BeUpright: Posture Correction Using Relational Norm Intervention

Jaemyung Shin
KAIST
Republic of Korea
jmshin@nclab.kaist.ac.kr

Bumsoo Kang
KAIST
Republic of Korea
steve.kang@kaist.ac.kr

Taiwoo Park
Michigan State University
USA
twp@msu.edu

Jina Huh
University of California San Diego
USA
jina.huh@gmail.com

Jinhan Kim
KAIST
Republic of Korea
jinhankim@kaist.ac.kr

Junewha Song
KAIST
Republic of Korea
junesong@nclab.kaist.ac.kr

ABSTRACT
Research shows the critical role of social relationships in behavior change, and the advancement of mobile technologies brings new opportunities of using online social support for persuasive applications. In this paper, we propose Relational Norm Intervention (RNI) model for behavior change, which involves two individuals as a target user and a helper respectively. RNI model uses Negative Reinforcement and Other-Regarding Preferences as motivating factors for behavior change. The model features the passive participation of a helper who will undergo artificially generated discomforts (e.g., limited access to a mobile device) when a target user performs against a target behavior. Based on in-depth discussions from a two-phase design workshop, we designed and implemented BeUpright, a mobile application employing RNI model to correct sitting posture of a target user. Also, we conducted a two-week study to evaluate the effectiveness and user experience of BeUpright. The study showed that RNI model has a potential to increase efficacy, in terms of behavior change, compared to conventional notification approaches. The most influential factor of RNI model in the changing the behavior of target users was the intention to avoid discomforting their helpers. RNI model also showed a potential to help unmotivated individuals in behavior change. We discuss the mechanism of RNI model in relation to prior literature on behavior change and implications of exploiting discomfort in mobile behavior change services.

Author Keywords
Behavior change; relational norm intervention; posture correction; social persuasion; negative reinforcement; other-regarding preferences.

CHI'16, May 07-12, 2016, San Jose, CA, USA

DOI: http://dx.doi.org/10.1145/2858036.2858561

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous; J.4. Social and Behavioral Sciences.

INTRODUCTION
Advances in mobile computing technologies have brought new opportunities for real-time behavior monitoring and behavior change [38]. Small-scale sensors and mobile devices have enabled a variety of measures for everyday life activities, such as step counts [42], emotions [27], sleep quality [24], and mood [34]. Based on such measures, a number of mobile services have been designed to help individuals understand their behavior patterns [22,43], as well as to deliver persuasive feedback to users in situ [19,21], thereby shaping their behavior into a better form.

Online social support has also been used for shaping an individual's behavior. A common online social support for behavior change includes forming a group to share members' behavior information such as step counts [42] and frequency of water-drinking events [28]. Researchers have also proposed direct ways to create associations between individuals' behaviors. One example is peer-rewarding [1], giving individuals an incentive, not for their own effort but for ones of other group members. With an assumption of *active* participation of users, such social supports have shown their potential in shaping individuals' behavior.

In this paper, we propose Relational Norm Intervention (RNI) model, featuring passive social support and (bad) behavior-driven discomfort. The model consists of two individuals (i.e., a target user and a pre-assigned helper) and a mobile system. Once the mobile system detects that the target user has violated a target behavior, it delivers the helper a discomfort such as locking the helper's phone for a prolonged period of time. The mechanism of the proposed model in leading the target user's behavior change is twofold: (1) the target user will stop violating the target behavior to avoid discomforting the helper, and (2) the helper will directly send the user a negative feedback.

The contributions of this paper include:

- We propose a novel intervention model for behavior change that employs discomfort to paired helpers.
- We provide design considerations for applications using the model and implement a sample application BeUpright.
- We report the effectiveness and initial user experiences of the application through a user study with 18 participants.

BACKGROUND

With the help of mobile technologies and online social networks, behavior change applications are becoming immersed in our daily lives. Smartphones and wearable devices enable real-time behavior monitoring, bringing opportunities of automated persuasion methods, such as behavior change. Also, volunteered social support from a distance has become available using online social networks.

Mobile sensing technologies for automated persuasion

Real-time sensing of human behavior using mobile devices has enabled the automated delivery of persuasive messages in situ. UbiFit [42] encourages everyday physical activities by providing summaries of activities obtained from activity motion sensors. Haug et al. and Hou et al. proposed context-aware text message reminders for smoking cessation [19] and medication adherence [21], respectively.

The major drawback of these automated intervention is user habituation, which explains a user's decreasing attention to persuasion. Anderson et al. and Kalsher et al. explained frequent exposure to intervention stimuli (e.g., messages or alarms) could lead to disregarding the stimuli [8,25]. These studies implied that there is a need to find less-structured, unanticipated stimuli that do not facilitate the habituation process. One solution is to use people to balance between machine- and peer-generated stimuli for persuasive applications. Playful bottle [28] and Houston [43] support persuasive social reminders between individuals in a group to encourage drinking-water behavior and physical activity, respectively. Several studies show social reminder was more effective. Still, such peer-generated stimuli are initiated by a few number of active participants [43].

Social networks, awareness, and norms for behavior change

Social relationships provide an effective platform for behavior change [1,5]. With the increasing number of mobile networks, the potential for using social relationships to change behavior has emerged. Social relationships in the forms of social networks, awareness, and norms influence behavior change through various mechanisms.

Shmueli et al. described two computer-mediated persuasion processes for behavior change: (1) using social networks and (2) increasing social awareness [38]. The former is to provide both a direct communication path between peers and a shared goal for peers to collaborate on; they can even compete against other groups [30,31]. The motivations behind such collaborative, mutual support in a group can stem from altruism [48] and group dynamics [4,15]. Studies showed highly context-sensitive results regarding whether competition or cooperation is more effective in behavior change [10,13].

Increasing social awareness entails providing individuals with the group's summary of a target behavior to encourage self-reflection and improvement. Example target behaviors for social awareness include participating in group activities (e.g., discussions) [14,23,44] and healthier decision-making processes [16]. Social cognitive theory [3] explains the mechanism behind this social process, by indicating that a person models her behavior based on the behaviors of others.

Performing the against behavior of surrounding others can be interpreted as a violation of social norms. A social norm violation refers to prescriptions of behaviors and attitudes that are considered unacceptable or undesirable in a given social unit [37]. Violations, also called counter-normative behaviors, are often controlled because people believe that others do not expect these behaviors from them [11]. If uncontrolled, these counter-normative behaviors are likely to result in negative reactions and feedback, including exclusion from a social group [7,35]. Social norms have been frequently employed to change socially significant behaviors, such as alcohol consumption, drug use, disordered eating, gambling, littering, and recycling [36].

Discomforting others as an aversive stimulus of negative reinforcement

In behavioral psychology, *reinforcement* is one of the core methods to increase an individual's desired behavior. Reinforcing desired behavior by avoiding an aversive stimulus is called negative reinforcement [39]. In the Skinner box, a well-known example of negative reinforcement, a rat presses a lever more frequently to avoid electric shocks. The aversive stimulus is the electric shock in this case, which is the *negative reinforcer*. We use *discomforting others* as a negative reinforcer to change one's behavior. Discomforting others can act as an effective negative reinforcer because people are reluctant to inconvenience others, due to Other-Regarding Preferences [40]. Other-Regarding Preferences describes people imagine what they expect from the others' position [12]. The dictator game [17] is a famous experiment that shows the Other-Regarding Preferences. In this experiments, the first player decides how to split an endowment to the second player. Even though they do not know each other, the first player will share the benefit. This presents people have a tendency to consider others.

Areas covered in this paper

From the aforementioned literature of mobile social networks to change behavior, we see that the following three areas need further investigation:

- *Relational norm based behavior change*. In studies examining social norms as mechanisms to change behavior, the norms have been developed mostly based on the larger social group (e.g., I learn how to maintain my trash can based on the way my neighbors maintain their trash cans). We further explore how relational norms between a small number of individuals can shape one's behavior.
- *Passive social help*. Existing social help through social networks assumes that active help comes to a peer from other peers in the same group; otherwise, the chance of such social help will decrease. Active help is triggered through motivations that are parallel to the goal of the target behavior (e.g., I want to help John lose weight to improve his health). On the other hand, passive help can be triggered by motivations that do not necessarily align with the goals of the target behavior (e.g., I want to help John lose weight because my phone will be locked otherwise).
- *Discomforting others for positive results*. One way to build passive social help is to make users want to break out of a negative event that possibly discomforts others. However, existing approaches seek to minimize the inconvenience that users might experience in voluntary tasks [32]. We argue that intentional discomfort toward the goal of behavior change is worth investigating. The primary challenge would be to find the right level of discomfort that maximizes the effectiveness of behavior change while achieving a reasonable level of helper discomfort.

RELATIONAL NORM INTERVENTION MODEL

Relational Norm Intervention (RNI) model consists of three entities: a target user, a helper, and a mobile system interacting between those of the user-helper pair. The model reinforces an individual's (i.e., target user's) desired behavior by leveraging her willingness to avoid an aversive stimulus that may discomfort a pre-assigned partner (i.e., a helper). The model requires an artificial causal relationship between the target user's violation of the desired behavior and the helper's discomfort (see Figure 1 for the overall process). As a promising medium for discomforting events, we propose mobile phones the everyday companions of many individuals with which individuals frequently interact in their daily lives [45]. For example, we can easily discomfort users by locking their phones for a while. The overall mechanism of the model is threefold:

- **Alert:** The mobile system monitors the target user and alerts her when she performs against a (desired) target behavior.
- **Discomforting Event:** If the target user continues to perform against the target behavior, the helper's phone will generate an event that will discomfort him (e.g., lock his smartphone for a while).
- **Feedback:** The helper can ask the target user to perform the target behavior in order to stop the discomforting event.

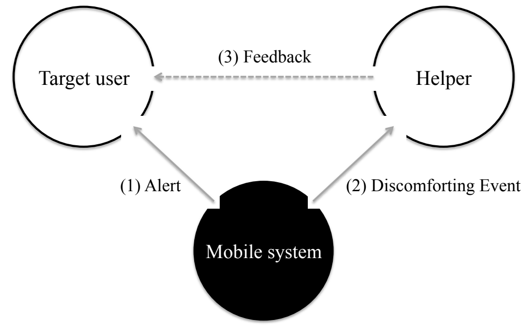

Figure 1. Overview of Relational Norm Intervention model.

APPLICATION DESIGN WORKSHOP

Method

To design prototype applications based on RNI model, we conducted a design workshop consisting of two phases. The goal of the first phase was to determine an appropriate target behavior, and the goal of the second phase was to extract design considerations for the feedback interfaces of both the target user and the helper. We recruited 16 people (6 for the first phase and 10 for the second phase) from the authors' personal contacts. The participants were students at a public research university in South Korea who are interested in mobile application development and user experiences.

In the first phase, we conducted a 2-hour focus group discussion with 6 of the participants. We began by explaining the concept of RNI model and soliciting their ideas and suggestions for potential target behaviors and discomforting events. After receiving sufficient suggestions for target behaviors and discomforting events, we further discussed the suitability of the candidates and the intervention model. At the end of the phase, we chose the most feasible target behavior and developed a conceptual prototype based on the participants' feedback.

For the second phase, we introduced a conceptual prototype developed based on the first phase workshop to the remaining 10 participants. We then solicited their feedback and suggestions using semi-structured questions followed by an open discussion. The key leading questions were: "Do you want to use the app, and why?", "Do you think this app would be helpful for behavior change?", and "Which part of the app should be improved?"

Workshop results

First phase: Good sitting posture for the target behavior

The focus group discussion resulted in the following requirements for deciding the target behavior:

- **Pervasiveness of violating the target behavior:** Violations of the target behavior should be frequently observable in daily life so as to cause helpers discomfort.
- **Change with minimal effort:** The effort required for changing the behavior should be reasonably small and should not distract from daily tasks.

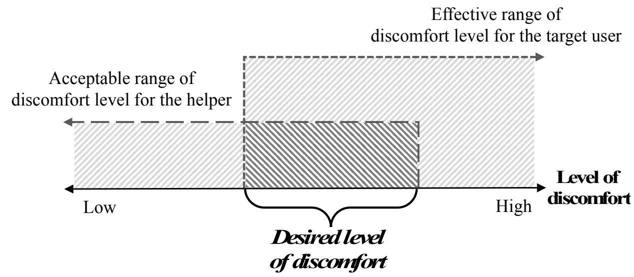

Figure 2. Conceptual diagram for discomfort level.

- **Clear benefit:** It should be generally accepted that the benefit of the behavioral change outweighs its cost.
- **Feasibility of demonstration:** In terms of complexity and ease of use, implementation should be feasible as the first demonstrative prototype of the model.

Several candidate behaviors emerged: walking 1 hour everyday, drinking 8 cups of water a day, and quitting smoking. The participants agreed to choose *good sitting posture* for the target behavior considering the above criteria. Next, the participants came to choosing *lock the phone* as a discomforting event among the several candidates, including slanting the screen and making a loud noise considering the above criteria as well.

Using the results, the conceptual prototype included the following: The mobile system will alert the target user (Figure 1, (1) *Alert*) if a poor posture is detected. If the target user continues with the poor posture, the helper's phone will be locked (Figure 1, (2) *Discomforting Event*) until the target user corrects her posture.

Second phase: Adjusting discomfort, and quick feedback

After introducing the conceptual prototype, 6 out of 10 participants responded that they were not likely to use the application. We distilled three design considerations by asking these respondents what made the model unattractive.

First, the helper needs the authority to cancel the discomforting event at any time. In our conceptual prototype, the act of locking the helper's phone may cause a severe burden to the helper, especially in situations when the helper needs to use the phone urgently. Most of the participants disliked such situations. Regardless of how close they were with the target users, the helpers refused to grant the authority to unlock their phones to an external factor over which they would not have control.

Second, setting the level of discomfort for the helpers was one of the most challenging parts of the design. The participants said they would not use the application as a helper because they could not endure the discomfort. However, the following open discussion revealed that a low discomfort level for the helper might not motivate the target users to change their behavior. Figure 2 shows the concept of this desired level of discomfort; it should be acceptable (i.e., low enough) for helpers but also effective (i.e., high enough) for target users.

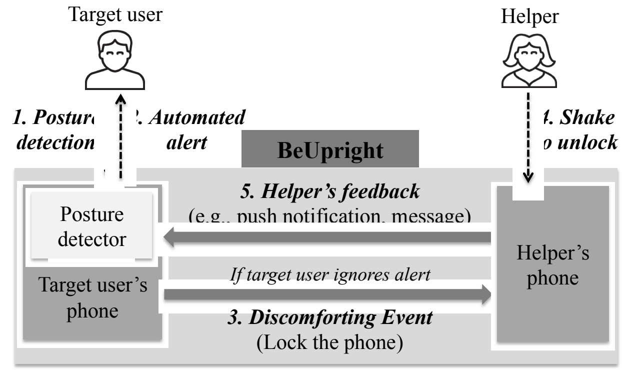

Figure 3. BeUpright overview.

Third, the participants also requested a simplified way to give feedback to their partners. Some suggested providing a shortcut for direct messages to target users. However, 2 participants argued that such messaging would be burdensome and emphasized the need for a more convenient way of communicating, such as "poking." That is, these participants only wanted to give the target user a simple signal to show that the helper has been discomforted by the target user's behavior.

After the design workshop, we revised the design of the discomforting event (i.e., the phone lock); a helper can now unlock the phone at any time. However, this reduced the level of discomfort, which has a negative effect on motivating target users. Thus, to meet a desired level of discomfort, we elicited *shaking the phone 10 times* as a way to unlock the phone. Other candidates included shaking the phone, solving a quiz, and waiting for some time period. Lastly, we decided to provide shortcuts for helpers to quickly give feedback to target users.

BEUPRIGHT: DESIGN AND IMPLEMENTATION

Following the design considerations extracted from the design workshop, we implemented BeUpright, a mobile application to help individuals maintain good sitting postures. Figure 3 shows the execution sequence of BeUpright:

1) **Posture detection:** The target user's sitting posture is monitored by the *posture detector.*
2) **Automated alert:** If a poor posture is detected, the target user's phone will give an initial alert to the target user.
3) **Discomforting Event:** If the target user ignores the alert and keeps the poor posture, the helper's phone will be locked.
4) **Shake to unlock:** The helper can unlock the phone by shaking it 10 times.
5) **Helper's feedback:** After unlocking, the helper will see a floating head on the screen which makes it easy for the helper to give feedback to the target user.

BeUpright consists of three major components: posture detector, the target user interface (target UI), and the helper

Figure 4. Sensor for sitting posture detection.

user interface (helper UI). We explain the implementation details of the three components below.

Posture detector

We implemented the sitting posture detector by referring to previous work using motion sensors, including studies on locomotion, body balance-related clinical studies, and machine learning and cybernetics studies [47,49].

The detector identifies two types of poor sitting postures: *leaning backward* and *leaning forward*—the most frequently observable cases while sitting [17]. Postures leaning more than six degrees from a "good" posture are classified as "poor" postures [46]. To detect the amount of posture leaning, we used the accelerometer to measure the target user's angle of tilt by comparing the acceleration of gravity and individual's vertically downward acceleration.

To filter out sporadic behaviors, such as body stretches, posture detector gives 20 seconds of grace period before confirming that the current posture is poor. This decision was made in consultation with an orthopedic specialist. Once a poor posture is detected, it notifies the target UI of the event. Reflecting individual differences in sitting posture, the detector allows posture calibration before use. Users can set or reset their 'good' posture before and during use (see Figure 5, right).

The detector employs the TI CC2650 SensorTag, a tiny sensor device featuring a variety of sensing modalities, including a 3-axis accelerometer as well as Bluetooth 4.0 wireless connectivity (see Figure 4). We set the position of the sensor on a user's shirt, about one inch below the collarbone[1]. For convenience of attachment, we used two small rare-earth magnets to attach the sensor to the cloth.

We implemented the detector on the Android mobile platform. It communicates with the SensorTag via the Bluetooth API provided by the Android framework. Once BeUpright runs and a wireless connection is established with the sensor, the detector is immediately initiated and begins to monitor a target user's posture.

Target and helper user interfaces

Once the target UI receives a poor posture event from the posture detector, it gives the target user a vibration alert.

[1] We borrowed the concept of placing a sensor under the collarbone from the Lumo lift, which is a commercialized product for posture detection.

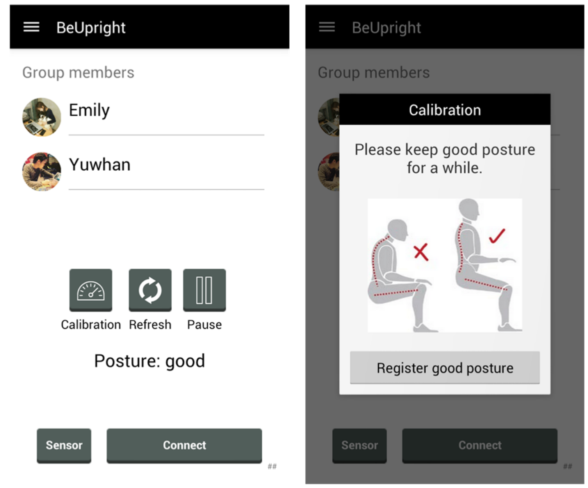

Figure 5. Screenshots of the target user interface: (left) main screen, (right) calibration dialog.

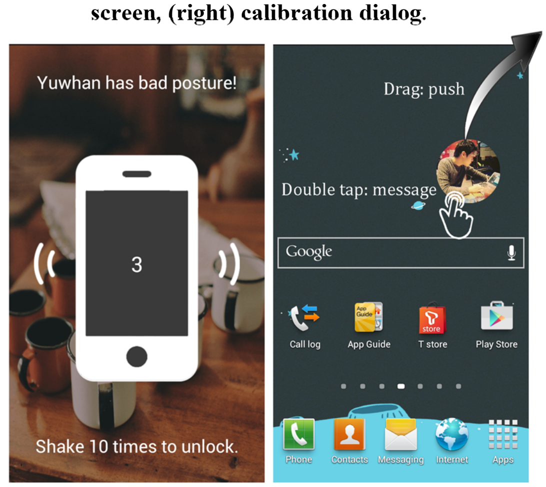

Figure 6. Screenshots of the helper user interface: (left) a screen when the phone is locked, (right) dragging out floating head sends a push feedback, and double tapping floating head helps to send a message feedback.

We set the duration of the vibration as 2 seconds, to help users distinguish it from other general phone notifications. If the user does not change her posture within 10 seconds after the first vibration alert, it requests the helper UI to give the helper the discomforting event (i.e., phone lock).

If the target users are in a situation where it is hard to keep a good posture (e.g., in a restroom), they can pause the posture detector for a while using a pause button (see Figure 5, left). Also, users can recalibrate the "good" posture whenever they want and check their posture information in real time.

Immediately after the helper UI receives a discomforting event request, it will lock the helper's phone (see Figure 6, left) and the helper is required to shake the phone 10 times to unlock it. When the helper unlocks the phone, the helper will see the target user's image as a floating head on top of the phone screen (see Figure 6, right). If the helper drags out the floating head from the screen, the helper UI will request a push notification to the target UI, informing the target user that the helper's phone had been locked recently. If the helper double taps the floating head, it will launch a messaging application for the helper to give direct feedback to the target user.

THE 2-WEEK EVALUATION STUDY

To investigate the user experience and the effectiveness of RNI model, we conducted a two-arm evaluation study (control vs. RNI) that included: (1) pre-study surveys and interviews, (2) using BeUpright for 2 weeks, and (3) a post-study survey and an interview. We measured the posture correction rate as the main outcome.

Participants

We posted a recruitment flyer to an internal online community of students and staff at a public research university in South Korea. We were interested in recruiting those who have not started to change their behavior (i.e., sitting with good posture). We recruited 12 participants and randomly assigned them into the control and test groups (i.e., RNI). We asked RNI target users to bring their helpers on their own. In total, we had 12 target users and 6 helpers. The participants were students and research staff (Ages: 21-34). All of the target users were male, and three helpers were female. All of the participants were rewarded with about $20 worth of gift certificates.

Study procedure

<table>
<tr><th colspan="2">Procedure</th><th>AAI (control)</th><th>RNI-Target-user</th><th>RNI-Helper</th></tr>
<tr><td rowspan="4">Pre-study</td><td rowspan="2">Interviews</td><td colspan="2">Motivations for posture correction</td><td>N/A</td></tr>
<tr><td>Automated alert</td><td colspan="2">Automated alert, discomforting event, helpers' feedback</td></tr>
<tr><td rowspan="2">Surveys</td><td rowspan="2">Q1a</td><td colspan="2">Q1a, Q2a</td></tr>
<tr><td>$Q3a_t$</td><td>$Q3a_h$</td></tr>
<tr><td colspan="2">Intervention</td><td>AAI</td><td colspan="2">RNI</td></tr>
<tr><td rowspan="2">Post-study</td><td>Interviews</td><td colspan="3">Reflections on their experiences with BeUpright</td></tr>
<tr><td>Surveys</td><td>Q1b</td><td colspan="2">Q1b, Q2b, Q3b</td></tr>
</table>

Control group vs. test group design

As the control intervention, we used the same BeUpright interface, but without the helper and their feedback component. We will call the control group the Automated Alert Intervention (AAI) group. When the target users from AAI group maintained a poor posture for 20 seconds within the grace period, they received the same *automated alert* that RNI group received. If the target users did not change their posture within 10 seconds after that alert, the poor posture was logged to BeUpright application. As the test intervention, we used BeUpright with all components including the helpers and their feedback.

Pre-study

Introduction of BeUpright: Before the study, we first introduced the features of BeUpright system to the participants. We told AAI group about the automated alert, which is the only function their BeUpright system included; and we told RNI group how RNI works in BeUpright system.

Pre-interview: We then conducted interviews to discuss the participants' initial motivations around sitting posture correction, their relationships with their helpers (for RNI group), and their initial perceptions toward using BeUpright system.

Pre-survey: The participants also completed a survey before the study. The participants were given questions regarding their initial perceptions toward BeUpright based on the introduction. For both groups, the first survey question was: Q1a. *How much do you agree that the automated alert will be helpful in correcting [your, your target user's] posture*? The participants responded in a 5-point Likert scale—Strongly Disagree—Disagree—Neutral—Agree—Strongly Agree. RNI group was also asked the following question: Q2a. *How much do you agree that the {discomforting events, push feedback, feedback messages} will be helpful in correcting [your, your target-user's] posture*. Each item in the curly braces was asked separately. The last survey question was regarding RNI group's perception toward the discomforting event. To the target users, the survey asked: $Q3a_t$. *How much do you agree with the following statement: the helper will be bothered by the discomforting event.* To the helpers, the survey asked: $Q3a_h$. *How much do you agree with the following statement: I think I will feel bothered by the discomforting event.* The responses were again in a 5-point Likert scale—Strongly Disagree—Disagree—Neutral—Agree—Strongly Agree.

Intervention

The participants used BeUpright for 2 weeks (10 days, only on weekdays). During the intervention, the target users wore the sensor once they arrived at work, and they took off the sensor before they left the office. We logged the events of wearing and taking off the sensors with a remote server. Each day, we sent a short text message to the participants who had not worn the sensors by 10AM. We asked those who did not use the application for 10 days in 2 weeks due to business trips or personal emergencies to continue to complete 10 days.

Post-study

Post-survey: For the surveys, we asked the same set of questions: Q1b, Q2b, and Q3b, but asking about their actual experience. For instance, Q2a was modified to Q2b, which was: *How much do you agree that the {discomforting events, push feedback, feedback messages} was helpful in correcting [your, your target-user's] posture*.

Post-interview: We also conducted interviews on participants' experiences in relation to the survey results on the influential factors and the expected versus experienced discomfort levels. Also, we asked their impressions about the automated alert, the discomforting event, and the user interface. We walked through their results together to ask background information on why such results occurred.

All of the interviews were recorded and transcribed in Korean. We then conducted translation and back-translation [9] into English. We used open coding [41] to examine the emerging themes. With the open codes, we conducted axial coding using affinity diagramming [6] to understand the main themes across the interview data, narrowing the codes into a set of five themes.

EVALUATION OF THE STUDY FINDINGS

We discuss five main findings on: (1) posture correction outcomes between AAI and RNI group, (2) the target users' vs. helpers' perceptions on the discomforting event, (3) RNI and unmotivated participants, (4) the choice of push vs. message feedback, and (5) RNI and the pair's relationship.

Outcomes on target users' posture correction

Table 1 shows the average correction rates during the participating period. The correction rates indicate how many times the target users corrected the poor postures when the poor-posture alerts were given. RNI group had a higher correction rate (*M=74%, SD=10.41*) than AAI group (*M=55%, SD=15.6*). According to a t-test, the difference was significant (*t=-2.57, p=0.031*). We also conducted General Estimating Equation (GEE) analysis to take into account the autocorrelation of repeated measures, which is for analyzing longitudinal data. The results showed that the correction rates in both the controlled and treated groups (*0=AAI, 1=RNI*) were significantly different (*B=16.93, SE=3.98, p<0.001*).

Three factors that influence posture correction

Our model suggests three potential factors that influence target users' posture correction in RNI group: *the discomforting event*, the *helpers' push feedback*, and the *helpers' message feedback*. Figure 7 shows the target users' expected versus experienced impact of these three factors in RNI group. Before the study began, the participants expected that the message feedback would play the most significant role in posture correction. After the study, however, the participants reported wanting to avoid discomforting others played the biggest impact on their posture correction.

From the interviews with RNI group, the participants explained the discomforting event as the most influential factor for changing their posture. The participants did not want to bother the helpers in using their phones:

AAI group						
Participant	P7	P8	P9	P10	P11	P12
Corr. rates	41%	40%	52%	50%	82%	61%
#Correction/ #Bad posture	116/ 280	101/ 250	322/ 618	137/ 272	147/ 179	156/ 257
RNI group						
Participant	P1	P2	P3	P4	P5	P6
Corr. rates	66%	64%	86%	86%	77%	65%
#Correction/ #Bad posture	79/ 120	118/ 185	64/ 74	260/ 304	302/ 393	101/ 156

Table 1. Average correction rates in AAI and RNI groups.

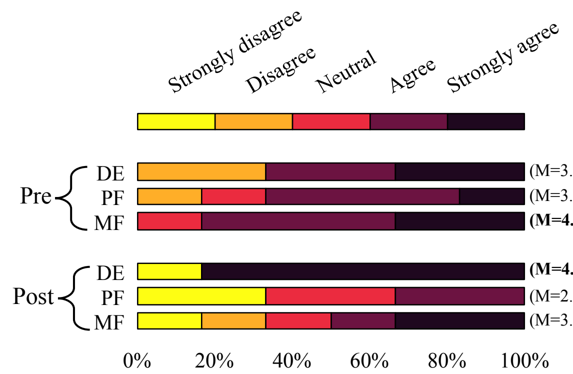

Figure 7. The survey results of how much three factors affect target user's posture correction in RNI group. (*DE: Discomforting Event, PF: Push Feedback, MF: Message Feedback*)

"The fact that my posture might annoy my partner was always on my mind… I tried as much as possible to not bother her." (RNI-T-1[2])

"If I have a poor posture, my girlfriend will become uncomfortable. So I tried not to burden her…" (RNI-T-4)

Effects of intervention over time for AAI and RNI

AAI-target users stated that they became insensitive to the alerts after being exposed to them repeatedly:

"Over time, I became insensitive to the alerts. The alerts were no longer 'alerting,' and I lost the motivation to correct my posture." (AAI-T-9)

Following the Q1 survey questions, 3 out of 6 target users in AAI group said that the effect of the stimuli diminished over time, whereas all of the target users in RNI group said the stimuli of BeUpright persistently intervened for them to correct their posture correction. Some of the target users said the stimuli bothered them more over time:

"The fact that I was causing my partner discomfort bothered me more and more over time. The feedback from my partner was a constant reminder that she was continually discomforted, and I felt sorry towards her." (RNI-T-6)

In addition, in AAI group, the correction rate was negatively associated with the days of app use (*B*=-1.139, p<0.001); however, that association was positive in RNI group (*B*=0.803, p=0.036). In other words, the intervention of AAI group had a tendency to be less affected, while the intervention of RNI group did not.

[2] We refer to each participant using the notion of the following: [AAI or RNI]-[T (Target user) or H (Helper)]-[unique participant #]

Two AAI-target users said that alerts were not enough, especially when they did not have the need to their correct posture: *I didn't change my posture each time the alert came. If my phone vibrated due to the alert, I put it away or just turned off the sensor. I'm not even interested in posture correction. Why should I correct my posture?* (AAI-T-8) They also shared that a harsher penalty might be helpful for changing their behavior, and alerts that annoy surrounding people might be effective: *When BeUpright alerted while somebody was around me, I corrected my posture because I felt bad for causing the vibration noise. I think if the alerts can annoy others, people will correct their posture a little more* (AAI-T-7).

AAI group participants were not aware of RNI group. Coincidentally, AAI group participants suggested that we should use discomforting events of others to nudge people toward behavior change, which was one of the main components of RNI model.

Perceptions on the discomforting event

In RNI group, in contrast to the initial concerns of the target users, most of the helpers did not feel bothered by the discomforting event of their phones being locked. As a result of survey Q3, 5 out of 6 target users expected that locking helpers' phones due to their poor posture would annoy the helpers (see Figure 8). An RNI target user explained his thoughts behind this expectation:

"Locking someone's phone came to me as a huge pressure because it might make the person very uncomfortable. Even if unlocking the phone required shaking the phone only once, it still would be uncomfortable for the person. Even a small discomfort—I would still feel guilty about it." (RNI-T-3)

P5 was the only target user who responded that his helper would not be agitated about his phone being locked. P5 knew that his helper did not use his phone frequently:

"I know my helper doesn't use his phone that frequently. He seemed to not mind even if I had a poor posture. So I didn't feel that guilty about bothering him that much with the feature." (RNI-T-5)

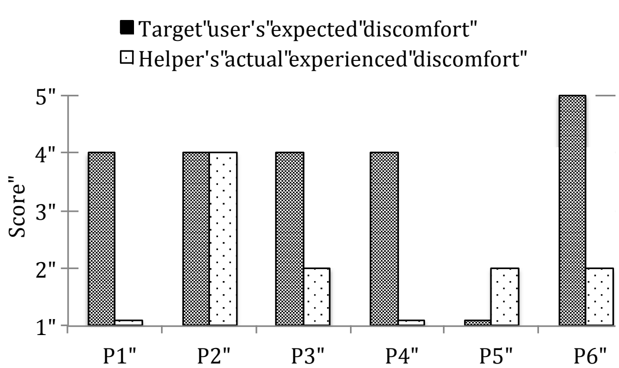

Figure 8. The level of discomfort that expected by target users and experienced by helpers.
(*1: Not at all, 2: Not really, 3: Undecided, 4: Somewhat, 5: Very much*)

In contrast with the target users, 5 out of 6 helpers said they did not feel agitated by the discomforting event (see Figure 8). Some of the helpers further said that the feature made them feel positive (e.g., glad, bonding) rather than negative (e.g., inconvenient, irritated):

"[Shaking the phone to unlock was] not that burdensome to me. It felt like an exercise. I shook my phone even harder to make it an exercise." (RNI-H-4)

"[About the floating head,] It is really funny and cute. And it didn't bother me in using the phone that much. I didn't care whether the floating head had appeared on the screen or not. " (RNI-H-1)

P2 was the only helper who responded that the discomforting event bothered him because he was very sensitive to being interrupted while using the phone:

"(Locking the phone) bothers me. I am a person who really hates any disturbance to my phone use." (RNI-H-2)

While the target users thought they might cause the helper discomfort, in reality they did not. This finding implies that the discomforting event of BeUpright has a discomfort level in the desired range, which is a crucial factor for RNI to work appropriately.

RNI and unmotivated participants

We found that RNI can be effective regardless of the target users' motivation for the target behavior. Unmotivated participants in AAI group corrected their postures less compared to motivated participants. RNI group, however, showed a more consistent and higher correction rate than AAI group in general, regardless of the participants' motivation for the target behavior.

In the post study interview of RNI group, the target user of P1, who was not motivated to correct posture, responded that he willing to continue using BeUpright, if his helper suggested him to keep using it. He just needed to find a persistent helper. Other participants also said they would keep using BeUpright if their helpers were fine with it:

"I'm not that willing to use the app because I don't have any needs for posture correction, but I will use it if my partner and I can use it together." (RNI-T-1)

"Of course I will use it. My girlfriend is saying that she will help me even thought she might face discomfort. She is totally doing this for me so I'm willing to use it." (RNI-T-4)

Here, the participants showed the importance of choosing the helpers and their willingness to help. Next, we discuss how the helpers' feedback played roles in RNI.

Choice of push vs. message feedback

Our initial assumption for potential factors playing into the helpers' choices on which feedback to use—push or message feedback—was the closeness between the helper and target user pair. We assumed that the closer the relationship, the more message feedback the helpers would send to the target users. Contrary to our belief, the closeness in the pair's relationship did not matter; the results showed that the choice on which feedback to use depended on the level of the helpers' perceived discomfort, personal preferences in communicating over the phone, and consideration for the target user.

To intervene with the target user, the helpers frequently used the push feedback over the message feedback in general. When the discomfort level increased due to repeated locking of their phones, the helpers started using the message feedback:

"I usually used the push feedback. I didn't feel the necessity to send a message since my phone was locked once or twice a day." (RNI-H-3)

"When my phone was locked many times, almost 4~5 times in a row, I sent the target user a message." (RNI-H-4)

In addition to the perceived level of discomfort, the differences in preferences of using mobile communication features, personality, and context mattered in choosing feedback. For P2, only 1% of all feedback was message feedback. P2 in general preferred not to type on the phone:

"I mostly used the push feedback because typing bothers me. I really don't like online communities or messengers… so I didn't intervene through text messages." (RNI-H-2)

Compared to P2, 49% of P5's feedback was message feedback. For P5, the choice of push feedback over message feedback was related to efficiency:

"When I want to use the phone, sending a push feedback is faster than sending a message feedback (to remove the floating head). So I used push feedback when I use the phone in purpose, and I used the message feedback when I was just checking the phone." (RNI-H-5)

Furthermore, the target users' reactions of feeling guilty for triggering the discomforting event affected the helpers' choice of feedback:

"When I received a message from my partner, it didn't feel like she was nagging me, but it reminded me that I bothered her again. This made me feel guilty." (RNI-T-4)

"I was very motivated to help my partner and intervened with him with messages in the beginning… But it seemed like he felt guilty about locking my phone, which in turn made me feel sorry for him [for sending a message]. I just wanted to let him know his posture needs to be corrected. But it seemed like I give him huge pressure. So I didn't intervene in his posture with messages later." (RNI-H-6)

The participants continued to try hard not to violate the norms, and modified their behavior (e.g., by not using messages anymore) as they observed how they reacted to one another's reactions in using BeUpright. Even with the discomforting component in the intervention, the participants expressed the positive relationship formed among the pairs.

RNI and the pairs' relationship

The participants felt that the discomforting event created an intimate communication pathway which the pair could heighten the awareness of each other. The helpers felt connected with the target users; the discomforting event constantly reminded the helpers of the target users' status, making the helpers constantly think about the target users:

"(BeUpright) feels like an interlink. It was good to know my partner's status. Also the locked screen was like an incoming message. The floating head showing his face makes me wonder what he is doing." (RNI-H-4)

3 out of 6 pairs responded that the discomforting event and the helper's message feedback in BeUpright initiated interactions between the helper and the target user and promoted continuous communication:

"Usually, during the day, we don't really communicate other than asking whether he had lunch. But now, when my phone is locked, I say something to my partner, and ask him what he is doing now. This triggers further communication not only about posture itself, but also about why he had bad posture or what situation he was in." (RNI-H-1)

"We usually didn't communicate during working hours unless there were special events… But now BeUpright locks my girlfriend's phone when I have a poor posture, and it causes her to send me messages or push feedback. It then leads to more conversations." (RNI-T-4)

The pairs replied that BeUpright has increased their interaction mostly in close relationships, including close friends or significant others. However, the participants who were not in close relationships responded that the helpers' feedback and the discomforting event initiated interaction but the interaction was hard to sustain.

Summary of the findings

We found that: (1) RNI was more effective in correcting posture compared to AAI; (2) the most influential feature of BeUpright was the discomforting event; (3) the discomforting event did not bother the helpers, unlike the target users, who were highly concerned about agitating the helpers; (4) RNI model has the potential to modify the behavior of the target users, including even unmotivated individuals; (5) the helpers' choice of feedback types depended on the discomfort level, personality, preferences, and context; and (6) BeUpright made pairs feel connected to each other and promoted increased interaction among the pairs.

DISCUSSION

In this section, we discuss how our findings translate to learning about the main components of RNI model. We first discuss the efficacy of RNI, including the effectiveness of the intervention, even with those who had low motivation to change. We then discuss at length how future researchers and designers can use RNI model to develop persuasive systems.

Efficacy of RNI

There was a disparity between the expected level of discomfort by the target users and the actual experience of the helpers (the former was higher). This result showed a unique potential for RNI model. That is, RNI model benefits from the tendency of the target users to overestimate the burden of the helpers. However, it is unclear, if the effect will diminish after the target users recognize the disparity between their perception and the actual experience. A long-term study can explain whether understanding the helpers' felt experience of the discomforting event will affect the behavior change motivation of the target users.

The finding that AAI target users' motivations to change their behavior degraded over time is consistent with previous studies showing that users are likely to be habituated to machine-generated alerts [8,25]. The target users of RNI group were receiving helpers' feedback, which was situational and not automated. Thus, RNI will help with such challenges around habituation because of the situatedness of the intervention. The helpers were in fact benefiting from the habituation process, in which they repeatedly received the same discomforting events. Our study revealed that the helpers became habituated to the discomforting events, which may decrease their level of discomfort over time.

Motivating users who are unwilling to change

Behavior change for unmotivated individuals is a critical challenge (e.g., a smoking cessation program for a person who is unwilling to stop smoking [33]). Our findings indicated that RNI motivated even unmotivated participants to change their behavior. The individuals are motivated to change their behavior due to not wanting to discomfort others, rather than the internal motivation to change their behavior. In addition, the helpers' act of good will, or an altruistic act (e.g., being a helper), can positively affect the target users to feel gratitude toward the helper, thereby motivating the target users to change [26].

Cultural factors in RNI

According to Hofstede [20], people from collectivistic societies have an increased preference for maintaining social harmony. This tendency causes people to avoid discomforting others. On the other hand, in individualist cultures, the transgression of norms leads people to feel guilty. Consequently, discomforting others may work as a light transgression, and thus, individuals will try to avoid it. This contrast shows that our approach could theoretically work in both cultural contexts, although using different underlying mechanisms.

Toward personalized relational norm intervention

RNI model uses people's general tendency to avoid violating social norm (e.g., discomforting others). We observed three factors influencing the efficacy and experience of the intervention: (1) personal and relational traits of self-pressure against discomforting others, (2) the perceived level of discomforting events, and (3) the burden for escaping from these events.

Each participant felt differently when discomforting others; some reported a significant sense of self-pressure, while others did not. Understanding such differences will help in personalizing the level of discomfort. P3 responded that he was under a high pressure when he made the system send discomforting events to his helper. However, P1 commented that he did not feel much guilt, because he believed that his wife would not get angry just for shaking the phone 10 times, if it would help him. In this case, trust between the two [29] played a role in reducing stress and tension when applying the model. Providing personalized features to fully exploit such specific traits will help RNI model to be more effective. Also, it will be worth exploring how the model works for different types of relationships. In detail, the self-pressure of a target user will be affected by the relationship with a helper (e.g., a family member, friend, acquaintance, or supervisor in a workgroup), and the pressure will affect the efficacy of behavior change.

The discomforting event should be agitating enough for the intervention to be effective, but within the boundaries of acceptable violation of relational norms. Our findings indicated that a low level of discomfort for the helpers would be appropriate when the target users frequently have a bad posture. If such bad behavior occurs only occasionally (e.g., a light smoker), a high level of discomfort would be more effective. Examples of discomforting events with various discomfort levels include (from low to high): ignorable notifications, a slanted phone screen, or a screen lock. Example activities to stop the discomforting event include (from easy to difficult): shaking a phone, answering a quiz, or jumping 5 times.

CONCLUSION

In this paper, we proposed Relational Norm Intervention model. The fundamental concept of the model is using people's tendency to avoid norm violation and translating it to motivation for behavior change. Our study proved the effectiveness of RNI model. We also gained many insights that we can apply to other areas of behavior change. Our study's sample size was relatively small, and we will have to conduct a longer intervention to see the impact on sustained behavior change. However, our first step to testing RNI model has helped us understand the feasibility of the system with rich qualitative and formative findings. This study contributes to novel ways of designing persuasive systems using intricate dynamics among social relations.

ACKNOWLEDGEMENT

This work is partly supported by the National Research Foundation of Korea (NRF, 2011-0018120) and Civil Military Technology Cooperation Centre (12-DU-EB-01). Taiwoo Park is the corresponding author.

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