Does *Who* Matter? Studying the Impact of Relationship Characteristics on Receptivity to Mobile IM Messages

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ABSTRACT

This study examines the characteristics of mobile instant-messaging users' relationships with their social contacts and the effects of both relationship and interruption context on four measures of receptivity: Attentiveness, Responsiveness, Interruptibility, and Opportuneness. Overall, interruption context overshadows relationship characteristics as predictors of all four of these facets of receptivity; this overshadowing was most acute for Interruptibility and Opportuneness, but existed for all factors. In addition, while Mobile Maintenance Expectation and Activity Engagement were negatively correlated with all receptivity measures, each such measure had its own set of predictors, highlighting the conceptual differences among the measures. Finally, delving more deeply into potential relationship effects, we found that a single, simple closeness question was as effective at predicting receptivity as the 12-item Unidimensional Relationship Closeness Scale.

CCS CONCEPTS

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

KEYWORDS

Mobile notifications; mobile receptivity; relationships; opportune moment; interruptibility; ESM

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1 INTRODUCTION

In a permanently online and connected world [57], mobile-device users receive large numbers of notifications per day. The notifications that smartphone users value most highly are those generated by instant-messaging (IM) apps [43,49,53]. However, users also display differing degrees of attentiveness and responsiveness across different message types [5,39]. For example, Chang et al., Mehrotra et al. and Pielot et al. [5,29,39] have shown that the presence of alerts affects users' attentiveness and responsiveness to messages. Phone-interaction context – i.e., whether the user has recently interacted with his/her phone – is also predictive of users' attentiveness to instant messages [34,39]. Users' tasks at hand [1,4,5,7,8,14] and how deeply they are engaged in those tasks have also been found to affect their receptivity to incoming interruptions [37], which in turn affects users' perceptions both of disruption [19,21] and of the opportuneness of the timing of interruptions [19,23,32]. Social context, including whom the users are collocated and/or conversing with, also influences their perceptions of being interrupted [16,34,52].

In addition to such contexts, however, *who* has sent the message may also play a role. For example, relationship type (e.g., family, social, work) is found to affect both users' responsiveness [30] and their perceptions of interruption or disruption [29,30,60]; and smartphone users' communication practices and frequencies have been found

to differ according to their tie strengths with their interlocutors [31,59,61]. This paper questions whether tie strength, i.e. relationship alone, is sufficient to represent the various facets of interpersonal relationships. Specifically, prior research has shown that perceived expectation, obligation, and dependence between the sender and the recipient are correlated with the amount of communication between them [18]; yet, there has been little systematic investigation of *how* these relationship characteristics, along with interruption context, affect smartphone users' receptivity to instant messages (which is commonly measured via four measures: Attentiveness, Responsiveness, Interruptibility, and Opportuneness). The current study helps fill this research gap, and makes three major contributions:

- It shows that interruption context generally overshadows relationship characteristics in predicting the four measures of receptivity, albeit more so for the subjective feelings Interruptibility and Opportuneness, and less obviously for the two action-based measures, Attentiveness and Responsiveness.
- In addition to identifying variables predictive of most or all receptivity measures, it shows that each such measure has its own unique set of predictors, highlighting the conceptual differences among the four.
- It demonstrates that a single closeness question such as Inclusion of the Other in the Self Scale (IOS) or a newly devised Simple Closeness Measurement (SCM) was as effective at predicting receptivity as the 12-item Unidimensional Relationship Closeness Scale (URCS).

2 RELATED WORK

2.1 Interruption Context

Interruptibility researchers have examined the effects of context on users' receptivity to interruptions, including social context [16,34,52], activity (task) context [1,16,30,34,36,50,55], phone interaction context [34,39], and emotional context [36,50]. In the case of activity (task) context, it has been suggested that the type and the complexity of the task/activity at hand [6,30,36,50] and the depth of the user's engagement in it [37] affect how receptive he/she is to interruptions. For this reason, researchers have sought to identify breakpoints [13,22,32,50,54] and opportune moments [40,44] for the optimal delivery of interruptions.

Social context has been found to affect users' availability for both incoming phone calls [20] and instant messages [52]. Pejovic and Musolesi [36] have proposed a model of when best to interrupt based on a particular user's social context. In the workplace, the presence of others affects workers' interruptibility [6], and two studies [51,52] have suggested that users' face-to-face conversations affect their receptivity to notifications.

The status of a user's phone can also be used to infer his/her state. Recent interactions with the phone tend to indicate a user's level of attention to it: for example, whether the user has used the phone within the past minute is a strong predictor of opportuneness [37,39], and a person will generally respond to a new message more quickly if he/she recently had a conversation with the same messaging partner [3]. Researchers have also used phone sensors to predict users' receptivity to interruptions [30,36,37,44,47,50]. For example, their choices of ringer mode may indicate how much they currently welcome interruptions, while also affecting how likely they are to notice an alert, which in turn affects their receptivity to it [5,29,30,39].

In addition to interruption context, the characteristics of the interruption itself, including but not limited to message content [3,30], can influence user receptivity to it [14].

2.2 How Relationships Relate to Communication

2.2.1 Frequency, Intensity, and Responsiveness. Research on the influence of relationships on communication frequency, intensity, and responsiveness often focuses on relationship types. For example, it has been found that the type of relationship between IM users has a significant effect on the length of the messages they exchange, but not on their responsiveness [3,4]. One study's participants were more interruptible when those interrupting them were people they knew rather than strangers [60]. Researchers have also studied how relationship closeness relates to communication characteristics. For example, emotional closeness positively impacts how quickly people respond [46], the numbers of calls, and the frequency of face-to-face contacts [61]. Wiese et al. [59] found that higher communication frequencies and call durations both indicated strong relationship ties. As compared to the work reviewed above, however, the present paper explores a larger set of relationship characteristics, and examines the combined effects of such characteristics and contextual factors on receptivity and its four measures.

2.2.2 Communication Mode. Prior work indicates that mobile users communicate via different channels according to the type and/or closeness level of their relationships with their chat partners [9,10]. In particular, complementary use of

phone calls and text messaging is higher in closer friendships, whereas phone calls and video chats are complementary when closeness is low [48]. Mobile phones have been found to reinforce strong ties, while text-based media are used more in weaker relationships, especially when the goal is to strengthen or deepen them [25]. IM tends to be employed to sustain relationships that are already very close, e.g., with partners and best friends [45]; and decay in relationships can be inferred from declines in mobile communication [31].

2.2.3 Communication Expectations and Obligations. Research shows that people perceive higher obligation to respond than expectation of a response toward loose acquaintances or socially superior chat partners, and tend to have higher expectations of a response when chatting with close friends and romantic partners [27]. Students have been reported to reply to messages more quickly than others because they assume that the sender expects a quick answer [57]. Hall and Baym [18] found that the stronger an individual message recipient's perception that the sender expects him/her to text throughout the day (known as *mobile maintenance expectation* or MME), the more the two parties will communicate. However, high MME can lead to overdependence, which is negatively correlated to friendship satisfaction [18].

3 RESEARCH FOCUS AND INSTRUMENTS

The primary goal of this research is to examine how sender-recipient relationship characteristics affect mobile instant-message recipients' attentiveness to, responsiveness to, perceptions of being interrupted by, and perceptions of the opportuneness of the timing of, such messages. While interpersonal relationships have a vast array of characteristics, this study focuses on a subset measurable via self-reports: Closeness, Dependence, MME, Answering Expectation (AE) and Perceived Obligation to Answer (POA). It is guided by the following research question: When activity context, social context, phone-interaction context, and ringer mode are taken into consideration, to what extent does each of them affect the four measures of receptivity?

3.1 Measures of Relationship Characteristics

Data on all of the above-mentioned relationship characteristics were collected using existing instruments. The participants were required to complete each instrument separately for each contact selected by them and the research team.

3.1.1 Closeness. Two instruments were used to measure closeness: the IOS [2] and the URCS [8]. The IOS is a simple universal scale designed to measure all types of relationships, and contains only one item to measure the perceived inclusion of the other in the self: *"Please choose the picture below which best describes your relationship."* Despite its brevity, its results correlate highly with other scales measuring closeness [17].

URCS was developed as a shortened version of the widely used Relationship Closeness Inventory (RCI) [8], which reduced the number of items from 34 to 12. Each item is answered using a seven-point Likert scale and all scores are averaged to create a relationship closeness score, with a higher score indicating a closer relationship. Prior studies have found the URCS to be valid and reliable [8,56].

Since the IOS and the URCS measure slightly different concepts, we included both in the questionnaire. In addition, inspired by several prior studies [7,28,58], we included the question *"How close do you feel to this person?"* on a five-point Likert scale, and referred to it as a Simple Closeness Measurement (SCM) Thus, our final questionnaire contained three measures of closeness in total, aimed at measuring the closeness between participants and their selected contacts.

3.1.2 Dependence. We used the Interdependence Scale developed by Parks and Floyd [35] to measure our participants' relational dependence to their selected contacts. This scale has previously been used to study mobile-phone use in close friendships [18]. It contains seven items, all answered via a five-point Likert scale.

3.1.3 Mobile Maintenance Expectation. We adapted the MME scale [18] to measure our participants' expectations regarding mobile IM (the original instrument was designed to measure expectations about texting). Its questions involve routine or mundane day-to-day activities (e.g., *"My friend expects me to use instant messages to keep them updated"*). The scale contains nine items on a five-point Likert scale.

3.1.4 Answering Expectation and Perceived Obligation to Answer. AE reflects the level of a user's expectation that a specific person to whom he/she has sent a message will respond immediately [27]. POA is the degree to which a user feels obliged to respond to a given person's message right away [27]. The two instruments used to measure these constructs each contained six items scored on five-point Likert scales, with higher values indicating higher AE or POA.

3.1.5 Relationship Type. This study divided each of the participants' selected contacts into one of 11 relationship categories. These were: Immediate family member (child, sibling, parent); Extended family member; Superior at work; Subordinate at work; Colleague; Client; Service provider; Friend; Acquaintance; Significant other; and Other. For purposes of analysis, we further grouped these categories into Strong-tie, Work, and Social types [12,33,38], with the Strong-tie category comprising Immediate family members and Significant others [38].

3.2 Measures of Interruption Context

3.2.1 Social Context and Activity Engagement. We asked the participants about whom they were interacting with [30] and grouped the answers into the following four classes for data analysis: Social Context (Strong-tie), Social Context (Social), Social Context (Work), and Social Context (Strangers). With regard to Activity Engagement, the participants were asked, on a five-point Likert scale, how much they were involved in an activity when a given notification arrived.

3.2.2 Ringer Mode and Phone Interaction. We extracted mobile users' ringer-mode settings and phone-interaction contexts from phone logs. Specifically, phone-interaction data was obtained from the Android system's Accessibility Service*. In line with a prior study's finding that mobile users on average attend to their phones within five minutes when a notification arrives [11], we measured whether each of our participants had interacted with his/her mobile phone within five minutes prior to a notification arriving, as a binary variable.

3.2.3 Within-session Conversation. Following [24], we considered a message to be part of the same session as the previous message if it arrived no more than five minutes later. We also derived session information from the message log provided by the participants according to this heuristic. Below, sets of messages that meet this criterion are referred to as Within-session Conversations.

3.3 Four Measures of Receptivity

Measures of receptivity to mobile notifications commonly used in the literature include attentiveness, responsiveness, perceived interruption by the notification, and perceived opportuneness of the notification's timing. Data on all four of these categories were obtained via an experience sampling method (ESM) questionnaire.

3.3.1 Attentiveness. Participants reported when they first noticed each message had arrived, and responded to the question *"Did you take a look at the message right away?"* with a binary answer of yes or no.

3.3.2 Responsiveness. We measured the participants' responsiveness by asking them, *"When did/will you respond to this message?"*, in terms of the time elapsed since they had first seen it. A user was defined as responsive to a message if he/she reported either *"I will respond/responded to it immediately"* or *"I will respond/responded to it in a couple of minutes."*

3.3.3 Interruptibility. We adopted a question developed by Mehrotra et al. [30] to assess participants' perceptions of interruptive quality of a message. This question was, *"How interruptive do/did you find the message?"* on a five-point Likert scale ranging from *"not interruptive at all"* (1) to *"very interruptive"* (5). A user was defined as having *High Interruptibility* in the case of a particular message if he/she answered either 1 or 2.

3.3.4 Opportuneness. We followed [36] in asking our participants, *"What do/did you think about the timing of the message?"* A user was defined as perceiving the moment to be opportune if he/she answered either *"the timing is/was great"* or *"the timing is/was good."*

4 METHODS

4.1 Experience Sampling Method

ESM was used to capture smartphone users' in situ experience with messages. We developed an Android research application (app) that recorded incoming notifications from Facebook Messenger and Line Messenger, the two most popular mobile IM apps in Taiwan. It also recorded contextual information about the notifications; the user's location and physical activity; the phone's status (e.g., ringer mode, battery level); and sensor data on the phone. User actions were also logged, but via the Android Accessibility Service.

The research app (see Figure 1a) triggered an ESM prompt when a participant received a mobile instant message that was 1) not from the same contact as the previous responded-to ESM, and 2) not among that person's top two contacts (as measured by ESM). This design was adopted to balance the social contacts sampled by ESM. The ESM prompt consisted of an Android notification that led the participant to an online questionnaire. That notification arrived without an alert, so as not to influence the participants' attention to their own notifications.

*https://developer.android.com/reference/android/accessibilityservice/AccessibilityService

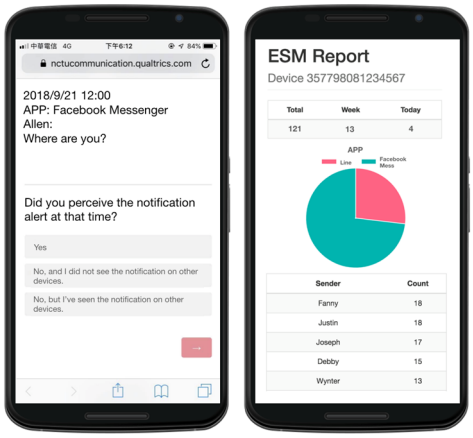

Figure 1. Research Application: (a) ESM questionnaire; (b) ESM statistics

A minimum duration of 45 minutes was interposed between any responded-to ESM prompt and the next such prompt, to avoid overwhelming participants or needlessly duplicating message contexts. To minimize inaccurate self-reporting caused by recall bias, an ESM prompt was dismissed after 15 minutes, but once it expired, the app could trigger another ESM as soon as it detected another instant message that met the criteria above. Each ESM questionnaire had up to 17 multiple-choice items and one fill-in-the-blank question about users' attentiveness, responsiveness to the notification and perceived disruption, perceived timing of the notification and their context when notified. The actual questions participants saw depended on their responses to previous questions, such that they did not have to answer questions inapplicable to them. The questionnaire was in Mandarin, but an English translation is provided in the Supplemental Material.

4.2 Recruitment and Participants

We initially recruited 46 participants who were at least 20 years old and who actively used Facebook Messenger and/or Line Messenger, via a subject pool created at our own and at a neighboring university; on the largest bulletin-board system in Taiwan; and on the research team members' social-media pages. A total of 12 participants withdrew during the experiment, 10 because the app could not run successfully on their phones. The remaining 34 included 20 students and 14 non-students, 17 males and 17 females, aged 20 to 50 (M=25.33, SD=6.8). All participated for at least four weeks, with some extending the duration of the experiment voluntarily, the mean duration being 37.5 days (SD=5.88). All participants self-reported that they received at least 10 personal messages per day and chatted with at least 10 different contacts on Facebook Messenger or Line Messenger.

4.3 Study Procedure

Every participant attended one pre-study and one post-study meeting. In the first meeting, the research team helped the participants install the research app on their phones. After installation, the participants used a research web dashboard to complete questionnaires measuring their personality and relationship traits. They also listed the first 10 contacts with whom they expected to communicate in the coming month. An additional 10 contacts were subsequently selected by the research team, based on how often they were sampled in ESM. Each participant was asked to complete questionnaires for all 20 of their selected contacts before the post-study meeting. After the field study, the participants uninstalled the research app and were asked to attend a post-study meeting to label a heatmap with places they had frequently been when receiving IM notifications during the study. They also provided message logs of their interactions in Facebook Messenger and Line Messenger with the 20 selected contacts. The 31 participants who had agreed to participate in semi-structured interviews via email were provided with their ESM responses to help them recall the situations of each one. Participants received compensation of NT$1,600 (approximately US$52) for the ESM study, and an additional NT$400 if they participated in an interview.

4.4 Data Cleaning and Analysis

We received 4,570 ESM responses on the questionnaire server, but due to a data transfer issue, 70 of them lost their associations with phone-log data. Thus, we analyzed only the remaining 4,500 responses. According to the phone-log data, a total of 13,870 ESM questionnaires were sent out, and each participant received an average of 11.47 ESM prompts per day. The low response rate, 32.4%, could have been due to the length of the questionnaire. With regard to data cleaning of the ESM responses, we ignored ESM responses regarding all but the 20 contacts selected for each participant, and filtered the ESM responses that could be linked to other data sources (i.e., scales, phone-log data, and message logs) so that we could analyze the effects of context and relationship variables on receptivity measures. Inconsistent and conflicting ESM responses and those associated with incomplete information were excluded from data analysis.

After data cleaning, the number of ESM responses that remained for our analysis comprised 1,269 for Attentiveness, 2,307 for Responsiveness, 2,386 for

Interruptibility, and 2,386 for Opportuneness. The percentages of participants who were rated as "high" in respect to the same four variables were 80.6%, 73.3%, 60.1%, and 42.6% respectively. Of the total of 2,386 messages that were analyzed, 55.2% were delivered by Facebook Messenger and 44.8% by Line Messenger. In terms of their sources, 23% were from Strong-tie, 50% from Social, and 27% from Work contacts.

To study the impact of relationship characteristics on receptivity, we built three mixed-effect logistic-regression models – a Context Model, a Relationship Model, and a Combined Model – for each receptivity measure. The first model included measures of interruption context; and the second, measures of relationship characteristics, including Closeness, Dependence, MME, POA, AE, Relationship Type, and an interaction effect between Closeness and Relationship Type. Lastly, the Combined Model included all the above-mentioned measures of both interruption context and relationship characteristics. All those measures were treated as fixed effects, while *Participant* was included as a random effect to account for individual differences. Relationship Type was a categorical variable, with *Social* set as the reference.

5 FINDINGS

5.1 Contexts were More Predictive than Relationships

Table 1 presents the performance of the Context Model (C), the Relationship Model (R), and the Combined Model (C+R) for all receptivity measures. Since we were uncertain about which closeness measure would be more predictive of receptivity, different versions of each model were built for each closeness measure. This revealed that interruption context overshadowed relationship characteristics: with R^2 in Context Models outperforming those in Relationship Models overall, especially in the prediction of Interruptibility and Opportuneness. Moreover, adding relationship characteristics did not noticeably increase R^2 in Combined Models as compared to Context Models.

One possible confounding factor we considered involved the burden of responding to a lengthy ESM. Specifically, participants could have been more likely to fill out an ESM at moments when they were interruptible, in which case, ESM would have been biased toward interruptible moments, and thus neglected relationship effects. To explore this, we examined the IM logs for the distribution of participants' responded-to instant messages, classified by closeness (i.e., High (4,5), Mid (3), Low (1,2), using SCM) during the periods around ESM prompts (15 minutes before and after the ESM prompt, i.e., 30 minutes in total).

Table 1. Conditional R^2 for Each Model

(R^2)	Model	Att	Res	Int	Opp
	C	0.52	0.29	0.34	0.29
URCS	R	0.45	0.27	0.15	0.16
	C+R	0.52	0.33	0.35	0.3
SCM	R	0.48	0.28	0.16	0.17
	C+R	0.53	0.33	0.35	0.3
IOS	R	0.45	0.27	0.15	0.16
	C+R	0.51	0.33	0.34	0.3

Note. **Att=Attentiveness; Res=Responsiveness; Int=Interruptibility; Opp=Opportuneness; C=Context Model; R=Relationship Model; C+R=Combined Model**

We found that during this 30-minute window where ESM prompts were responded, the distribution of the senders whose messages were responded by the participants was: High: 67%, Mid: 21%; and Low: 11%, suggesting that the majority of the messages that obtained a response were those from close contacts. With a similar distribution, during the 30-minute window where ESM prompts were NOT responded, the distribution of the senders was High: 71%; Mid: 19%; and Low: 10%. We also examined the response rate for these two cases. The participants' response rates to instant messages associated with responded-to ESM prompts were 67% (High), 71.1% (Mid), and 76.2% (Low), as compared to 52.2% (High), 54.1% (Mid), and 56.5% (Low) for non-responded-to ESM prompts. These results indicate that ESM did capture users' more responsive moments; however, decreases in IM response rates for non-responded-to ESM prompts did not vary markedly according to closeness of contacts. Because response rate was the only measure we could obtain from outside ESM, we could not discern how interruptible participants were or how opportune the moment they felt if they did not respond to an ESM prompt. Nevertheless, interruption context on the whole appeared to be more predictive of subjective perception (Interruptibility and Opportuneness) than of actual action (Responsiveness and Attentiveness).

5.2 One Closeness Item Suffices to Measure Receptivity

Another interesting finding (Table 1) was that SCM, IOS, and URCS led to very similar R^2 in the Relationship Models and Combined Models. Indeed, models using SCM seemed to achieve slightly better performance than those using IOS and URCS. This suggests that a single, simple closeness item is sufficient to predict receptivity.

Table 2. Non-standardized Coefficients of Mixed-effect Logistic Regression Models Predicting Receptivity Measures, with a Random Effect to Account for Each Participant

Dimension	Attentiveness (N=1269, 80.6%)				Responsiveness (N=2307, 73.3%)				Interruptibility (N=2386, 60.1%)				Opportune Moment (N=2386, 42.6%)			
	M (SD)	C	R	C+R	M (SD)	C	R	C+R	M (SD)	C	R	C+R	M (SD)	C	R	C+R
Conditional R squared		.52	.48	.53		.29	.28	.33		.34	.16	.35		.29	.17	.3
Intercept		3.28***	1.65*	2.8**		2.01***	-.15	.79		2.32***	-.59	1.42**		.77*	-1.5***	-.31
Mobile Maintenance	2.63 (1.19)		-.25	-.31*	2.61 (1.18)		-.18*	-.2*	2.6 (1.18)		-.14*	-.18*	2.6 (1.18)		-.18**	-.23**
Obligation to Answer	2.92 (0.93)		.02	.02	2.83 (0.97)		.12	.12	2.82 (0.97)		.01	.04	2.82 (0.97)		.11	.15
Answering Expectation	2.82 (0.93)		.22	.24	2.71 (0.96)		.29*	.29*	2.71 (0.95)		.07	.01	2.71 (0.95)		.02	-.03
Dependence	3.25 (0.89)		-.36	-.22	3.35 (0.91)		.02	.08	3.35 (0.91)		-.01	.05	3.35 (0.91)		.07	.13
Closeness	3.72 (1.10)		.47*	.32	3.80 (1.11)		.2	.12	3.78 (1.12)		.35**	.31**	3.78 (1.12)		.3**	.24*
Relation (Strong-tie)	22%		-3.34*	-3.61*	22%		-1.31	-1.49	23%		-.08	-.19	23%		-.37	-.42
Relation (Work)	27%		-.06	-.06	27%		-.13	-.35	27%		.5	.4	27%		.57	.43
Relation (Strong-tie) * Closeness			.71*	.77*			.24	.28			-.03	.02			.04	.07
Work * Closeness			-.07	-.06			.04	.1			-.17	-.16			-.16	-.14
Activity Engagement	3.1 (1.17)	-.45***		-.42***	3.32 (1.12)	-.32***		-.33***	3.32 (1.12)	-.72***		-.73***	3.32 (1.12)	-.55***		-.55***
Social Context (Stranger)	3%	.44		.38	2%	.96*		.88*	2%	.65		.61	2%	.94**		.91**
Social Context (Strong-tie)	11%	-.63*		-.61*	12%	-.17		-.11	12%	-.09		-.09	12%	-.09		-.08
Social Context (Social)	12%	-.03		0	12%	-.11		-.09	12%	-.33*		-.34*	12%	0		0
Social Context (Work)	14%	-.21		-0.2	13%	-.32		-.3	13%	-.27		-.26	13%	-.32*		-.33*
RingerMode (Silent)	5%	-1.01		-.85	6%	-.4		-.34	6%	-.44		-.42	6%	-.88**		-.82**
RingerMode (Vibrate)	65%	-.63		-.62	66%	-.3		-.29	66%	-.11		-.09	66%	-.21		-.19
Interaction 5 minutes	78%	.62**		.61**	74%	.22		.19	74%	.93***		.92***	74%	1.01***		1***
Session Within	82%	.5*		.59**	83%	.53***		.55*	83%	.02		.01	83%	.27*		.28*

Note. **Each column represents a distinct model predicting a particular receptivity measure. Gray cells indicate effects that are not included for that particular model. C=Context Model; R=Relationship Model; C+R=Combined Model. Significance: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$**

In addition, all the correlations between SCM, IOS and URCS were high (SCM vs. IOS, r=0.87; SCM vs. URCS, r=0.83; IOS vs. URCS, r=0.87; all p<0.001). As such, and due to limitations of space, Table 2 presents SCM only.

5.3 Effect across Receptivity Measures

As shown in Table 2, all effects of Responsiveness, Interruptibility and Opportuneness in the Context and Relationship Models remained after those models were combined. This indicates that, although interruption context overshadowed relationship type, each explained some variances that the other did not, suggesting that relationship still matters when predicting receptivity.

MME and Activity Engagement both had negative main effects on all four receptivity measures. This is consistent with previous findings that users are less receptive to interruption when they have been engaged in an activity [37]. And while high MME has previously been associated with lower relationship satisfaction [18], we found that it was also linked to lower receptivity. Phone Interaction Context also had a positive effect on all measures except responsiveness. This is consistent with prior findings [30,30,36,44,47,50] that recent phone interaction is a good indicator of the user's recent attention on the phone. Moreover, as two previous studies indicated [3,5], already being in a conversation implies the availability for sending messages; we also found that Session Within had a positive effect on all measures except interruptibility.

On the other hand, POA and Dependence had no effect on any aspect of receptivity. This seems counterintuitive, because POA is conceptually related to responding. This implies that one's feelings of obligation to respond may not lead to actually doing so.

5.4 Receptivity Measures' Unique Predictors

Each receptivity measure also had its own set of predictors, i.e., was uniquely correlated or uniquely not correlated with variable(s) as compared to the other three measures, highlighting the conceptual differences among these facets of receptivity.

5.4.1 Responsiveness. Responsiveness was the only measure of receptivity that Phone Interaction Context and Closeness did not predict. This might suggest a temporary gap between interacting with the phone and responding to a message. Interestingly, Responsiveness was uniquely predicted by AE, implying that expecting the sender to be responsive increased the recipient's own responsiveness to the sender.

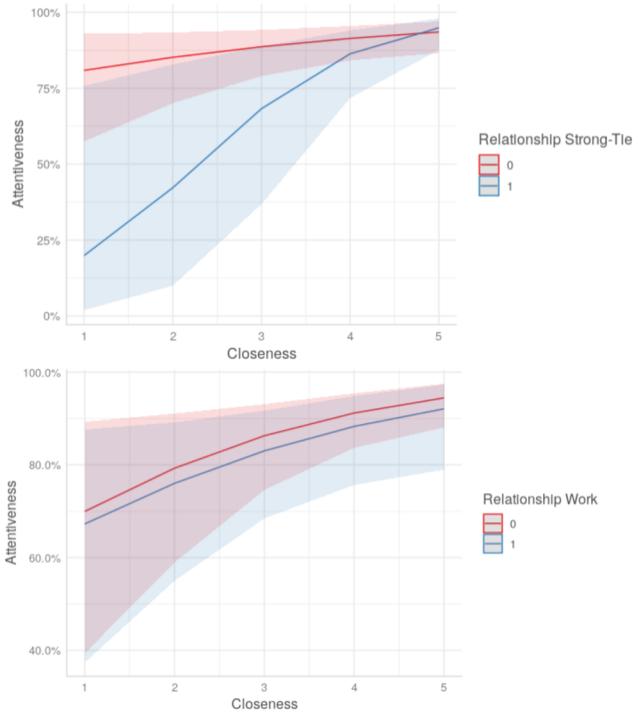

Figure 2. Interaction Effects of (a) Strong-tie Relationship and Closeness on Attentiveness and (b) Work Relationship and Closeness

5.4.2 Attentiveness. Attentiveness had a uniquely high intercept in the model, indicating participants' generally high attentiveness to notifications. This could explain its relatively few positive main effects. Moreover, it was the only measure predicted by Relationship (Strong-tie). Interestingly, the effect of Relationship (Strong-tie) was negative, but the interaction effect of Relationship (Strong-tie) and Closeness was positive (see Figure 2, Top). This suggests that, while the participants were attentive across all contacts, they tended to read messages from Strong-tie contacts less quickly than those from non-Strong-tie ones, unless the Strong-tie contacts were also close. We suspect that this might have been because the Strong-tie category included both immediate family and significant others. Social Context (Strong-tie) was also predictive of Attentiveness alone among the four facets of receptivity. It seems likely that, when their relations with immediate family and significant others were generally good, the participants did not pay much attention to their messages, and thus felt less interrupted by them.

5.4.3 Interruptibility and Opportuneness. Interruptibility and Opportuneness are similar to each other, in that they shared four of the same main effects, including the positive effects of Closeness and Phone Interaction Context. This implies that the closer the participants perceived the sender to be, and the more recently they had used the phone, the less interruptive and the more opportune they perceived their messages to be. These two receptivity measures also had their own unique predictors: Interruptibility was uniquely predicted by Social Context (Social), implying that participants more often considered a message to be interruptive when they were socializing; and Opportuneness was uniquely negatively correlated with Silent Mode.

6 DISCUSSION

6.1 Interruption Context vs. Relationship Characteristics

We considered a variety of relationship characteristics along with interruption context to predict receptivity, and arrived at some interesting results. First, although it is intuitively obvious that relationships matter in personal communication, we found that when predicting receptivity to instant messages in particular, interruption context overshadowed relationship characteristics, especially in predicting Interruptibility and Opportuneness. Interestingly, however, our Context Model and Relationship Model performed similarly in Attentiveness and Responsiveness, meaning that we could not simply conclude that relationships did not matter. Rather, the results could suggest that relationships matter more to actual action (i.e., attending and responding) than to subjective feeling (i.e., perceived interruptiveness and timing). For instance, in certain contexts, the participants could have felt that *most* messages were intrusive or sent at an inopportune moment, but subsequently attended and responded to them differentially according to who the senders were. Here, it is also worth noting that Closeness

had a main effect on Interruptibility and Opportuneness, but not on Attentiveness or Responsiveness. This might be because Interruptibility and Opportuneness were not as closely correlated with other relationship characteristics as Attentiveness and Responsiveness were. However, it also suggests that Closeness plays some role in mitigating people's perception of interruption and timing. As the relationships between these variables can be highly complex, further study is needed.

Second, we expected to see a strong negative effect of Activity Engagement across all receptivity measures, consistent with prior research [29,30,37], but a negative effect of MME on those measures was surprising to us. This implies that the more participants perceived message senders as expecting them to maintain mobile communication, the less attentive and responsive the former were, and the more interruptive and ill-timed they found the senders' messages to be. While some studies [18,26] suggest that MME may lead to social pressure, we observed that such pressure manifested not only in participants' perceptions, but also in their actual mobile-communication actions.

Third, although one of our original aims was to examine the effectiveness of URCS, we learned that a one-item IOS or SCM sufficed to predict receptivity. It is possible that this was because some aspects of the URCS overlapped with other relationship-characteristic variables. We are encouraged by this result, as a simple closeness scale would be less burdensome for participants in future studies.

6.2 Receptivity Measures Differ Conceptually

As briefly noted above, our observations also provide evidence of conceptual differences among the four studied receptivity measures. Regarding interruption context, while Attentiveness and Opportuneness could be predicted by both Phone Interaction Context and Within-session Conversations, Interruptibility was related only to the former, and Responsiveness only to the latter. This implies that, within the broad category of mobile availability, users' willingness to *check* their phones can be distinguished from their willingness to *converse* and that feeling being interrupted also differs from feeling whether a message is well-timed.

Social Context was also predictive of different receptivity measures. Our participants were less attentive to messages when they were physically collocated with partners and close family members, and less interruptible when with friends. In addition, they were less likely to perceive an instant message as well-timed when they were physically collocated with work-mates, and more likely to perceive it as well-timed (and to be more responsive to it) if the people nearby were strangers. The effect of Ringer Mode (Silent) also suggests a distinction between Interruptibility and Opportuneness: whereas the participants did not generally consider an instant message to be interruptive when their phones were silent (since there's no alert), they still can regard it as inopportune.

Regarding relationship characteristics, Responsiveness was distinct from other receptivity measures in that it was the only one not correlated with Closeness, but correlated with AE. Thus, interestingly, the desire to obtain responses to his/her own messages may have been more effective than POA in rendering the participants responsive. This implies that modern smartphone users have considerable autonomy when it comes how responsive they are, i.e., basing their responsiveness on intrinsic needs rather than external requirements. Attentiveness was uniquely predicted by Relationship Type and its interaction with Closeness, possibly due to the participants' tendency to be highly attentive to messages [41,42]. Future research should consider both together when measuring attentiveness.

6.3 Limitations

This paper is subject to several limitations. First, we recruited participants with particular characteristics. They were generally young, more than half being students who might have had relatively simpler social circles than non-students. In addition, our participants were all users of Facebook Messenger and Line Messenger, the features of which differ from those of other IM services popular in other countries. It is thus unclear how generalizable our results are to other populations of smartphone users. Second, we used a lengthy ESM to capture a variety of data but, as shown earlier, it oversampled moments when participants were responsive to their contacts, and could therefore also have oversampled interruptible moments. Future researchers should be more selective of context and receptivity measures based on the results of this study. Third, to simplify analysis, we did not consider group chats, to which participants' receptivity might have differed. Fourth, although we created models with all closeness measures, page limits meant that only SCM-based models could be shown. Similarly, limitations of space meant we could not report the interaction effect between Relationship Type (Social) and Closeness. Fifth, although the principal goal of this study was to explore how various relationship characteristics affected receptivity to mobile IM, we could not have selected more than 20 social contacts per participant, because answering any further relationship

questionnaires would have been burdensome; and making the study longer than four weeks also would have seemed to require an excessive level of participant commitment. However, we are aware of the dynamic nature of relationship characteristics, and therefore, our findings related to relationships should be interpreted as characteristics of *four-week* relationships with the selected contacts, rather than as evidence of long-term, static ones. It is likely that participants' perceived closeness with the selected contacts changed during the study, and it is unfortunate that analysis of such change was not possible. Finally, we captured factors such as activity type, message characteristics, location, physical activity, personality traits, and qualitative feedback, but did not include them in the analysis.

7 CONCLUSION

We measured the characteristics of the relationships between smartphone users and sets of 20 of their respective social contacts using a number of existing instruments, and investigated the effects of such relationships and of interruption contexts on Attentiveness, Responsiveness, Interruptibility, and Opportuneness. Overall, interruption context overshadowed relationship characteristics in predicting receptivity, and especially its measures Interruptibility and Opportuneness. However, we also identified effects on specific receptivity measures, confirming that important differences among such components are clearly discernible. In addition, this paper has shown that a lightweight one-item closeness measure such as IOS or SCM performed equally well at predicting receptivity as the 12-item URCS. We consider the current paper to be a preliminary investigation into the influence of relationship characteristics on receptivity to mobile IM messages. Although the results seem to show that context matters more than relationships, they also indicate that relationship characteristics do play a role at certain times. Further research is needed if we are to gain a more holistic view of these phenomena.

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