse location sufficient to determine when a participant enters the area of interest. At the same time, it turns off all other sensors to conserve battery.

The battery-efficient sensor selection algorithm considers the following location and movement sensors commonly found in a smart phone: cell-ID, accelerometer, Wi-Fi, and GPS sensors, which are listed in order of increasing energy consumption. How the CVS trip detection algorithm uses each of these sensors is describes as follows. (1) The cell-ID sensor detects a phone entering the area of interest by matching the phone-detected cell-ID(s) to those belonging to the area. (2) The accelerometer sensor detects the presence/absence of user movement. Presence of user movement triggers continuous location update, and absence of user movement discontinues location update. (3) The Wi-Fi sensor is used for place detection [7] that identifies a participant making a transition between places (e.g., moving from an office to a CVS outlet) vs. a stop at a place (e.g., shopping at a CVS outlet). Phone-received Wi-Fi signature is also used to recognize a specific CVS outlet by matching the phone-received Wi-Fi signature to the Wi-Fi APs previously profiled and located nearby the CVS outlet location. (4) The GPS sensor provides inbound/outbound paths to a CVS store. GPS signals from a phone can also be used to detect any indoor/outdoor transition. When a participant/phone enters a building, the GPS signals become weak or undetectable.

Figure 4 shows the battery-efficient sensor selection algorithm which chooses the optimal sensor(s) according to the phone's spatial context. The three spatial states are defined as follows.

- *(S1) Outside the area of interest*: The sensor selection algorithm turns on only the low-power cell-ID sensor which checks if the phone enters the area of interest with the appearance of cell-ID(s) belonging to that area.
- *(S2) Outdoor and inside the area of interest*: The sensor selection algorithm turns on all sensors except accelerometer. These selected sensors are used as follows. The cell-ID sensor checks when the phone leaves the area of interest with the disappearance of cell-ID(s) belonging to that area. GPS sensor detects any transition from outdoor to an indoor building. GPS sensor also logs any inbound/outbound path to a place such as a CVS store. Wi-Fi sensor identifies a specific CVS store by matching the phone-received Wi-Fi signatures to those belong a CVS outlet.
- *(S3) Indoor and inside the area of interest*: The sensor selection algorithm turns on the cell-ID, accelerometer, and GPS sensors. Cell-ID sensor checks when the phone leaves the area of interest with the disappearance of cell-ID(s) belonging to that area. The accelerometer detects presence/absence of user movement to continue/discontinue location update. In the presence of user movement, the algorithm turns on the GPS sensor at a low sampling rate, e.g., every other minute, to detect any transition from an indoor building to outdoor.

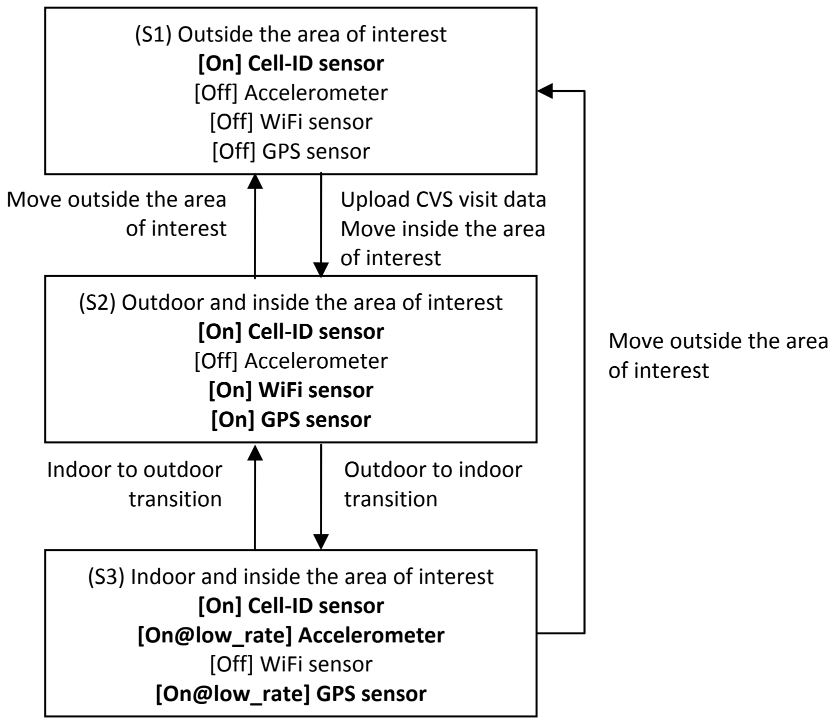



**Figure 4. The state diagram of the battery-efficient sensor selection algorithm. Three states are S1(outside the area of interest), S2(inside the area of interest and outdoor) and S3(inside the area**

**of interest and indoor). Each state shows the selected sensor(s) as [On] and unselected sensor(s) as [Off].**

We performed an experiment to determine the accuracy of this battery-efficient CVS trip detection algorithm. Data were analyzed from 394 CVS visit logs from the user study (described in the next section) involving 42 participants. To calculate detection accuracy, we assume that a CVS visit leaves GPS log trace around locations of CVS outlets. Therefore, we define detection accuracy as how well the CVS trip detection algorithm correctly classifies events where participants only pass through a CVS store without entering it (defined as a non-visit) from events where participants enter a CVS store (defined as a visit). To obtain the ground-truth CVS visits, participants were asked to take photographs of purchase receipts as ground truth evidence of CVS visits (described in the phone user interface subsection above). Any unmatched receipt photograph or any unmatched phone-detected visit constitutes an error in the CVS visit detection algorithm. Table 3 shows the accuracy result in a confusion matrix. The detection accuracy of CVS visits was 94.16%, which was better than the detection accuracy of CVS non-visits at 90.08%. Most of the detection errors came from participants standing near the entrance to a CVS store where the phone-received Wi-Fi signature is similar to the in-store's Wi-Fi signature, thus caused detection errors. We have found that 90% plus CVS detection accuracy is sufficient for consumer behavior research. At the same time, during actual user experiment with 42 participants, we did not find any participant who reported a recharged phone in the morning ran out of battery at the end of their day using our battery-efficient sensor selection algorithm.

**Table 1. Confusion matrix measures the accuracy of CVS in-store visit detection**

| Detection / Actual | Visits | Non-visits |
|---|---|---|
| Visits | 371 | 23 |
| Non-visits | 24 | 218 |

**Data uploading**
To protect location privacy of participants, only the CVS trip data will be uploaded from phones to the server. From the phone user interface, participants click the uploading button to initiate any data uploading in which they must give explicit permission to the phone application on each data uploading operation. To reduce the amount of data transmission, the phone application packs and compresses CVS trip data before transferring them to the server.

## 2.2. Back-end Server

Figure 5 shows the design of the backend server, which includes the following three components (1) the web portal, (2) the data repository, and (3) the data analysis and visualization tools. The following subsections explain each server component in details.

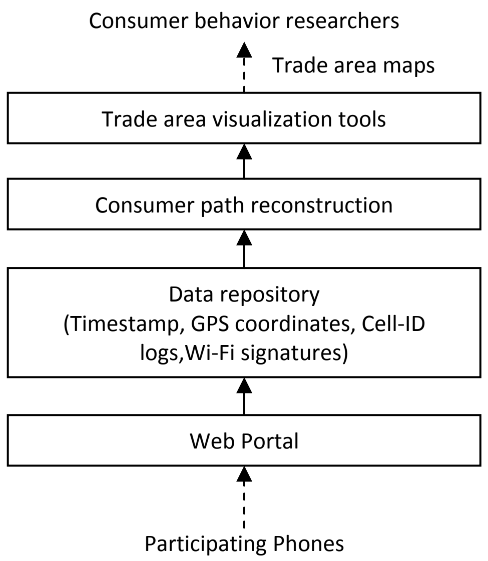



**Figure 5. Design of the back-end server.**

**Web portal**

Interested individuals can browse through the portal's web pages that provide information about this consumer behavior research and its data collection process, including descriptions about the purpose of this study, user qualifications to participate in this study, reward and incentive policies, etc. After individuals agree to participate in this study, the web portal asks them to complete questionnaires whose purpose is to screen their qualifications for this study. The questionnaires include questions such as whether they live and work within the area of interest, how frequent they visit the neighborhood CVS outlets, whether they own and carry smart phones capable of running the ConvenienceProbe phone application, etc. If they meet these qualifications, the web portal asks them to fill out their contact and user profile information and to create individual accounts where they will upload data and receive micropayments. Finally, the web portal asks them to sign a consent form agreeing to release their data for this study.

Each time a participant uploads data to the server, the website summarizes the amount of money earned and the amount of data contributed to the server's data repository. To encourage participants to upload data to the server in a timely fashion, the reward policy reduces payout for any late upload (i.e., longer than two days) by calculating the elapsed time between the time when a phone logs data and the time when a user uploads data to the server. The reason for requesting timely upload is that human recall errors increase over time, i.e., participants would make less recall errors when they correct mistakes made by automated sensing and/or label meta-data description on the uploaded CVS trip data.

**Data repository**

The data repository provides a centralized storage of all CVS visit data uploaded from participants. The uploaded CVS trip data consists of (1) raw sensor data including timestamp, GPS coordinates, cell-ID log, and received Wi-Fi signatures, and (2) phone-detected store visits and any meta-data description labeled by participants. The marketing research and retail trade area analysis, described in the Introduction Section, retrieve data from the data repository and performs customer data analysis and visualization.

**Customer path reconstruction.** For each phone-detect CVS trip, the system reconstructs the corresponding consumer paths. Each consumer path has three elements. (1) An inbound path is the store-arrival path taken by a customer starting from a previous destination place (e.g., participant's home or office building) and arriving at the store. (2) In-store time is the amount of time that a customer stays at the store. (3) An outbound path is the store-departure path taken by a customer leaving the store to his/her next destination. GPS data from phones plot these consumer paths and form routes.

**Retail trade area visualization.** Figure 10(a) shows an example of a retail trade area map computed from the Bounding Wedge-Casting method [17]. This method divides a store's surrounding area into directional wedge sectors. The store is the hub located at the center of all wedge sectors. For example, the retail trade area map in Figure 10(a) contains twelve 30-degree wedge sectors. Each wedge sector grows from the store location in the center outwards to cover locations of additional customers until the cumulative number of customers exceeds a threshold such as 80% of customers.

# 3. User Study

The effectiveness of the ConvenienceProbe system was tested in a user study in which we collected real customer flow of three competing CVS stores situated within the same neighborhood area. To compare the data collected using the ConvenienceProbe system to those using the traditional data collection method, we also ran a pen-and paper survey that involved face-to-face interviews with customers of these CVS stores. This section describes the design and experimental results of this comparative user study, which were guided by the following inquiries:

- What was the relative *data quality* and *quantity* collected from the ConvenienceProbe system compared to the traditional face-to-face interview?
- What was the *trade area analysis result* obtained from the ConvenienceProbe system compared to the traditional face-to-face interview?

Exactly how well the ConvenienceProbe system collects data was evaluated by comparing similarity in the spatial patterns obtained from the traditional face-to-face interview (i.e., used as a baseline) with those obtained from the ConvenienceProbe system. To make a meaningful comparison, the comparison study was designed to differ on the aspect of data collection methods, i.e., the traditional face-to-face interview method (called the *interview method* from here) vs. the ConvenienceProbe method (called the *phone method* from here), while maintaining consistence in other aspects of studies, including the same CVS outlets in the focal neighborhood, the same qualification criteria on selecting participants, the same result analysis methodology on the customer flow data (inbound/outbound paths and source/destination points), etc.

## 3.1 Physical setting

We chose a triangular block near university campus and within a highly populated city as the study area. Figure 7 marks this study area in green boundary lines. The size of this triangular area measures approximately 0.128 square kilometer, and the lengths of triangular edges are approximately 470, 540, and 640 meters. This focal area has three competing CVS outlets whose locations are marked on Fig. 7 as (A) Family Mart, (B) Xinsheng 7-11, and (C) Roosevelt 7-11.


**Figure 7. The triangular dotted boundary lines mark the focal area. This area is adjacent to a university campus (X). There are three CVS stores: (A) Family Mart, (B) Xinsheng 7-11, and (C) Roosevelt 7-11. Other landmarks near the focal area include Gongguan (Y) and Tai-Power (Z) metro rapid transit (MRT) stations.**

### 3.2 Participants

In the ConvenienceProbe campaign, we recruited 42 participants who either already owned HTC Android phones capable of running our phone application or borrowed one compatible HTC Android phone from us for the duration of this study. The age distribution of participants ranged between 18 and 53 (the mean age was 25). Their occupations included students, clerks, sales, engineers, housekeepers, etc. All participants were residents or worked nearby or within the focal area, and they regularly patronized the selected CVS stores. Compensation to participants was weekly payment with a guaranteed base NT$500 (approximately US$17) plus an extra daily bonus NT$30 (approximately US$1) directly related to the number of days with uploading CVS visit data. To prevent influencing consuming behavior, a maximum weekly payment was set at NT$700 (approximately US$23.7) so that participants would not increase their CVS visits due to the minor daily incentive. From 42 participants, we collected 394 visits to the three CVS stores, specifically 182, 154, and 58 visits to the stores A, B, and C respectively.

In the interview method, we surveyed 90 customers (i.e., 30 customers per store) outside of the three CVS stores.-The profiles of customers visiting these CVS stores vary by time and other less predictable factors such as special sale events, etc. In order to reduce the impact of the time-dependant factors on the characteristics of customers, respondents were recruited independently to cover different hours of a day (10 am ~ 8 pm) and also both weekdays and weekends. The age distribution of the respondents ranged between 12 and 73 (the mean age was 29). These respondents regularly patronized these CVS stores. Their occupations were similar to occupations of participants recruited in the ConvenienceProbe campaign.

The profiles of participants in both mobile phone and survey modes are listed in Table 2. Doubled-tailed T-test results show no significant difference between these two groups in sex (p=0.619), ages (p=0.200), store visit frequency (p=0.972), and disposable income levels (p=0.725).

**Table 2. Demography of participants in ConvenienceProbe and the traditional human-interview campaigns**

| Data Collection | # of | Male | Age | # of | Store visit | Disposable income |
|---|---|---|---|---|---|---|

| Methods | Subjects | (Female) | distribution | store visits | frequency (per week) | levels v.s. the number of subjects | |
|---|---|---|---|---|---|---|---|
| ConvenienceProbe system | 42 | 23 (19) | 18~53 (mean=25, std=7) | 394 | 0.5~10 (mean=3.85, std=2.26) | Less than Monthly PDI[1] | (34) |
| | | | | | | More than monthly PDI | (8) |
| Traditional human-interview | 90 | 54 (36) | 12~73 (mean=28, std=13) | 90 | 1~20 (mean=3.55, std=2.85) | Less than Monthly PDI | (66) |
| | | | | | | More than monthly PDI | (24) |

## 3.3 Procedure

**Procedure in the phone method.** The procedure consisted of two phases: (1) a screening phase to select qualified subjects and collect background information and (2) the experiment phase. Consumers were recruited via the Internet ad and snowball introduction. The selection criteria were those who either lived or worked in the focal area, as well as frequently shopped at one of the three CVS stores. Qualified participants began performing data collection tasks and were asked to regularly upload their data.

In the screening phase, interested candidates first filled questionnaires on the web portal. The questions are listed in Table 3 which investigated the candidates' familiarity with the digital devices (C1 ~ C3) and their daily consumption habits (S1 ~ S3). These questions determined whether candidates had basic technical skills and whether they regularly patronized the selected CVS stores. After they passed the screening stage, candidates were asked to fill out a pre-study questionnaire with their personal profiles, and disposable monthly income. They also set up their personal accounts for uploading data later. After completing all questions, our system summarized the degree of matching for candidates for further confirmation. Finally, qualified participants were asked to attend an orientation on how to use the system.

**Table 3. Questions for screening subjects.**

| | ID | Questions |
|---|---|---|
| Familiarity with the digital devices | C1 | Do you usually use high-tech products? |
| | C2 | Do you use a smartphone as your primary phone? |
| | C3 | Which model is your smartphone? (HTC Magic, Hero, Legend, Desire, iPhone or others) |
| Daily consumption habits | S1 | Do you live or work in the focal area? |
| | S2 | Do you patronize at least one target CVS every three days? |
| | S3 | Please select the CVS stores that you regularly patronize in your daily life? ("none of them", "Xinsheng 7-11", "Family Mart", "Roosevelt 7-11" or "more than one store") |

The experiment phase ran for 2-3 weeks when participants carried phones that recorded inbound/outbound paths of their CVS trips. Participants were responsible for recharging these phones at the end of each day.

**Procedure in the interview method.** This procedure involved the two following steps. (1) Deployed interviewers outside the CVS stores and approached customers when they left the CVS store. (2) If the approached customers were regular customers of these CVS store, interviewers assisted these customers in filling out a short questionnaire about their origin/destination points of the current store visit and other consumer behavior.

[1] According to the survey of family income and expenditure conducted by the Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan, the monthly personal disposable income (PDI) of 2009 in Taiwan is 642 USD.

### 3.4 Evaluation metrics and results

**Evaluation metric for inbound/outbound directions.** To determine how well customer flow data collected from the phone method match with those collected from the interview method, the primary evaluation metric is the similarity in customer inbound/outbound directions to/from a CVS store between these two methods. High similarity means that the data collected from the phone and interview methods have little difference in term of customer flow information. Recall that customer inbound/outbound directions (described in Section 2.2) represented which route customers took to enter/leave a store. Figure 9 shows the location of stores A, B, and C with 3-4 possible customer inbound/outbound directions entering/leaving these stores.

Denote $S_d$ as a metric for measuring similarity in customer inbound/outbound directions between the phone and interview methods. The compositions and calculations of this $S_d$ value are described as follows. (1) We divided all the CVS store visits into different flow components according to customer inbound/outbound directions. (2) We formed a *customer flow vector* for each CVS store for each of the two data collection methods. A customer flow vector contains vector components whose scalar values correspond to the percentages of customers entering/leaving the store from a specific direction. As shown in Fig. 9(a), store B has two customer flow vectors from the phone method (denoted as $\vec{\mathbf{V}}_{\mathbf{phone}}$) and from the interview method ($\vec{\mathbf{V}}_{\mathbf{interview}}$). Each customer flow vector $\mathbf{V}$ has vector components corresponding to its multiple flow directions: ($\vec{\mathbf{V}}_{\mathbf{interview\ or\ phone}}$ = ($D_1$, $D_2$, .., $D_m$). For example, store B in Fig. 9(a) has four flow directions (NW, SW, SE, NE): $\vec{\mathbf{V}}^{\mathbf{B}}_{\mathbf{interview\ or\ phone}}$ = ($D_{NW}$, $D_{SW}$, $D_{NE}$, $D_{SE}$) = ($D_1$, $D_2$, $D_3$, $D_4$). The scalar value $D_{NW}$ is the percentage of customers entering/leaving the store from/to the northwest direction. (3) For each store, we compute the Cosine-based correlation between the two customer flow vectors, $\vec{\mathbf{V}}_{\mathbf{phone}}$ and $\vec{\mathbf{V}}_{\mathbf{interview}}$, as the measure of their similarity.

$$S_d = \frac{\vec{\mathbf{V}}_{phone} \bullet \vec{\mathbf{V}}_{interview}}{|\vec{\mathbf{V}}_{phone}||\vec{\mathbf{V}}_{interview}|} \tag{1}$$


(a) Store A (b) Store B (c) Store C

**Figure 9. The inbound/outbound directions of each CVS store. Store A and C are located at 3-way T-intersections with three inbound/outbound directions, and store B is located in a lane with four inbound/outbound directions.**

**Evaluation result for inbound/outbound directions.** Table 4 shows the similarity results indicated by customer flow vectors of the three CVS stores. Data were obtained by analyzing customer inbound/outbound paths collected from the phone method (Column 2) and the interview method (Column 3). Column 4 of Table 4 calculates the Cosine-based correlation similarity scores ($S_d$) between phone/interview methods on the inbound/outbound directions of three stores using Equation (1). For all three stores, similarity scores between phone/interview methods are higher than 92%. For stores A and B, similarity scores between phone/interview methods reach nearly 100%. The average similarity score among the three stores is 96%. For statistical validation, we conducted the Chi-square ($\chi$2) equality of proportion test for equality of distributions on data obtained by the phone method (i.e., the observed) and the interview method (i.e., the expected). Since the Chi-square equality test does not take percentages, we counted the customer flow occurrence for each inbound/outbound direction to each store and used that number for the Chi-square equality test. Column 5 of Table 4 shows the $\chi^2$ value for each store. The $\chi^2$ value indicates a good fit between the phone method (observed) and the interview method (expected) for all three stores (respectively, $\chi^2(2) = 0.10$, $p < 0.05$ for store A; $\chi^2(3) = 3.61$, $p < 0.05$ for store B; $\chi^2(3) = 6.28$, $p < 0.01$ for store C).

**Table 4. Similarity results between the flow vectors (i.e., a store's customer inbound/outbound directions) of the phone and interview methods for each of three CVS stores. Similarity scores are computed using Equation (1).**

| CVS stores *Inbound/outbound directions* | Flow vector from the phone method (n=42, #visits=394) | Flow vector from the interview method (n=90, #visits=90) | Similarity score ($S_d$) | $\chi^2$ value |
|---|---|---|---|---|
| Store A | | | 98.42% | 0.10 ($p$<0.05) |
| $D_1$ | 17.3% | 13.4% | | |
| $D_2$ | 27.8% | 36.6% | | |
| $D_3$ | 54.7% | 50.0% | | |
| Store B | | | 98.557% | 3.61 ($p$<0.05) |
| $D_1$ | 38.2% | 32.2% | | |
| $D_2$ | 25.7% | 25.5% | | |
| $D_3$ | 17.9% | 25.0% | | |
| $D_4$ | 17.9% | 17.8% | | |
| Store C | | | 92.38% | 6.28 ($p$<0.01) |
| $D_1$ | 24.1% | 24.3% | | |
| $D_2$ | 37.9% | 55.1% | | |
| $D_3$ | 37.9% | 20.6% | | |

**Evaluation metric for retail trade areas.** To determine how well the retail trade area obtained from the phone method matches with that obtained from the interview method, we define the following three metrics to measure similarity of two trade areas from the phone and interview methods. (1) Denote *overlapping ratio* as the intersection trade area of the phone/interview methods and divided by the trade area of the interview method (i.e., as the baseline area). (2) Denote *miss ratio* as the trade area found in the interview method but not in the phone method and divided by the trade area of the interview method. (3) Denote *extra ratio* as the trade area found in the phone method but not in the interview method and divided by the trade area of the phone method.

High overlapping percentage suggests that data collected from the phone and interview methods have little difference in term of analyzing trade area results. Recall from Section 2.2 (Bounding Wedge-Casting Method) that a retail trade area consists of wedges in which each wedge is a directional sector area that grows from the store's location outwards to cover customers' locations. Wedge distribution provides a directionality view on where a store's customers come from or leave for in different directions. To plot a conservative wedge, we counted only the closer point to the store between the source and destination points. For example, if a customer visited a home-neighborhood CVS store while traveling from a far-away office location (i.e., the source point) to her home (i.e., the destination point), plotting a trade area conservatively counted only the home location (which was closer to the store and produced a smaller wedge sector) rather than the office location (which is further away from the store and produced a larger wedge sector). Figure 10 plots the conservative retail trade areas of stores A, B, and C in the 30-degree wedge presentation.

For similarity results at the individual wedge level, Table 5 also shows the intersection/miss/extra ratios comparing two methods' wedge sectors.

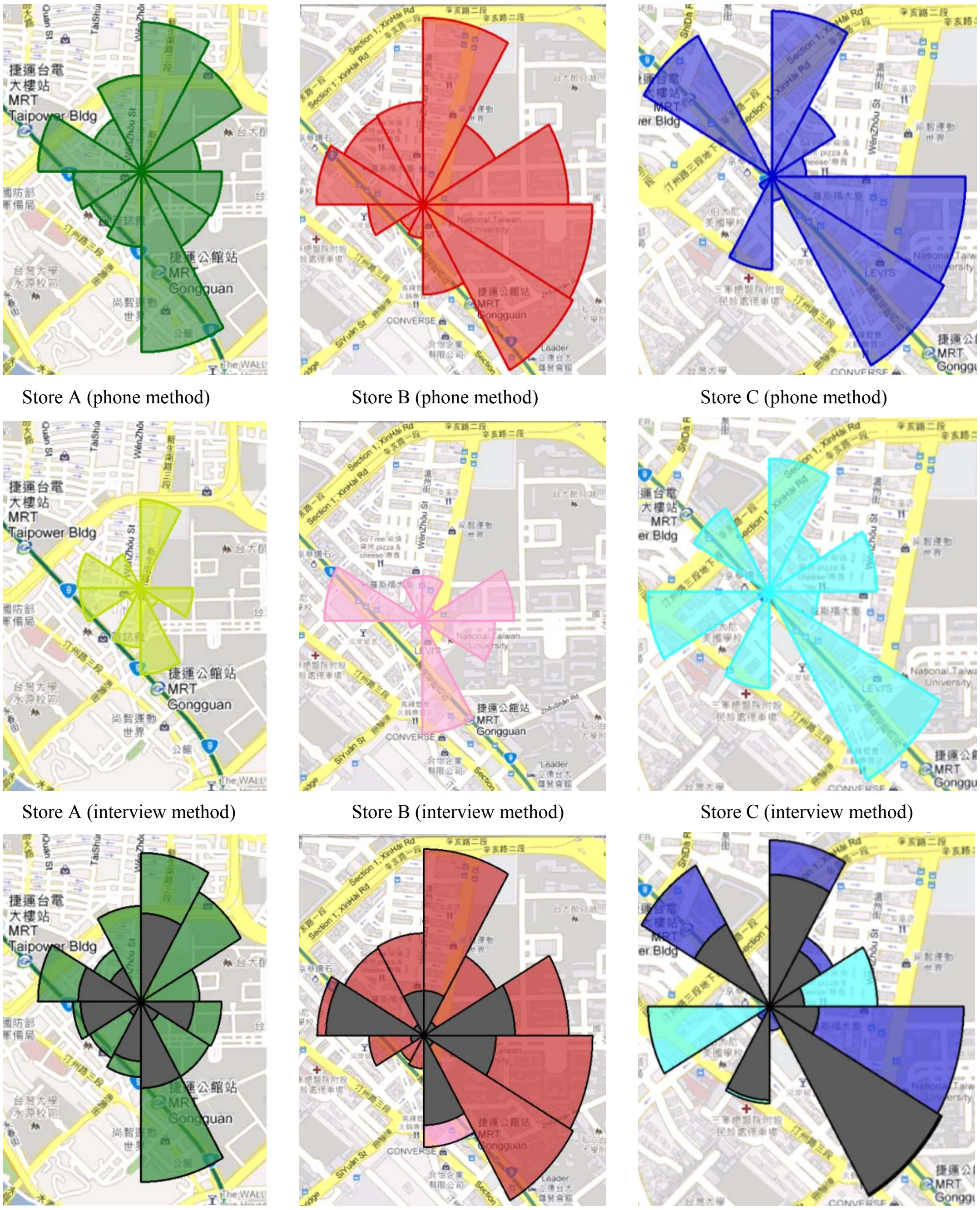
**Evaluation result for retail trade areas.** Table 5 shows the similarity results indicated by retail trade areas of the three CVS stores. Data were obtained by analyzing customer origins/destinations collected from the phone and interview methods. Overlapping ratios (Column 5) were calculated from the retail trade areas and wedge sectors of stores from the phone and interview methods. The average overlapping ratio from 36 wedge sectors was high at 89.5%, suggesting that the phone method was able to capture most trade areas of the interview method. Similarly, the average miss ratio (Column 6) was low at 10.3%, suggesting that the phone method missed little trade areas of the interview method. The average extra ratio (Column 7) was high at 73.9%, suggesting that the phone method captures a lot more trade area than the interview method. The reason was due to the following limitation in the interviewing method - the respondents during interviews often used landmarks on their paths to/from the store as approximate locations to their actual source and destination points, because it was easy for respondents to verbally communicate locations using landmarks. As a result, the use of landmark locations resulted in smaller trade areas from the interview method than those from the phone method. We will discuss this limitation in more details in Section 4.

**Table 5. Similarity results between the trade areas (i.e., area where a store's customer come from) of the phone and interview methods for each of three CVS stores. Similarity is measured by overlapping, miss, and extra ratios (defined in the previous paragraph) separated into each individual wedge sector. "-" means that the ratio has a zero denominator and not dividable.**

| | Phone method wedge area ($km^2$) (n=42, visits=394) | Interview method wedge area ($km^2$) (n=90, visits=90) | intersection area ($km^2$) | Overlapping ratio(%) | Miss ratio(%) | Extra ratio(%) |
|---|---|---|---|---|---|---|
| Store A | | | | | | |
| Overall trade area | 7.631 | 1.959 | 1.695 | 86.5% | 13.5% | 77.8% |
| 1'clock wedge | 1.373 | 0 | 0 | - | - | 100% |
| 2'clock wedge | 0.906 | 0 | 0 | - | - | 100% |
| 3'clock wedge | 0.221 | 0.485 | 0.221 | 0.455 | 54.5% | - |
| 4'clock wedge | 0.409 | 0 | 0 | - | - | 100% |
| 5'clock wedge | 0.409 | 0.087 | 0.087 | 100% | 0% | 78.9% |
| 6'clock wedge | 1.976 | 0.250 | 0.250 | 100% | 0% | 87.3% |
| 7'clock wedge | 0.355 | 0.234 | 0.234 | 100% | 0% | 34.0% |
| 8'clock wedge | 0.236 | 0.014 | 0.014 | 100% | 0% | 94.0% |
| 9'clock wedge | 0.292 | 0.219 | 0.219 | 100% | 0% | 25.1% |
| 10'clock wedge | 0.679 | 0.466 | 0.466 | 100% | 0% | 31.5% |
| 11'clock wedge | 0.203 | 0.028 | 0.028 | 100% | 0% | 86.0% |
| 12'clock wedge | 0.573 | 0.176 | 0.176 | 100% | 0% | 69.2% |
| Store B | | | | | | |
| Overall trade area | 4.520 | 1.071 | 0.963 | 89.9% | 10.1% | 78,7% |
| 1'clock wedge | 0.909 | 0.052 | 0.052 | 100% | 0% | 94.3% |
| 2'clock wedge | 0.211 | 0.006 | 0.006 | 100% | 0% | 97.1% |
| 3'clock wedge | 0.570 | 0.226 | 0.226 | 100% | 0% | 60.4% |
| 4'clock wedge | 0.764 | 0.140 | 0.140 | 100% | 0% | 81.7% |
| 5'clock wedge | 0.906 | 0.004 | 0.004 | 100% | 0% | 99.6% |
| 6'clock wedge | 0.207 | 0.316 | 0.207 | 65.7% | 34.3% | - |
| 7'clock wedge | 0.029 | 0 | 0 | - | - | 100% |
| 8'clock wedge | 0.021 | 0 | 0 | - | - | 100% |
| 9'clock wedge | 0.080 | 0.005 | 0.005 | 100% | 0% | 94.4% |
| 10'clock wedge | 0.314 | 0.266 | 0.266 | 100% | 0% | 15.2% |
| 11'clock wedge | 0.239 | 0.003 | 0.004 | 100% | 0% | 98.4% |
| 12'clock wedge | 0.270 | 0.053 | 0.053 | 100% | 0% | 80.3% |
| Store C | | | | | | |
| Overall trade area | 2.894 | 2.134 | 1.626 | 76.2% | 23.8% | 43.8% |
| 1'clock wedge | 0.530 | 0.326 | 0.326 | 100% | 0% | 38.6% |
| 2'clock wedge | 0.111 | 0.071 | 0.071 | 100% | 0% | 36.3% |
| 3'clock wedge | 0.0232 | 0.229 | 0.023 | 10.1% | 89.9% | - |
| 4'clock wedge | 0.733 | 0.048 | 0.048 | 100% | 0% | 93.4% |
| 5'clock wedge | 0.843 | 0.827 | 0.827 | 100% | 0% | 1.9% |
| 6'clock wedge | 0.011 | 0 | 0 | - | - | 100% |
| 7'clock wedge | 0.169 | 0.179 | 0.169 | 94.2% | 5.8% | - |
| 8'clock wedge | 0.004 | 0 | 0 | - | - | 100% |
| 9'clock wedge | 0 | 0.292 | 0 | 0% | 100% | - |
| 10'clock wedge | 0 | 0 | 0 | - | - | - |
| 11'clock wedge | 0.468 | 0.162 | 0.162 | 100% | 0% | 65.4% |
| 12'clock wedge | 0 | 0 | 0 | - | - | - |

## 3.5 Trade area visualization and analysis

Figure 10 shows the trade areas of stores A, B, and C, which are obtained from analyzing data collected from the phone method (upper three graphs in Fig. 10), the interview method (middle three graphs in Fig. 10) and overlapping trade areas of these two methods (lower three graphs in Fig. 10). For the phone method, the trade area of store A comprises of almost all directions of the focal area, whereas the customers of stores B and C mainly come from the lower portion of the focal area. This trade area distribution is due to the location of store A which has easy access to consumers from all directions. To elaborate, store A is located directly across a gate of the university campus with a traffic light at front, enabling students from the east side of the focal area to reach this store easily. To most of the local residents within the focal triangular region (Fig. 7), store A is closer than the other two stores. Local residents may also leave the focal area through the traffic light across the main street (i.e., Xinsheng South Road).



Store A (phone method) Store B (phone method) Store C (phone method)

Store A (interview method) Store B (interview method) Store C (interview method)

Store A (overlapping ne/interview) Store B (overlapping phone/interview) Store C (overlapping phone/interview)

**Figure 10. The trade areas of stores A, B, and C obtained from the phone method (the upper graphs) or interviewing method (the middle graphs). The bottom row shows overlapping trade areas of these two methods. The black regions indicate the intersection regions between two methods.**

In comparison to store A, store C is also located on one side of a main street (i.e., Roosevelt Road), yet it has the smallest trade area of the three stores. Most of its customers are local residents within this triangular region, comprising the lower portion of the focal area. Few customers come from the other side of the main road, producing a smaller trade area in the lower portion of the focal area. This is due to the facts that (1) the other side of Roosevelt Road is less populous, and (2) consumers are generally unwilling to cross the street to shop when the south side also has some small shops.

Another observation is that although the location of store B is not as good as store A, its trade area still covered most of the primary trade area of store A. Due to the marketing strategies of store B, some consumers preferred to shop at store B to accumulate loyalty program points even though store A was closer to these consumers than store B. The trade areas of store A and B also reveal the brand strength of these two CVS stores.

All these observations consistently appear in the resulting trade areas of both the phone and interview methods. However, the main difference is that the radiating lengths of the wedges from the interview method are shorter than those from the phone method as indicated by the dark-color areas (dark green, red and blue colors areas) in the bottom row of Fig. 10. The reason is that when we interviewed respondents their origin/destination points in the focal area, most of them had difficulty giving precise locations. As a result, they provided colloquially-labeled landmarks on their store-arrival paths, whose locations are closer to the store than their actual origin/destination points.

# 4. DISCUSSION

This section discusses pros and cons associated with the phone method (the ConvenienceProbe system) and the interview method (the traditional face-to-face interview).

**Causes of imprecise data (phone sensory errors vs. human recall/communication errors)**

We have found that the phone method collected more *elaborated* and *precise* consumer flow data than the interview method. For marketing research, detailed and accurate customer source/destination points and path information are critical in obtaining accurate trade area results and for understanding the trade areas in the focal region. We give two reasons for this data quality difference between these two methods.

First, the interview method relied on human memory and human spatial cognitive capabilities to recall and communicate source & destination points during face-to-face interviews. Since a face-to-face interview was limited to only a few minutes, respondents often used colloquially-labeled landmarks as their source/destination locations, e.g., “nearby the McDonald restaurant”, “nearby the church”, “nearby the bus station”, etc., which were verbally quick to communicate but lacked fine-grained spatial accuracy. Additionally, respondents often had difficulty in communicating their store-arrival and -departure paths precisely due to a lack of spatial orientation and directions. We found that even with the help of a map, respondents had problems correctly locating themselves on the map and pinpointing travelled paths. In contrast, the phone method recorded and mapped customer flow data using sensors and software tools. Although our phones’ GPS sensors have an average positional error of 10-15 meters, we believe that the sensory errors, which could be corrected in post-processing, were considerable less than imprecise human communication.

Second, since face-to-face interviews took places where respondents came out of stores, we could only ask respondents what were their *expected* destination points and expected departure paths, which might be different from the *actual* destination points and departure paths taken by respondents. In contrast, the phone method did not have this problem by tracking continuous movement of consumers leaving stores.

**Compensation models (paying customers vs. paying interviewers)**

The phone method placed the burden of data collection on customers who owned, maintained, and operated the data collection devices, i.e., their phones. In contrast, the interview method placed the burden of data collection on human interviewers who traveled to the stores and manually collected data from the customers. This different effort structure produced different compensation models between these two methods. In the phone method, most compensation went to paying the customers for their device management time and efforts. In the interview method, most compensation went to paying the human interviewers for their interview time and efforts.

The phone method offers additional flexibility and potential for extending its compensation model to include real-time and context-based rewards such as in-store coupons, which could be delivered over each participant’s phone and tailored specifically toward his/her location and historical consumer behavior. Including this context-relevant coupon service could enhance the incentive for participation in the study and reduce the direct payouts needed from the marketing researchers, which could be significant if the study involved a large number of participants. In other words, flexibility in the compensation model in the phone method offers scalability potential in attracting a large number of everyday users as participants. This scalability potential is described further in the next paragraph.

**Scalability potentials in data collection (longitudinal data)**
The phone method has several scalability potentials, including longitudinal scalability, geographical scalability, and across many types of stores. These scalability potentials are difficult and/or expensive to achieve using the traditional interview methods. On geographical and store scalability, the phone method collects consumer flow data not just on CVS stores within a focal area, but also other types of stores, restaurants, movie theaters, etc., both inside and outside of the focal area. If retailers outside of the focal area are interested in obtaining these consumer flow data, e.g., for the purpose of mapping their own stores' trade areas, they can participate by sharing the cost of this data collection or by offering phone-based coupons as described in the previous paragraph. Aggregating compensation from multiple retailers over a large geographical area enables spatial scalability and store multiplicity. In contrast, since the interview method is only able to target customers of specific store(s), its consumer data is usually applicable to one or a few retailer(s) only, thus more difficult to scale its compensation structure to other retailers.

The phone method can sustain longitudinal consumer data collection, as the data collection software needs one-time setup on a participant's phone while minimizing user effort through automated sensing. In contrast, the traditional human-based approach relies on self-reporting diaries, repeated survey schedule, or other human effort based methods that are difficult to sustain over long time and data quality often degrades over time with human recall and communication errors described previously.

# 5. RELATED WORK

We organize related work as follows. First, we review traditional techniques in collecting consumer behavior data while explaining the benefits of our phone-based data collection approach. We then review related studies of applying mobile and ubiquitous computing (UbiComp) technologies in marketing and consumer research. Finally, we discuss related phone-based behavior sensing systems.

## 5.1 Traditional Data Collection Techniques in Marketing and Consumer Research

[Prof. Bei can help with this section.] Traditional data collection techniques for consumer behavior data include human shadowing and recording [2], or consumer surveys [citation]. Human shadowing and recording techniques involve posting human observers at stores who directly follow or indirectly survey ingoing/outgoing customers to determine their trajectories upon entering/leaving and/or their origins/destinations. Human observers also keep track of the number of incoming/outgoing customers of a store to determine the number of store visits. Due to the limitations of human memory in recalling the origins of their consumer paths and the difficulty to precisely describe the location of one's destination,

, human metering methods either lose the association between customers and their visits, or their intermediate inbound or outbound behavior. Other human recording [4][5] or surveying techniques records subtle consuming behavior but require intensive human labors. For these reasons, existing techniques based on human-labor suffer from information loss or require costly labor.

Other techniques for analyzing trade area are based on the concepts of the spatial monopoly or market penetration. The concentric rings methods, drive time/distance polygons or Thiessen (Voronoi) polygons, or [and?] utilizing probabilistic trade area surfaces [9] are examples of the spatial monopoly approach. These techniques are often simplified and fail to incorporate the effects from competing nearby stores. The Huff model [8] is an example of the market penetration approach, which includes the effect of competing stores by modeling a spatial variation in the proportion of households served by each surrounding store. However, this technique requires a calibration phase in which customer survey results are given out to compare the relative attractiveness of nearby stores. Furthermore, this technique only estimates the extents of trade area without the intermediate inbound/outbound trajectories.

## 5.2 Mobile and UbiComp Technologies in Marketing and Consumer Research

Previous studies have explored how to augment shopping experiences or promote the use of UbiComp technologies at stores [23]. Girgensohn *et al.* [21] uses fixed cameras to monitor in-store activities of retail shoppers and to aggregate traffic flow of different store sections. By analyzing surveillance videos captured from these cameras, this system detects and aggregates specific shoppers' activities, and visualizes these shoppers' activities using heat maps which are effective representation for managing retail spaces. Shopping Tracker [22] proposes a phone-based shopping tracking system to monitor customers' in-store shopping time. This system uses a phone's movement sensor to recognize unique shopping movement trajectories resulting from specific stores aisle layouts. Moiseeva *et al.* [18] detects activities of retail shoppers, including their transportation modes and in/out building activities, from their multi-day GPS traces. They investigated the potential benefit of incorporating GPS, cell phone and RFID technologies to reduce self-reporting effort from respondents on their shopping trips. The collected pedestrian movement data and consumer patterns provide insights on understanding the retail store location and customer time-space preferences. To enhance the shopping experience, Meschtscherjakov *et al.* [27] situated a dynamic store map in a retail store. The store map combines customer activity visualization (e.g. sales ranks) with traditional map elements (e.g., product locations). Reitberger *et al.* [28] set an interactive mannequin in front of a shop window to persuade bypassing customers to extend their time of stay. The persuasive interactive mannequin is displayed on a large LED screen and reacts to the presence of a user by altering body positions and looking in their direction. A social robot was presented by Kanda *et al.* [29] which distinguishes potential customers from passer-bys. Customer's shopping trajectories are recorded in a public space and used as the bases for the identification and prediction of potential customers. The Innovative Retail Lab [36] focuses on creating technologies to assist consumer shopping experience. For example, a *smart fridge* enables consumers to create electronic shopping lists at home and later they can access the list via an *instrumented shopping cart* at stores. Digital assistants such as the *Cereal Assistant* helps consumers select cereals based on nutrition data. Decker *et al.* [37] implemented the RFID-based *Smart Shelf* technology that tracks basic actions performed on items by customers, such as *take*, *return* and *remove*. The data collected provides higher detail consumer in-store shopping behavior tracking. Gordon *et al.* [38] studied the outcome of implementing a wireless sensor network in a consumer electronics retail store. Sensor nodes were attached on cell phones for sale. The sensors recorded the frequency and duration in which each phone was picked up by a consumer. Leobbecke [39] explores early use of RFID technology in a major supermarket. The study identified how use of *RFID on pallets and cases* improves tracking efficiency of products in the supply chain and also conducted initial testing of *RFID item tagging*. To the best of our knowledge, none have proposed a phone-based data collection platform to collect everyday consuming flow data for researchers on analyzing trade areas of stores.

## 5.3 Phone-based Behavior Sensing Systems

There have been extensive research works that use phones to sense human activities. Madan *et al.* leverage a phone's Wi-Fi sensors, Bluetooth proximity sensors, and call logs to capture social interaction and detect social patterns. A further study from Madan *et al.* [19] built upon this phone-based sensing system for epidemiological human behavioral patterns, in which they found that individuals presented distinctive changes in behavior (e.g. changes in frequency of communication) when they were sick. With the ability to detect behavior changes, the authors stated the possibility of determining individual health status and modeling epidemiological contagion between people without medical heath reports. Madan *et al*. [24] captured the interactions of users to predict their political opinion changes during the US presidential election campaign. User's exposure to diverse opinions was estimated from phone collected data. With this estimation, a predictive model of an individual's future opinion was constructed.

Health related phone sensing projects aim to enhance the health of users through persuasion. Playful Bottle [30] is mobile persuasive system which encourages office workers to drink healthy quantities of water. A mobile phone attached to a mug detects the amount and regularity of water consumed by the user. The UbiFit Garden system [31] encourages physical activities using on-body sensing and personal displays on phones. UbiFit displays user exercise levels on a virtual flower garden shown on the phone screen.

Utilizing mobile phones to sense transportation behavior has been widely explored. The UbiGreen project [32] makes use of personal ambient displays on mobile phones to provide users with feedback on the environmental impact of their transportation behaviors. Focusing on different aspects of transportation behavior, Reddy *et al.* [35] and Zhen *et al.* [26] sense the transportation mode of users by classifying and modeling phone-collected [location- or movement-] data. A public transportation comfort measuring system was developed by Lin *et al.* [25]. The system matches phone-collected transportation data with authorized data from the public transportation systems and provides detailed transportation comfort statistics.

CenseMe [33] uses the microphone and accelerometer of mobile phones to infer the user's activity and social settings. SoundSense [34] exploits the microphone to record sounds from users' daily lives.

Machine Learning techniques classify general sounds (e.g. music, voices) and indentify novel sound events of special meaning to users. Other projects tracked user location-visit history to recommend better routes or spots. GeoLife [11] is a friend & location recommender system. Based on human trajectories traces recorded by GPS-enabled devices, the system models the location history of individuals and identifies similarities among users. A user's interests can then be inferred and the system makes touring spot/route and friend recommendations. Biketastic [12] utilized the GPS sensors of smartphones to record cycling trajectories and speeds. With the accelerometer and microphone sensors on the phone, this system was able to infer road roughness and the general noise level along routes. Finally, each participant could provide his/her experiences of the route along with tags and descriptions while riding. In comparison to previous work, our system expands the breadth of these works by bringing mobile sensing into customer behavior research.

# 6. CONCLUSION & FUTURE WORK

This paper describes a novel application of phone-based data collection to consumer behavior and marketing research. We use mobile phones to outsource consumer data collection to everyday consumers, and to automate sensing of consumer behavior from their phones. We have developed and deployed this phone-based data collection system, called ConvenienceProbe, to collect real customer flow data to neighborhood convenience stores. Results from a comparison user study show that it is possible to use mobile phones to collect quality consumer flow data and to obtain accurate spatial patterns in consumer behavior comparable to those from a traditional face-to-face interview method. Given the ubiquity of mobile phones, this work opens a door on practical use of phones from everyday consumers to sense and report consumer behavior in consumer behavior and marketing research. In other words, this work goes beyond traditional *consumer self-reporting* to UbiComp's *phone automated-reporting*, i.e., toward an invisible data collection without affecting natural consumer behavior.

The current ConvenienceProbe system has several limitations which are also directions for our future work. First, our current data collection software only runs on several selected HTC Android mobile phones, which limits participation to those who have these HTC phones. Our future work will extend this data collection software to run on other major phone platforms. Second, our current data collection software stores the collected sensor data on phones and asks/requires user authorization prior to uploading each store visit data to the server. Our future work will consider other security and privacy mechanisms that are informative about the data that users are uploading on the server in return for payment. Third, the current GPS sensor errors create problems in customer path/trajectory reconstruction. Our future work will incorporate advanced post-processing techniques, such as pedestrian walkways constraints, to improve accuracy of customer path/trajectory reconstruction.

Finally, we believe that this work promotes this new area of applying everyday phone sensing to consumer behavior and marketing research. The development of phone-based data collection systems will lead to better quantity and quality of consumer data available to physical store retailers for analysis and understanding of their customers, i.e., matching those available to online retailers.

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