IM Receptivity and Presentation-type Preferences among Users of a Mobile App with Automated Receptivity-status Adjustment

Ting-Wei Wu
National Yang Ming Chiao Tung University
Hsinchu, Taiwan
tingwei.cs06g@nctu.edu.tw

Yu-Ling Chien
National Yang Ming Chiao Tung University
Hsinchu, Taiwan
moneychien.nl06g@nctu.edu.tw

Hao-Ping Lee
National Yang Ming Chiao Tung University
Hsinchu, Taiwan
dimension4.cs03@nctu.edu.tw

Yung-Ju Chang
National Yang Ming Chiao Tung University
Hsinchu, Taiwan
armuro@cs.nctu.edu.tw

ABSTRACT

Researchers have long attempted to estimate instant-messaging (IM) users' attentiveness, responsiveness, and interruptibility. Yet, IM users' self-presentation of their receptivity, and their perceptions of automated adjustment/revelation of their receptivity status (e.g., Facebook Messenger's green dot that deems a user to be "active"), remain under-explored. We therefore told our 43 participants that our IM app, IMStatus, was capable of automatically estimating and adjusting their receptivity status to responsive, attentive, or interruptible based on their smartphone activity. These statuses were also presented to their IM contacts in three different styles. Over a two-week period, the participants rarely chose the status interruptible, and when they did, it was usually to indicate low availability. Textual presentation was usually chosen to express statuses precisely, especially at high and low extremes of receptivity; while graphical and numeric presentations were preferred when self-perceived receptivity levels were more ambiguous. Conflicts between recipients' and senders' perspectives are also discussed.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

availability, receptivity-status adjustment system, presence, mobile receptivity

ACM Reference Format:
Ting-Wei Wu, Yu-Ling Chien, Hao-Ping Lee, and Yung-Ju Chang. 2021. IM Receptivity and Presentation-type Preferences among Users of a Mobile App with Automated Receptivity-status Adjustment. In *CHI Conference on Human Factors in Computing Systems (CHI '21), May 8–13, 2021, Yokohama, Japan.* ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3411764.3445209

CHI '21, May 8–13, 2021, Yokohama, Japan

ACM ISBN 978-1-4503-8096-6/21/05…$15.00
https://doi.org/10.1145/3411764.3445209

1 INTRODUCTION

Instant messaging (IM) is a popular channel of day-to-day communication. It allows conversational dyads to exchange messages not only synchronously (i.e., with minimum delays, as in a face-to-face conversation), but also asynchronously (i.e., with varied, sometimes lengthy response delays, as in other forms of written correspondence). An inherent problem caused by the dual nature of this medium is that its users lack cues about one another's availability for communication or "presence" [24]. Some IM services are equipped with online status indicators (OSIs) [18], a blanket term for features designed to show whether their users are online or offline and if online, whether they are available for messaging or not. However, OSIs have been criticized as not accurately reflecting IM users' actual receptivity to communication [22, 24, 27, 51] or their ability to respond [42]. Over the past decade, an increasing number of research projects have addressed the sensing, estimation, and prediction of different notions of receptivity, including attentiveness, interruptibility, responsiveness, and opportune moments [22, 59, 82]. Advancements in data-capture and machine-learning technologies, meanwhile, have made estimation and prediction of receptivity status more accurate and reliable. Anticipating that future IM services are likely to incorporate these techniques, enabling their users' statuses to be estimated and shared with their contacts, it is crucially important to understand users' needs and preferences regarding the presentation of their receptivity and how they perceive such a system. Unfortunately, while a growing body of evidence shows high feasibility and accuracy of receptivity estimation, of up to 80% in some cases (e.g. [22]), it remains unclear RQ1) *what kind(s)* of receptivity information – e.g., attentiveness, responsiveness, and/or interruptibility – IM users would prefer their messaging systems to estimate and present their contacts with, and RQ2) *how* they would like such information to be presented. Answers to these two questions may help future researchers to prioritize their receptivity-estimation foci, and thus move closer to effective real-world deployments of receptivity-estimation systems.

To help answer them, we developed a research tool called IMStatus: an Android app that automatically estimates IM users' receptivity levels and presents such levels in several different ways. The levels comprised *attentiveness* (how quickly one can read a message), *responsiveness* (how quickly one can respond to a message), and *interruptibility* (how prepared one is to deal with a message). The app's three presentation types, meanwhile, were textual, graphical, and numeric. We invited 14 groups of IM users, in total 43 main participants, to use IMStatus for two weeks, and captured their in-situ status preferences using experience sampling method (ESM) questionnaires, which were delivered via the IMStatus app. In the study, IMStatus estimated and adjusted participants' receptivity to IM messages automatically based on the recent condition of their phones, and participants were able to alter their presentation type and receptivity level via the system or via ESM. To obtain more context for and insights into the participants' situated preferences for certain receptivity types and presentation types, we conducted semi-structured interviews with 19 of them who volunteered.

This study's findings make four main contributions to the computer-mediated communication (CMC) and receptivity literature. First, we found that the participants preferred setting their estimated status to *responsive* or *attentive*, and used the status *interruptible* primarily to express low receptivity. Second, we established that they preferred to present their statuses textually, to precisely show their status; with graphical and numeric presentations more often used to show ambiguous statuses, typically in the middle range of receptivity. Third – unexpectedly, in light of their preferences as receivers mentioned above – we found that, as senders, they did not like their contacts' high-receptivity statuses to be presented textually. And fourth, while the motivations for participants' status changes included privacy, as expected, they also included a desire to shape, or avoid, specific interpretations of their response behavior being made by their contacts.

2 RELATED WORK

2.1 Sensing, Estimating, and Presenting Receptivity in the Workplace

Prior research has investigated a variety of techniques for sensing and collecting a user's IM context in work-related desktop environments. The contextual cues that such research has selectively combined to model a user's availability have included audio and video information [26, 68], location [5, 13, 27, 35, 40, 57], calendar information [6, 13, 27, 40, 57], computer activity [6, 13, 27, 40, 57], and sensor data [6, 75]. A system called Montage [82], for example, provides lightweight audio-video glances that collocated teams can share to establish and negotiate opportunities for interaction and communication. MyVine [27] uses icons to present its users' context information, and each person's image to show his/her availability. Lilsys [6] uses patterns of lights to indicate contextual cues including motion, sound levels, whether the user's office door is open, whether s/he is on the phone. Additionally, it allows its users to switch their statuses between online and offline, and to turn automatic sensing of such statuses on and off. More recently, Züger et al. [83] used a physical "traffic-light" device to show whether individuals were available, busy, too busy to be disturbed, or away. While a large body of such work has utilized low-level data such as location, ambient sound, sensor data, and motion status to estimate and represent users' receptivity to incoming interruptions, Hincapié-Ramos et al. [29] argued that such data can easily be misinterpreted, and that it would be more beneficial to present high-level abstractions based on the aggregation of low-level data: i.e., estimated availability statuses.

2.2 Sensing, Estimating, and Presenting Receptivity on Mobile Phones

As communication activity increasingly moves to mobile and ubiquitous platforms [21, 41], measuring individuals' receptivity across constantly changing contexts is becoming more challenging. Prior research used various contextual factors in its attempts to estimate and predict various notions of receptivity, including attentiveness [22, 57], responsiveness [38, 43], interruptibility [48, 50, 52, 53, 55, 73, 77], and opportune moment [25, 31, 37, 39, 56, 59, 78, 79]. For example, Dingler and Pielot [22] predicted mobile users' attentiveness to incoming messages using logs of their phone usage, and achieved an accuracy rate of close to 80%. Lee et al. [43] likewise predicted users' responsiveness to their IM contacts based on IM chat logs, with up to 71% accuracy (AUROC). Pielot et al. [58], on the other hand, predicted mobile users' attentiveness to notifications via their interactions with the notification center, their screen activity and ringer mode, and other phone-sensor data, again with an accuracy of slightly over 70%. And Komninos et al.'s [38] attempt to predict responsiveness to mobile notifications, which utilized data such as time of day, screen status, and ringer mode, achieved a very high accuracy of up to 90%.

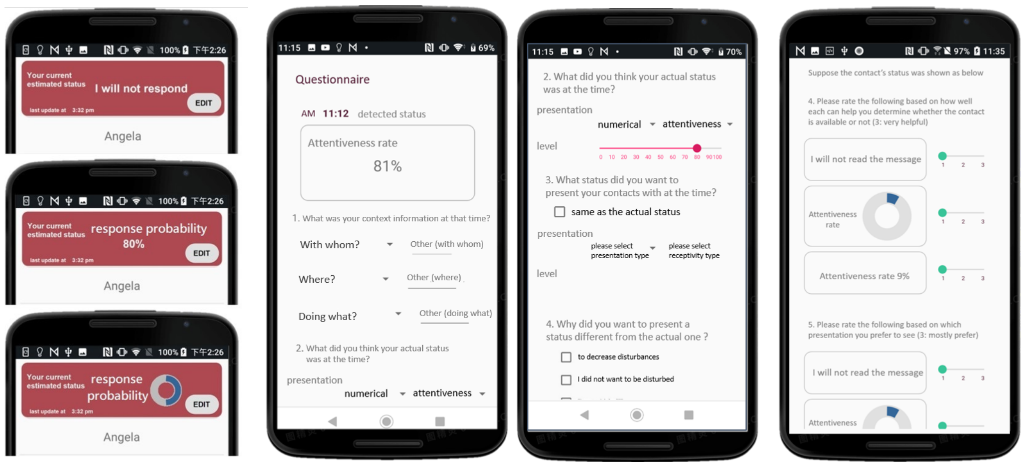
The considerable, but broadly similar amount of research interest in each of these different receptivity types appears to suggest that researchers perceive them as similarly important. However, users' preferences about their own receptivity types, and how/if they are shared with others, have seldom been explored. The current study therefore investigates such preferences to complement and inform the existing body of work on receptivity prediction.

2.3 Privacy Concerns about Online Status Indicators

Researchers have also studied users' OSI usage behaviors and perceptions, and found that those that present context information, location, video cues and calendar information [19] often provoke privacy concerns. Buchenscheit [11] also suggested that OSI may be used to infer users' daily routines and habits, such as bedtimes and waking-up times; when they deviate from such routines and habits; whether they are using systems when they are expected not to, e.g., when they are meant to be working; and even whom they are communicating with (see also [7, 12, 23]). Therefore, users sometimes seek to deactivate OSI features or to otherwise manage their own online status: including by controlling what information is being shared, at what granularity, and with whom [8, 10, 21, 32, 41, 70, 80]. Previous studies of status sharing have consistently found that individuals prefer to appear either away or offline, i.e., to remain "invisible" [17, 54].

3 METHODS

We used a mixed-methods approach to study which receptivity type our 43 participants preferred to project to their contacts, and how they would like to present it. Our IMStatus app estimated these users' receptivity level every 10 minutes and automatically adjusted it. The ESM questionnaires delivered through the app were aimed at capturing these users' in-situ preferences about receptivity-status presentation.



(a) (b) (c)

Figure 1: English translations of screens from the Chinese-language IMStatus app used in this study, showing (a) three formats for presenting receptivity status; (b) a sample ESM questionnaire for message recipients; and (c) a sample ESM questionnaire for message senders

3.1 IMStatus

In light of our study's primary objectives, we designed IMStatus in part to inspire its users with a belief that it was sensitive to their behaviors and to their phone-status information, and that it was inferring their receptivity based on such information. Since a learning-based app also cannot estimate receptivity perfectly, we decided to develop a simple heuristics-based algorithm for estimating users' receptivity. The results of a pilot study we conducted with 13 IM users confirmed that such an algorithm would suffice for our purposes.

3.1.1 Receptivity Estimation. Inspired by prior research (e.g., [38, 47, 58]) that consistently showed a high correlation between receptivity and several aspects of recent and current phone condition, notably including screen status, IM-app usage time, time elapsed since the last typing event on the phone, and current ringer mode, we used those four aspects to build the above-mentioned heuristics-based algorithm to estimate IMStatus users' receptivity level. IMStatus captured each of these aspects at intervals of 10 seconds, and used that data to estimate and update the user's receptivity status every 2 minutes. The estimation heuristics were inspired by prior interruptibility research (e.g. [59, 82]). For instance, when our algorithm detected that someone's phone was currently unlocked and s/he had recently typed on it, that person's receptivity on a scale of 0-100 was estimated to be higher. Numerical scores from 0 to 100 were also mapped onto five discrete levels, to facilitate their expression in textual form.

3.1.2 Randomized Presentation Type and Receptivity Type. Each time a new receptivity level was estimated, IMStatus randomly selected a presentation type from among numeric presentation (e.g., "Response probability 80%"), graphical presentation (as shown in Figure 1a), and textual presentation, which could be of either of two kinds: one using a statement like "Probably will respond", and the other using a label like "Response Likelihood: High". This was because we did not know, but wished to observe, which of these two styles of textual status description users might prefer. Then, the system randomly assigned the user a receptivity type – i.e., one of attentiveness, responsiveness, and interruptibility. Because a computed receptivity level is a numeric value that could be directly presented either numerically or graphically, we chose to randomize all three receptivity types across the numeric and graphical presentation styles. Due to prior findings that IM users tend to interpret how fast their contacts can respond to their messages based on textual descriptions of those contacts' likely responsiveness [24, 54], our textual descriptions included more ways of displaying responsiveness information. Since these design choices of including more textual description and responsiveness information essentially influenced the count and time duration of each receptivity and presentation type being presented by our app, our analysis did not consider such original count or duration each receptivity and presentation type was used. Rather, we treated these estimated statuses simply as prompts for users' ESM reflections on 1) what their actual status was, 2) what status they wanted to project, and 3) how they wanted to project it; and within our ESM questionnaires, we allowed them to specify any receptivity type and any presentation type they preferred. In this way, we were able to obtain their preferences regarding both of our presentation types, without being influenced by the initial imbalanced distribution of statuses as set by the system.

3.1.3 User Adjustment. Finally, IMStatus was adjustable by users at any time. That is, if a user was not satisfied with the estimated status provided by the app, s/he could change it by clicking the "Edit" button next to that status.

3.2 Capturing In-situ Status Preferences Using ESM

This study used three distinct forms of ESM. The form we used to obtain the participants' in-situ reflections on their in-situ preferences throughout a given day is known as "signal-contingent" sampling [20]. That is, an ESM questionnaire was triggered when the participant's estimated receptivity level was particularly high, or particularly low, or when there was a sharp change in his/her receptivity levels over a short period of time. Targeting these three types of moments allowed us to capture users' preferences in more diverse situations and receptivity levels than would have been possible using ESM questionnaires that were purely randomized.

Each signal-contingent ESM questionnaire (Figure 1b) showed a specific time when it had been triggered. It first asked participants about their context information at that time. Then, it asked them *"What do you think your actual status was at the time?"*, with options to choose any of the receptivity types, presentation types, and receptivity levels. Then they were asked *"What status did you want to present your contacts with at the time?"* They were provided a checkbox *"Same as the actual status"*, as well as the same options as for the previous question regarding receptivity type, presentation type, and receptivity level. If an individual gave different answers to these two questions, s/he was then asked to provide reasons for that discrepancy.

Additionally, because we were also interested in situations where users self-initiated adjustments to their statuses, an "event-contingent" ESM questionnaire [20] was triggered when they did so. That type of questionnaire mainly asked about the participant's contextual information and why his/her status-adjustment decision had been made.

Finally, when a participant checked a contact's receptivity status, a different event-contingent ESM questionnaire was triggered. This questionnaire inquired why the participant had checked the contact's status, and asked him/her to rate 1) the *helpfulness* of each status-presentation they had seen (all three types being provided, as shown in Figure 1c); and 2) his/her *preference* for each of the three status-presentation types.

We set a minimum interval of one hour between any two signal-contingent ESM questionnaires, and did not send them any before 10 a.m. or after 10:30 p.m. on any day of the study. Our participants in the end received 8-10 ESM questionnaires per day, and the average was 9.33. We did not place any time limit on the completion of a given ESM questionnaire; however, only those responses provided within 30 minutes from delivery were included in our analyses. This limit was more relaxed than in much prior research, which has typically set expiration times of around 15 minutes [49, 74]. This was because we felt a strict expiration time might prevent us from capturing the participants' preferences in low-receptivity situations, which we hypothesized might differ fundamentally from their preferences in high-receptivity situations.

3.3 Recruitment and Participants

We recruited groups of at least three participants who were at least 20 years old and who actively contacted each other using Facebook Messenger and/or LINE Messenger, the two most popular IM applications in Taiwan, in their daily lives. We advertised for such groups in several Taiwanese Facebook groups geared toward experimental-subject recruitment, as well as on the research team members' personal social media pages. In the event, this resulted in the recruitment of 13 groups of three people and 1 group of four people. None of the participants had previously participated in the pilot study. In these fourteen groups, there were 43 participants (22 females, 21 males). We referred to them as the *main participants*. 41 of them aged between 20-24, and the other two were 25-34. Three were non-students, and the remaining 40 participants were students. The relationship between main participants were eight groups consisting entirely of friends; five groups, of a mixture of classmates and friends; and the remaining one, of friends, classmates, and a romantic couple.

Besides, we encouraged the main participants to invite their social contacts to join the study as *partial participants*. There were 16 partial participants. Thus, in total there were 59 participants (43 + 16) in the entire study. The purpose of adding this peripheral participant pool was to increase the diversity of the relationships among the individuals in each group. The partial participants were the main participants' parents, siblings, and classmates. Each main participant's IMStatus contact list included all other main and all partial participants s/he invited.

3.4 Study Procedure

In our recruiting advertisements, we claimed that IMStatus was an intelligent system that estimated smartphone users' receptivity to messages and that we wanted to recruit users to experience the system and to give us feedback about how they would like to present their status within it, to help us improve it. When participants signed up, we once again made sure that they were aware of this supposed feature. If they asked us how the app achieved this functionality, we provided them with a high-level idea about what kind of information is used to make estimations. The main participants in each group were invited to a pre-study meeting at which we installed the IMStatus app on their phones and gave them a tutorial on how to use it. After this meeting, each main participant was sent a questionnaire covering his/her type of relationship and closeness with each of the other group members, both main and partial. Partial participants were taught how to install and use IMStatus by whichever main participant had invited them. At the end of the first week of the study, an emailed questionnaire was sent to those main participants who had proactively modified their receptivity status at any point, asking them to recall why they had done so and what their prevailing situation had been. This was done in the hope of boosting their recall of those situations during any post-study interview that they might participate in. Upon completion of the full two-week ESM study, the 19 participants who had been most active were invited to a semi-structured interview via email. They were provided with their ESM responses to further help them recall the situations of each one and to reflect on the context and reasons behind their choices of receptivity-status presentation types. The main participants received NT$800 (approximately US$26) for the ESM study, with bonuses of NT$100 for each partial participant they had successfully recruited. They received an additional NT$200 if they participated in an interview.

3.5 Data Cleaning and Analysis

We received a grand total of 208 sender-side questionnaires and 4,955 recipient-side questionnaires. The latter group comprised 4,913 that were signal-contingent, and 42 that were event-contingent, i.e., triggered by participant-initiated receptivity-status adjustments of their status. After elimination of questionnaires that had not been completed within 30 minutes of receipt, to avoid possible recall errors as discussed above 4,593 remained: including 201 on the sender side, and on the recipient side, 4,350 that were signal-contingent and all 42 that were event-contingent.

As noted earlier, our analytical focus was the participants' self-reported preferences about how to present their statuses, rather than the original statuses provided to them by the system. Because we anticipated that some participants might have a tendency to not change those original statuses, we primarily focused on instances where participants *adjusted* them in any respect, i.e., receptivity level, receptivity type, and presentation type. To simplify this analysis, we categorized the five levels corresponding to the original numeric estimates of receptivity – i.e., <20, 20-39, 40-59, 60-79, and 80+ – into three discrete levels: unavailable (containing 1="highly unavailable" and 2="unavailable"), medium (3="medium"), and available (containing 4="available" and 5="highly available").

To examine the effect of presentation type and receptivity type on receptivity level, we used mixed-effects logistic regression. We chose this statistical-analysis technique because each participant had repeated observations over the two-week period, and we used a random effect of *participants* to account for their individual variances. Dummy-variable coding (i.e., either 1 or 0, as a binary variable) was used in the regression analysis. For example, when examining whether participants used a textual presentation more often than the other presentation types to express an extreme receptivity level, we used *presentation type* as a fixed effect, and whether or not the expressed level was an extreme receptivity level as the predicted outcome. We ran mixed-effects logistic regression in the R software[1], which allowed us to observe the contrast between levels in a categorical/binary variable as a fixed effect.

We used affinity diagramming [33] to analyze the interview transcripts. The themes that emerged through iterative grouping and labeling were preference/interpretation of presentation type; preference/interpretation of receptivity type; the timing of people's revelations of their actual statuses; and interpretations of and trust in the (supposedly) automated receptivity-status adjustment system.

4 RESULTS

4.1 Receptivity Levels Adjusted More Often than Presentation Types and Receptivity Types

Of 4,392 recipient-side responses that we analyzed, 43.6% (n=1,913) involved adjustments to receptivity status. Notably, such adjustments were more common in the first week of the study: i.e., involved 52.2% of recipient-side responses that week, as compared to 35.2% in the second week. This was probably because of the novelty effect [36], whereby engagement with an intelligent system gradually decreases [81]. It is also likely that participants' compliance simply declined [46, 66] in the second week: a well-documented phenomenon in ESM studies [62].

Among the instances of status adjustment, our participants more often adjusted their receptivity levels than either their receptivity types or presentation types. Up to 56.3% of the time (1,077 out of 1,913 responses), they adjusted their receptivity level only. Adjustments to only presentation type or only receptivity type, in contrast, were very rare, at 3% and 6%, respectively. Both these aspects were more often adjusted at the same time as another: i.e., receptivity level + presentation type (8%) and receptivity level + receptivity type (15%).

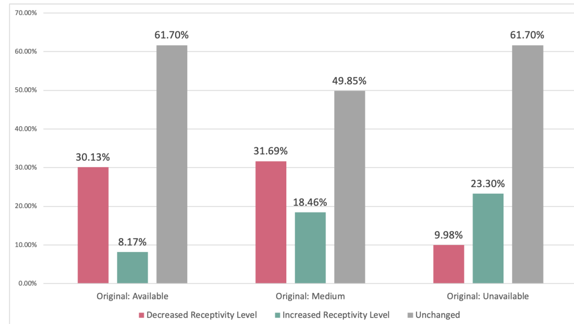


Figure 2: How participants adjusted their receptivity levels

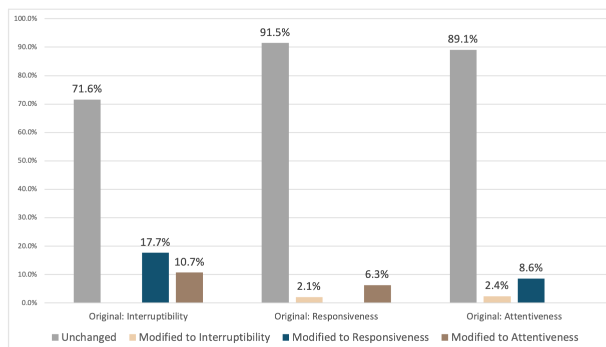


Figure 3: How participants adjusted their receptivity types

4.2 Lowering Receptivity Levels Was More Common than Raising Them

As a group, the participants exhibited a tendency to lower their receptivity levels. As shown in Figure 2, when IMStatus initially assigned them a receptivity level of "medium" or "high", they decreased it 31.69% and 30.13% of the time, respectively. And, nearly 10% of the time, when their app-assigned receptivity level was already "low", participants wanted to lower it further still. At the other extreme, roughly 8% of the time, participants chose to increase their receptivity levels even when their app-assigned receptivity level was already "high".

[1] https://www.r-project.org/

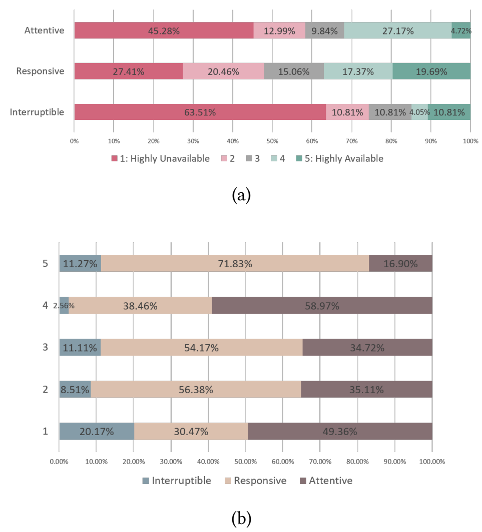


Figure 4: (a) Percentages of each receptivity level expressed by each receptivity type, and (b) choices of receptivity type by receptivity level. 1="Highly Unavailable"; 5="Highly Available"

4.3 Preferences and Interpretations of Receptivity Types

4.3.1 Preferences of Receptivity Types in ESM. As shown by the grey bars in Figure 3, our participants tended to keep the original receptivity type assigned to them by the app.

Among those who did change it, roughly three times as many shifts were away from "interruptible" (28.4%, 277 out of 976) than away from either "attentive" (11.0%, 110 out of 1,005) or "responsive" (8.5%, 200 out of 2,366). And, as shown in Figure 4(a), when participants changed their label *to* "interruptible", they were much more likely to project extreme unavailability (63.51%, 47 out of 74) than any other receptivity level. This percentage was significantly higher than the equivalent extreme-unavailability percentages that followed their shifts to "attentive" (45.28%, 115 out of 254, Z=-2.368, p=0.0179) or to "responsive" (27.41%, 71 out of 259, Z=-4.966, p<.001), as Figure 4(a) shows.

When shifting to "responsive", the levels they wanted to express were also more balanced in general. Figure 4(b) shows, for each receptivity level, how often the participants chose each receptivity type. From this perspective, it is also clear that participants more often chose to label themselves as "interruptible" to indicate their receptivity level was very low. Likewise, the participants infrequently used the label "attentive" to express high receptivity, instead mostly deeming themselves "responsive" in that scenario.

Together, these results indicate that "interruptible" was the least popular of our app's three status labels, and that there was a fairly clearly structured relationship between certain labels and certain levels of receptivity, e.g., "interruptible" was often used to express that a person was very unreceptive, and "responsive" to indicate that his/her receptivity was very high.

4.3.2 Interpretations of Receptivity Types. From the interviews, we learned that participants' usage of IMStatus's receptivity types depended on not only their needs, but also on their subjective interpretations of what each type level meant. The reason that they rarely switched to "interruptible", more often switching away from it to other receptivity types. We learned from our interviewees that this was because many of them were unsure about how to interpret the term "interruptible" and how their contacts would interpret it, and therefore what it meant for IM communication in terms of how fast they would read and respond to messages. As P24 explained, *"I was unsure about the definition of interruptibility. But I was sure about the meanings of the probability of responding to and reading messages. So I used those two labels to represent my status."*. Similarly, P3 stated, *"I think 'responsive' more clearly conveys whether you can respond or not. But if you show 'interruptible', others wouldn't know whether they can contact you now."* Interestingly, some participants mentioned that "interruptible" expressed their emotions, in a way that "attentive" and "responsive" did not: *"I usually felt annoyed to see messages when I was in class or when I was busy. [...] I liked to project that feeling through my status [...]. So I changed my status to the probability of being interrupted. It's my emotional feeling."* (P18). Other interviewees also consistently said they most often used "interruptible" to signal to their contacts not to send them messages, in preference to the other two labels, which they described as objective and emotionally neutral. *"I was watching videos and doing exercise at that time. [...] Because I'd feel disrupted if I got a message, I changed it to show that if they messaged me, I would be interrupted."* (P7).

Participants generally favored the "responsive" label because it clearly indicated whether they could respond or not. However, for "attentive", participants had a wider variety of interpretations. Here, it should be noted that, on the app, we used the term "reading" to operationalize attentiveness, i.e., as "probability of reading messages", as this was how it was measured in prior research. Yet, the phrase "reading messages" was still subject to different interpretations. While some took its meaning literally, as we intended, others associated it with responsiveness or awareness. Specifically, some participants considered attentiveness to be very close to responsiveness conceptually because, to them, the two things either happened together or did not happen. As P4 put it, *"In my mind, they [attentiveness and responsiveness] are the same thing, because I have almost never read messages without responding to them. If I read a message, I respond to it."* These participants thus found it both difficult and unnecessary to distinguish between "attentive" and "responsive", and used the latter term, since it seemed clearer. Some other participants interpreted "attentive" as reflecting awareness, i.e., knowing that a message has arrived, as P10 explained: *"I see reading probability as: I'm likely to see who replies to my messages, but I don't click into the message."* P28, when trying to distinguish between responsiveness and attentiveness, said, *"I thought reading probability was like: oh, I knew there was a message, and responsiveness was more like whether I can respond to it now."* Similarly, P24 said, *"The way I understood the reading rate was that I was aware of the message, but I would not read them."* These interpretations will resonate with the quantitative result we show later that the participants very often chose "attentive" to express that their phones

(a) (b)

Figure 5: (a) Usage of three presentation types, and (b) choices of presentation types at different receptivity levels. 1="Highly Unavailable"; 5="Highly Available"

were not with them and that they would therefore not be aware that messages had arrived.

4.4 Preferences and Interpretations of Presentation Types

4.4.1 Preferences of Presentation Types in ESM. On those occasions when participants modified the presentation style of their receptivity statuses, nearly half of the time (51.6%) they changed them to a textual presentation, as compared to 34.2% to numeric and 14.2% to graphical. A chi-square test of independence showed a strong relationship between presentation type and receptivity level (χ^2=6351.5, p<.001).

When we looked deeper into what receptivity levels participants were attempting to express by shifting to these presentation types, we found that – as Figure 5(a) shows – they tended to use textual presentation to express more extreme receptivity levels, i.e., 1 ("very low") or 5 ("very high"), which between them accounted for 65.06% of textual-presentation use. This "extreme" use of textual presentation was significantly more prevalent than "extreme" use of either numeric (46.71%, Z=-3.185, p=0.0014) or graphical presentation (42.85%, Z=-2.644, p=0.0081). Moreover, textual presentation was hardly ever used to express the most neutral level, 3 (6.55% of the time).

From the perspective of receptivity levels, Figure 5(b) also supports this observation. That is, at the two extreme receptivity levels, textual presentation accounted for the majority of usage: 57.30% at the very high level, and 62.03% at the very low level.

When using graphical and numeric presentations, in contrast, our participants more often expressed a relatively neutral receptivity level: i.e., 2, 3 or 4 out of 5. In particular, participants using graphical presentation expressed the highest level of receptivity only 9.52% of the time; and conversely, as shown in Figure 5(b), within all occurrences of someone projecting the highest receptivity level, graphical presentation was only used 6.74% of the time, dramatically lower than the average for its usage (i.e., 14%). Finally, Figure 5(b) shows that when participants' receptivity level was set to neutral, they used numeric presentation 50.94% of the time, more often than at any other receptivity level.

To sum up, these results imply that when expressing extreme levels of receptivity, whether low or high, the participants preferred to use textual presentation, but when their receptivity was not at either extreme, they preferred using graphical and numeric presentations over textual ones.

4.4.2 Interpretations of Presentation Types. Our interviewees' comments about the app's textual presentation mode were broadly consistent: such presentations explicitly, clearly, and precisely described their actual status, and seemed unlikely to lead to rival interpretations. Thus, when they wanted to clearly convey their specific status, they tended to choose it. As P24 said: *"Sometimes it was hard for me to estimate my probability of responding. Then I would just use text, like 'I will not respond.' [. . .] It's more complete and summarizes my situation [better than percentages]."* Similarly, P9 said: *'If I wanted to present a status that matched my actual status, I used the text presentation. Text would not cause people to have different interpretations like it would if I used numbers."* Interestingly, when wanting to express an ambiguous state, a few participants wanted to express it precisely, including P11: *"Text more precisely describes your condition, [even when] the condition is ambiguous, like 'I might not respond."'*

Participants' perceptions and interpretations of graphical presentations were also quite similar, insofar as most thought it vague, with some even calling it quite hard to interpret. Thus, many were reluctant to use it to present their statuses, out of concern that their contacts might misinterpret it. *"I found it laborious to interpret the circle [graphical presentation], like how much exactly it represents. It [the level] seems like above the half but also like not above the half. Then you have no idea, what's that exactly?"* (P26). *"The circle also represented a ratio, why not just use numbers to represent the ratio? It would be more clear and precise. The graph was more vague."* (P1).

However, a minority of the participants said they liked the ambiguity of the graphic presentation, on the grounds that it made space for their contacts to speculate about their status and intent at the time. As P18 said, *"I think text can reveal you're busy; but like graphs, it can better reveal the idea that my response depends on my mood. [...] Compared to numbers and text, graphs are better at showing whether a person is in the mood of reading your message or not."* P4 noted, *"you can tell from the graph that it's nearly half but a little under it. So the others would think that I have fifty percent possibility to respond but I'm a little bit toward being unavailable. And they would speculate about your attitude toward responding."*

The interviewees generally thought the numeric presentations were clearer than the graphical ones. They also liked that the former provided them with flexibility to signal to their contacts that they might not respond to all their incoming messages, and would be selective, depending on the urgency of the messages or other factors. As P7 explained, *"If I show response probability ninety percent, it means that I still have ten percent room for not responding. But if I used text like 'I will respond', I would feel that I must respond."* P9 also appreciated such "room": *"When using, say, a response probability of forty or fifty percent to show that I might or might not respond to messages as my status, my contacts would feel that I might or might not reply. This would prevent my contacts from expecting me to respond within a certain period of time."*

All in all, the findings above suggest that two different kinds of desires were at work in the participants' choices of a presentation type: 1) a desire to show explicit, precise information to shape contacts' specific interpretations about their status, and 2) a desire to maintain a sense of mystery and ambiguity, geared toward preserving their autonomy to respond selectively, or even simply to stimulate speculation about their current status or activities on the part of their contacts. These findings resonate with, and help to explain, why participants tended to use more precise vs. more vague presentation modes at different receptivity levels.

4.5 Revelation of One's Actual Status

Most of the time (98.8%), the participants claimed to have presented their receptivity statuses honestly. Only in 55 responses did they admit to projecting a misleading or inaccurate one. These 55 responses were spread across 16 main participants, suggesting that a need to "fake" one's receptivity affected 37.2% of IMStatus users at one time or another. When we looked into the differences between these users' actual statuses and the ones they preferred to present to their contacts, we found that they more often wanted to show an artificially low receptivity level than an artificially high one. Interestingly, on 11 of these 55 occasions, they lowered their receptivity level further, i.e., to 1, when their genuine status was already low, i.e., 2.

According to their ESM responses, the participants' top two reasons for falsifying their receptivity status were *"did not want to be disturbed"* (34.3%) and *"wanted to decrease disturbance"* (32.9%). Among the 36 instances in which a participant selected one of those two reasons, 27 pertained to showing their status as the lowest possible level of receptivity. The third most popular reason given for "faking" statuses was that the participant wanted to show contacts that s/he *"could be interrupted"*. Interestingly, in nine of the 11 instances associated with that reason, the participant's actual receptivity was reportedly medium or lower – even the lowest level – implying a desire to receive messages despite the recognition of their own non-receptivity. Finally, six of the 55 deceptive-status cases (8.6%) were ascribed simply to not wanting others to know their true status; and interestingly, a textual presentation was chosen on all six of those occasions.

In summary, we found that participants' deceptive status projections were usually aimed at decreasing disturbance. Only very rarely did they exaggerate their actual receptivity to express their openness to conversations.

4.6 Reasons for Proactive Adjustment

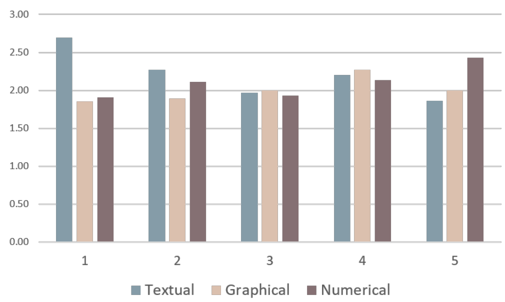
Only 42 ESM responses were triggered by participants' self-initiated status adjustment. In those cases, the participants more often changed their receptivity level (84.6%) than their receptivity type (66.7%) or their status-presentation type (64.3%). Two of the top reasons they provided for these proactive adjustments were not wanting to be disturbed (28.3%) and wanting to decrease disturbance (19.6%). Among the 21 occasions on which one of these two reasons was chosen, 16 saw the participant choose the lowest receptivity level, and 12 saw them choose textual presentation. Another major reason cited for proactive adjustments was that they wanted to render their statuses more precise (28.3%). Of the 13 ESM responses that cited this reason, 10 were associated with a shift to textual presentation. The fourth main reason for proactive adjustments was the participant's wish to indicate that s/he could be interrupted (21.7%), with seven of these 10 occasions being associated with a shift to the highest receptivity level. Interestingly, none of these 42 responses involved a decision to make a person's receptivity status more ambiguous.

4.7 Context Effects

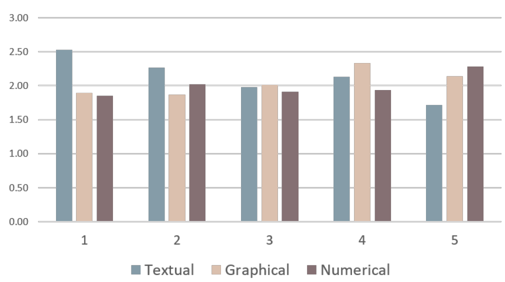
When we further examined how the participants modified their statuses across different activity contexts, we found that the top five activities during which they decreased their receptivity levels were: taking a bath (34.6%), moving/driving (29.4%), taking a class/attending a meeting (26.6%), working (23.1%), and sleeping (22.6%). Interestingly, however, six of the eight responses that cited taking a bath involved a status label of "attentive". That is, when users' phones were not near them, they tended to highlight their *unavailability to read messages* rather than their *inability to respond*, perhaps because the former was a necessary precondition of the latter [3]. Participants more often increased their receptivity level, on the other hand, when they were using computers (40.6%), killing time (35.5%), shopping (28.2%), playing computer/mobile games (27.3%), and watching TV/videos (26.2%). Notably, when killing time, the likelihood of raising responsiveness was up to 66.7%. Across all five of those activity contexts, "responsive" or "attentive" labels were used on 65 out of 70 of occasions (92.8%) and "interruptible" only on five. This resonates with our previously reported finding that the "interruptible" label was mainly used to express unavailability.

4.8 Discrepancies between Recipient and Sender Perspectives

We observed some interesting conflicts between sender-side and recipient-side preferences. When participants checked their contacts' statuses, they were prompted to rate the usefulness of, and their own preference for, each type of presentation of that contact's receptivity level. As shown in Figure 6, we observed a decreasing trend in the usefulness ratings assigned to textual presentations of contacts' higher receptivity levels; and an opposite, increasing trend in the reported usefulness of graphical and numeric presentations of the same receptivity levels. In other words, in their roles as message-senders, our participants increasingly thought that graphical or numeric indications of high contact availability were better than their textual equivalents. Moreover, they preferred to see, and



(a)



(b)

Figure 6: Senders' (a) usefulness perceptions and (b) preferences among three presentation types, by receptivity level. 1=the contact was highly unavailable; 5=the contact was highly available

found it more helpful to see, textual indications of their contacts' receptivity when those contacts were unavailable for communication. Importantly, this contradicted some of their preferences as recipients: including their preference for textual presentations, and against graphical ones, when expressing the highest receptivity level. Careful design decisions need to be made to deal with these tensions.

4.9 Interpretations of and Trust in the IMStatus

Finally, as the aims of our study were to inform researchers and practitioners about how people might use and perceive a IM system that automatically estimated and adjusted their receptivity status, their experience of IMStatus was also a focus of the qualitative interviews. While many of the interviewees thought it was interesting and felt fresh to use this type of system, some thought it the level of precision/accuracy supposedly offered by IMStatus was beyond what was really necessary. Two main reasons for this attitude were cited. The first was that the estimated receptivity information could never be more than a rough guideline; that is, regardless of the status the system estimated, it was ultimately system users who read and responded to messages, or declined to. Thus, being more accurate or precise would not be helpful. P20 noted, *"I did not care much about the status, because I thought its role is more like support. We have all used social-media tools for a long time. We should all be able to reason about why someone might be unresponsive. So, having a system be super accurate about it would not help that much. Yeah, it can distinguish, but it's not necessary to be very precise."* Similarly, P28 said: *"I'm not too concerned with the status it presents. After all, at the end of the day, I'm the one who makes the final decision. Whether to read or reply or not is up to me."*

The other main reason the interviewees cited for not desiring such a system to be precise was privacy, which would worsen as the system's capabilities improved. P28 noted that receptivity-status estimation, *"if made very comprehensive and powerful, would be kind of troubling, and even scary. You probably would not want other people to know what you're doing, but the system would just tell them automatically."* One interviewee (P43) also worried that its precision would mislead their contacts into thinking they were still responsive if they suddenly became busy or otherwise unavailable. To avoid violation of contacts' expectations, she hoped the system could be made less sensitive, or more conservative about their status.

5 DISCUSSION

We believe our findings are an important first step in understanding how to make future receptivity-prediction features more user-friendly. Below, we discuss our findings' specific implications for researchers and practitioners.

5.1 The Need for Different Receptivity Types

5.1.1 Which Receptivity Type Should Be Predicted/Presented? Our results suggest that, despite their seemingly unbalanced usage, all three of the focal receptivity labels had distinct merits. Our quantitative and qualitative results consistently indicate that "responsive" was more often used by our participants because it was the easiest of the three to understand. This result is not surprising, in light of prior research findings [54]. On the flip side, its explicitness and clarity also represented a limitation, because users sometimes wanted to express their uncertainty about whether they would be aware of message notifications in their current situations. They sometimes also wanted to explicitly express not only that they were unavailable, but also that – on an emotional level – they would not welcome any interruptions. The notion of responsiveness, from their perspective, could not help them clearly express these two meanings, and thus on such occasions they chose to switch to "attentive" or "interruptible", respectively. This resonates with recent findings by Cobb [19], that people use their online statuses to express various ideas and meanings. Despite our study being primarily focused on the presentation of estimated receptivity, we can recognize that our three receptivity categories alone are insufficient to convey the various personal or emotional states users might like to convey.

5.1.2 Specific Definition and Measurement of Receptivity is Needed. Our results also suggested IMStatus users' varying intuitive conceptions of each receptivity label profoundly affected their choices. That is, a clear definition of how a receptivity concept is measured and what kind of status it estimates would help people to determine the kind of receptivity they desire such a system to estimate and share with their contacts in different situations. Doing so would also tend to reduce the confusion users experience upon seeing discrepancies between their system-estimated statuses and their perceptions of their own current behavior. For example, prior research has suggested that there are essential differences between responsiveness and attentiveness, including that they represent different stages in the notification-response process [15, 73] and that they are associated with different individual characteristics [42]. Yet, such distinctions are not necessarily perceived by all system users, in part because of variation in their prior IM and other experiences. As we showed earlier, some participants reportedly thought that responsiveness and attentiveness had identical meanings, at least to them personally, because they seldom if ever failed to respond to an IM message immediately after reading it. For this subgroup of our participants, confusion would be likely to arise if their estimated attentiveness and estimated responsiveness were distinct from each other. Other participants, on the other hand, perceived our category of "reading" a message to merely mean noticing that it was there; this corresponds to the early *react* step in Turner [73], and the *sensing* step in Chang et al. [14], both of which occur before consuming and processing the content of a message. Discrepancies in users' interpretations of the term "attentive" matter considerably, as they may not only lead to user dissatisfaction with IM systems, but conflicts between message senders and message recipients.

Notably, most – perhaps all – prior research on users' attending actions on their phones has used a mixture of user actions and sensed cues (e.g., screen-unlocking and app-opening data) to infer the user's reading of notifications. This is largely due to the variety of pathways through which users can notice and read the content of their messages. Despite it being commonplace in research to group actions broadly indicative of message-reading into a single category, "attentiveness", many of our participants evidently considered these actions to be separate, and exhibited clear awareness of the nuanced differences between them. More importantly, individuals even associated the simple word "reading" with widely differing sets of actions. It is therefore probably time to think about whether it is worthwhile to predict and estimate each of these specific actions separately, especially in light of calls by other researchers to distinguish between responding, attending, and noticing/sensing of notifications (e.g. [24, 72, 73]). We would argue that this line of research should go even deeper: i.e., estimate and predict more specific steps, or even specific attending actions such as unlocking the phone vs. reading notification in the notification drawer vs. opening the app. However, more research will first need to address the question of when, where, and indeed if users would desire an IM system to capture, analyze and share these specific types of information.

5.2 Presentation Type: Precision vs. Ambiguity

Previous studies have frequently noted that people tend to blur their statuses [30, 61], or use them to show they are "busy" or "unavailable" when in fact they are not [54]. Our results are consistent with these previous findings, in that our participants also tended to lower the receptivity that was ostensibly estimated for them by our system. However, we observed that our participants often did not want to blur their status, but rather, on many occasions, wanted to make it precise and clear. In addition, we observed a general pattern in the relationship between receptivity level and choice of presentation type. That is, participants tended to use textual presentation to express receptivity levels at both extremes. This was mainly because they wanted to precisely indicate particular levels of receptivity, and avoid the misinterpretations they felt might be caused by graphical or numeric presentations. Conversely, when their receptivity levels were relatively neutral and *ipso facto* ambiguous, the participants used graphical and numeric presentations more often, which further strengthened the ambiguity that was already present.

To sum up, users' choices of presentation types suggest an interesting tension between their intentions to project precise statuses and ambiguous ones, which we found were driven not only by a desire to maintain their privacy and autonomy, as previous works have suggested [30, 58], but also by a desire to shape and/or avoid particular interpretations. The latter desire was not only displayed in their choices of presentation types, but also reflected in their concerns that our system's estimation was too sensitive and accurate. Their hope that such systems will be more conservative, as a means of avoiding mis-expectations on the part of their contacts, is an important avenue for further research to pursue.

5.3 What's Next? Receptivity-status Estimation Systems as Social Tools

We anticipate that the main purposes of future automated receptivity-status systems will be pitched as better availability management. While a system that automatically estimates and predicts one's status seems convenient and appealing at first glance, it is important to think about what actual role users would desire such a system to fill: i.e., a fully automatic agent, vs. an assistant that supports users in managing their availability. A number of studies and theses related to human-AI interaction (e.g., [2, 16, 44]) have provided important insights into how users might interact with and perceive AI-embedded systems, and how such systems should be designed to support them. But as our findings indicate, a receptivity-status adjustment system incorporated into IM services would encounter an array of challenges, not least because availability management transcends the management of one's own attention, to also include privacy control [11], coordination of communication [4, 9, 28, 45, 64, 69], self-presentation [54, 63, 76], and relationship management [34, 60, 65, 71]. Our study also revealed how individuals used such a system to shape and avoid their contacts' interpretations. In other words, any receptivity-status adjustment system is, by nature, a social tool; and designers of such systems need to concern themselves not only with how message recipients perceive their own statuses, but also how they perceive senders would perceive those statuses. Therefore, while existing receptivity research has primarily based receptivity prediction on features that are relatively personal – e.g., the condition of the users' phone – future receptivity-estimation systems will not be able to sidestep their inevitable roles as social tools, and all the communicative nuances that such roles entail.

5.4 Design and Research Implications

Our four main recommendations for a future receptivity-status system are that it incorporate: 1) user control, 2) customizability, 3) preference-awareness, and 4) mechanism clarification. As a general guideline, developers should take account of the general patterns of preferences for precision vs. ambiguity that we identified. The idea of making *both* receptivity type *and* the style in which it is presented context-aware may be worth pursuing. On the other hand, individual differences exist in these preferences; and the social nuances and situations in which users would want to present a more ambiguous vs. precise status would probably be challenging for a machine to learn, at least in the beginning. As such, we think the core of such a system should be user configuration: i.e., users should be granted control over their status, which they can exercise at any time, and the system should actively learn from the adjustments that they make while communicating in the real world. While we think the inclusion of preference awareness is optional, it could be beneficial if a person's switching between receptivity types became frequent and repetitive. Users' effort could be further reduced by allowing them to customize the automation of these repetitive actions in specific situations using rules, as they already are in some commercial services that configure routine automations (e.g. Google Home Routine [1]). On the other hand, special attention needs to be given to whether dynamically changing both presentation and receptivity types would lead to user confusion or perceptions of inconsistency, and thus to expectation breakdowns. Moreover, while context shifts are sometimes ad hoc or unanticipated, a user-prompting mechanism that reminds users about their apparent changes of status, or asks them for permission to make status changes for them, should also be considered. And it may be worth exploring presenting a hybrid status that combines multiple receptivity types, e.g., *"Likely to be interrupted; response probability 70%"*, given that these types were found above to mean different things to different users.

Finally, to reduce confusion and misinterpretations, not only between users and the system but also between users, it is vital to clearly communicate how the system works, i.e., how the estimated target is measured and inferred. As shown in recent work, disclosing some details of intelligent systems' data collection and inference-drawing can help people to better understand how to use and improve them [16, 44]. However, to avoid overwhelming users with low-level details, it may be worthwhile to consider disclosing such information progressively [67].

5.5 Research Limitations

This preliminary exploration of how automated IM-receptivity estimation might be received and used in people's daily lives has a number of limitations that should be acknowledged. First, our system had a narrow range of presentation types. Visual presentations other than textual, numeric, and graphical ones are equally worth examining; and we did not provide our participants with full flexibility to customize their statuses, which – if we had allowed it – might have enabled us to observe a wider range of status descriptions, including ambiguous ones. Second, IMStatus was a standalone application, not incorporated into the interface of an existing IM service. This could have reduced users' motivation to check their own and their contacts' statuses, because of the extra effort required. We might also have seen fewer kinds of social nuances because of this limitation. Third, given that our focus was primarily on observing users' preferences about receptivity statuses and how those statuses were presented, we did not build a machine-learning model for receptivity estimation. Thus, we cannot claim that we were able to observe all the behaviors and perceptions that users would have displayed if they had been using an actually learning-based system. Fourth, during the study, our participants might have been paying more attention to their phones because of the ESM; this might cause IMStatus to more often estimate participants' status to be receptive. Fifth, because we only implemented IMStatus on Android OS, our main participants could not invite partial participants whose phones were of other types. Given this recruitment difficulty, we also placed no limits or targets on the types of relationships they could have with the partial participants they recruited; and thus, the diversity of the relationships within each group was limited. Finally, all participants in our study were residents of Taiwan, aged from 20 to 34, mostly students, and mostly existing users of Facebook Messenger and LINE Messenger. Therefore, it is unclear whether our results can be generalized to other age groups, users of other IM services, and other parts of the world.

6 CONCLUSION

We developed a research tool called IMStatus, an Android app that ostensibly estimated IM users' receptivity levels and automatically adjusted their statuses accordingly, presenting those statuses in three receptivity types and three presentation styles. We studied 43 main participants' usage of IMStatus using a mixed-methods approach comprising a two-week ESM study and semi-structured interviews. We found that these participants preferred their statuses to be labeled as "responsive" or "attentive" rather than "interruptible", the latter being used primarily for expressing very low receptivity as well as negative emotions toward IM contact. We also found that our participants preferred using textual presentation when their goal was to present their status precisely, and when it was of an extreme level. Graphical and numeric presentations were used more often than textual ones to show ambiguous statuses: typically, neutral levels of receptivity. Overall, these users' choices of receptivity labels and presentation styles reflected a tension between their desire for precision and their desire to keep things ambiguous; and we found that their choices were driven not only by privacy concerns, but also by a desire to manage their contacts' interpretations of what they were doing. Based on our results, we provided design and research implications for future work on receptivity, which we believe will help others in this field to prioritize their focus on receptivity estimation and move forward to effective deployments of their receptivity-estimation systems on users' phones.

ACKNOWLEDGMENTS

We thank all the participants in our study and pilot studies. We also thank the Ministry of Science and Technology, R.O.C. (MOST) for their support (107-2218-E-009-030-MY3, 109-2634-F-007-016).

REFERENCES

[1] [n.d.]. *Google Home – Apps on Google Play.* https://play.google.com/store/apps/details?id=com.google.android.apps.chromecast.app&hl=en_GB
[2] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N. Bennett, Kori Inkpen, Jaime Teevan, Ruth Kikin-Gil, and Eric Horvitz. 2019. Guidelines for Human-AI Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in*

Computing Systems (CHI '19). Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300233

[3] Daniel Avrahami and Scott E. Hudson. 2006. Responsiveness in instant messaging: predictive models supporting inter-personal communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. Association for Computing Machinery, New York, NY, USA, 731–740. https://doi.org/10.1145/1124772.1124881

[4] Elizabeth Bales, Kevin A. Li, and William Griwsold. 2011. CoupleVIBE: mobile implicit communication to improve awareness for (long-distance) couples. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work (CSCW '11)*. Association for Computing Machinery, New York, NY, USA, 65–74. https://doi.org/10.1145/1958824.1958835

[5] Louise Barkhuus, Barry Brown, Marek Bell, Scott Sherwood, Malcolm Hall, and Matthew Chalmers. 2008. From awareness to repartee: sharing location within social groups. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. Association for Computing Machinery, Florence, Italy, 497–506. https://doi.org/10.1145/1357054.1357134

[6] James "Bo" Begole, Nicholas E. Matsakis, and John C. Tang. 2004. Lilsys: Sensing Unavailability. In *Proceedings of the 2004 ACM conference on Computer supported cooperative work (CSCW '04)*. Association for Computing Machinery, Chicago, Illinois, USA, 511–514. https://doi.org/10.1145/1031607.1031691

[7] James "Bo" Begole, John C. Tang, Randall B. Smith, and Nicole Yankelovich. 2002. Work rhythms: analyzing visualizations of awareness histories of distributed groups. In *Proceedings of the 2002 ACM conference on Computer supported cooperative work (CSCW '02)*. Association for Computing Machinery, New York, NY, USA, 334–343. https://doi.org/10.1145/587078.587125

[8] Michael Benisch, Patrick Gage Kelley, Norman Sadeh, and Lorrie Faith Cranor. 2011. Capturing location-privacy preferences: quantifying accuracy and user-burden tradeoffs. *Personal and Ubiquitous Computing* 15, 7 (Oct. 2011), 679–694. https://doi.org/10.1007/s00779-010-0346-0

[9] Frank R. Bentley and Crysta J. Metcalf. 2007. Sharing motion information with close family and friends. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '07)*. Association for Computing Machinery, New York, NY, USA, 1361–1370. https://doi.org/10.1145/1240624.1240831

[10] Igor Bilogrevic, Kévin Huguenin, Berker Agir, Murtuza Jadliwala, and Jean-Pierre Hubaux. 2013. Adaptive information-sharing for privacy-aware mobile social networks. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 657–666. https://doi.org/10.1145/2493432.2493510

[11] Andreas Buchenscheit, Bastian Könings, Andreas Neubert, Florian Schaub, Matthias Schneider, and Frank Kargl. 2014. Privacy Implications of Presence Sharing in Mobile Messaging Applications. In *Proceedings of the 13th International Conference on Mobile and Ubiquitous Multimedia (MUM '14)*. ACM, New York, NY, USA, 20–29. https://doi.org/10.1145/2677972.2677980

[12] Matthias Böhmer, Brent Hecht, Johannes Schöning, Antonio Krüger, and Gernot Bauer. 2011. Falling asleep with Angry Birds, Facebook and Kindle: a large scale study on mobile application usage. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. Association for Computing Machinery, New York, NY, USA, 47–56. https://doi.org/10.1145/2037373.2037383

[13] J. J. Cadiz, Gina Venolia, Gavin Jancke, and Anoop Gupta. 2002. Designing and deploying an information awareness interface. In *Proceedings of the 2002 ACM conference on Computer supported cooperative work (CSCW '02)*. Association for Computing Machinery, New Orleans, Louisiana, USA, 314–323. https://doi.org/10.1145/587078.587122

[14] Yung-Ju Chang, Yi-Ju Chung, and Yi-Hao Shih. 2019. I Think It's Her: Investigating Smartphone Users' Speculation about Phone Notifications and Its Influence on Attendance. In *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services* (Taipei, Taiwan) *(MobileHCI '19)*. Association for Computing Machinery, New York, NY, USA, Article 14, 13 pages. https://doi.org/10.1145/3338286.3340125

[15] Yung-Ju Chang and John C. Tang. 2015. Investigating Mobile Users' Ringer Mode Usage and Attentiveness and Responsiveness to Communication. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 6–15. https://doi.org/10.1145/2785830.2785852

[16] Yi-Shyuan Chiang, Ruei-Che Chang, Yi-Lin Chuang, Shih-Ya Chou, Hao-Ping Lee, I-Ju Lin, Jian-Hua Jiang Chen, and Yung-Ju Chang. 2020. Exploring the Design Space of User-System Communication for Smart-home Routine Assistants. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376501

[17] Hyunsung Cho, Jinyoung Oh, Juho Kim, and Sung-Ju Lee. 2020. I Share, You Care: Private Status Sharing and Sender-Controlled Notifications in Mobile Instant Messaging. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (May 2020), 034:1–034:25. https://doi.org/10.1145/3392839

[18] Camille Cobb. 2019. *User-to-User Privacy in Social and Communications Applications*. Thesis. https://digital.lib.washington.edu:443/researchworks/handle/1773/44135 Accepted: 2019-08-14T22:31:29Z.

[19] Camille Cobb, Lucy Simko, Tadayoshi Kohno, and Alexis Hiniker. 2020. User Experiences with Online Status Indicators. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376240

[20] Tamlin S. Conner and Barbara J. Lehman. 2012. Getting started: Launching a study in daily life. In *Handbook of research methods for studying daily life*. The Guilford Press, New York, NY, US, 89–107.

[21] Sunny Consolvo, Ian E. Smith, Tara Matthews, Anthony LaMarca, Jason Tabert, and Pauline Powledge. 2005. Location disclosure to social relations: why, when, & what people want to share. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '05)*. Association for Computing Machinery, New York, NY, USA, 81–90. https://doi.org/10.1145/1054972.1054985

[22] Tilman Dingler and Martin Pielot. 2015. I'll be there for you: Quantifying Attentiveness towards Mobile Messaging. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. Association for Computing Machinery, Copenhagen, Denmark, 1–5. https://doi.org/10.1145/2785830.2785840

[23] Trinh Minh Tri Do, Jan Blom, and Daniel Gatica-Perez. 2011. Smartphone usage in the wild: a large-scale analysis of applications and context. In *Proceedings of the 13th international conference on multimodal interfaces (ICMI '11)*. Association for Computing Machinery, New York, NY, USA, 353–360. https://doi.org/10.1145/2070481.2070550

[24] Mirko Fetter. 2019. *New Concepts for Presence and Availability in Ubiquitous and Mobile Computing: Enabling Selective Availability through Stream-Based Active Learning*. University of Bamberg Press. Google-Books-ID: knqIDwAAQBAJ.

[25] Joel E. Fischer, Chris Greenhalgh, and Steve Benford. 2011. Investigating episodes of mobile phone activity as indicators of opportune moments to deliver notifications. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. Association for Computing Machinery, New York, NY, USA, 181–190. https://doi.org/10.1145/2037373.2037402

[26] Robert S. Fish, Robert E. Kraut, Robert W. Root, and Ronald E. Rice. 1992. Evaluating video as a technology for informal communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '92)*. Association for Computing Machinery, Monterey, California, USA, 37–48. https://doi.org/10.1145/142750.142755

[27] James Fogarty, Jennifer Lai, and Jim Christensen. 2004. Presence versus availability: the design and evaluation of a context-aware communication client. *International Journal of Human-Computer Studies* 61, 3 (Sept. 2004), 299–317. https://doi.org/10.1016/j.ijhcs.2003.12.016

[28] Carla F. Griggio, Midas Nouwens, Joanna McGrenere, and Wendy E. Mackay. 2019. Augmenting Couples' Communication with *Lifelines*: Shared Timelines of Mixed Contextual Information. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300853

[29] Juan David Hincapié-Ramos, Stephen Voida, and Gloria Mark. 2011. A design space analysis of availability-sharing systems. In *Proceedings of the 24th annual ACM symposium on User interface software and technology (UIST '11)*. Association for Computing Machinery, Santa Barbara, California, USA, 85–96. https://doi.org/10.1145/2047196.2047207

[30] Roberto Hoyle, O. H. Oberlin, Srijita Das, Apu Kapadia, Adam J. Lee, and Kami Vaniea. 2017. Was my message read?: Privacy and Signaling on Facebook Messenger. (2017). https://vaniea.com/papers/chi2017.pdf

[31] Shamsi T. Iqbal and Brian P. Bailey. 2005. Investigating the effectiveness of mental workload as a predictor of opportune moments for interruption. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems (CHI EA '05)*. Association for Computing Machinery, New York, NY, USA, 1489–1492. https://doi.org/10.1145/1056808.1056948

[32] Leslie K. John, Alessandro Acquisti, and George Loewenstein. 2010. Strangers on a Plane: Context-Dependent Willingness to Divulge Sensitive Information. *Journal of Consumer Research* 37, 5 (08 2010), 858–873. https://doi.org/10.1086/656423

[33] Jiro Kawakita. 1991. The original KJ method. *Tokyo: Kawakita Research Institute* 5 (1991).

[34] Ryan Kelly, Daniel Gooch, and Leon Watts. 2018. 'It's More Like a Letter': An Exploration of Mediated Conversational Effort in Message Builder. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (Nov. 2018), 87:1–87:23. https://doi.org/10.1145/3274356

[35] Johannes Knittel, Alireza Sahami Shirazi, Niels Henze, and Albrecht Schmidt. 2013. Utilizing contextual information for mobile communication. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. Association for Computing Machinery, Paris, France, 1371–1376. https://doi.org/10.1145/2468356.2468601

[36] Michael Koch, Kai von Luck, Jan Schwarzer, and Susanne Draheim. 2018. The Novelty Effect in Large Display Deployments – Experiences and Lessons-Learned for Evaluating Prototypes. (2018). https://doi.org/10.18420/ecscw2018_3 Accepted: 2018-04-30T19:58:18Z Publisher: European Society for Socially Embedded Technologies (EUSSET).

[37] Andreas Komninos, Jeries Besharat, Vassilios Stefanis, and John Garofalakis. 2018. Perceptibility of Mobile Notification Modalities during Multitasking in Smart Environments. In *2018 14th International Conference on Intelligent Environments (IE)*. 17–24. https://doi.org/10.1109/IE.2018.00011 ISSN: 2472-7571.

[38] Andreas Komninos, Elton Frengkou, and John Garofalakis. 2018. Predicting User Responsiveness to Smartphone Notifications for Edge Computing. In *Ambient Intelligence (Lecture Notes in Computer Science)*, Achilles Kameas and Kostas Stathis (Eds.). Springer International Publishing, Cham, 3–19. https://doi.org/10.1007/978-3-030-03062-9_1

[39] Kostadin Kushlev, Bruno Cardoso, and Martin Pielot. 2017. Too tense for candy crush: affect influences user engagement with proactively suggested content. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3098279.3098569

[40] JENNIFER Lai, ANTHONY Levas, PAUL Chou, CLAUDIO Pinhanez, and MARISA Viveros. 2002. BlueSpace: personalizing workspace through awareness and adaptability. *International Journal of Human-Computer Studies* 57, 5 (Nov. 2002), 415–428. https://doi.org/10.1006/ijhc.2002.1028

[41] Scott Lederer, Jennifer Mankoff, and Anind K. Dey. 2003. Who wants to know what when? privacy preference determinants in ubiquitous computing. In *CHI '03 Extended Abstracts on Human Factors in Computing Systems (CHI EA '03)*. Association for Computing Machinery, New York, NY, USA, 724–725. https://doi.org/10.1145/765891.765952

[42] Hao-Ping Lee, Kuan-Yin Chen, Chih-Heng Lin, Chia-Yu Chen, Yu-Lin Chung, Yung-Ju Chang, and Chien-Ru Sun. 2019. Does *Who* Matter? Studying the Impact of Relationship Characteristics on Receptivity to Mobile IM Messages. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, Glasgow, Scotland Uk, 1–12. https://doi.org/10.1145/3290605.3300756

[43] Hao-Ping Lee, Tilman Dingler, Chih-Heng Lin, Kuan-Yin Chen, Yu-Lin Chung, Chia-Yu Chen, and Yung-Ju Chang. 2019. Predicting Smartphone Users' General Responsiveness to IM Contacts Based on IM Behavior. In *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '19)*. Association for Computing Machinery, Taipei, Taiwan, 1–6. https://doi.org/10.1145/3338286.3344387

[44] Q. Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3313831.3376590

[45] Rich Ling and Chih-Hui Lai. 2016. Microcoordination 2.0: Social Coordination in the Age of Smartphones and Messaging Apps. *Journal of Communication* 66, 5 (Oct. 2016), 834–856. https://doi.org/10.1111/jcom.12251 Publisher: Oxford Academic.

[46] Derrick C. McLean, Jeanne Nakamura, and Mihaly Csikszentmihalyi. 2017. Explaining System Missing: Missing Data and Experience Sampling Method. *Social Psychological and Personality Science* 8, 4 (May 2017), 434–441. https://doi.org/10.1177/1948550617708015 Publisher: SAGE Publications Inc.

[47] Abhinav Mehrotra, Robert Hendley, and Mirco Musolesi. 2019. NotifyMeHere: Intelligent Notification Delivery in Multi-Device Environments. In *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval (CHIIR '19)*. Association for Computing Machinery, Glasgow, Scotland UK, 103–111. https://doi.org/10.1145/3295750.3298932

[48] Abhinav Mehrotra, Veljko Pejovic, Jo Vermeulen, Robert Hendley, and Mirco Musolesi. 2016. My Phone and Me: Understanding People's Receptivity to Mobile Notifications. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. Association for Computing Machinery, New York, NY, USA, 1021–1032. https://doi.org/10.1145/2858036.2858566

[49] Christie Napa Scollon, Chu-Kim Prieto, and Ed Diener. 2009. Experience Sampling: Promises and Pitfalls, Strength and Weaknesses. In *Assessing Well-Being: The Collected Works of Ed Diener*, Ed Diener (Ed.). Springer Netherlands, Dordrecht, 157–180. https://doi.org/10.1007/978-90-481-2354-4_8

[50] Mikio Obuchi, Tadashi Okoshi, Takuro Yonezawa, Jin Nakazawa, and Hideyuki Tokuda. 2017. Interruptibility Map: Geographical analysis of users' interruptibility in smart cities. In *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. 357–362. https://doi.org/10.1109/PERCOMW.2017.7917588

[51] Tadashi Okoshi, Julian Ramos, Hiroki Nozaki, Jin Nakazawa, Anind K. Dey, and Hideyuki Tokuda. 2015. Attelia: Reducing user's cognitive load due to interruptive notifications on smart phones. In *2015 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 96–104. https://doi.org/10.1109/PERCOM.2015.7146515

[52] 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 (UbiComp '15)*. Association for Computing Machinery, New York, NY, USA, 475–486. https://doi.org/10.1145/2750858.2807517

[53] Tadashi Okoshi, Kota Tsubouchi, Masaya Taji, Takanori Ichikawa, and Hideyuki Tokuda. 2017. Attention and engagement-awareness in the wild: A large-scale study with adaptive notifications. In *2017 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 100–110. https://doi.org/10.1109/PERCOM.2017.7917856 ISSN: 2474-249X.

[54] Donald J. Patterson, Christopher Baker, Xianghua Ding, Samuel J. Kaufman, Kah Liu, and Andrew Zaldivar. 2008. Online everywhere: evolving mobile instant messaging practices. In *Proceedings of the 10th international conference on Ubiquitous computing (UbiComp '08)*. Association for Computing Machinery, Seoul, Korea, 64–73. https://doi.org/10.1145/1409635.1409645

[55] Veljko Pejovic, Mirco Musolesi, and Abhinav Mehrotra. 2015. Investigating The Role of Task Engagement in Mobile Interruptibility. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 1100–1105. https://doi.org/10.1145/2786567.2794336

[56] Martin Pielot, Bruno Cardoso, Kleomenis Katevas, Joan Serrà, Aleksandar Matic, and Nuria Oliver. 2017. Beyond Interruptibility: Predicting Opportune Moments to Engage Mobile Phone Users. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (Sept. 2017), 91:1–91:25. https://doi.org/10.1145/3130956

[57] Martin Pielot, Karen Church, and Rodrigo de Oliveira. 2014. An in-situ study of mobile phone notifications. In *Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services (MobileHCI '14)*. Association for Computing Machinery, Toronto, ON, Canada, 233–242. https://doi.org/10.1145/2628363.2628364

[58] Martin Pielot, Rodrigo de Oliveira, Haewoon Kwak, and Nuria Oliver. 2014. Didn't you see my message? predicting attentiveness to mobile instant messages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. Association for Computing Machinery, Toronto, Ontario, Canada, 3319–3328. https://doi.org/10.1145/2556288.2556973

[59] Benjamin Poppinga, Wilko Heuten, and Susanne Boll. 2014. Sensor-Based Identification of Opportune Moments for Triggering Notifications. *IEEE Pervasive Computing* 13, 1 (Jan. 2014), 22–29. https://doi.org/10.1109/MPRV.2014.15 Conference Name: IEEE Pervasive Computing.

[60] Kimberly B. Pusateri, David J. Roaché, and Ningxin Wang. 2015. The Role of Communication Technologies in Serial Arguments: A Communicative Interdependence Perspective. *Argumentation and Advocacy* 52, 1 (June 2015), 44–60. https://doi.org/10.1080/00028533.2015.11821860 Publisher: Routledge _eprint: https://doi.org/10.1080/00028533.2015.11821860.

[61] Yasmeen Rashidi, Kami Vaniea, and L. Jean Camp. 2016. Understanding Saudis' privacy concerns when using WhatsApp. (2016). http://www.vaniea.com/papers/usec2016.pdf

[62] Aki Rintala, Martien Wampers, Inez Myin-Germeys, and Wolfgang Viechtbauer. 2019. Response compliance and predictors thereof in studies using the experience sampling method. *Psychological Assessment* 31, 2 (2019), 226–235. https://doi.org/10.1037/pas0000662 Place: US Publisher: American Psychological Association.

[63] Jian Raymond Rui and Siyue Li. 2018. Seeking help from weak ties through mediated channels: Integrating self-presentation and norm violation to compliance. *Computers in Human Behavior* 87 (Oct. 2018), 121–128. https://doi.org/10.1016/j.chb.2018.05.022

[64] Emily Schildt, Martin Leinfors, and Louise Barkhuus. 2016. Communication, Coordination and Awareness around Continuous Location Sharing. In *Proceedings of the 19th International Conference on Supporting Group Work (GROUP '16)*. Association for Computing Machinery, New York, NY, USA, 257–265. https://doi.org/10.1145/2957276.2957289

[65] Vivian C. Sheer and Ronald E. Rice. 2017. Mobile instant messaging use and social capital: Direct and indirect associations with employee outcomes. *Information & Management* 54, 1 (Jan. 2017), 90–102. https://doi.org/10.1016/j.im.2016.04.001

[66] Paul J. Silvia, Thomas R. Kwapil, Kari M. Eddington, and Leslie H. Brown. 2013. Missed Beeps and Missing Data: Dispositional and Situational Predictors of Nonresponse in Experience Sampling Research. *Social Science Computer Review* 31, 4 (Aug. 2013), 471–481. https://doi.org/10.1177/0894439313479902 Publisher: SAGE Publications Inc.

[67] Aaron Springer and Steve Whittaker. 2019. Progressive disclosure: empirically motivated approaches to designing effective transparency. In *Proceedings of the 24th International Conference on Intelligent User Interfaces (IUI '19)*. Association for Computing Machinery, New York, NY, USA, 107–120. https://doi.org/10.1145/3301275.3302322

[68] John C. Tang, Ellen A. Isaacs, and Monica Rua. 1994. Supporting distributed groups with a Montage of lightweight interactions. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work (CSCW '94)*. Association for Computing Machinery, Chapel Hill, North Carolina, USA, 23–34. https://doi.org/10.1145/192844.192861

[69] Alexander Thayer, Matthew J. Bietz, Katie Derthick, and Charlotte P. Lee. 2012. I love you, let's share calendars: calendar sharing as relationship work. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work (CSCW '12)*. Association for Computing Machinery, New York, NY, USA, 749–758. https://doi.org/10.1145/2145204.2145317

[70] Eran Toch and Inbal Levi. 2013. Locality and privacy in people-nearby applications. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 539–548. https://doi.org/10.1145/2493432.2493485

[71] Penny Trieu, Joseph B. Bayer, Nicole B. Ellison, Sarita Schoenebeck, and Emily Falk. 2019. Who likes to be reachable? Availability preferences, weak ties, and bridging social capital. *Information, Communication & Society* 22, 8 (July 2019), 1096–1111. https://doi.org/10.1080/1369118X.2017.1405060 Publisher: Routledge _eprint: https://doi.org/10.1080/1369118X.2017.1405060.

[72] Liam D. Turner, Stuart M. Allen, and Roger M. Whitaker. 2015. Push or Delay? Decomposing Smartphone Notification Response Behaviour. In *Human Behavior Understanding (Lecture Notes in Computer Science)*, Albert Ali Salah, Ben J.A. Kröse, and Diane J. Cook (Eds.). Springer International Publishing, Cham, 69–83. https://doi.org/10.1007/978-3-319-24195-1_6

[73] Liam D. Turner, Stuart M. Allen, and Roger M. Whitaker. 2017. Reachable but not receptive: Enhancing smartphone interruptibility prediction by modelling the extent of user engagement with notifications. *Pervasive and Mobile Computing* 40 (Sept. 2017), 480–494. https://doi.org/10.1016/j.pmcj.2017.01.011

[74] Niels van Berkel, Denzil Ferreira, and Vassilis Kostakos. 2017. The Experience Sampling Method on Mobile Devices. *Comput. Surveys* 50, 6 (Dec. 2017), 93:1–93:40. https://doi.org/10.1145/3123988

[75] Roel Vertegaal, Connor Dickie, Changuk Sohn, and Myron Flickner. 2002. Designing attentive cell phone using wearable eyecontact sensors. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems (CHI EA '02)*. Association for Computing Machinery, Minneapolis, Minnesota, USA, 646–647. https://doi.org/10.1145/506443.506526

[76] Neil J. Vickers. 2017. Animal Communication: When I'm Calling You, Will You Answer Too? *Current Biology* 27, 14 (July 2017), R713–R715. https://doi.org/10.1016/j.cub.2017.05.064

[77] Aku Visuri, Niels van Berkel, Chu Luo, Jorge Goncalves, Denzil Ferreira, and Vassilis Kostakos. 2017. Predicting interruptibility for manual data collection: a cluster-based user model. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3098279.3098532

[78] Dominik Weber, Alexandra Voit, Jonas Auda, Stefan Schneegass, and Niels Henze. 2018. Snooze! investigating the user-defined deferral of mobile notifications. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3229434.3229436

[79] Dominik Weber, Alexandra Voit, Philipp Kratzer, and Niels Henze. 2016. In-situ investigation of notifications in multi-device environments. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. Association for Computing Machinery, New York, NY, USA, 1259–1264. https://doi.org/10.1145/2971648.2971732

[80] Jisuk Woo. 2006. The right not to be identified: privacy and anonymity in the interactive media environment. *New Media & Society* 8, 6 (2006), 949–967. https://doi.org/10.1177/1461444806069650

[81] Rayoung Yang and Mark W. Newman. 2013. Learning from a learning thermostat: lessons for intelligent systems for the home. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 93–102. https://doi.org/10.1145/2493432.2493489

[82] Fengpeng Yuan, Xianyi Gao, and Janne Lindqvist. 2017. How Busy Are You? Predicting the Interruptibility Intensity of Mobile Users. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. Association for Computing Machinery, Denver, Colorado, USA, 5346–5360. https://doi.org/10.1145/3025453.3025946

[83] Manuela Züger, Christopher Corley, André N. Meyer, Boyang Li, Thomas Fritz, David Shepherd, Vinay Augustine, Patrick Francis, Nicholas Kraft, and Will Snipes. 2017. Reducing Interruptions at Work: A Large-Scale Field Study of FlowLight. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. Association for Computing Machinery, Denver, Colorado, USA, 61–72. https://doi.org/10.1145/3025453.3025662