Understanding User Contexts and Coping Strategies for Context-aware Phone Distraction Management System Design

INYEOP KIM, Korea Advanced Institute of Science and Technology, South Korea
HWARANG GOH, Inha University, South Korea
NEMATJON NARZIEV, Inha University, South Korea
YOUNGTAE NOH*, Inha University, South Korea
UICHIN LEE*, Korea Advanced Institute of Science and Technology, South Korea

Smartphones are often distraction for everyday life activities. In this work, we envision designing a context-aware system that helps users better manage smartphone distractions. This system design requires us to have an in-depth understanding of users' contexts of smartphone distractions and their coping strategies. However, there is a lack of knowledge regarding the contexts in which users perceive that smartphones are distracting in their everyday lives. Furthermore, prior studies did not systematically examine users' preferred coping strategies for handling interruptions caused by smartphones, possibly supported by context-aware systems that proactively manage smartphone distraction. To bridge this gap, we collect in-situ user contexts and their corresponding levels of perceived smartphone distraction as well as analyze the daily contexts in which users perceive smartphones as distracting. Moreover, we also explore how users want to manage phone distraction by asking them to write simple if-then rules. Our results on user contexts and coping strategies provide important implications for designing and implementing context-aware distraction management systems.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile devices**; **Empirical studies in ubiquitous and mobile computing**; *Empirical studies in HCI*.

Additional Key Words and Phrases: Smartphone distraction, interruption handling, context-aware systems, trigger-action programming

ACM Reference Format:
Inyeop Kim, Hwarang Goh, Nematjon Narziev, Youngtae Noh, and Uichin Lee. 2020. Understanding User Contexts and Coping Strategies for Context-aware Phone Distraction Management System Design. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 4, Article 134 (December 2020), 33 pages. https://doi.org/10.1145/3432213

1 INTRODUCTION

Despite its many advantages, the pervasiveness and availability of smartphones in everyday life can be considered two sides of the same coin. Smartphone notifications can deliver timely information, but they disrupt users'

*The corresponding authors

Authors' addresses: Inyeop Kim, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon, South Korea, 34141, kiyeob4416@kaist.ac.kr; Hwarang Goh, Inha University, 100 Inha-ro, Michuhol-gu, Incheon, South Korea, 22212, hrgoh@nsl.inha.ac.kr; Nematjon Narziev, Inha University, 100 Inha-ro, Michuhol-gu, Incheon, South Korea, 22212, nnarziev@nsl.inha.ac.kr; Youngtae Noh, Inha University, 100 Inha-ro, Michuhol-gu, Incheon, South Korea, 22212, ytnoh@inha.ac.kr; Uichin Lee, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon, South Korea, 34141, uclee@kaist.ac.kr.

2474-9567/2020/12-ART134 $15.00
https://doi.org/10.1145/3432213

work (i.e., external interruption) [63]. Habitual checking behaviors, as part of an internal interruption, may lower a user's work productivity [43, 66]. Frequent and unpredictable external or internal interruptions may lead to off-task multitasking, which can significantly impair people's productivity and efficiency during their daily activities (e.g., lowering work focus, and making mistakes) [16]. Here, smartphone distraction depicts a user's mental *state* where their attention is diverted for off-task phone use [53], and the user fails to allocate or prioritize sufficient attention to the primary tasks [81].

To avoid such issues, people can proactively manage smartphone distraction. For example, if they perceive smartphone distraction, they can re-configure smartphone settings such as ringer mode to silence notifications, customizing options for receiving notifications (e.g., silence notifications for messages sent by certain people), switching on the Do Not Disturb mode provided by mobile operating systems, or even downloading intervention tools, such as Forest, Freedom, or RescueTime. However, it might be cumbersome for people to manually configure the smartphone setting for managing distractions according to the current contexts [36].

There is an opportunity to leverage context-awareness typically used to provide context-relevant information and/or services to users [20] in various service domains such as healthcare [23], smart-home [83], safety [9], and location-based recommendations [69]. A previous study highlighted that "*it is desirable for mobile devices to automatically configure themselves based on the context of the environment and user preferences.*" [36] Likewise, automatically reconfiguring phone settings to enable context-aware distraction management is possible.

Designing context-aware distraction management services basically assumes two aspects: (i) *contexts* wherein people perceive smartphones as distracting and (ii) corresponding *actions* for handling interruptions. However, there is a lack of knowledge regarding the context in which people *actually perceive* smartphones to be distracting throughout the day. Existing studies have addressed the adverse effects of off-task smartphone use on daily contexts such as studying, attending classes [38, 39], social interaction [43, 67], and working [40]. These studies were mostly based on surveys and controlled experimental methods which acquiring *in-situ contexts* (e.g., current location and activity) and *experiences related to smartphone distractions* is challenging due to recall biases and limited scenarios. In addition, prior studies did not systematically examine various user requirements for handling interruptions caused by smartphones. For example, some people may need to avoid being interrupted by notifications while studying, while others may want to limit off-task smartphone use (e.g., YouTube, social media, or games). Some people may prefer restrictive actions (e.g., locking a device), but others may want to use less restrictive ones (e.g., display warnings). Thus, understanding various user needs is critical for building context-aware systems.

As the first step toward developing solutions for a generalized population, we study college students as they are considered to be vulnerable to smartphone distraction due to diverse factors such as academic stress and social expectations [34, 48]. Therefore, our work aims to answer the following research questions:

- RQ1. In what daily context do college students perceive smartphone distraction?
- RQ2. How do college students want to manage smartphone distraction?

To answer our research questions, we built a lock screen-based Experience Sampling Method (ESM) app that asks students to report their contexts (e.g., location and activity) and how much they perceive smartphones to be distracting during a captured time duration. To minimize the participants' load for responding, we carefully selected the opportune moments for collecting a survey (i.e., when participants voluntarily turn on the phone screen during stationary periods). We conducted a three-week field study with 34 college students and collected 9,131 responses. After the field study, we conducted an online survey and an exit-interview. In the survey, we asked participants to generate free-text rules on how they want to manage smartphone distraction in a format similar to that in trigger-action programming (TAP). This is an intuitive, accurate, and expressive way of specifying trigger context and action [22] (e.g., *"Silence all notifications except wake-up calls during sleeping"*).

Thirty-four participants made 216 distraction management rules. A follow-up exit interview was conducted with 17 participants to better understand distractive contexts and TAP rules.

Our analysis of ESM responses with multilevel linear regression revealed that there were various contexts relevant to perceived smartphone distraction that significantly differed across different users. Intuitively, there are well-known contexts where students commonly perceive that concentrations are needed (e.g., studying, taking the class), but they also reported other distracting contexts (e.g., eating, or spending time for leisure). Moreover, we observed that perceived smartphone distraction can be explained better when considering individual differences together. We examined 34 individual regression models to check how the contexts related to smartphone distraction differ among participants. We observed that each participant had a different range of contexts, judging smartphone distraction differently, even in similar contexts. Our analysis of free-text TAP rules revealed a variety of requirements for managing smartphone distraction. Our results demonstrated that there are four critical components constituting distraction management rules: triggering conditions, filtering options, action rules (e.g., muting notifications or locking up the phone for 30 min), and releasing conditions of the applied actions. This multi-stage component model contributes to the body of knowledge on existing TAP models for enabling context-aware distraction management.

The major contribution of this study involved collecting in-situ user contexts and its corresponding levels of perceived smartphone distraction as well as analyzing the daily contexts in which users perceive smartphones to be distracting. Furthermore, we explored how users want to manage smartphone distraction by investigating user-generated TAP rules. Our results provide important considerations for designing and implementing context-aware distraction management systems, by identifying the what contexts and functionalities should be considered for effective distraction management.

2 RELATED WORK

2.1 Smartphone Interruption and Distraction

Many prior studies have addressed that smartphones cause interruptions [44, 48, 49]. Users may be often distracted by unexpected new tasks [59] and, in some cases, two tasks may be simultaneously conducted (known as concurrent multitasking). There are two types of interruptions: external interruptions and internal interruptions [2, 58]. External interruptions result from events in the environment that surrounds users. Smartphones may also deliver interruptive notifications [63], which increase cognitive load [46], making people more prone to errors and distractions [67]. One study reported that college students received more than 400 notification per day, on average, with the majority of notifications from instant messaging [48]. Users can also interrupt themselves during ongoing work and then change focus to a different task, even without external events (known as internal interruptions) [17]. Users can be "habitually" distracted, due to functionalities and the pervasive accessibility to online content and smartphones [43, 66]. Self-interruptions can be more disruptive, especially when it leads to off-task smartphone use such as checking social media or playing games [26, 51]. Prior studies have indicated that both external and internal interruptions can cause multitasking situations in which different tasks are combined at the same time [27, 58]. Many studies in the cognitive psychology field have addressed that multitasking is harmful [64, 79]. For example, multitasking can negatively affect cognitive functioning, such as filtering irrelevant information [64, 70]. Furthermore, frequent and unpredictable external and internal interruptions can cause people to make mistakes and impair their efficiencies during their daily lives [16, 45]. Therefore, smartphones can interrupt and disrupt ongoing activities in our daily lives and everyday contexts.

2.2 Contexts Relevant to Smartphone Distraction

Researchers have studied various contexts associated with smartphone distractions, such as learning, socializing, health care, and driving. In academic contexts, despite their positive effects as learning tools, smartphones are also considered as a major distractor due to off-task smartphone use in the classroom environment [38]. Wei and Wang [76] conducted a survey (n=228) and found that distractive phone use, such as texting while taking class, is related to usage habits and media gratification. A recent study that utilized smartphone usage data reported that the average student receives an external interruption, such as a notification every 3-4 minutes during class and that in-class smartphone use is negatively related to GPA [39]. A large-scale survey (n = 1,774) revealed that students frequently conduct multitaskings, including searching content not related to the course, checking Facebook, and texting [33]. Using Facebook and texting while studying were negatively associated with overall college GPA [33]. David et al. [18] conducted a large-scale survey (n = 992) to investigate the effect of multitasking smartphone use when studying or doing homework. The results indicate that utilizing social media and texting while studying were related to smartphone distraction. They also found that changes in smartphone distraction were associated with individual characteristics or app use patterns (e.g., gender). Beasley et al. [10] developed a survey instrument to investigate the effects of college student smartphone use on academic distraction, which showed that the degree of smartphone distraction is depend on the detailed study contexts (e.g., preparing quizzes or exams, social setting).

In addition to academic performance, there are other contexts such as socializing, health care, and driving. Ko et al. [43] conducted a study to investigate the ways in which smartphones distract during group settings and how people perceive the necessity for managing smartphone distraction in this context. The results indicate that many people experience smartphone distraction during group activities and agreed on limiting smartphone usage. Other studies have shown that people perceive external interruption (e.g., notifications) during a conversation as being distracting [67] and that using smartphones during social interactions impairs the quality of the social interactions [44] such as mealtimes [60]. In health-care work settings, smartphones can be a source of distraction for healthcare providers [25], which may lead to adverse events that can threaten patient safety [13]. One main cause of distraction while driving is smartphone use [78]. Ortiz et al. [65] investigated the effect of texting on simulated driving performance and found a negative effect of texting messages during driving.

2.3 Smartphone Distraction Management Strategies

To handle external interruptions, users may change the ringer mode in which all incoming notifications and calls are set to silent. Mobile operating systems (e.g., Android, iOS) provide further features for distraction management. Both Android and iOS offer Do Not Disturb mode, which allows a smartphone user to handle external interruption by silencing calls, alerts, and notifications while the device is locked. The user can also schedule Do Not Disturb mode (e.g., from 2-3 PM, while in the classroom) and allow calls only from specific persons [6].

In addition, mobile OS offers default distraction management tools. Android provides Digital Wellbeing, designed to help Android users limit or monitor their phone and app usage [5]. Digital Wellbeing includes several functions such as Wind Down, Focus Mode, Dashboard, App Timers. Wind Down turns the screen to grayscale and silences notifications with Do Not Disturb during a preset bedtime (i.e., screen configuration and handling external interruptions). Focus mode allows users to select apps to pause temporarily (i.e., blocking blacklist app). Dashboard presents the amount of time a user spends in apps, which apps sent the user the most notifications, and how often the user unlocks the phone (i.e., self-tracking). iOS also provides similar features: Downtime (i.e., only allowing calls and whitelist apps), and App Limits (i.e., goal setting and blocking blacklist apps).

Lyngs et al. [56] analyzed 367 applications, including browser extensions, to investigate common distraction management features. They found that the most common features are blocking or removing distractions (e.g., pausing apps, handling external interruptions), self-tracking, goal advancement (e.g., a reminder), and reward/punishment (e.g., points/streaks, social sharing).

2.4 Context-aware Application and End-User Programming

Context-aware applications use contexts surrounding users to provide relevant information and/or services [20]. These applications can dynamically adapt to changes in the user's activities and environments, so that users can receive the most relevant information or services [21]. In the field of digital distraction, many context-aware applications have been proposed. For example, Lock n' LoL provides the limiting function for mitigating smartphone distractions in group contexts [43], while Let's FOCUS provides location-based (e.g., classroom) smartphone distraction management [38]. One study suggested a notification management system that detects breakpoints in social contexts [67]. Scatterbox delivers relevant messages to a user's mobile device, according to interruptibility by reasoning a user's dynamic contexts [42]. Another study also suggested a system that identifies a user's context and filters out unnecessary mobile messages to the user in order to mitigate distraction [84].

The distraction management rule that these systems use was mainly determined by the system. The behavior of a context-aware application can be defined using end-user programming [21, 28], which refers to programming activities (e.g., creating/modifying the computing systems via simple programming) by end-users who are not professional software developers. End-user programming can be offered through various programming models such as trigger-action programming [50], visual block programming [3, 41], and programming by demonstration [52]. Trigger-action programming is based on if-then conditional rules, and it is one of the widely used end-user programming models in the context-aware applications that allow people to connect many possible events with desired actions [50]. Representative current trigger-action programming services include IFTTT and Bixby routine. Also known as *IF This Then That*, IFTTT is a tool that allows users to generate rules, called applets. An applet may be triggered by changes within web services such as Gmail, Instagram, or other context states (e.g., time), and it automatically carries out tasks designated by users. IFTTT is also used for home automation, for instance, turning on physical devices like smart lights or electronics [32]. Bixby routine allows a user to define a rule (i.e., routine) that can be triggered by a context defined by users: location, time, or event. For example, when a user arrives at home, they can set the phone's alert modality to "sound mode" or have different app shortcuts displayed on the lock screen [68].

3 STUDY PROCEDURE

In order to collect in-situ user context and the corresponding smartphone distraction experiences, we implemented an Android data collection app that asks users to report their current contexts (i.e., their locations and activities) and to what extent participants perceive that their attention being diverted by off-task smartphone use. We carried out field data collection for three weeks using our app. Then, we performed an online survey to ask people how they would like smartphone distractions to be managed. In this section, we outlined the data collection app and presented the process of field data collection. Finally, we showed them how we conducted the online survey.

3.1 Data Collection App Design

We used a mobile Experience Sampling Method (ESM) since it has many advantages for collecting *in-situ* user context (e.g., inexpensive, unobtrusive, and customizable for research purposes) [24]. Many recent studies that collected users' context have also adopted the mobile ESM approach [14, 24, 55]. Our app consists of two principal functions: (1) detecting moments for experience sampling and (2) receiving responses to contexts and perceptions of smartphone distraction. In the following, we explain each function in detail. Then, we present a brief description of the implementation procedure.

3.1.1 Detecting Moments for Response Sampling. Requesting responses from users at inappropriate times can cause inconvenience for users, as it may interfere with their ongoing activities. Therefore, finding the right opportunity for sampling experience is essential [14]. It may be a more critical consideration for our study, because asking a user to respond to a survey at an inconvenient time can lead to negative experiences with the app, which may in turn affect the perceived smartphone distractions we want to measure.

For a straightforward method, we can consider utilizing push notifications at certain times to ask users to respond to a survey. However, push notification may interrupt users at inconvenient times, which will distract the users and discourage their participation.

Some studies reported that people habitually or intentionally check their smartphones without external triggers, such as notifications [43, 66], at this moment, we can confirm that task-switching is happened by the users. Therefore, we assumed that asking users to answer the survey when using their smartphones would be acceptable because it, in itself, may not interrupt users' activities. We also assumed that the use of smartphones usually begins with *lock screen*. It may mean that when a user uses their smartphones without external triggers, the lock screen would be a suitable medium for delivering a survey. Therefore, we decided to display survey questionnaires on the lock screen when users turn on their smartphones so that they can recognize the survey without being interrupted. There also have been many studies on experience sampling or asking users to perform simple tasks when the smartphone screen is turned on by users [11, 72, 74]. However, merely displaying the lock screen and asking users to respond to the survey every time they turn on the smartphone may not be an ideal way to conduct sampling. Asking users to respond to the survey every time they turn on their smartphones would be a significant burden, since people frequently check their phones habitually [7]. Therefore, in order to reduce the burden on users, defining adequate conditions for displaying the lock screen is necessary.

Our approach was capturing a time slot during which one activity lasts and asking users to report the context during that time slot rather than asking whenever users turn on their smartphones. We also assumed that when continuing the activity, a user would be stationary , since when the user moves, their context may change. We also only considered the time slot during which users did not use smartphones because their smartphone use may not be related to the activity they are currently engaged in and most importantly, our goal was to identify in what contexts users *perceive* smartphones as distracting. Therefore, to determine when to display the survey lock screen, we decided that two conditions should be satisfied: (1) the user is stationary and (2) the user has not been using their smartphone for a certain amount of time. The app has an internal timer to count to three minutes. If either condition is not satisfied, the app will reset the timer. Once both conditions have continued to be met for three minutes, the app will display the survey lock screen when the user turns on their smartphone. We empirically selected three minutes as the minimum duration of time slot.

To monitor a user's movement status, we used the Google Activity Recognition API. This API automatically detects and returns info on a user's physical state (e.g., still, running, walking, cycling, driving) by periodically reading short bursts of sensor data and processing them [19]. If the Google Activity Recognition API returns data that indicates the user's state as still, the app considers the user to be stationary. To track the user's smartphone usage status, we implemented a background service in the app. It captures event triggers of the system related to smartphone use (i.e., on/off the screen). The background service calculated the time duration between usage events and was able to compute how long the user had not used the smartphone.

Based on the method we suggested, the ESM app could not capture movement activity (e.g., walking). There were several reasons for excluding movement activity for our ESM study. First, we assumed that people focus on an activities when in a stationary state. We also assumed those stationary activities would account for a large portion of daily activities. So, we considered that the ratio of movement activity would be relatively small. Second, we considered the fixed location contexts for the ESM study since we wanted to understand the perceived smartphone distractions in a specific location. However, locations may change while moving (e.g., walking or running). That is why we decided to exclude location transitions based on moving. Of course, people can move with vehicles (e.g., public transportation), but we regarded it as locations [14]. Finally, it was assumed that responding to the survey while moving (e.g., walking) could result in severe safety problems. Using a smartphone while walking impairs attention and increases the risk of accidents [61]. We avoided these dangerous situations by excluding completing the survey while walking.

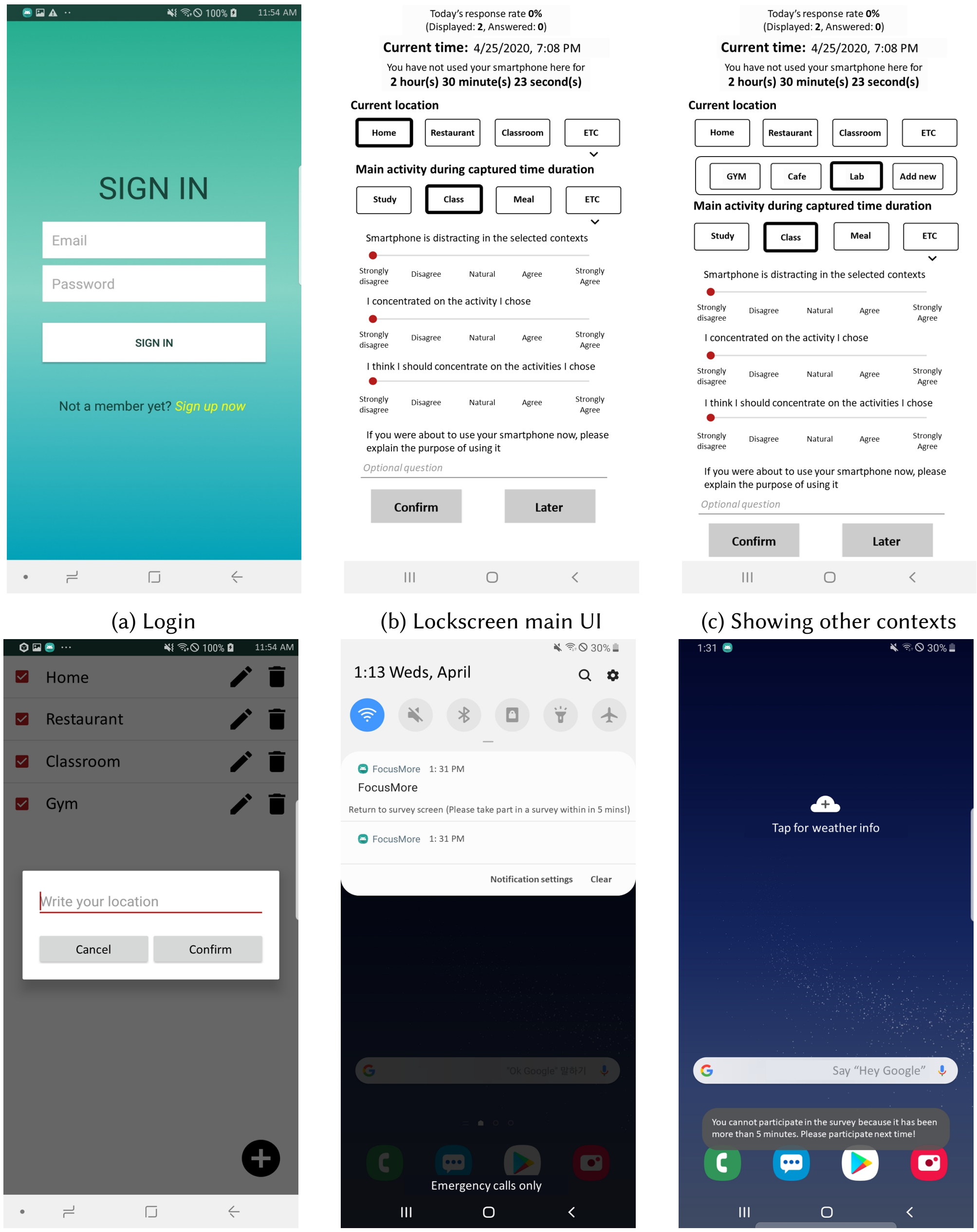
3.1.2 Receiving Contexts and Perception of Smartphone Distraction. As shown in Figure 1b, once the app detects an opportunity for context sampling, it asked the users to report their current contexts during the captured time slot and the perception of distractions caused by smartphones. Collecting as much as possible is the ultimate goal; however, we should choose a few representative contexts, since asking for many different contexts could increase the load for the response. Many studies defined the location, activity, and time as the representative contexts [1] (i.e., a location where the user is present, the activity that the user is currently engaged in, and the temporal information of the situation). The app could collect time context by automatically logging a timestamp. We can also automatically collect the user's physical location information (e.g., GPS coordinates [39], Wi-Fi fingerprint [38]), and the user's physical movement information (e.g., the bunch of values of acceleration or acceleration sensors mounted on a mobile device [71] or the Google Activity Recognition API [19]). However, it is difficult to infer the meaning of the location (i.e., semantic location [30]) such as home, place of work, classroom, and activity. Thus, we collected user-labeled semantic locations and activities.

A user can report their contexts during the captured time-slot by selecting location and activity boxes. The selected boxes are highlighted. The app shows the top three-context items most frequently answered locations and activities so that the user can quickly select their usual context (See Figure 1b). When the user touches an *ETC.* box, the set of contexts is displayed to allow the user to select a context item not included in the top-three contexts list (See Figure 1c). Considering our target participants were students, we initially entered "*home*," "*restaurant*," and "*classroom*" as location items, "*study*," "*class*," and "*meal*" as activity items. The app allowed the user to modify the list of the context items by touching the *ETC.* box and the *Add new* button. Then, the app displays an interface through which the user can add or remove a context item or modify contexts (See Figure 1d). After selecting the location and activity contexts, users can rate how they perceive their smartphone to be distracting in the selected contexts (i.e., "Smartphone is distracting in the selected context") on a 5-point Likert scale, ranging from 1 "strongly disagree" to 5 "strongly agree" [35].

In order to collect additional information during the captured time slot, we prepared further questions related to how much the users concentrated on the activity they chose (i.e., "I concentrated on the activity I chose."), and how much the users think they should concentrate on their activity (i.e., "I think I should concentrate on the activities I choose.") on a 5-point Likert scale. The app also required users to write the purpose of using a smartphone (i.e., "If you were about to use your smartphone now, please explain the purpose of using it."). Answering this question was not mandatory.

A user can ignore or answer the survey later by touching the *Later* button. If the user touches the button, the lock screen will be unlocked. At the same time, a reminder will be displayed on the notification bar so that the user can return to the survey screen by touching the reminder (See Figure 1e), letting them answer the survey. However, if too much time elapses after postponing, the user's contexts or perception of smartphone distraction may be affected. We set the duration of valid ESM responding if it is answered within five minutes. If the user did not return to the survey lock screen within five minutes, the survey expired. In this case, if the user touches the reminder, a message saying that the user cannot participate in the survey will be displayed (See Figure 1f). We determined the five-minute period assuming that it is a sufficient amount of time for occasional smartphone use [43]. When a user touches the *Confirm* button on the lock screen, the app sends the response to the remote server database. The user can log in to the app with their own email. The user's email is used as the user identifier when investigating ESM response data.

The lock screen displayed how much time has elapsed since the user did not move and did not use the smartphone. This information provided temporal information on the most recent activity, allowing the user to *accurately* recall the activity. At the top of the survey lock screen response rate for the day is displayed.



(a) Login (b) Lockscreen main UI (c) Showing other contexts

(d) Editing the list of contexts (e) Survey reminder (f) Expired survey

Fig. 1. Overview of data collecting app

We adopted a rapid iterative design process to improve the app's usability and functionality to implement the data collection app. We performed two low-fidelity prototype tests with three participants (i.e., a total of six participants) and one high-fidelity prototype test with three participants. Each participant group was made up of different people. Prototype test participants did not participate in the final study. During each pilot test, we informed the participants about the purpose of the ESM, presented the survey interface, and requested feedback on how the app could be improved. We came up with three design guidelines based on feedback: (1) allow users to complete a survey easily, in several seconds, (2) allow users to handle situations where they do not have time to answer a survey (e.g., they need to use their smartphone quickly), and (3) use simple and clear questions for the survey. We reflected the guidelines in the system through the design iterations. For example, participants could complete their answer with just a few taps and could cancel or postpone the survey (i.e., using the Later button). Participants also reported that the questions were understandable.

3.2 Field Data Collection

To recruit participants for field data collection, we uploaded promotional posts online bulletin boards for two large universities in Korea. Participants were required to have an Android phone. We recruited 36 participants (10 females; age: M = 22.64, SD = 2.52) from two universities in May 2019. The reason we chose college students for our research is because the young adult group is tech-savvy and are likely to provide diverse coping strategies with various functions smartphones provide (For RQ2). Participants consisted of 31 undergraduates, and five graduates, all with varying majors. Participants attended an offline orientation. We briefly explained how to install and use the app and the overall data collection procedure, including the reward policy. We helped each participant install the data collection app and checked whether the app was working well properly. We asked that the participants maintain at least a 50% response rate to surveys. During the field data collection session, two participants dropped out because one student changed to an iOS Phone and the other student quit due to inconvenience of the ESM. The remaining 34 participants completed the three-week data collection period. Each participant was compensated with approximately with 70 USD.

After the field data collection session, we sent emails and text messages requesting exit-interviews to gain a detailed understanding of how the participants perceived distractions due to their smartphones, and 15 participants (4 females) accepted our request. For the interview, we prepared interview materials that summarized the contexts (i.e., locations and activities) and the average level of perceived smartphone distraction in these contexts. During each interview, the interviewee and we reviewed the interview materials together. The interviews were semi-structured. We asked about how they experienced the smartphone distraction in the context in which they reported a high level of perceived distraction. The interviews lasted between 30 and 40 minutes. All of the interview sessions were recorded, transcribed, and separated by sentence for thematic analysis. Each interviewee was compensated with an additional 10 USD.

3.3 Online Survey: Collecting Rule for Smartphone Distraction Management

After the field data collection session, we conducted an online survey to investigate how participants want to manage smartphone distractions. Users may want to block certain apps to avoid off-task smartphone use or silence notifications to avoid being interrupted when they need to focus. A way of managing smartphone distractions can be defined as the appropriate behaviors of smartphones in distracting situations. We found that trigger-action programming, a paradigm that allows people to connect many possible contexts with desired system actions [50, 73], has many advantages for our work. We sent emails and text messages requesting participants to take the survey. The survey asked participants to describe how they want to manage smartphone distraction using a free-text format similar to trigger-action programming (if-then). We required participants to assume that the smartphone will operate as desired. In addition, several examples were presented to help them understand how to generate rules: "*During the class, block SNS apps and silence all notifications*," or "If a call is received during a meeting, automatically send a message to the sender letting them know that I can't answer now." We asked participants to generate at least five rules, and all participants completed the survey. There was no additional reward for participating in the online survey.

4 DATA ANALYSIS

In this section, we present how we analyzed ESM response data, interview data and distraction management rule data.

4.1 ESM Response Analysis

We first present the methodology used to filter out invalid ESM responses and the handling of incorrect contexts. Then, we explain how we categorized the locations and activities reported in each ESM response. Finally, we present the regression analysis used to identify the contexts associated with the level of perceived smartphone distractions.

4.1.1 Modification and Exclusion of ESM Responses. During three weeks of the data collection session, we collected 9,180 ESM responses from 34 participants. We received an average of 270.0 (SD = 89.8) responses per participant, and the average response rate was 76.0%.

It is essential to check data-integrity for valid results since the ESM responses are participants-generated. For example, users' unintended mistakes can generate contradictory cases (e.g., taking a shower in the classroom). while scanning through the responses as a whole, we found some cases that were responded to inappropriately and needed to be corrected or removed. We determined that these cases should be handled as much as possible. In order to identify cases to correct, we used the users' answers for *the purposes of smartphone use*, the last questionnaire item for the ESM survey (See Figure 1b). The reason being that participants manually typed the answer to this question and we found that participants sometimes specified location and activity for this question, even when the question was non-mandatory (e.g., "*To check the phone after arriving library*"). We found that there were a few cases when the location or activity specified in *the purpose of smartphone use* conflicted with the location or activity contexts reported in the first and second questionnaire items (See Figure 1b). We assumed that *the purpose of smartphone use* was a more reliable response because it was manually entered. We independently marked these conflict cases. Each author scanned the entire ESM responses (n = 9,180). Then, the marked cases were collaboratively reviewed together and corrected after discussion.

We also found a few contradicting cases in ESM responses (e.g., taking a shower in the classroom). To identify contradictory cases, we decided to consider only activities deemed extremely unlikely to occur in the location (e.g., taking a shower in the classroom, drying hair on the bus, and fitness in the car). And if a contradictory case was identified as a singular case among the whole response, we judged that the case was a participant's mistake. We independently marked contradicting cases from all the ESM responses, and collaboratively reviewed marked cases together, then decided whether to remove or not after discussion. As a result, we corrected 18 cases and removed 49 cases, and analysis was conducted with the remaining 9,131 ESM responses.

4.1.2 Categorizing Locations and Activities. During the data collection session, a wide variety of locations and activities were reported from our participants. We categorized the locations and activities reported in the ESM responses, for this process, we manually examined locations and activities in the ESM responses using an affinity diagram to iteratively develop a coding scheme in order to categorize locations and activities. This work was continued until a consensus was reached between researchers [29]. We generated 15 location contexts and 18 activity contexts. The categorization criteria, as well as the categorized locations and activities are presented in appendix.

4.1.3 Regression Analysis. We repeatedly collected user context through mobile ESM. If an individual responded repeatedly, the entire ESM responses could be clustered by individual (average of 270 responses per individual), and this resulted in heterogeneity between clusters (i.e., individual differences). Multilevel models are well known to capture the heterogeneity of a population. If heterogeneity is not separately considered, a cluster effect is reflected in the error term, and this error is meaningful. In this case, the error is not noise, and thus, the result of the model estimation is unreliable. Therefore, we performed a multilevel regression analysis to separate the effects (i.e., individual differences) that can affect the overall level of perceived smartphone distractions. We set the level of perceived smartphone distractions as a dependent variable. Categorized location and activity contexts (as fixed effects) and participants (as random effects) were set as independent variables. The goodness-of-fit of the model was computed with the marginal and conditional R^2, where marginal R^2 indicates variance explained by fixed effects and conditional one indicates variance explained by both fixed effects and random effects [62]. We also generated a multiple linear regression model for each participant (n=34) to analyze how the set of contexts associated with the level at which smartphones are perceived to be distracting differs between participants.

4.2 Rule Data Analysis

We present how we filtered out rules that are unrelated to distraction management or are invalid. Then, we describe how we analyzed the distraction management processes described in the user-generated rules.

4.2.1 Exclusion Criteria of Rule Data. From the online survey, we collected 231 rules from 34 participants. We received an average of 6.8 rules per participant. We found that some rules are not for distraction management. For example, there was a rule stating "*if watching a video on a smartphone for more than 20 minutes, turn on the power saving mode.*" We deemed that this rule would be used for saving smartphone battery life, not for managing distractions. Note that we asked our participants to write the rules in the format of trigger-action programming. However, we found that there were rules that do not consist of trigger and action (e.g., "*When entering the library*"). This rule only describes when he/she wants to manage distractions. For analysis, we excluded rules that were not related to distraction management (n=10) or that are not written in the format of trigger-action programming (n=5). We analyzed the remaining 216 rules.

4.2.2 Diagramming the Process of Distraction Management. The participants generated rules describing the processes that smartphones take certain actions to help participants deal with situations where they might be distracted by smartphones. We generated state diagrams to represent the distraction management process described in the rules. We composed the initial state diagram with trigger conditions and actions, which are components of the traditional IFTTT model (If This, Then That). The first few rules could be expressed with the initial state diagram. However, we found that the initial state diagram has limitations when representing more complex distraction management rules. Therefore, we considered that a more comprehensive state diagram was needed, and we expanded the initial state diagram by reviewing the rules one by one. We repeatedly reviewed the comprehensive set of rules until the state diagram was no longer improved. The finalized state diagram mainly consists of 4 parts (i.e., trigger condition, filtering condition, action, releasing action). We present each part in detail in the results section.

4.2.3 Categorizing Distracting Situations and Smartphone Actions. We also analyzed the situations (or contexts) where participants want to handle smartphone distraction and their corresponding coping strategies (i.e., actions). We manually examined the rules using an affinity diagram to categorize contexts and actions, which were iteratively done until consensus was reached. We present the data analysis results in detail in the results section.

4.3 Interview Data Analysis

To analyze the interview in which we asked participants about their experiences of smartphone distraction, we conducted a thematic analysis to understand the detailed situational contexts in which the participants perceive that the smartphone is distracting. We conducted an open coding process in which codes were labeled to significant text instances (i.e., sentences). Codes were then classified with similar themes. We iteratively analyzed the codes and sentences with affinity diagramming; this process was repeated until we reached an agreement on the finalized themes.

5 RESULTS

5.1 RQ1. Contexts Relevant to Perceiving Smartphone Distraction

5.1.1 General Relationships Between Contexts and Perceived Smartphone Distraction. We examined how the level of perceived smartphone distraction and daily contexts were related in general, and for this we built a linear regression model. The dependent variable was the normalized level of perceived smartphone distraction with a range of 0 to 1. We considered gender as a confounding factor because it can affect the daily smartphone usage pattern [4]. We grouped participants based on gender and then performed multilevel linear regression for each group. The results were shown in Table 1. We attached small graphs in the table to visualize the relative importance (i.e., beta values).

Interestingly, the multilevel regression results showed that the participants perceived smartphone distraction not only in contexts that were commonly perceived that concentration is required, such as studying and taking classes, but also in many other contexts, such as sleeping and doing part-time work. Waking up was considered as a context in which participants perceived smartphones as distracting, and one possible explanation for this is that when participants might try to turn off an alarm in the morning, our app displayed the survey lock screen, which may have bothered them. One participant stated, "*After waking up in the morning, I tried to turn off the alarm. I could not turn it off right away due to the lock screen. The continuous noise was a bit annoying to hear.*" (P2). We also found that smartphones were less distracting when participants were on public transportation or at home. This lower level of perceived distractions might indicate that smartphones are generally perceived to be less distracting in these contexts than in others.

We examined whether there was a difference in perceived smartphone distraction between genders and found that the number of statistically significant distracting contexts in the male group was greater than that in the female group, specifically, fourteen contexts as opposed to six. Male participants tended to report that smartphones were distracting during club activities, meetings, personal affairs, research, and socializing as well as when they were somewhere for leisure or working out. We could not find statistically significant relationships for these contexts in the female group. One notable difference is that female participants tended to perceive smartphones as distracting while they were eating. Likewise male participants showed increased perceived distraction when using other personal devices, such as computers, while female participants conversely showed lower perceived distraction. Lower smartphone distraction on weekends was only observed among male participants, so all these results indicate that distractive contexts can vary according to gender.

As we can see from the goodness-of-fit of the models of both genders (i.e., marginal R^2 vs. conditional R^2), the variance of perceived smartphone distraction levels can be explained by contexts to a certain extent. However, it would be much better explained when considering the user's contextual factors together. In the following, we present results on how the contexts in which smartphones are perceived to be distracting differ among participants.

5.1.2 Individual Differences in Perceiving Smartphone Distraction. We examined how the contexts related to perceived smartphone distraction differ among participants. For each participant, we built a linear regression

Table 1. Results of regression on the perceived smartphone distraction (grouped by gender)

	Perceived smartphone distraction level (normalized range: 0 to 1)					
	Male			Female		
Independent variables	β	p-value		β	p-value	
Time context						
weekend	-0.03	0.002	**	0.01	0.752	
night	0.00	0.777		-0.03	0.176	
morning	0.00	0.887		0.00	0.811	
Location context						
café	0.00	0.781		-0.04	0.028	*
classroom	0.00	0.992		-0.07	0.036	*
club room	-0.01	0.597		-0.03	0.126	
dormitory	0.01	0.566		-0.07	0.082	
home	-0.07	<0.001	***	-0.21	<0.001	***
laboratory	0.02	0.341		-0.07	0.103	
library	0.00	0.776		-0.02	0.386	
outdoor	0.00	0.683		-0.11	<0.001	
place for leisure	0.03	<0.001	***	0.03	0.14	
place for part-time work	-0.05	0.054		-0.04	0.218	
place for personal affair	-0.02	0.014	*	-0.04	0.014	*
place for workout	0.03	0.031	*	0.00	0.903	
public transportation	-0.04	<0.001	***	-0.12	<0.001	***
pub	0.02	0.196		-0.05	0.008	**
restaurant	-0.01	0.347		-0.08	0.001	**
Activity context						
class	0.29	<0.001	***	0.19	<0.001	***
club activity	0.08	<0.001	***	0.02	0.211	
drinking	-0.02	0.218		-	-	
eating	0.03	0.125		0.06	0.022	*
leisure	-0.01	0.276		0.03	0.17	
meeting	0.04	<0.001	***	-	-	
moving	-0.04	0.001	**	0.01	0.421	
part-time work	0.10	<0.001	***	0.07	0.049	*
personal affair	0.03	0.006	**	-0.04	0.107	
preparing for sleep	0.02	0.095		-0.03	0.102	
researching	0.16	<0.001	***	0.02	0.652	
resting	0.03	0.110		0.03	0.191	
sleeping	0.14	<0.001	***	0.11	<0.001	***
socializing	0.06	<0.001	***	0.01	0.811	
studying	0.33	<0.001	***	0.32	<0.001	***
using other personal devices	0.07	<0.001	***	-0.04	0.034	*
waking up	0.11	<0.001	***	0.10	<0.001	***
workout	0.03	0.039	*	-0.01	0.693	
marginal R^2	0.177			0.154		
conditional R^2	0.454			0.440		

Table 2. Three participants' individual models that predict the level of perceived smartphone distraction. Independent variables are user contexts during the data collection.

	Model 1 (P17)		Model 2 (P34)		Model 3 (P8)	
Independent variables	β	p-value	β	p-value	β	p-value
weekend	0.06	0.288	-0.05	0.415	-0.07	0.225
night	-0.10	0.132	0.23	0.011*	0.06	0.418
morning	-0.01	0.930	0.00	0.961	0.02	0.813
Café	-	-	-	-	0.16	0.056
classroom	-0.08	0.497	-0.10	0.342	0.17	0.269
dormitory	-	-	-	-	0.25	0.111
home	-0.20	0.004**	-0.29	0.009**	-	-
library	0.04	0.468	-	-	-	-
ourdoor	-0.05	0.391	-0.15	0.095	0.02	0.706
place for leisure	-	-	-0.26	0.174	0.12	0.120
place for part-time work	0.00	0.952	0.25	0.005**	-	-
place for personal affair	-	-	-0.09	0.217	0.09	0.134
place for workout	-	-	-0.32	0.173	0.17	0.005**
public transportation	-0.06	0.341	-	-	-	-
restaurant	-	-	0.10	0.365	-	-
class	0.25	0.037*	0.58	0.002**	0.23	0.008**
drinking	-	-	0.30	0.002**	-	-
eating	0.07	0.214	0.34	0.103	0.11	0.246
leisure	0.01	0.837	0.60	0.003**	-0.20	0.048*
meeting	-	-	0.37	0.004**	-	-
personal affair	-	-	0.06	0.551	-0.15	0.061
preparing for sleep	-	-	0.26	0.017*	-	-
resting	-	-	0.61	0.018*	-	-
sleeping	0.02	0.770	0.36	0.002**	0.28	<0.001***
studying	0.16	0.010**	0.51	0.006**	0.45	<0.001***
using other personal devices	-	-	0.18	0.172	-	-
waking up	-	-	0.22	0.046*	0.18	0.002**
workout	-0.06	0.283	0.54	0.030	-	-
Adjusted R^2	0.103		0.216		0.386	
p value	<0.001***		<0.001***		<0.001***	

*p<0.05, **p<0.001, ***p<0.001

model that predicts the level of perceived smartphone distraction. We selected three of the 34 models to present individual differences in perceiving smartphone distraction (Table 2). We empirically chose three participants based on the following criteria: (1) They were interview participants, and (2) they consistently responded to surveys (e.g., above the average number of ESM responses, with a relatively uniform time intervals between responses to ensure ESM responses were not biased in specific contexts).

As can be seen from the three participant models, we found that each participant had a different range of contexts in which they perceived smartphones distraction. According to Model 1, P17 perceived that her smartphone was distracting when she was in class or studying. During the interview, she said, "*When I take class, vibrations or lights indicating that I had received notifications continued to draw my attention, and I was distracted.*" On the other hand, she perceived smartphone distraction less frequently at home. According to Model 2, P34 perceived smartphone distraction during class or while studying and was less likely to perceive smartphone distraction at home, like P17. However, P34 perceived distraction in more diverse contexts than P17. P34 perceived smartphone distraction while drinking alcohol, leisure activities, meetings, sleep-related activities, and exercise.

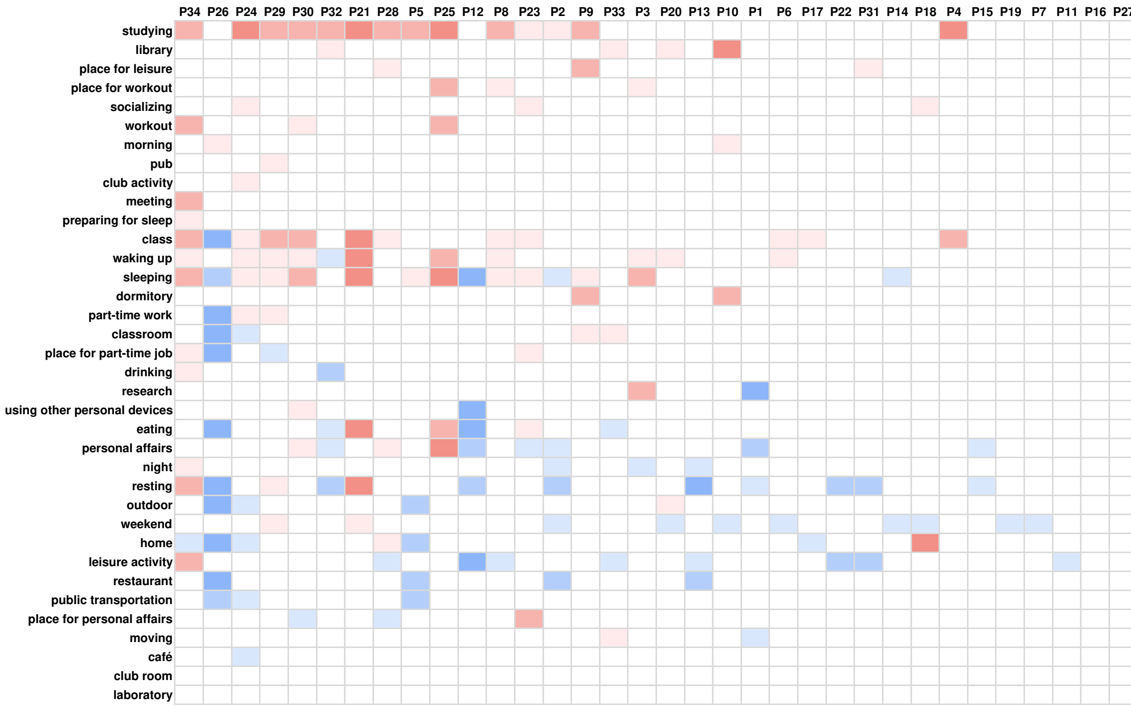


Fig. 2. The individual models were visualized to show the relationships between contexts and distraction level. Each column and row in the table indicates an individual participant and the context, respectively. Blue color means negative relation with perceived smartphone distraction (i.e., less distracting). Orange color denotes positive relation with perceived smartphone distraction (i.e., more distracting).

He also perceived smartphone distraction at night, or when he was at the places for part-time work. P34 said, "*While playing billiards with my friend, I couldn't play as I wanted after using my smartphone to respond to the KakaoTalk message.*" We also found that participants may perceive smartphone distraction differently in similar contexts (i.e., intra-participant differences). P8 perceived distraction differently from P34 in a similar context (i.e., leisure activity) and stated, "*When I played board games, I immersed myself in the game with a strong desire to win. Therefore, when I received a notification, I didn't care about it, so the smartphone did not distract me.*"

We visualized the 34 individual models in Figure 2 to present the relationships between perceived smartphone distractions level and contexts. Each column and row indicates a participant and context, respectively. Colored cells denote statistically significant relationships with perceived smartphone distraction. Blue color means negative correlation with perceived smartphone distraction (i.e., less distracting). Orange color means positive correlation with perceived smartphone distraction (i.e., more distracting). Here, the darker the color, the stronger the correlation with perceived smartphone distraction. The columns (i.e., individual participants) were sorted by according to the number of contexts related to perceived smartphone distraction. In addition, the rows (i.e., contexts) were also sorted based on the frequency of participants reporting those contexts as distracting.

As with the results from the three individual models, we could again confirm that different participants had different contexts in which they perceive smartphones as distracting and that participants may differently perceive smartphone distraction, even in the same contexts.

There were contexts in which some participants perceived that smartphones were distracting, while others reported that they were not distracting. We hypothesized that the different perceptions toward smartphone distraction in the same contexts could be related to how much participants actually concentrated in the contexts (i.e., the level of actual concentration) or how much they thought they should concentrate (i.e., the level of expected concentration). Regarding the relationship between the high level of actual concentration and perceived smartphone distraction, P29 said, "*The smartphone was distracting when I receive unwanted notifications while focusing on a conversation with others.*" On the other hand, P22 said, "*I usually concentrate on activities for which I have a passion. [...] When I do these activities, I ignore smartphone notifications, so I'm not affected.*" About the relationship between the high level of expected concentration and perceived smartphone distraction, P2 said, "*I receive personal training at the gym. [...] Since I am in a position to learn, I need to focus. [...] I separate my phone from myself, so even if notifications come, they don't bother me.*" While P31 indicated, "*A lecture is an activity in which to learn. [...] However, when a notification appears on my phone, it draws my attention, and I keep seeing it. I know I don't have to check it, but I keep looking at my phone habitually.*"

To confirm matters statistically, we calculated the values of Pearson's correlation coefficient (PCC) between the level of perceived smartphone distraction and the level of actual and expected concentration for each participant. In the relationship between perceived smartphone distraction and actual concentration, we obtained statistically significant PCC values from 29 participants, ranging from -0.62 to 0.83. Twelve participants showed positive PCC values, and 17 showed negative PCC values. Similarly, in the relationship between perceived smartphone distraction and expected concentration, we obtained 32 statistically significant PCC values with ranges of -0.56 to 0.89. Eighteen participants showed positive PCC values, and 14 showed negative PCC values, respectively. This means that perceived smartphone distraction might be related to both how much participants actually concentrated and how much they thought they should concentrate in each context, and these relationships varied among the participants.

Twenty-four participants had distractive contexts in which they perceived smartphone distraction, meaning they might need to manage smartphone distraction in these contexts. In particular, some participants had relatively many distractive contexts (e.g., P34, P29, P8, P30), and they might need to manage smartphone distractions in more contexts. In contrast, eight participants only showed contexts in which smartphones were perceived as less distracting. These participants might have already done smartphone distraction management or exercised sufficient self-regulation on smartphone use. P3 said, "*While watching a performance or a movie, I set it to airplane mode in order to not disturb the people around me and to prevent myself from being distracted,*"and P14 said, "*When I'm doing homework or reading a paper for a long time, I set my cell phone to silent.*"

5.1.3 User's Contextual Factors Relevant to Perceiving Smartphone Distraction. The multilevel regression models and individual models showed that individual differences were primarily associated with perceived smartphone distractions. This means that even if people are engaged in the same activity at the same location, the degree of perceived smartphone distraction can vary from individual to individual. It is challenging to explain why there were individual differences in perceiving smartphone distractions because ESM responses failed to deliver sufficient contextual information. In follow-up interviews, we asked participants why they perceived or did not perceive distractions from smartphones. After thematic analysis using interview data, we uncovered four general user contextual factors relevant to perceiving smartphone distraction: (1) relevance to ongoing activity, (2) smartphone checking habits, (3) awareness of normative behaviors and coping strategies, and (4) state of engagement. These qualitative results illustrate the inter-personal and intra-personal diversity observed in the quantitative data (i.e., ESM responses).

Relevance to ongoing activity: Participants said that they perceived smartphone distractions differently depending on whether their smartphone use was relevant to ongoing activities they were engaged in. Participants mentioned that *on-task smartphone* use was associated with a lower level of perceived distraction because on-task smartphone use supported the ongoing activities. P18 said, "*I usually look for files related to studying, and I often ask [something related to studying] friends in group chat rooms, or look for related news articles and information [using a smartphone], so I don't think the smartphone distracts me [while studying].*". Similarly, P34 said, "*While I am in meetings, I have to look at previous materials and refer to how I have worked before. At that time, I usually use Google Drive, so, it seems that the level of distraction [while meeting] was lower than other activities.*"

In contrast, many participants said that smartphones were distracting when they used them for off-task purposes. For example, one participant commented that he was distracted because he continually turned his attention to off-task smartphone use: "*Using something like social media or web surfing means I'm focused on it. When I start looking at it, I kept looking at it, so I get distracted.*" (P22). When participants thought that they needed to use a smartphone for their ongoing activities, they used it for a specific purpose (i.e., searching for information). Sometimes, however, on-task smartphone use digresses to off-task smartphone use, resulting in being distracted. One participant said, "*There were situations where I finished searching for information during class and I naturally did something else [using the smartphone]. I thought I was being disturbed at that time.*" (P14).

We identified that participants may differently perceive smartphone distraction depending on what purpose they are using their smartphones i.e., off- or on-task smartphone use). This result provides a possible explanation for the individual differences in perceiving distractions by smartphones that were identified through the ESM data analysis in Sections 5.1.1 and 5.1.2. In other words, it may mean that even if participants are in the same context (i.e., the same activity and location), they may report different levels of perceived smartphone distraction depending on whether smartphone use was relevant to their ongoing activities.

Smartphone checking habits: Many participants also stated that they perceived distractions owing to their smartphone checking habits. Participants said that they felt the urge to check their smartphones even without external triggers (e.g., notifications); that is, they unconsciously checked their smartphones. Participants said that they were distracted by smartphones even though they did not use them. For example, one participant mentioned, "*I realized that I had a habit of checking my smartphone even though I hadn't receive anything [...] I don't think notifications disturb me; it just seems like my will or habits interfered with my activities.*" (P8). When participants received notifications from instant messaging apps, some responded to notifications right away, and therefore, they said smartphones were distracting because their primary task was interrupted in response to notifications. One participant commented, "*When I get a message or a call while studying, I think I need to respond immediately. When I study, exercise, or drive, I'm likely to reply right away, so I think smartphones are distracting.*" (P2). This result might explain why there is an individual difference in perceiving smartphone distraction which is hard to explain with ESM response analysis. This result shows that participants who frequently check their smartphone or immediately respond to external interruptions are more prone to distraction than other participants in the same context. In many cases, habitual checking behaviors may lead to off-task smartphone use (e.g., utilizing apps irrelevant to ongoing activities), leading to increased smartphone distraction [26].

Normative behaviors and coping strategies: We identified that participants' awareness of normative behaviors and how they should behave were also associated with the degree of perceived smartphone distraction. Participants thought they should regulate smartphone use and focus on their primary task while being aware of the normative behavior required in the given contexts. One participant said, "*Well, first of all, since I am a student, I have to focus on taking classes and studying. When doing these things, I thought using a smartphone would be a distraction.*" (P34). Some participants mentioned *social norms*, and one participant commented, "*I'm working as a counselor who converses face-to-face with students, and I do not think it's okay to use smartphones when talking to someone.*" (P31). Another participant also mentioned, "*Sometimes I go to karaoke alone, but when I go with a group of people and continuously use my smartphone, I feel like I'm ruining the atmosphere.*" (P8).

Some participants noted specific coping strategies for handling interruptions when they thought they should concentrate and regulate smartphone use (e.g., physically distancing from the smartphone, silencing notifications, turning the smartphone face-down, turning it off). Participants responded that adopting coping strategies was associated with a lower level of smartphone distraction. For example, one participant said, "*When I do experiments, I put my phone in my pocket and don't look at it whether I get a notification or not. I set my smartphone to silent mode, so it doesn't matter much anyway.*" (P3).

However, we also identified that even when participants adopted coping strategies (e.g., silencing notifications), they were distracted by notifications. For example, one participant said, "*I set my smartphone to silent mode, but even if the phone was set to silent, notifications still appeared on the screen. In that case, they caught my attention, so I got distracted.*" (P3). These results show that perceived distraction may differ depending on how participants perceive normative behaviors and how they behave in certain contexts. In particular, it shows that participants who handle interruption with specific coping strategies can perceive smartphone distraction less than other participants, even if they are in the same context. However, it was not always possible to successfully manage interruptions through coping strategies because participants were distracted merely by seeing the notifications on the screen. Furthermore, setting notifications to silent may not be an effective coping strategy for those who habitually check their smartphones.

States of engagement: We identified that the extend to which participants engage in ongoing activities can also affect perceived distraction. High engagement states were associated with a low level of perceived smartphone distraction. Participants showed a high engagement state in activities that require high performance. One participant said, "*In the laboratory, concentration is required to obtain accurate experimental results.*" (P2). Participants also showed high engagement states in their favorite or competitive activities: "*At that time, I was reading a book I really wanted to read, so I didn't pay attention unless my phone rang. And so, the smartphone didn't bother me.*" (P22). And when participants were investing resources, such as money for activities, they showed very highly engaged states. One participant said, "*I went to the cafe to study on purpose, so I thought I should study efficiently since I paid to do it.*" (P5). Participants were very engaged in urgent activities. For example, one participant commented, "*I thought I should concentrate on the work that was nearing a deadline.*" (P5).

We identified that when participants were very engaged, they were less interested in their smartphones. For example, one participant said, "*When I watched a documentary video, I wasn't disturbed by my phone because I didn't care about it.*" (P22). In this case, even when using a smartphone, there was a tendency to use it for a purpose (i.e., on-task smartphone use), and a low level of perceived smartphone distraction was reported. One participant commented, "*In the library, there were many times when I didn't really focus on studying. However, if I decided to study at home, I tried to study earnestly. At times like this, smartphones were used to search for information, so the level of distraction was low.*" (P17). Additionally, participants ignored notifications, and this was associated with lower smartphone distraction. "*Smartphone notifications didn't get in the way when I was immersed in the activity because I didn't check notifications even though I saw them.*" (P1). However, there were cases wwhen smartphones were distracting even when the participants were very immersed. This may be related to the absence of a coping strategy for handling external interruptions. One participant said, "*I am very immersed in what I am interested in, and I try to avoid looking at my phone, but if I look at the notifications in the middle of an activity, the flow is broken and I am distracted.*" (P1).

Interestingly, we found that even in very low engagement states, participants may be associated with low perceived smartphone distraction. Participants did not think that their smartphones were interfering with their ongoing activities because they were already distracted and unable to concentrate. One participant commented, "*Smartphones did not bother me that much because I was not studying. I think it is because I don't have much intention to study anyway.*" (P10).

Participants said that if they were able to re-engage quickly, their smartphone was less distracting even if the ongoing activity was interrupted. This means that the level of burden to resume the activity after being interrupted is associated with perceived smartphone distraction. One participant said, "*When I focused on watching television, even if a notification appeared, I checked the phone for a moment and focused on television again, so it didn't get in the way.*" (P22). However, if the cost of a distraction was significant (e.g., missing important parts or

Table 3. States and events to define the context where participants perceive the needs to manage smartphone distractions. A rule may consist of one or more states or events.

(a) Location (state)

context	# of rule
classroom	19
library	16
laboratory	8
place for leisure	8
home	5
public transportation	3
café	1
pub	1
restaurant	1
place for part time job	1
dormitory	1
miscellaneous (location)	9
sum	73

(b) Activity (state)

context	# of rule
studying	15
preparing for sleep	15
sleeping	14
class	12
while using app	11
meeting	10
research	9
exercise	6
drinking	5
socializing	5
driving	4
moving	3
using other personal devices	3
eating	2
part time work	1
resting	1
miscellaneous (activity)	7
sum	123

(c) Time (state)

context	# of rule
time	26

(d) Social state (state)

context	# of rule
social state	10

(e) External interruption (event)

context	# of rule
notification	119
call	38
sum	122

(f) Phone usage trigger (event)

context	# of rule
phone usage stat	31

miscellaneous (event)	1

having difficulty re-engaging), participants perceived huge smartphone distractions. One participant said, "*It was hard for me to concentrate again after I got the notification. In that sense, I think there was a lot of distraction with smartphones during class.*" (P2).

The results showed that perceived smartphone distraction might differ depending on how well participants were engaged in ongoing activities. Participants, in particular, showed low smartphone distraction while they were highly engaged in the activity; the high immersion in activities lowered a user's interest in smartphone use. Participants showed low perceived smartphone distraction even when they were barely engaged in the activity. Our interview result shows that participants demonstrated different levels of distractions even if they were in the same context (as shown in the quantitative data). They also show that even one participant can perceive smartphone distractions differently even if he or she participated in the same activity.

5.2 RQ2. Smartphone Distraction Management Rules

Our thematic analyses of 216 user-generated rules revealed four themes that constitute the rules: (1) Trigger condition, (2) filtering condition, (3) action, and (4) releasing action. Figure 3 shows a diagram that represents the overall process of rules for smartphone distraction management; a detailed version of the diagram is presented in the appendix.

5.2.1 Triggering Condition. Our participants defined context conditions specifying when smartphone configurations or certain actions should be done so that they could manage smartphone distraction. We found that participants used two different types of conditions, *state* and *event*. According to the definition in a study by Huang and Cakmak [31], a state is "*Boolean conditions that can be evaluated to be true or false at any time.*" If we apply this definition to our study, a participant may specify a specific location (e.g., the library) as a state condition where they do not want to be distracted by a smartphone. Unlike the state condition, the event condition is related to an occurrence at a specific point of time (i.e., "*instantaneous signals*"). For example, when receiving an

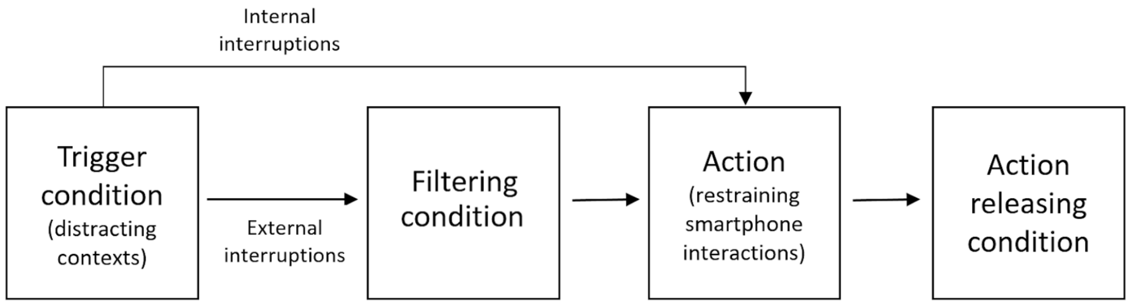


Fig. 3. Overall process of user-generated smartphone distraction management

app notification, we can say that an event context has occurred. Table 3 shows the categorized states and events that were used to define context conditions under which participants want to manage smartphone distractions.

Participants described locations, activities, times, and social states as state contexts. In particular, our participants wanted to manage smartphone distractions when they were doing their primary tasks, such as studying (15 rules), taking the classes (12 rules), meeting others (10 rules), and researching (9 rules). The locations related to participants' primary work, such as a classroom (19 rules), library (16 rules), and laboratory (8 rules), were also specified as state contexts. It might mean that participants do not want to be distracted by smartphones when they are doing their primary activities. Example rules are "*If in the classroom, a game is not available.*" and "*When studying, turn off notifications.*"

Our participants also wanted to manage smartphone distraction while preparing for sleeping (15 rules) or being asleep (14 rules) (e.g., "*Silence all notifications except alarms while sleeping*"). Interestingly, participants did not want to be disturbed by their smartphones even when they were using their smartphones (11 rules). For example, participants wanted to avoid being disturbed when they are doing smartphone activities such as playing games, watching YouTube videos, or doing other tasks (e.g., "*Stop receiving notifications while playing games*" and "*Do not display banner notifications when using a banking app.*").

Participants wanted to manage smartphone distractions in places for leisure such as theaters (8 rules). The intention may be to prevent themselves not only from being disturbed but also from disturbing others. Home was also a place where smartphone management was needed (5 rules). Some participants wrote rules because they wanted to focus on some activities without being interrupted, and they did not want to be contacted with work-related tasks while they were at home. (e.g., "*Block work-related contacts at home.*").

Participants set the time when they needed to manage smartphone distractions (26 rules), and they primarily specified when they usually sleep or work (16 of 26 rules). We also found that not only specific times of day but also periods of several days were specified (4 rules). For example, one rule described, "*Disable apps for fun during exam periods.*" Participants also didn't want to be disturbed by smartphones when they were with others (10 rules), such as, "*When meeting my girlfriend, set the phone to silent.*"

Although it is well-known that driving is an activity that should not be disturbed by smartphones for safety reasons [77, 78], driving was not mentioned much in the distraction management rules that we collected, which may be due to the low proportion of Korean undergraduates and graduate students who owned a car.

The event contexts included the arrival of a notification and the event of exceeding the limited phone usage. One hundred twenty-two rules specified an event context, meaning that many participants may have perceived that receiving information or contacts through smartphones as being distracting. We found that participants generated more rules specifying receiving app notifications than incoming calls (119 rules and 38 rules, respectively).

The event of exceeding limited phone usage occurs when a user uses a smartphone or designated apps more than a goal he/she has set in advance. Thirty-one rules specified exceeding limited phone usage, and most of the goals were defined as usage duration rather than usage frequency (29 rules and two rules, respectively). Example rules included "*When lying down to sleep, YouTube cannot be used for more than 30 minutes*" and "*While studying, certain apps are blocked after 10 minutes of use"*.

Most of the distraction management rules specified event contexts along with state contexts (140 out of 151 rules). This means that participants wanted to manage smartphone distraction when the distracting event contexts occur in various given state contexts. There are also other rules that only specified event contexts without mentioning any state contexts (11 rules). For examples, one rule was given as, "*Stopping the use of the SNS application if it is used for more than 30 minutes.*" Another rule states, "*Daily phone usage time is limited to two hours.*"

5.2.2 Filtering Condition. We found that our participants preferred to filter out distracting notifications or calls, but they still wanted to receive important notifications or calls. The participants defined specific conditions for filtering how notifications or calls should be handled. Thirty percent of the rules specified handling conditions for incoming calls or notifications (40 out of 122 rules). Conditions were defined as such: Where did the notification or incoming call originate? (33 rules), what topic is it related to? (7 rules), and what are the arrival patterns? (2 rules). The participants wanted to handle notifications differently, depending on where they had originated. For example, some participants did not want to receive certain apps' notifications (18 rules) (e.g., *"KakaoTalk notifications are not displayed in the library*"). Other wanted to handle incoming calls and app notifications originating from particular individuals (21 rules) (e.g., "*From midnight to 6 am, silence all notifications except those of specific people.*"). Some rules specify apps and individuals together (6 rules) (e.g., "*Hide KakaoTalk notifications from certain friends during meetings with a professor*"). Participants also wanted to handle notifications differently depending on the topic of each notification (7 rules) (e.g., "*Block notifications irrelevant to work during work hours*"). There were also rules for participants to capture arrival patterns over time (2 rules) (e.g., "*During sleep, only calls received more than three times within 10 minutes are received by sound*).

5.2.3 Action for Handling Interruptions. If the context conditions and filtering conditions (regarding app notifications or incoming calls) are met, certain smartphone actions are taken so that participants can handle interruptions. Our participants mainly specified three types of actions: handling notifications or calls (119 rules), only allowing or blocking certain apps or locking the smartphone (75 rules), and changing smartphone configurations (28 rules).

Participants want to handle app notifications or incoming calls by silencing (59 out of 119 rules) or hiding them (55 out of 119 rules). Silencing means receiving notifications or incoming calls without feedback such as sound or vibration (e.g., "*Silence all notifications during classes or meetings.*"). Hiding means not sending any indication that notifications or incoming calls have arrived, so that a user cannot recognize them (e.g., "*Disable all notifications after midnight*"). Some participants wanted to inform senders that they were currently unable to respond to messages or calls by automatically sending a reply message (8 out of 119 rules) (e.g., "*When receiving a call during a meeting, send a message saying I am in a meeting*").

Participants designated one or more blacklist apps (42 rules) or whitelist apps (17 rules). Example rules included "*While exercising, all apps are unavailable except exercise-related and music apps*" and "*During exam periods, limit the usage time of entertainment apps.*" Some participants wanted more restrictive or coercive actions. They wanted to lock their smartphones so they could not use any features (e.g., "*Make it impossible to unlock the lock screen when a smartphone is used more than a limited amount of time in bed at night*"). Some participants specified a duration of time during which smartphone use would be limited (e.g., "*limit executing a specific SNS app for about an hour if it is executed too often"*). We also found that some participants generated more coercive rules than others. For example, some participants wanted to set goals for smartphone usage first, and then restrict smartphone use when they exceeded the usage goals (33 rules), while others wanted to restrict use as soon as state contexts were satisfied (42 rules). However, some participants just wanted displaying a warning message when blacklist apps were used beyond their usage goals.

Participants also defined actions altering the smartphone configurations. The most common actions were changing the ringer mode (17 out of 28 rules). Example rules were "*When listening to a lecture, set the phone to silent mode*" and "*Set to vibrate mode when arriving at a dormitory.*" Participants also wanted to control media sound volume or screen brightness (5 and 4 rules, respectively). For example, one rule stated, "*Block all notifications and darken the phone screen as much as possible at the cinema.*" Another rule stated, "*Set the media sound to be silent when inside the classroom.*"

5.2.4 Releasing Action. Actions should be released when users no longer need handling interruptions. However, we found that there are cases where the conditions for actions being released are not specified in the rules. For example, one rule stated, "*Block all notifications and darken the phone screen as much as possible at the cinema.*" Actions of blocking notifications and darkening the phone screen should be released when the user leaves the cinema, however, the condition for when such actions will be released is not specified in this rule. Another rule stated, "*After midnight, set the phone to lock*", but this rule does not specify the conditions for releasing the lock.

There are also interesting exceptional cases. Six participants specified particular conditions for releasing actions while the actions are being enforced. These rules were related to actions that restrict smartphone use, and the participants specified conditions to temporarily release the actions. It could be that the participants wanted to limit smartphone use in certain contexts, but there may be a demand for use in certain situations (e.g., taking a break using a phone, searching for information, handling an urgent contact). For example, one rule stated, "*In the library, [...] to use other apps, it is necessary to solve complex arithmetic.*" and another stated, "*Before going to bed, prevent app use with a warning message. However, it can be released when the use of an app is necessary.*"

6 DISCUSSION

6.1 Diversity of User Contexts Relevant to Smartphone Distraction

Our result shows that participants may perceive smartphone distraction not only in contexts that were commonly perceived to require concentration (e.g., studying, taking classes), but also in other contexts (e.g., eating, in place for leisure). Our work extended the findings of studies focused on contexts where people are known to perceive that concentration is needed (e.g., class, studying, working, driving) [33, 47, 65, 76, 80]. These findings highlight the need for further studies on smartphone distraction in everyday contexts. For example, it may be possible to investigate why and how much people are (or not) distracted by smartphones in daily contexts and how these daily distractions are related to people's overall state (e.g., health, depression, stress, emotions) or task performance (e.g., academic or work performance). Our study is limited in that we did not receive ESM responses for safety reasons while participants were in motion (e.g., walking). Further explanations would be needed to understand how people perceive smartphones during the moving state. For example, using a smartphone while moving may be particularly distracting or dangerous because it decreases one's ability to respond to changes in the situation caused by movement [82]. However, depending on contexts, smartphones may be less distracting (e.g., using a smartphone while walking in a large park), or people may need to use smartphones (e.g., using map apps to get to a destination). Therefore, it would be necessary to understand in what context the smartphone is distracting or not when people are moving, and to investigate how to handle smartphone distraction [37].

6.2 Diversity of User Perceptions of Smartphone Distraction

Our quantitative and qualitative findings show that there are noticeable inter- and intra-participant differences in perceptions of smartphone distraction. Results of the individual linear regression presented that different participants had different sets of contexts where smartphones were perceived as distracting. In addition, there were inter-participant differences in perceptions of smartphone distraction even in similar contexts. Through ESM responses, we also identified intra -participant differences showing that each participant perceived smartphone distraction differently even in the same context. There have been studies on how people are distracted by smartphones in specific contexts (e.g., studying, class, socializing) [38, 67] and what adverse consequences could be caused by smartphone distractions. We further focused on not only contexts (e.g., location, activity), but also individual differences and diversity of user requirements for distraction management (heterogeneous even in same contexts). We also suggest that a user's contextual factors can influence individual differences in perceiving distractions (e.g., relevance to ongoing activities and states of engagement). Our study also provides comprehensive insights into how various contexts interact with each other, and affect perceiving smartphone distractions. Further investigation is needed on how the individual traits, states, and other factors may affect smartphone distraction. We also suggest that existing studies on context-aware distraction management systems should be also extended with improved flexibility and suitability for providing interventions by considering the user's diverse contextual factors.

6.3 Diversity of Coping Strategies for Distraction Management

Our study showed that coping strategies for smartphone distractions are strongly user-dependent, as different users perceived smartphone distractions differently and preferred to handle interruptions in different ways, even in identical contexts. Therefore, it is essential to understand factors affecting perceptions of smartphone distractions (i.e., external interruption vs. internal interruption) and strategies for managing them (e.g., filtering of external interruptions or limiting of smartphone use). Existing studies on smartphone distraction management systems have provided users with fixed intervention mechanisms and evaluated their usefulness and user experiences without considering individual differences (e.g., preferred coping strategies). Our study suggests that a comprehensive smartphone distraction management system is needed and provides insight on how such a system should be designed. Furthermore, our study provides a foundation for another important research direction: i.e., distraction management should provide the wide degree of coercion for handling internal interruptions (i.e., permissive vs. coercive). For example, if a permissive distraction management mechanism is provided to a user who lacks self-control, the intervention is unlikely to be effective. Further research is needed on the influence of individual characteristics in coercion settings.

6.4 Design Implications for Context-aware Distraction Management

6.4.1 Supporting Context Diversity and Individual Differences in Perceiving Smartphone Distraction. Our study showed that the contexts where people perceive smartphone distraction were diverse, and that each person perceived smartphone distraction differently according to his/her traits, states, or situational environments. This finding suggests that a context-aware distraction management system should well detect diverse daily contexts and individual differences. If the system can directly or indirectly access information associated with context, the contexts would be easily inferred. For example, we can consider locations where a user resides (e.g., home, dormitory) or visits regularly (e.g., classroom, laboratory). The locations can be defined and detected using direct information of the locations (e.g., GPS coordinates [39], Wi-Fi fingerprint [38], Bluetooth signals [12]). With existing sensing technologies, indirect information of the context can also be used for detecting contexts (e.g., inferring sleeping, conversation [75], and physical activity [19]). However, there may be certain situations in which defining/detecting contexts is challenging.

We discuss four challenging cases. The first case is a situation in which there is direct context information but the system may not have the context information at the stage in which the contexts are defined. For example, a user may want to mute all notifications in a specific indoor location, but the system may not have information about that location (e.g., Wi-Fi fingerprints of that indoor location). In this case, we can defer contextual binding until the system can accurately acquire the exact information of the context. For example, if the information regarding a user's desired context is not readily accessible (e.g., Wi-Fi fingerprint of the indoor location), the system may require the user's approximate information not directly associated with the contexts but may remind the user to register the context later (e.g., time or approximate GPS information).

The second case is a situation where users require *generic contexts* rather than providing exact information of contexts. For example, one participant defined generic contexts in a rule "*Set up silent notifications during meetings.*" However, these generic contexts (e.g., café, restaurant, theater, meeting, resting) are challenging for the system to detect because the information of context is not well defined. For example, the system cannot identify meeting activity if it is not determined how many participants have participated in the meeting as well as the location of the meeting. Moreover, the meeting activity may require different normative behaviors depending on detailed contextual information (e.g., a critical meeting with a professor versus a casual meeting with lab mates). Therefore, in such cases, therefore, additional contextual information (e.g., from calendars as context sensors [54]) is required for a clear context definition. The semantic place-learning method can also be considered [15].

The third case is that detecting contexts is technically difficult with existing context-aware technology (e.g., processing sensing values). Many participants have defined "studying" or "taking a class" activities as trigger contexts in distraction management rules. However, detecting studying is non-trivial because a smartphone is sometimes physically separated from users while studying, and it is a stationary activity (but could happen at noisy places such as coffee shops). One way of enabling context-sensing is to ask users to detail the contexts. For example, taking a class usually occurs in a designated classroom (i.e., location context) at a predefined time (i.e., time context). Therefore, taking a class can be redefined and detected if the location and time contexts are correctly specified.

The fourth case is a situation where the information or signal for detecting the context is not accessible (e.g., "*silence all notifications when I am with my girlfriend.")*. One possible way of detecting a social context (e.g., co-location with someone) is to capture the Bluetooth signals of the devices [12]. However, when the system attempts to scan a Bluetooth signal to detect a specific person, the Bluetooth function of the person's device may be disabled (e.g., disabled Bluetooth scanning). In such cases, as it is not possible for the system to detect context, the system should inform the user of the possibility of inaccessibility to the context information and when such a situation may occur.

6.4.2 Supporting Interruption Handling. We present system design implications related to supporting interruption handling (i.e., handling external and internal interruptions and releasing actions). For handling external interruptions, the distraction management system should support the filtering of external interruptions. Our participants reported three conditions for filtering external interruptions: (1) from where external interruptions originated, (2) the topic related to external interruptions, and (3) the arrival patterns of external interruptions. The system should also provide diverse modality options for receiving external notifications or incoming calls (e.g., vibration, silent, and hidden). Other methods, such as deferring notifications [67] and automatic-replying to the sender of interruptions (specified in the rules of this study) are possible. Existing distraction management systems have also provided filtering external interruptions. However, filtering conditions are mainly determined by the system and not by user requirements [42, 84].

For handling internal interruptions, smartphone distraction management systems should provide mechanisms having a wide range of limiting intensities, rather than providing one fixed limiting mechanism. Our participants reported a need for different intensities of mechanisms to limit smartphone use (e.g., ranging from less restrictive to highly restrictive). This means that while a certain limiting mechanism may be suitable for some people, this mechanism may be too restrictive or too loose for others. We identified three types of mechanisms for handling internal interruptions: (1) delivering warning messages without limiting smartphone use, (2) allowing limited smartphone use, and (3) blocking all smartphone use. With regard to allowing limited smartphone use, our participants mentioned specifying whitelisted or blacklisted apps, allowing the limited use duration or number of app executions, as well as allowing temporary use after being limited (e.g., allowing use after performing certain tasks such as calculations).

For *releasing actions*, the system should require users to clarify not only trigger conditions but also releasing conditions for current actions. In many cases, participants specified only conditions for 'triggering actions' for handling interruptions without specifying conditions for 'releasing actions.' In context-aware applications, if the system continues to provide the service when the user no longer needs it, this can negatively affect the user experience. In the case of distraction management, it may be more inconvenient because the system may restrict smartphone interaction to handle both external and internal interruptions. Therefore, releasing conditions for interruption handling should be carefully considered to provide context-aware distraction management services (e.g., validating users' rules on releasing conditions, and nudging users to fix logical errors)

6.4.3 Supporting End-User Programming. We presented four components that constitute context-aware distraction management rules. However, different users have different contexts in which they perceive smartphone distraction and coping strategies for managing distractions. To meet diverse user requirements, allowing users to define how the context-aware system works would be appropriate (i.e., end-user programming) rather than providing predefined operations. Several prior tools (e.g., Dey's a CAPpella) [21] have been proposed for supporting end-user programming. Especially, TAP is one of the widely used end-user programming models, allowing users to connect possible conditions to the desired actions for context-aware applications [50]. However, despite its usefulness, the existing TAP model does not support sufficient expressiveness for defining user-generated distraction management rules because it only supports two components: trigger condition and action. Our study indicates that the existing end-user programming model should be further extended to support context-aware distraction management systems.

We suggest that context-aware distraction management systems should enable improved expressivity for handling interruptions so that users can express the desired system behaviors. For example, our participants required diverse conditions for handling external interruptions. Participants wanted to handle external interruptions differently depending on the origins of external interruptions (e.g., from certain apps or persons), what they are about (e.g., topic), and their arrival patterns (e.g., three times within 10 min) by setting different modalities (e.g., vibrating, silencing, and hiding). It would also be possible to define conditions with two or more conditions (e.g., only receiving notifications related to certain topics and are from certain apps). Further participants required diverse intensities of mechanisms for limiting their smartphone use. Some participants requested for the allowance of temporary use after smartphone usage was restricted. The system should also require users to clarify the conditions for releasing interruption handling actions (e.g., blocking). If these limiting actions are not released when users no longer need to handle interruptions, users may experience inconvenience (e.g., missing important contacts, being blocked when they want to use the smartphone). Therefore, the system should require users to clarify not only trigger conditions but also the releasing conditions for interruption handling. However, we also suggest that allowing less tech-savvy groups to generate the desired rules should be considered. For this, the trade-off between improving expressivity and ease of use should be explored. We consider visual block programming, one of end-user programming methods, that allows users to make their own programs (e.g., rules) by providing a graphical user interface. This enables users who may be less tech-savvy to easily create rules [8].

We also suggest that context-aware distraction management systems should provide validity checks. Even if the user can define distraction management rules, it may be defined differently from users' intentions owing to the users' mental model mismatches [31]. Therefore, a process of *validating* whether user-defined rules are valid would be required. For this, context-aware distraction management system designers can consider simulating distraction management rules and allowing users to modify the rules based on simulation results(i.e., rule debugging) [57].

7 CONCLUSION

The major contribution of this work is to collect in-situ user contexts and its corresponding experience of smartphone distraction and to identify in what daily contexts, users perceive smartphones as distracting. We also explore how users want to manage smartphone distraction by dissecting user-generated rules. Our results provide important considerations for designing context-aware distraction management systems. The key takeaway of our study is that distraction perceptions are context-diverse and user-dependent, and user specified rules require sufficient expressivity including filtering and action releasing. However, our results reflect the characteristics of a certain population (i.e., college students), and thus the generalizability of this work is limited. We call for further studies on designing distraction management systems that consider technical knowledge and ability (including accessibility needs) of target user groups.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (2017M3C4A7083534, 2020R1A4A1018774).

REFERENCES

[1] Gregory D Abowd, Anind K Dey, Peter J Brown, Nigel Davies, Mark Smith, and Pete Steggles. 1999. Towards a better understanding of context and context-awareness. In *International symposium on handheld and ubiquitous computing*. Springer, 304–307.

[2] Rachel F Adler and Raquel Benbunan-Fich. 2013. Self-interruptions in discretionary multitasking. *Computers in Human Behavior* 29, 4 (2013), 1441–1449.

[3] Sonya Alexandrova, Zachary Tatlock, and Maya Cakmak. 2015. RoboFlow: A flow-based visual programming language for mobile manipulation tasks. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 5537–5544.

[4] Ionut Andone, Konrad Błaszkiewicz, Mark Eibes, Boris Trendafilov, Christian Montag, and Alexander Markowetz. 2016. How age and gender affect smartphone usage. In *Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing: adjunct*. 9–12.

[5] Google Android. 2020. *Digital Wellbeing*. Retrieved May 14, 2020 from https://www.android.com/digital-wellbeing/

[6] Apple. 2020. *Use Do Not Disturb on your iPhone, iPad, and iPod touch*. Retrieved May 14, 2020 from https://support.apple.com/en-us/HT204321

[7] Asurion. 2020. *Americans Check Their Phones 96 Times a Day*. Retrieved May 14, 2020 from https://www.prnewswire.com/news-releases/americans-check-their-phones-96-times-a-day-300962643.html

[8] Nayeon Bak, Byeong-Mo Chang, and Kwanghoon Choi. 2020. Smart Block: A visual block language and its programming environment for IoT. *Journal of Computer Languages* 60 (2020), 100999.

[9] Jakob E Bardram and Niels Nørskov. 2008. A context-aware patient safety system for the operating room. In *Proceedings of the 10th international conference on Ubiquitous computing*. 272–281.

[10] Robert E Beasley, Jacob T McMain, Mathew D Millard, Dylan A Pasley, and Matthew J Western. 2016. The effects of college student smartphone use on academic distraction and dishonesty. *Journal of Computing Sciences in Colleges* 32, 1 (2016), 17–26.

[11] Larry Chan, Vedant Das Swain, Christina Kelley, Kaya de Barbaro, Gregory D Abowd, and Lauren Wilcox. 2018. Students' Experiences with Ecological Momentary Assessment Tools to Report on Emotional Well-being. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–20.

[12] Zhenyu Chen, Yiqiang Chen, Lisha Hu, Shuangquan Wang, Xinlong Jiang, Xiaojuan Ma, Nicholas D Lane, and Andrew T Campbell. 2014. ContextSense: unobtrusive discovery of incremental social context using dynamic bluetooth data. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*. 23–26.

[13] Sumi Cho and Eunjoo Lee. 2016. Distraction by smartphone use during clinical practice and opinions about smartphone restriction policies: A cross-sectional descriptive study of nursing students. *Nurse education today* 40 (2016), 128–133.

[14] Woohyeok Choi, Sangkeun Park, Duyeon Kim, Youn-kyung Lim, and Uichin Lee. 2019. Multi-Stage Receptivity Model for Mobile Just-In-Time Health Intervention. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (2019), 1–26.

[15] Yohan Chon, Nicholas D Lane, Fan Li, Hojung Cha, and Feng Zhao. 2012. Automatically characterizing places with opportunistic crowdsensing using smartphones. In *Proceedings of the 2012 ACM conference on ubiquitous computing*. 481–490.

[16] Sheldon Cohen. 1980. Aftereffects of stress on human performance and social behavior: a review of research and theory. *Psychological bulletin* 88, 1 (1980), 82.

[17] Laura Dabbish, Gloria Mark, and Víctor M González. 2011. Why do I keep interrupting myself? Environment, habit and self-interruption. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3127–3130.

[18] Prabu David, Jung-Hyun Kim, Jared S Brickman, Weina Ran, and Christine M Curtis. 2015. Mobile phone distraction while studying. *New media & society* 17, 10 (2015), 1661–1679.

[19] Google Developer. 2018. *Activity Recognition API*. Retrieved May 14, 2020 from https://developers.google.com/location-context/activity-recognition

[20] Anind K Dey. 2001. Understanding and using context. *Personal and ubiquitous computing* 5, 1 (2001), 4–7.

[21] Anind K Dey, Raffay Hamid, Chris Beckmann, Ian Li, and Daniel Hsu. 2004. a CAPpella: programming by demonstration of context-aware applications. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 33–40.

[22] Anind K Dey, Timothy Sohn, Sara Streng, and Justin Kodama. 2006. iCAP: Interactive prototyping of context-aware applications. In *International Conference on Pervasive Computing*. Springer, 254–271.

[23] Giuseppe Fenza, Domenico Furno, and Vincenzo Loia. 2012. Hybrid approach for context-aware service discovery in healthcare domain. *J. Comput. System Sci.* 78, 4 (2012), 1232–1247.

[24] Andrea Gaggioli, Giovanni Pioggia, Gennaro Tartarisco, Giovanni Baldus, Daniele Corda, Pietro Cipresso, and Giuseppe Riva. 2013. A mobile data collection platform for mental health research. *Personal and Ubiquitous Computing* 17, 2 (2013), 241–251.

[25] Preetinder S Gill, Ashwini Kamath, and Tejkaran S Gill. 2012. Distraction: an assessment of smartphone usage in health care work settings. *Risk management and healthcare policy* 5 (2012), 105.

[26] Jeremy Glassman, Marilyn Prosch, and Benjamin BM Shao. 2015. To monitor or not to monitor: Effectiveness of a cyberloafing countermeasure. *Information & Management* 52, 2 (2015), 170–182.

[27] Victor M González and Gloria Mark. 2004. "Constant, constant, multi-tasking craziness" managing multiple working spheres. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 113–120.

[28] Jonna Häkkilä, Panu Korpipää, Sami Ronkainen, and Urpo Tuomela. 2005. Interaction and end-user programming with a context-aware mobile application. In *IFIP Conference on Human-Computer Interaction*. Springer, 927–937.

[29] Karen Holtzblatt and Hugh Beyer. 1997. *Contextual design: defining customer-centered systems*. Elsevier.

[30] Haibo Hu and Dik-Lun Lee. 2004. Semantic location modeling for location navigation in mobile environment. In *IEEE International Conference on Mobile Data Management, 2004. Proceedings. 2004*. IEEE, 52–61.

[31] Justin Huang and Maya Cakmak. 2015. Supporting mental model accuracy in trigger-action programming. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 215–225.

[32] IFTTT Inc. 2020. *IFTTT: Every thing works better together*. Retrieved May 14, 2020 from https://ifttt.com/

[33] Reynol Junco and Shelia R Cotten. 2012. No A 4 U: The relationship between multitasking and academic performance. *Computers & Education* 59, 2 (2012), 505–514.

[34] Jonathan J Kandell. 1998. Internet addiction on campus: The vulnerability of college students. *Cyberpsychology & behavior* 1, 1 (1998), 11–17.

[35] Dagmar Kern, Paul Marshall, Eva Hornecker, Yvonne Rogers, and Albrecht Schmidt. 2009. Enhancing navigation information with tactile output embedded into the steering wheel. In *International Conference on Pervasive Computing*. Springer, 42–58.

[36] Ashraf Khalil and Kay Connelly. 2005. Context-aware Configuration: A study on improving cell phone awareness. In *International and Interdisciplinary Conference on Modeling and Using Context*. Springer, 197–209.

[37] Donghee Kim, Kyungsik Han, Jeong Seop Sim, and Youngtae Noh. 2018. Smombie Guardian: We watch for potential obstacles while you are walking and conducting smartphone activities. *PLoS one* 13, 6 (2018), e0197050.

[38] Inyeop Kim, Gyuwon Jung, Hayoung Jung, Minsam Ko, and Uichin Lee. 2017. Let's FOCUS: Mitigating Mobile Phone Use in College Classrooms. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–29.

[39] Inyeop Kim, Rihun Kim, Heepyung Kim, Duyeon Kim, Kyungsik Han, Paul H Lee, Gloria Mark, and Uichin Lee. 2019. Understanding smartphone usage in college classrooms: A long-term measurement study. *Computers & Education* 141 (2019), 103611.

[40] Jaejeung Kim, Chiwoo Cho, and Uichin Lee. 2017. Technology supported behavior restriction for mitigating self-interruptions in multi-device environments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–21.

[41] Seung Han Kim and Jae Wook Jeon. 2007. Programming lego mindstorms nxt with visual programming. In *2007 International Conference on Control, Automation and Systems*. IEEE, 2468–2472.

[42] Stephen Knox, Ross Shannon, Lorcan Coyle, Adrian K Clear, Simon Dobson, Aaron J Quigley, and Paddy Nixon. 2008. Scatterbox: Context-aware message management. *Revue d'intelligence artificielle* 22, 5 (2008), 549–568.

[43] Minsam Ko, Seungwoo Choi, Koji Yatani, and Uichin Lee. 2016. Lock n'LoL: group-based limiting assistance app to mitigate smartphone distractions in group activities. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 998–1010.

[44] Minsam Ko, Subin Yang, Joonwon Lee, Christian Heizmann, Jinyoung Jeong, Uichin Lee, Daehee Shin, Koji Yatani, Junehwa Song, and Kyong-Mee Chung. 2015. NUGU: a group-based intervention app for improving self-regulation of limiting smartphone use. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. 1235–1245.

[45] Kara A Latorella. 1996. Investigating interruptions: an example from the flightdeck. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 40. SAGE Publications Sage CA: Los Angeles, CA, 249–253.
[46] Nilli Lavie. 2010. Attention, distraction, and cognitive control under load. *Current directions in psychological science* 19, 3 (2010), 143–148.
[47] Kyung Young Lee, Minwoo Lee, and Kimin Kim. 2017. Are Smartphones helpful? An empirical investigation of the role of Smartphones in users' role performance. *International Journal of Mobile Communications* 15, 2 (2017), 119–143.
[48] Uichin Lee, Joonwon Lee, Minsam Ko, Changhun Lee, Yuhwan Kim, Subin Yang, Koji Yatani, Gahgene Gweon, Kyong-Mee Chung, and Junehwa Song. 2014. Hooked on smartphones: an exploratory study on smartphone overuse among college students. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 2327–2336.
[49] Luis Leiva, Matthias Böhmer, Sven Gehring, and Antonio Krüger. 2012. Back to the app: the costs of mobile application interruptions. In *Proceedings of the 14th international conference on Human-computer interaction with mobile devices and services*. 291–294.
[50] Nicola Leonardi, Marco Manca, Fabio Paternò, and Carmen Santoro. 2019. Trigger-action programming for personalising humanoid robot behaviour. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–13.
[51] Vivien KG Lim. 2002. The IT way of loafing on the job: Cyberloafing, neutralizing and organizational justice. *Journal of organizational behavior: the international journal of industrial, occupational and Organizational Psychology and Behavior* 23, 5 (2002), 675–694.
[52] James Lin, Jeffrey Wong, Jeffrey Nichols, Allen Cypher, and Tessa A Lau. 2009. End-user programming of mashups with vegemite. In *Proceedings of the 14th international conference on Intelligent user interfaces*. 97–106.
[53] William Little, Henry Watson Fowler, Jessie Coulson, and Charles Talbut Onions. 1973. *The shorter Oxford English dictionary on historical principles*. Technical Report. Oxford University Press.
[54] Tom Lovett, Eamonn O'Neill, James Irwin, and David Pollington. 2010. The Calendar as a Sensor: Analysis and Improvement Using Data Fusion with Social Networks and Location. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (Copenhagen, Denmark) *(UbiComp '10)*. Association for Computing Machinery, New York, NY, USA, 3–12.
[55] Kai Lukoff, Cissy Yu, Julie Kientz, and Alexis Hiniker. 2018. What Makes Smartphone Use Meaningful or Meaningless? *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–26.
[56] Ulrik Lyngs, Kai Lukoff, Petr Slovak, Reuben Binns, Adam Slack, Michael Inzlicht, Max Van Kleek, and Nigel Shadbolt. 2019. Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–18.
[57] Marco Manca, Carmen Santoro, Luca Corcella, et al. 2019. Supporting end-user debugging of trigger-action rules for IoT applications. *International Journal of Human-Computer Studies* 123 (2019), 56–69.
[58] Gloria Mark, Victor M Gonzalez, and Justin Harris. 2005. No task left behind? Examining the nature of fragmented work. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 321–330.
[59] Yoshiro Miyata and Donald A Norman. 1986. Psychological issues in support of multiple activities. *User centered system design: New perspectives on human-computer interaction* (1986), 265–284.
[60] Carol Moser, Sarita Y Schoenebeck, and Katharina Reinecke. 2016. Technology at the table: Attitudes about mobile phone use at mealtimes. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 1881–1892.
[61] Gabrielle Naïmé Mourra, Sylvain Senecal, Marc Fredette, Franco Lepore, Jocelyn Faubert, François Bellavance, Ann-Frances Cameron, Elise Labonté-LeMoyne, and Pierre-Majorique Léger. 2020. Using a smartphone while walking: The cost of smartphone-addiction proneness. *Addictive behaviors* 106 (2020), 106346.
[62] Shinichi Nakagawa and Holger Schielzeth. 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in ecology and evolution* 4, 2 (2013), 133–142.
[63] Tadashi Okoshi, Julian Ramos, Hiroki Nozaki, Jin Nakazawa, Anind K Dey, and Hideyuki Tokuda. 2015. Reducing users' perceived mental effort due to interruptive notifications in multi-device mobile environments. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 475–486.
[64] Eyal Ophir, Clifford Nass, and Anthony D Wagner. 2009. Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences* 106, 37 (2009), 15583–15587.
[65] C Ortiz, S Ortiz-Peregrina, JJ Castro, M Casares-López, and C Salas. 2018. Driver distraction by smartphone use (WhatsApp) in different age groups. *Accident Analysis & Prevention* 117 (2018), 239–249.
[66] Antti Oulasvirta, Tye Rattenbury, Lingyi Ma, and Eeva Raita. 2012. Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 16, 1 (2012), 105–114.
[67] Chunjong Park, Junsung Lim, Juho Kim, Sung-Ju Lee, and Dongman Lee. 2017. Don't Bother Me. I'm Socializing! A Breakpoint-Based Smartphone Notification System. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. 541–554.
[68] Samsung. 2020. What is Bixby Routines? Retrieved August 13, 2020 from https://www.samsung.com/global/galaxy/what-is/bixby-routines/
[69] Norma Saiph Savage, Maciej Baranski, Norma Elva Chavez, and Tobias Höllerer. 2012. I'm feeling loco: A location based context aware recommendation system. In *Advances in Location-Based Services*. Springer, 37–54.

[70] Clay Shirky. 2008. It's not information overload. It's filter failure. *Web. September* (2008).

[71] Daniel P Siewiorek, Asim Smailagic, Junichi Furukawa, Andreas Krause, Neema Moraveji, Kathryn Reiger, Jeremy Shaffer, and Fei Lung Wong. 2003. SenSay: A Context-Aware Mobile Phone.. In *ISWC*, Vol. 3. 248.

[72] Khai N Truong, Thariq Shihipar, and Daniel J Wigdor. 2014. Slide to X: unlocking the potential of smartphone unlocking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3635–3644.

[73] Blase Ur, Elyse McManus, Melwyn Pak Yong Ho, and Michael L Littman. 2014. Practical trigger-action programming in the smart home. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 803–812.

[74] Rajan Vaish, Keith Wyngarden, Jingshu Chen, Brandon Cheung, and Michael S Bernstein. 2014. Twitch crowdsourcing: crowd contributions in short bursts of time. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3645–3654.

[75] Rui Wang, Gabriella Harari, Peilin Hao, Xia Zhou, and Andrew T Campbell. 2015. SmartGPA: how smartphones can assess and predict academic performance of college students. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 295–306.

[76] Fang-Yi Flora Wei and Y Ken Wang. 2010. Students' silent messages: Can teacher verbal and nonverbal immediacy moderate student use of text messaging in class? *Communication Education* 59, 4 (2010), 475–496.

[77] Sharon C Welburn, Annie A Garner, Crystal A Franklin, Philip R Fine, and Despina Stavrinos. 2011. Psychometric validity of the Questionnaire Assessing Distracted Driving (QUADD). In *The 2011 University of Alabama at Birmingham Expo for Undergraduate Research Conference Poster University of Alabama at Birmingham Birmingham, AL*.

[78] Fernando A Wilson and Jim P Stimpson. 2010. Trends in fatalities from distracted driving in the United States, 1999 to 2008. *American journal of public health* 100, 11 (2010), 2213–2219.

[79] Wisnu Wiradhany and Mark R Nieuwenstein. 2017. Cognitive control in media multitaskers: Two replication studies and a meta-analysis. *Attention, Perception, & Psychophysics* 79, 8 (2017), 2620–2641.

[80] Eileen Wood, Lucia Zivcakova, Petrice Gentile, Karin Archer, Domenica De Pasquale, and Amanda Nosko. 2012. Examining the impact of off-task multi-tasking with technology on real-time classroom learning. *Computers & Education* 58, 1 (2012), 365–374.

[81] Kristie Young, Michael Regan, and M Hammer. 2007. Driver distraction: A review of the literature. *Distracted driving* 2007 (2007), 379–405.

[82] Nikki Zeichner, Phoenix Perry, Miranda Sita, Laura Barbera, and Tim Nering. 2014. Exploring HowMobile Technologies Impact Pedestrian Safety. *NYC Media Lab Research Brief* (2014).

[83] Daqing Zhang, Tao Gu, and Xiaohang Wang. 2005. Enabling context-aware smart home with semantic web technologies. *International Journal of Human-friendly Welfare Robotic Systems* 6, 4 (2005), 12–20.

[84] Sina Zulkernain, Praveen Madiraju, and Sheikh Iqbal Ahamed. 2010. A context aware interruption management system for mobile devices. In *International Conference on Mobile Wireless Middleware, Operating Systems, and Applications*. Springer, 221–234.

A APPENDIX

A.1 Categorization Criteria for Locations

Category	Definition	Example from ESM responses	Number of ESM
Home	a building in which people live alone or with family	Home	2880
Dormitory	a building in an university where students live	Dormitory	1246
Classroom	a room in a university where instructional group activities place	Classroom	1294
Laboratory	a room where scientific experiments or research are carried out	Laboratory	414
Library	a room where books are kept and places for study are provided for people	Library	721
Restaurant	a place where people can eat a meal and pay for it	Restaurant, cafeteria	462
Café	a place where people can buy drinks, simple meals, and snacks	Café	113
Pub	a building where people can have drinks, especially alcoholic drinks, and talk to their friends	Pub	123
Place for part time job	Place for part-time job	Café,restaurant, pub,library	301
Club room	Places which are provided by the institution for the students' club activities	Club room	154
Public transportation	Vehicles which used for transporting people	Taxi, bus, subway	191
Place for leisure	Places he or she visits to do activities that they enjoy	Karaoke, Internet café, billiard hall, department store,	147
Place for exercise	Places that is provided for exercise activities	Fitness center, swimming pool	56
Place for personal affairs	Places he or she visits for their personal affairs	Post office, hospital, beauty salon	21
Outdoor	Somewhere outside a building	Outdoor, playground	413
Miscellaneous	All other locations	Reserve force training area, funeral hall, accomodations during a trip, a friend's home, church, public place	595

A.2 Categorization Criteria for Activities

Category	**Definition**	**Example from ESM responses**	**Number of ESM**
Class	Attending official instructional group activities that need to focus on speakers or instructors	Class, seminar	979
Studying	Doing individual activities to studying by oneself	Studying, assignment, listening to Internet lectures	1702
Research	Doing individual or group activities related experiment trying to discover some facts	Research, reading papers	367
Meeting	Getting together with people to discuss or to make decision	Meeting	15
Eating	Eating some food or meal	Eating some food, meal	872
Drinking	Drinking alcoholic beverages	Drinking	77
Part-time work	Working for only part of each day or week	Part-time work, assistant work	303
Sleeping	Falling asleep	Sleeping	854
Preparing for sleep	Preparing for sleep in a bed	Preparing for sleep	24
Waking up	Being awakened from sleeping but still being in a bed	Waking up	191
Resting	Resting for relaxing and refreshing	Resting, smoking	1308
Club activity	Doing activities with group members who have common interests or goals	Club activity, practicing a performance (e.g., playing, musical band)	41
Socializing	Meeting other people for social purpose (generally conversation)	Social activity, conversing	197
Leisure activity	Doing specific activities with enjoyment without hurrying in one's free time	Leisure activity, watching TV, hobby, singing	504
Exercise	Doing exercise or training for health	Fitness, swimming	99
Moving	Moving by means of public transportation	Moving	145
Using other personal devices	Using other personal devices	Using computer, game, watching video	400
Personal affairs	Doing something related to one's personal affairs that are not public	Treatment, haircut, sending a package, shopping	314
Miscellaneous	All other activities		739

A.3 Results of Regression for Perceived Smartphone Distraction (Not grouped by gender)

Independent variables	perceived smartphone distraction level (ranging 0 to 1) β	p-value	
Time context			
weekend	-0.02	0.021	*
night	-0.01	0.370	
morning	0.00	0.974	
Location context			
café	-0.01	0.535	
classroom	-0.01	0.526	
club room	0.00	0.762	
dormitory	0.01	0.593	
home	-0.09	<0.001	***
laboratory	0.00	0.992	
library	-0.01	0.560	
outdoor	0.00	0.685	
place for leisure	0.03	<0.001	***
place for part-time work	-0.05	0.023	*
place for personal affair	-0.02	<0.001	***
place for workout	0.02	0.056	
public transportation	-0.05	<0.001	*
pub	0.00	0.952	
restaurant	-0.03	0.015	*
Activity context			
class	0.26	<0.001	***
club activity	0.06	<0.001	***
drinking	-0.01	0.386	
eating	0.03	0.038	*
leisure	0.00	0.750	
meeting	0.03	<0.001	***
moving	-0.03	0.004	**
part-time work	0.08	<0.001	***
personal affair	0.02	0.131	
preparing for sleep	0.01	0.397	
researching	0.13	<0.001	***
resting	0.01	0.538	
sleeping	0.12	<0.001	***
socializing	0.04	<0.001	***
studying	0.30	<0.001	***
using other personal devices	0.04	<0.001	***
waking up	0.10	<0.001	***
workout	0.01	0.220	
marginal R^2	0.152		
conditional R^2	0.470		

A.4 A Detailed Version of the Diagram for Presenting Process of User-Generated Smartphone Distraction Management