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Smombie Forecaster: Alerting Smartphone Users About Potential Hazards in Their Surroundings

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ABSTRACT With recent advancements in communication and smartphone technology, many convenient services, such as SNS, gaming, video streaming, and news, are now available to users. However, this wealth of options is disadvantageous in that it makes smartphone users smombies (i.e., users who focus on their smartphones and ignore their surroundings), which poses a safety hazard. For improving the safety of pedestrian smartphone users, attempts have been made to install traffic lights on sidewalks or warn users of approaching vehicles through mobile apps. However, the effectiveness of these smombie warning systems has not been investigated yet. In this article, we propose Smombie Forecaster, which uses inertial smartphone sensors and the BLE beacon, to detect the three most prevalent smombie settings (walkways, stairs, and crosswalks), provide relevant alerts to users, and log their compliance with these alerts. We conducted a field test with 24 participants under these three settings. The results verified the effectiveness of the proposed system; the smartphone pause time increased by 1.59 times, and the average frequency of steps taken by users decreased from 1.68 Hz to 1.47 Hz. A post-experiment survey, interviews conducted with participants of the experiment, and users' smartphone logs provide important design implications for the proposed smombie alerting system.

INDEX TERMS Situational awareness, Smombie alerting system.

I. INTRODUCTION

Recent advancements in smartphone technology have provided several useful services to users and have attracted even more people to the ubiquitous mode of mobile communication. These include messaging services offered via social media, gaming, videos, and news. However, this environment also has its drawbacks. A smombie refers to a pedestrian who is too absorbed in their smartphone to attend to their surroundings while walking. Smombies have impaired situational awareness that puts them at risk of accidents [1].

Many studies have been conducted to solve the problem posed by smombies. Kim *et al.* proposed Smombie Guardian [2], which is a smartphone app that alerts a pedestrian, using a smartphone, to their surroundings. However, Smombie Guardian can only detect possible collisions with obstacles using a single-lens rear camera. Research has also revealed that alerting users about an imminent collision may not be beneficial. It is preferable to warn them in general to not pay too much attention to their phones and be more cognizant of their surroundings.

Kim *et al.* installed an LED warning light on a pavement and designed a mobile application that sends warning messages to users about approaching vehicles. Such a smombie warning system has been installed at a road crossing in Ilsan in South Korea [3], and it is expected to be deployed nationwide. In Augsburg and Cologne, Germany, and Bodegraven, Netherlands, additional traffic lights have been installed on the ground so that pedestrians walking with their heads down, looking at their smartphones (*i.e.,* smombies), can see the traffic signals on the ground [4], [5]. To the best of our knowledge, the effectiveness of alerting smombies in such a manner had not been investigated until the present study was conducted; this is the major contribution of the study. To draw the design implications of smombie alert systems through such an assessment, we design Smombie Forecaster, which

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is a smartphone app that contains a data collector, a smombie detector, and an alert provider. We examined the effectiveness of Smombie Forecaster in three settings: walkaways, stairs, and crosswalks. The contributions are listed below.

- We conducted a perception survey of 49 respondents and extracted the three most prevalent smombie settings: walkways, stairs, and crosswalks (Section III).
- We designed and implemented Smombie Forecaster, which uses smartphone sensors and the BLE beacon to detect smombie-like behaviors, provides the relevant alerts, and logs the user's compliance with the alerts. The effectiveness of Smombie Forecaster was tested in three scenarios (Section IV).
- We conducted a field study with 24 participants to evaluate user compliance with the alert (Section V) and noted the following: 1) The proposed system was effective in alerting users about their surroundings. For instance, it increased the smartphone pause time and reduced the frequency of steps of the users; 2) A difference was observed between the user's perception and the use of the smartphone depending on the degree of perceived danger. Based on a post-experiment survey and the user logs, we also provide the design implications for such alerting systems in general (Section VI, VII).

II. RELATED WORK

A. SMARTPHONE-AIDED PEDESTRIAN SAFETY

Owing to increasing interest in smombie safety, various alerting apps on smartphones have been introduced in the market and the research community. Most of them warn users of impending obstacles such as, people, objects, and vehicles. Zhuang and Fang [6] proposed a framework that detects the motion of the smartphone using a sensor (e.g., GPS, gyroscope, accelerometer, and proximity) to determine whether the pedestrian user is a smombie when they cross an intersection. Wang *et al.* [7] proposed WalkSafe, which uses the rear camera of the smartphone to detect approaching vehicles via machine-learning algorithms. Hincap *et al.* proposed CrashAlert [8], which uses an additional depth camera connected to the smartphone to detect obstacles in front of the user. To cover more general scenarios, Foerster *et al.* proposed SpareEye [9], an application that uses the smartphone's built-in camera to detect obstacles and alters the user when they are active on the smartphone (e.g., text messaging, video viewing, and gaming). More recently, Kim *et al.* proposed the Smombie Guardian to warn users of an impending collision [2] by calculating the size of the obstacle and its distance from the user by tracking the ratio of user displacement to changes in image size to overcome the limitations of SpareEye. Jain *et al.* proposed LookUp that uses shoe-mounted inertial sensors to profile the ground gradients and step patterns to detect sidewalk–street transitions, and it warns pedestrians entering the road from the sidewalk or stepping over a curb.

B. SMARTPHONE-AIDED SITUATIONAL AWARENESS

Situational awareness is the perception and comprehension of one's surroundings. A person can take the appropriate action based on such awareness (e.g., for collision avoidance and moving around obstacles). Smartphones are equipped with a variety of inertial sensors (e.g., barometer, accelerometer, and ambient light sensor) that can detect the user's surroundings in an objective manner. Dai *et al.* have shown that smartphones can be used to detect driving maneuvers typically associated with drunk driving using the in-built accelerometer and orientation sensors [10]. Smartphones have also been used to detect in-vehicle accidents through accelerometers [11], [12]. Through inertial sensors used to measure temperature and humidity, smartphones can be used to adjust the settings of heaters, humidifiers, and ventilators through co-location information in smart homes [13], [14].

Interesting research has also been conducted on crowd/community sensing to enhance people's awareness of exposure to environmental hazards. Moderate amount of research has been devoted to applications of environmental monitoring to track and provide alerts about hazardous exposure (e.g., detecting carbon emission levels, air pollution, waste accumulation, and water toxicity) from sensor data (e.g., fusion of sound, light, and color) [15]–[17]. We investigate the effectiveness of Smombie Forecaster in different scenarios involving smombies.

III. STUDY DESIGN–PERCEPTION SURVEY

We first conducted a preliminary perception survey to identify cases in which a smombie might be at risk. These cases were then used to design Smombie Forecaster as well as a user field study to measure its effectiveness. We recruited 49 respondents to investigate people's perceptions and experiences of smombies based on the following four questions.

- *Q1:* How often do you use your smartphone while walking?
- *Q2:* Have you ever had a collision with people or objects (e.g., power poles and bicycles) while you were walking and using your smartphone?
- *Q3:* Choose a dangerous experience of walking while using the smartphone (multiple choice: escalator, stairs, crosswalk, bus or subway, obstacle)
- *Q4:* Please explain your answer to Q3.

A majority of the respondents admitted, in response to Q2, to being smombies themselves (Fig. 1). Twenty (40.8%) respondents said that they frequently used their smartphones while walking, and 13 (26.5%) said they always used them. In addition, thirty-four respondents (69.3%) said that they had experienced at least one collision when walking while using a smartphone. Based on the results, we confirmed the need for an app to prevent smartphone users from becoming smombies and putting themselves at the risk of accidents.

Q3 and Q4 were used to examine risky situations that the respondents were involved in because of being immersed

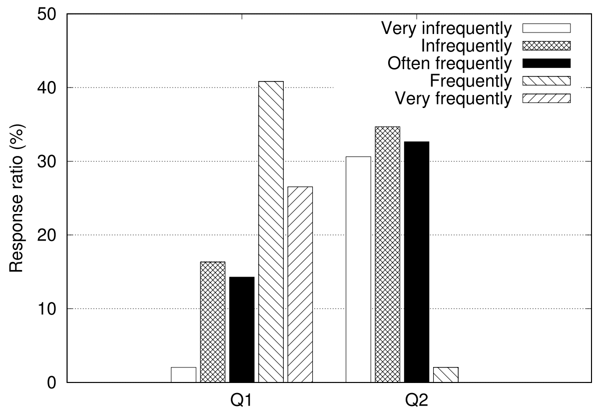

FIGURE 1. Smartphone usage habits and experiences of collisions while walking (Q1: How often do you use your smartphone while walking, Q2: Have you experienced a collision with people or objects (e.g., power poles and bicycles) while you were walking and using your smartphone?).

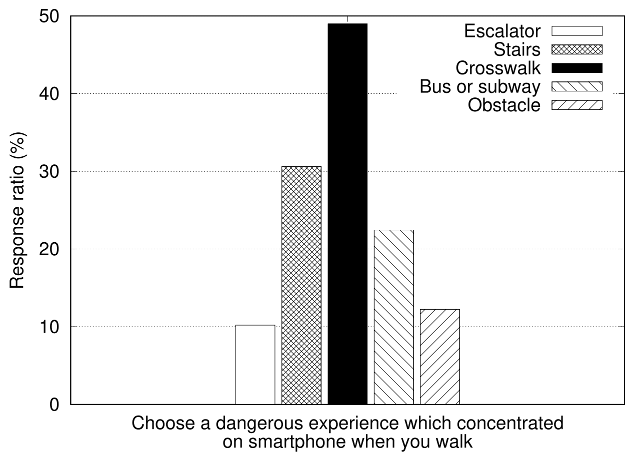

FIGURE 2. Results of perception survey (Q3).

in smartphones while walking (Fig. 2). Crosswalks were deemed risky by most users, 48.9% (N = 24). Some comments for this situation were as follows: *"I used my smartphone and went straight without knowing whether the signal had changed."* (P9) *"While crossing the crosswalk, I couldn't check the oncoming objects (e.g., bicycles and cars) because I was focused on my smartphone."* (P48). Stairs were determined to be the riskiest by 30.6% of the respondents (N = 15). Comments included *"knowing that you are on the stairs and falling without knowing that there is one more step,"* (P4) and *"swinging up the stairs and falling down"* (P25).

Based on the results of the perception survey, crosswalks, stairs, and general walkways were selected as scenarios to be supported by Smombie Forecaster and to be tested in the user field study. We considered the general walkway as a scenario for comparison with crosswalks and stairs, given that people often use their smartphones while walking. We divided the stair scenario into stairs-up and stairs-down because many respondents had indicated different experiences in terms of situational awareness for each case.

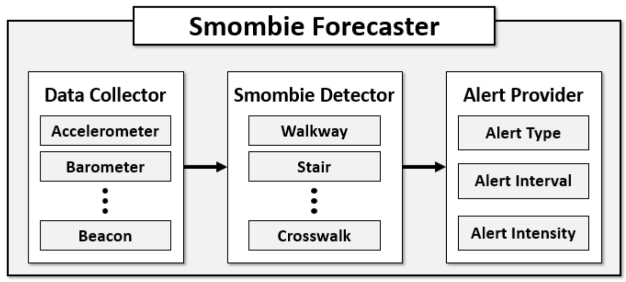

FIGURE 3. Smombie Forecaster system building blocks.

IV. SMOMBIE FORECASTER DESIGN AND IMPLEMENTATION

Smombie Forecaster consists of three components: a data collector, a smombie detector, and an alert provider.

A. DATA COLLECTOR

Smombie Forecaster collects data from various sensors (e.g., accelerometer, barometer, and beacon) and records the states of the smartphone (e.g., screen on/off and app usage), which are used to analyze the user's smartphone activity and information regarding the surroundings. However, collecting sensor values and monitoring the smartphone consumes battery power. To minimize battery consumption, the data collector can collect only sensor data while the smartphone screen is on (or a specific app is running in the foreground). The rate at which sensor data are collected should be carefully chosen. To reduce unnecessary sensor readings, we use the Google API [18]. The collected data are analyzed by the smombie detector to determine the risk of the user becoming a smombie.

B. SMOMBIE DETECTOR

The smombie detector can analyze smartphone activities and situational sensors in several environments. Our field study considered scenarios, featuring walkways, stairs, and crosswalks, based on the results of the perception survey. However, Smombie Forecaster can easily be extended to other settings such as walking on bumpy roads and crowded roads. The smombie detector is responsible for detecting whether the user is acting like a smombie. This includes checking the user's activities on the smartphone (e.g., gaming, reading article, texting, and SNS) while they pass a walkway, climb stairs, or go through crosswalks under our settings.

Walkway: In this setting, the smombie detector analyzes sensor readings from the smartphone to identify whether the user is passing a walkway while using the smartphone. It uses Google's step detection that is based on the user's foot hitting the ground and generating a high variation in acceleration. This sensor is used to detect each step as soon as it is taken. A condition was added to exclude the case in which the detector incorrectly determines that the user is walking simply because the smartphone is shaking. Research indicates that the average walking cycle of pedestrians is 1.5 Hz [19], and smartphone use slows them down [20]. The user was determined to have entered the walking state once seven steps or more had been detected for 10 seconds. Then, the smombie detector checks whether the user is running an app in foreground and whether they have taken a certain number of steps. If all the conditions are met, the smombie detector concludes that the user is acting like a smombie while passing the walkway and informs the alert provider regarding this.

Climbing/Descending Stairs: In this setting, the smombie detector determines whether the user is climbing or descending the stairs while using their smartphone. To detect stair ascent or descent, we use the barometer sensor on the smartphone. In general, the barometer sensor is sensitive and constantly changes owing to temperature, wind, and location, which makes it difficult to use it directly. As in LocMe [21], which implements an indoor localization service based on a smartphone sensor, we are interested only in changes in altitude over short distances and small spaces while the user is walking (e.g., altitude difference over a flight of stairs). Interference from values of the barometer due to changes in the weather can thus be neglected in these situations. In addition, we fixed the time of collection of values of the barometer sensor to when a step is taken. This reduces errors caused by the position of the smartphone while the user is walking and the sensitivity of the barometer. The alert provider signaled an alert if continuous smartphone use was detected while the user was walking up the stairs.

Crosswalk: In this setting, the smombie detector determined whether the user was on a crosswalk. For ease of detection, we placed beacons at the vertices of the crosswalk to detect its entrance. On the crosswalk, each beacon sent a BLE signal every 100 ms, and the user's smartphone collected the received signal strength indicator (RSSI) value from it. When more than three signals were received from a beacon, the phone performed triangulation to specify the location of the user within the crosswalk. However, the RSSI values are unstable owing to multiple paths (*i.e.,* small-scale fading) and obstacles between the smartphone and the beacon (e.g., user's body, other passengers, and cars). This makes it challenging to obtain the exact location of the smartphone within the crosswalk. To solve this problem, we use machine learning as described below.

The collected RSSI data were used in machine-learning models to identify when the user was crossing a crosswalk. We used the support vector machine (SVM), multilayer perceptron (MLP), the C4.5 algorithm, and random forest (RF). A total of eight features were obtained from four beacon RSSI signals as well as the distance (calculated based on the RSSI) between each of the four beacons and the smartphone. In/Out-labeling was performed according to where each feature was collected. The four classifiers (i.e., SVM, MLP, C4.5, and RF) were then trained using 70% of the collected data and tested with the remaining 30%. Table 1 shows the accuracy and F-score of the four classifiers. All of them recorded an accuracy exceeding 80%: RF delivered the best performance, with an accuracy of 93.6% and an F-score of 93.7%. We thus embedded the RF model into Smombie Forecaster for the field study.

TABLE 1. Results of crosswalk detection for four classifiers.

	Accuracy	F-Score
SVM	0.811	0.819
MLP	0.916	0.918
C4.5	0.932	0.933
RF	0.936	0.937

C. ALERT PROVIDER

If the user is behaving like a smombie, the alert provider in Smombie Forecaster generates an alert to warn them of a lack of situational awareness. It can configure three parameters: alert type, interval (or frequency), and intensity. As in [2], four types of alerts (i.e., border, pop-up, vibration, and sound) are supported. The alert provider can receive user input regarding the preference for any of these alerts and even set a combination of them. It can also change the frequency of alerts. For example, an alert can be generated only once as the user passes a walkway or with every step taken in the walkway. The alert provider can also change the intensity of alerts (e.g., the thickness of the border, toast/pop-up, intensity of the vibration, and volume of the sound). Smombie Forecaster can separately set parameters for the three scenarios.

V. DESIGN OF FIELD STUDY

To evaluate the effectiveness of Smombie Forecaster, we conducted a field study involving 24 participants. We integrated the three scenarios (*i.e.,* passing walkway, climbing/descending stairs, and crossing crosswalk) in a five-minute course. We focused on answering the following research questions:

- *RQ1:* Does a timely alert influence user behavior (*i.e.,* stopping smartphone activity)?
- *RQ2:* How does the extent of danger in the given settings affect the user's compliance with the warning issued?
- *RQ3:* How are the user's perceptions of the risk and actual compliance correlated?

A. DESIGN OF FIELD STUDY

The user study was conducted for two days (March 29 and 30, 2019). We employed an intra-subject model. Each participant was placed in both the control group (without Smombie Forecaster) and the experimental group (with Smombie Forecaster), and the sequence of group assignment was randomized. Twelve participants were assigned to the control group first (first session) and the other half to the experimental group; the two groups were subsequently switched. Between the sessions, a 10-minute break was given to minimize the learning effect of the previous experiment. A list of questions on a five-point Likert scale was used to quantitatively evaluate

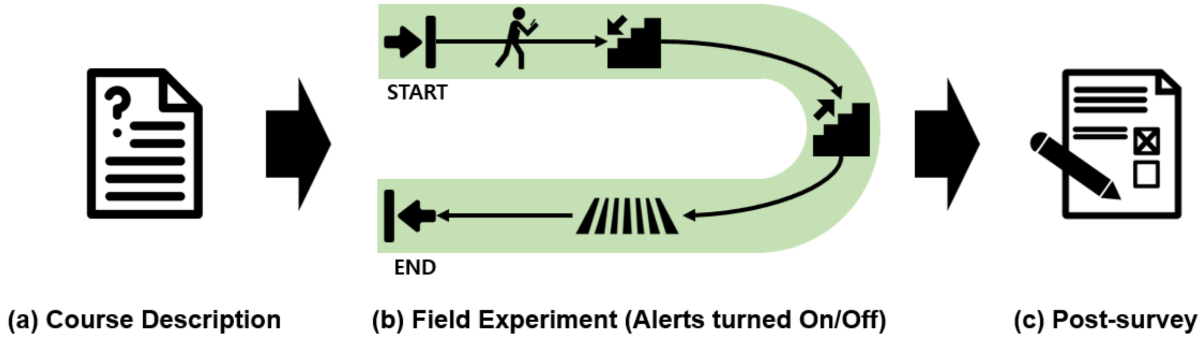

FIGURE 4. Procedure of the user field study: (a) We instructed the participants on the overall study procedure and requirements. (b) We randomly assigned the participants into one of two groups for an intra-subject study (*i.e.,* the participants in Group 1 walked the course without Smombie Forecaster first and then with it, whereas those in Group 2 walked the course in the opposite sequence). (c) After completing the course twice, the participants were interviewed.

the experiment, and a 15-minute interview was conducted for qualitative evaluation.

B. RECRUITMENT

A total of 24 participants (five females) were recruited through word of mouth, a university bulletin board, and social networks. The age range of the participants was 20–33 years. They were asked to test and evaluate Smombie Forecaster. The study was conducted on campus, which is typically crowded. The entire procedure, including the survey, application, and the interview afterward, took approximately 30 minutes in total for each participant. Once they had completed the study, the participants received a $10 gift certificate. Our study was approved by the Institutional Review Board (IRB), and we obtained the participants' consent before conducting the experiment.

C. PERSONALIZED ALERT FREQUENCY

Considering the differences in pace among the subjects, the alert frequency of Smombie Forecaster was adapted to each. We set the average walking speed for adults (in their 20s or 30s) [22] in Korea as the normal standard for the walking speed, and divided it into three categories: fast, normal, and slow. We controlled the number of alerts to occur 10 times during a round of the experiment and changed the alert interval for each of the three types of walking speeds.

D. PARTICIPANT TASK

Lamberg and Muratori found that when a pedestrian used a smartphone, their pace and trajectory changed significantly [20]. In particular, participants who sent text messages while walking moved 33% slower and deviated from the assigned course 61% more than those who did not. Similarly, we asked the participants in this experiment to read movie reviews on their smartphones while performing the assigned moving tasks. To prevent accidents (as the participant was a smombie), one of the researchers followed each participant without interrupting them. We chose five movie reviews in advance based on two criteria: (1) The movie should have been popular such that the participants would have been somewhat familiar with it, and (2) a review should have been long enough to last the entirety of the walking course. Each participant was asked to select two of the five movie reviews and to read one review per experiment. We asked the participants to choose the reviews because we expected that they would be more immersed in the text on their smartphones in this case.

E. FIELD STUDY PROCEDURES

Fig. 4 shows the overview of our field study. After recruitment, all the participants were informed of the purpose of this study, given a description of the walking course, and provided study guidelines.

Course Description: At the outset, we informed all the participants that Smombie Forecaster is a smartphone app designed to alert its user of the risk of becoming a smombie. The major goal here was to evaluate the effectiveness of Smombie Forecaster in terms of helping the users change their behavior in a timely manner in three representative scenarios (*i.e.,* walking, stairs, and crosswalk). We also instructed all the participants that the overall course comprised seven segments (*i.e.,* four regular walkways, two stairs, and one crosswalk).

Field Experiment: For an accurate comparison, the participants were randomly divided into two groups: (1) Members of Group 1 first walked the course with the Smombie Forecaster alert on and then with it off. (2) Members of Group 2 first walked the course with the Smombie Forecaster alert off and then with it on. We compared the results of the two groups. The first round of the course began with a regular walkway. Participants of Group 1 received the first alert when smombie behavior on the walkway segment was detected by Smombie Forecaster. Whenever a participant received the alert, they had multiple choices such as continuing to use the smartphone, locking it, stopping, changing the location of the smartphone, and looking around. If the participant decided to stop using the smartphone, to continuously observe their responses to the alert in the next segment, we asked them to restart the reading task at the beginning of each segment before the start of the experiment.

In the second segment, the participants climbed down a flight of stairs. Immediately after descending the stairs, they passed through another walkway, which was the third segment and the longest section of the course. At the end of the walkway was a flight of ascending stairs (fourth segment). After the ascent was a short walkway (fifth segment), followed by a crosswalk (sixth segment). For the sake of safety, we designed the course with a temporary crosswalk installed with no vehicles (cars) passing by. After the crosswalk, participants walked on the final walkway (seventh segment) to complete the course. In the segments introduced earlier, the participants were allowed to stop using the smartphone or take other actions after being alerted. In the second round of the experiment, members of Group 1 walked the same course without any alert.

VI. RESULTS

A. OBJECTIVE APP USAGE LOG ANALYSIS

To verify the effectiveness of Smombie Forecaster, we logged the smartphone sensors from all the participants to determine their compliance with the alerts and track the pause time of the smartphone in each segment.

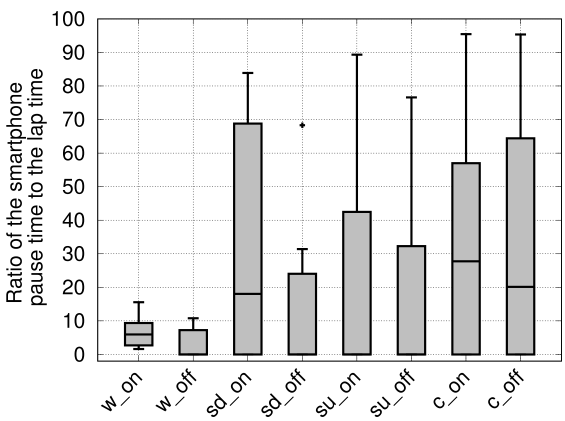

FIGURE 5. Ratio of the smartphone's pause time to the lap time by course (w_on/off: walkway alert on/off, sd_on/off: stair_down alert on/off, su_on/off: stair_up alert on/off, c_on/off: crosswalk alert on/off). In most cases, the duration for which the participant stopped using the smartphone increased when an alert was provided (average, 1.59 times).

Fig. 5 shows the ratio of the smartphone pause time to the lap time of the section according to whether an alert was provided for each segment. A high ratio indicated that the participant had stopped using the smartphone for a longer period of time in the given segment. The percentage of smartphone pause time out of each segment pass time in all the segments other than the crosswalk segment was longer when the alert was provided. The smartphone pause time in the entire course increased by 1.59 times on average when an alert was provided, compared with when one was not provided. The greatest difference occurred in the scenario involving descending stairs, where the average smartphone pause time of the participants provided an alert 2.69 times longer than the average for those without an alert (on average, off for 43.3 seconds with alert and 16.1 without an alert). In the walkway and stair ascent scenarios, when the alert was provided, the percentage of smartphone usage stopping time in the lab time was longer. On the walkway, five participants who had previously chosen to stop using their smartphones chose to continue using them if they had not been alerted. One continued to do so in the stair ascent scenario. In the crosswalk scenario, a high proportion of smartphone stopping usage time in the lab time when no alert was provided was observed. However, the number of participants who chose to stop using their smartphones when an alert was provided was larger than that when one was not provided.

Fig. 6 shows the frequency of steps per second before and after an alert, which shows each participant's reaction to the alert, regardless of compliance. The frequency of steps averaged 1.68 Hz (MD = 1.68, SD = 0.16) just before the alert was given and then decreased to 1.47 Hz (MD = 1.50, SD = 0.15) just after one was given. Following this, it gradually increased to the original value. This suggests that even if the participant had chosen to not stop using the smartphone, their behavior was likely to change when an alert was provided. The participant subsequently continued reading and regained pace.

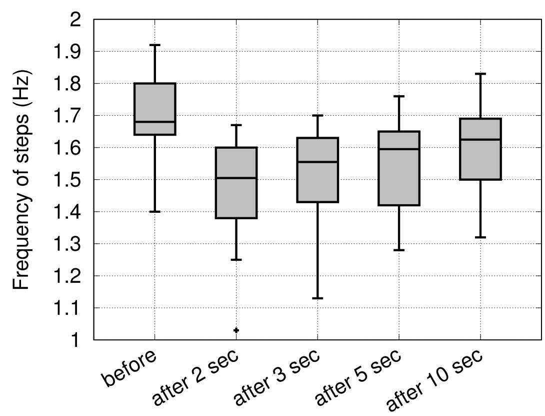

FIGURE 6. Changes in the frequency of the participant steps before and after an alert were provided. The average frequency of steps decreased from 1.68 Hz to 1.47 Hz when an alert was provided and then gradually recovered.

B. ANALYSIS OF SUBJECTIVE USER PERCEPTION (SURVEY)

After the experiment, each participant was asked to complete a short survey and take part in an interview with the researchers. We used these in comparison with smartphone logs, an objective indicator. The post-survey consisted of 11 questions, and we divided the results of the experiments into three cases: walkways, stairs, and crosswalks.

To check the effectiveness of Smombie Forecaster, we asked the same three questions for each scenario. Q1 inquired about the degree of perceived risk in each of the three scenarios. Q2 asked whether the participants' duration of smartphone use had decreased after the alert. Q3 was an open-ended question about what action they had taken after the alert. We asked nine questions on the scenarios (Q1, Q2, and Q3 for each scenario). We asked two more questions (Q4 and Q5) for a detailed assessment of the experiment.

- *Q1:* To what extent did you feel at risk in this scenario?
- *Q2:* When you received an alert, did you reduce your smartphone use?
- *Q3:* What action did you take when you received an alert (e.g., lock your smartphone screen, put down your smartphone, or stepped backward)?
- *Q4:* How effective is Smombie Forecaster in terms of preventing smombies?
- *Q5:* In addition to the three situations in the experiment (walkway, stairs, and crosswalks), what other scenarios can Smombie Forecaster help in?

TABLE 2. Results of Q1 and Q2 in different settings (SP: smartphone).

	Perceived risk (Q1)		Decreased SP usage time (Q2)	
	Mean	SD	Mean	SD
Walkway	2.54	0.87	2.79	1.26
Stairs	3.21	1.00	3.30	1.17
Crosswalks	3.00	1.26	3.17	1.25

Degree of Risk Perception: We interpreted the effectiveness of Smombie Forecaster by inquiring about the extent to which the participants felt at risk during the experiment. Table 2 presents the key statistics of the survey. The participants felt less at risk ($M = 2.54$, $SD = 0.87$) in the walkway scenario than in the staircase scenario ($M = 3.21$, $SD = 1$). The crosswalk scenario was judged to be in the middle in terms of risk ($M = 3$, $SD = 1.26$). To verify the difference among the scenarios, we conducted a one-way ANOVA. As Table 3 shows, there were marginally significant differences ($F(2, 69) = 2.41$, $p = 0.09$) in the degree of risk perception among the scenarios.

TABLE 3. Results of Tukey's HSD post-hoc analysis.

Group1	Group2	P-value
Walkway	Stairs	0.08†
Walkway	Crosswalks	0.31
Stairs	Crosswalks	0.76

**p<.01, *p<.05, †p<.10

We also conducted Tukey's post-hoc HSD to identify the differences among the scenarios (Table 3) and noted a marginally significant difference in risk perception between the walkway and the stair scenarios. However, no significant difference was found between the walkway and the crosswalk scenarios.

Behavioral patterns after alert: We expected participants who had been prevented from becoming smombies in the experiment to exhibit reduced smartphone usage (e.g., . by looking around, locking screen). We determined whether this had happened through Q2 and asked about their detailed actions in Q3.

As shown in Table 2, for the walkway scenario ($M = 2.79$, $SD = 1.26$), the participants reported feeling that their smartphone usage had not decreased, but they did report this for the stair ($M = 3.30$, $SD = 1.17$) and crosswalk ($M = 3.17$, $SD = 1.25$) scenarios. We then conducted a one-way ANOVA to determine the differences among the scenarios in which the participants' behaviors changed after receiving an alert. No significant difference was found ($F(2, 69) = 1.03$, $p = 0.36$).

When the participants received an alert, their behaviors were as follows: "keep using," "put down the smartphone," "check in front," and "lock smartphone screen." One unanticipated finding was that some participants had the same response to Q3 but completely opposite responses to Q2. For example, P9 responded with "strongly agree" to Q2 but "locked smartphone screen" to Q3, whereas P24 responded with the same "locked smartphone screen" to Q3 but "strongly disagreed" with Q2. *We found that actual log data and perceptions of reduced smartphone usage could differ depending on the participant*. This highlights a role of the smartphone sensor data in accurately detecting whether a user is acting like a smombie rather than relying on subjective perception.

Effectiveness of Smombie Forecaster: Q4 asked about the effectiveness of Smombie Forecaster for preventing smombie-like behavior. Fifteen participants (62.5%) found Smombie Forecaster to be effective. They said that the alert reminded them of the dangers around them and prevented them from becoming smombies (P11 and P16). P15 said that the alert was helpful, especially in the crosswalk scenario.

- *"Once the alert went off as I was concentrating on my smartphone, I looked around and walked more safely" (P11).*
- *"(Because of having focused on the smartphone), when I didn't recognize a potentially dangerous situation, the app's alert aroused me to the risk" (P16).*
- *"I didn't know I was at the crosswalk, but the alert informed, (which helped prevent danger)"(P15).*

Some participants had negative opinions about the effectiveness of Smombie Forecaster. Seven evaluated it as "moderate" in terms of usefulness, and two participants claimed it was "not effective." P3 and P10 said that the effect of the alert seemed inadequate because the vibration was either too weak or not different enough from other alerts. P18 said that he became cautious about his surroundings when he realized that the alert was from Smombie Forecaster. These results suggest that making the alert more noticeable can improve the app.

- *"It was difficult to distinguish the alert of Smombie Forecaster because it was the same as a common notification. It might be better to make the alerts more conspicuous. After one or two alert(s), I got used to the interface and used my smartphone as usual. I felt the effect of the alert had diminished" (P3).*
- *"The vibration (of the alert) was not very strong; so I ignored it" (P10).*

- *"There was no difference between it and other alerts; so I didn't know it was the alert from the app. The app's alert needs to be different from the alerts of other apps. I actually looked around when I recognized the alert was from Smombie Forecaster" (P18).*

VII. DISCUSSION

A. SMOMBIE FORECASTER

Smombie Guardian [2] alerts users about immediate risks. However, the limitations of the reaction speed of humans and the speed of moving obstacles imply that the user may still be at risk. Therefore, we proposed Smombie Forecaster to provide appropriate alerts when a user enters a potentially dangerous situation because of the risk of becoming a smombie. Based on the results of a perception survey, we developed Smombie Forecaster to detect and alert smombies in three risky scenarios: walkways, crosswalks, and stairs. However, it does not consider all potential risks to pedestrians who are absorbed in their smartphones in practice.

In addition, the barometer sensor used to detect stairs was sometimes too sensitive owing to particular smartphone models or changes in the environment. This was why Smombie Forecaster occasionally provided too many alerts to some users, which was burdensome. It used beacon RSSI values to detect risky situations. Crosswalks required the installation of an additional beacon. As it is unrealistic to install beacons on every crosswalk, we can explore image recognition methods using the smartphone camera as an alternative in a future study.

B. OBJECTIVE USAGE LOGS AND SUBJECTIVE PERCEPTIONS

Through the field experiments, we collected the objective indicators of the participants' behaviors (smartphone usage logs of Smombie Forecaster) as well as their subjective assessments on changes in their smartphone use when using the proposed app (through survey and interview data). Our comprehensive results provide interesting insights into the correlation between the two types of data.

On the one hand, in the walkway scenario, many participants reported not feeling that they had used their smartphones less; however, their smartphone usage time based on the logs indicated a reduction in use. This means that many participants' perceptions were mistaken. We propose further research to reduce the gap between user perception and behavior. For example, if a user does not make a behavioral change after receiving an alert, the app can induce in them the awareness of being a smombie by increasing the vibrational intensity or frequency of the alert.

On the other hand, in the staircase scenario, user perception was consistent with actual behavior. From these results, we can infer positive correlations between the user perception of risk and the effects of Smombie Forecaster. The participants perceived the stair scenario as the most dangerous, and the effectiveness of Smombie Forecaster for it was evident in the reduction in smartphone use. In particular, some participants mentioned that climbing down the stairs was more dangerous than climbing up and felt that the descent scenario needed to be addressed more effectively by Smombie Forecaster to prevent accidents. Note that the crosswalk scenario did not yield discriminative results between the log data and survey responses, indicating that the participants were fairly consistent in their smartphone use behavior and risk perception.

We also asked the participants of other scenarios that can be supported by Smombie Forecaster. Many wanted to use the app in situations that require stronger alerts, such as crowded areas and streets with obstacles. Notably, each participant had their own definition of what constitutes a smombie in a dangerous situation. Those additional scenarios could be considered through a technical lens; for example, alerts in the off-road situation could use computer vision technology to indicate whether a smartphone user deviates from the weather information. In addition, the app can allow a user to determine potential risks for themselves and customize the app to generate alerts in such risky situations.

C. LIMITATIONS AND FUTURE WORK

Although the experiments on Smombie Forecaster provided many insights, our study has some limitations. First, we conducted a user study involving 24 participants, which is insufficient for us to generalize the results and insights obtained. In addition, most of the participants were in their 20s and 30s, which limits our results. Our future research will be based on a wider age range and more users. Second, the perception survey identified the most common scenarios–stairs and crosswalks–in which users become smombies, and investigated the effectiveness of Smombie Forecaster in these scenarios. The post-survey showed, however, that Smombie Forecaster can be used in other situations. Our future work will consider them, and we will attempt to update Smombie Forecaster to handle these other situations.

VIII. CONCLUSION

In this study, we proposed and validated Smombie Forecaster, an app that alerts users who use their smartphones while walking, creating risky situations (e.g., using the smartphone on walkways, stairs, and crosswalks). It uses smartphone sensors and the BLE beacon to detect user motion and the environment, and it provides alerts at appropriate moments. A field study with 24 participants validated the effectiveness of Smombie Forecaster (smartphone pause time increased by 1.59 times; average frequency of steps decreased from 1.68 Hz to 1.47 Hz). We verified the effectiveness of Smombie Forecaster in different settings through experiments and gleaned design implications for such an alerting system. It would be preferable to deploy this system in more diverse settings (e.g., walking in crowds, rain, and snow and in the case of obstacles approaching). We found that the correlation between the user's perception to risky settings and their reaction to the alerts varied based on the setting.

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