Can you Turn it Off? The Spatial and Social Context of Mobile Disturbance

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Contemporary mobile devices continuously interrupt people with notifications in various and changing physical environments. As different places can have different social setting, understanding how disturbing an interruption might be to people around the user is not a straightforward task. To understand how users perceive disturbance in their social environment, we analyze the results of a 3-week user study with 50 participants using the experience sampling method and log analysis. We show that perceptions of disturbance are strongly related to the social norms surrounding the place, such as whether the place is considered private or public, even when controlling for the number of people around the user. Furthermore, users' perceptions of disturbance are also related to the activity carried out on the phone, and the subjective perceptions of isolation from other people in the space. We conclude the paper by discussing how our findings can be used to design new mobile devices that are aware of the social norms and their users' environmental context.

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CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **Ubiquitous and mobile computing design and evaluation methods**.

Additional Key Words and Phrases: Disturbance, mobile computing, social environment, context-aware, physical privacy

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1 INTRODUCTION

Mobile computing technologies are creating a pervasive computing experience, in which computing devices are almost always at arm's reach. Smartphones, currently the most common computing devices, are omnipresent in people's lives. People spend 90% of their time in the same room with their smartphone [21] and the median percentage of smartphone ownership is reaching 70%-80% in many countries [63]. Smartphone applications frequently push notifications and interrupt users about incoming calls, messages, news, and other newly available information. However, there is a growing awareness of the negative aspects of constant connectivity. several studies have shown that these notification can decrease productivity [41], increase stress levels [3], and even harm general well-being [2].

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Studying disturbance has mostly focused on understanding interruptions [66], with the objective of improving productivity [14, 38, 41, 45] or helping users focus their attention [3, 12, 34, 48]. However, several works have shown that interruption models are more accurate when considering information about the people in the vicinity of the user [31, 50] or about the the place in which the user is currently in [25, 43, 51]. Vignette studies demonstrate that there is a social component to interruptibility. Users prefer not to be interrupted in places that are crowded [24, 32], or preferred to be interrupted using a more private modality, such as a vibration rather than a ring [26].

Understanding how technology can diminish or enhance social interaction between collocated people is an emerging interest in the CSCW community [49]. While mobile devices can foster a beneficial connection with friends and family members [16, 69], there are growing accounts of the disruption they now create in the home [29, 47] and in the office [3]. Several experiments show that texting while conversing with another person hurts the perceived conversation quality [1, 22], especially when we remember the breadth and depth of face-to-face communication [35]. Going against the norms of face-to-face interaction is considered hurtful [4]. For example, *phubbing* – the act of snubbing someone in a social setting by concentrating on one's mobile phone – is negatively affected perceived communication quality and relationship satisfaction [18, 53].

People carry their smartphones with them continuously throughout the day and use them in different places. In each place, users might interact with a different group of people, while carrying out different activities, and under various social norms. People's receptivity to interruptions is subject to type of place [33], the number of people around [24], and the character of the conversation and the activity that is being carried out in that space [55, 56]. However, the current literature does not portray the role of social norms in perceived disturbance. A model of perceived disturbance should take into account the complex nature of daily behaviors and the way their occur in spatial-social contexts. Users' perception may also depend on the social norms that surround the place and on their own perceptions of isolation from other people in the space.

In this paper, we evaluate a model for social disturbance resulting from mobile device use in physical environments. We rely on theories from human geography [23] and urban design [28], which highlight the effect of social norms and perceptions of exclusion as regulators for social behavior in a physical context. We operationalize these theories by suggesting a framework that can take into account how public or private the place is, the user's perceptions of privacy concerning the surrounding people, and the interactions happening in the physical space and with the phone.

We have evaluated our model of perceived disturbance using a user study, in which 50 participants have carried our research application on their mobile phones for 3 weeks. In this time-frame, they were probed about the disturbance their phone can create in that location and time. We collected information about the people around the user, the norms that govern the place, perceptions of privacy, and the activities carried out in that place. We have also collected information about the locations and activities carried on the phone. We have analyzed the 1912 surveyed locations using ordinal mixed models and evaluated the effect of the different contextual factors. Finally, we discuss how our results can help in enhancing social interaction between collocated people and in designing better disturbance mechanisms.

2 BACKGROUND

Understanding how computing interacts with physical spaces is an inherently multidisciplinary question. In this section, we review theories and related works from human-computer interaction sources, as well as urban planning and privacy theories.

Mobile computing devices can disturb the physical environment in several ways – phone calls, application notifications, and drawing the user's attention to the device [7, 44]. Most research works in HCI have tried to understand and to reduce interruptions in order to improve concentration and task performance of the single user [12, 17, 32, 38, 42, 45, 45, 48, 52, 59, 60, 66]. Interruption models are more accurate when adding information about the people in the vicinity of the user helps in classifying interruptibility [31, 51], about the physical place [25, 43], or about the type of interaction happening in the place [55, 56].

There are several open questions related to the place of the spatial context on interruptibility. Interruptions can also have a social consequence [32, 33, 47], and the reaction to interruptions is also related to the norms that govern the actual location [30]. For example, when the phone call interrupts the user, the interruption will be perceived differently if the user is alone in their home or in a crowded lecture hall. The phone call merely *interrupts* the user in the former case but may cause a *disturbance* to the environment in the latter case. Kern et al. have used video annotation method to show that people identify crowded places, such as lecture halls and restaurants, as places in which the social interruptibility will be considered problematic [32, 33]. Schulze and Groh demonstrate that people's receptivity to interruptions is rooted in the social interaction in this place, and is subject to the character of the conversation, the activity that is being carried out, and other social factors [55, 56]. In a lab study, Exler et al. show that the activity of the user, the number of people around, and whether the user needs to focus play a role in determining interruptibility [24]. However, the number of people might not be enough to explain this difference. For example, a phone call will be perceived differently in a lecture hall and in a busy house party, even if the number of people around is similar. In the lecture hall, the call might be considered more disturbing: it may strongly violate the norms associated with the accepted behaviors in a particular place.

Mobile phones do not merely interrupt the people around them, breaking people's trains of thoughts, they create a deeper disturbance. Christian Licoppe frames the disturbance as an invasion to people's personal territory: *"Though legitimate, the presence of phones binds parties in a given situation to the possibility of their personal territory being invaded, and their activities under way being disturbed."* [39]. However, there is relatively little theory, and even fewer empirical findings, that can be used to study human-computer interaction in its geographical context [36, 37]. Therefore, it is necessary to ground mobile human-computer interaction in well-formed concepts of geographical space and in the social attributes that spaces carry. For example, Ames et al. show how mobile smartphones create a new social expectations of constant connection, complicating the relations between people who we interact with physically and virtually [6]. Suh et al. study of teen video-chatting provides a captivating example on how boundary regulation works in practice [61]. The differences in disturbance vary from room to room in various buildings, the people around the teen, and the people chatting with the teen online.

The way people interpret their social context context is tightly related to the interaction between people in a particular physical space [24]. This interaction is then largely dependent on the norms that govern the spatial space and the social context of the interaction [27]. For example, it is considered fine to walk barefoot at home, but less so in a restaurant. Specifically, the divide between public and private spaces is one of the main dimensions in which interpersonal interaction takes place [70]. We rely on the definition of public spaces as shared spaces that facilitate and regulate interpersonal relationships, allowing heterogeneous individuals to coexist, with fluid sociability among strangers and near-strangers [57]. These spaces can include publicly owned spaces, such as plazas and squares, as well as privately owned spaces, such as coffee shops or even a party happening in someone's house. In contrast, private spaces are controlled spaces, where activities and interactions are carried out on terms that are set by the individual.

Mobile computing is often perceived as a disruptive technology that challenges the public/private divide, leading researchers to see the public and private as a range of spaces rather than a clear divide [23, p. 52]. The critique of mobile technologies is a prominent theoretical thread, most often arguing that mobile technologies privatize public spaces, allowing people to remove themselves from the public. Urban environments are particularly susceptible to the impact of mobile technology as they provide an opportunity for people to pass through multiple types of spaces quickly [37]. Additionally, they require norms to support the coexistence of strangers. For example, [15] demonstrates how the Sony Walkman allows its users to remove themselves from the public.

The smart phone transform public places to "private-in-public hybrid" spaces, which are governed by both technological and geographical forces [58]. For example, a person can use a smartphone to create a more private space out of the shared public space (e.g., a coffee shop,) by limiting access of others to the self [30]. To describe this process, we can think of a mobile device as an enabler to a Portable Private-Personal Territory (PPPT) [28], which frames a mobile device as a tool that can allow people to have greater control over their personal space. Based on PPPT, we define social disturbance as an instance of friction between the personal territory of the users and the public territory that surrounds them [28]. This theoretical framing helps us portray situations in which the people negotiate their boundary with the people around them by conforming and sometimes challenging the social norms that regulate the place. The Deviance Regulation Theory, which maintains that "people try to maintain positive public and private self images by choosing desirable ways of deviating from social norms and by avoiding undesirable ways of deviating from social norms" [10]. We therefore define phone disturbance as the way a phone interruption will be perceived to be disturbing to the social environment by the person who can control the actual interruption.

3 RESEARCH MODEL

We analyze phone disturbance as part of a relationship between mobile computing and the social interaction of the user in the surrounding space. We model the context of a disturbance by enumerating possible properties that define it and may affect the perceptions of disturbance. We draw inspiration from models of context in ubiquitous computing [20, 62] and define several contextual properties that can describe the situations in which mobile devices may interact with physical spaces. We assume that the interaction takes place in a territory: a defined physical space that includes the primary user (the user who holds the mobile device) and other people that may be in the vicinity of the user, are aware of the user, and may interact directly with the devices (e.g., may hear a phone call or a notification) with the user.

The spatio-social context reflects the physical and the virtual elements that may influence the interaction between the user and the people around. Based on the Portable Private-Personal Territory (PPPT) model [28], we take a two-level view on these elements. At the first level there are relatively simple objective factors that characterize the spatio-social context of a place: **the number of people** that are around the user, and **activity**, the type of activity carried in the place (e.g., working, eating, learning). These factors were found to affect social disturbance in previous studies [24, 32, 56]. The second level factors represent the perceived social norms related to the use of the place, norms that regulate the boundary between the personal territory and the public territory that surrounds the users [28]. Those include **publicness**, which reflects whether the space is perceived as public or non-public. **Perceived privacy** reflects the perceptions of personal privacy in the territory, how isolated the user feels from other people in their vicinity. Based on the work of Suh et al. [61], we add a virtual construct: **device interaction**, how the users interact with their device in the location (e.g., gaming, talking, texting).

Our research questions ask to evaluate the spatial-social context factors and to see if they actually related to the perceptions of social disturbance. The perceptions of disturbing others can be different if the person is surrounded by other people or alone. It can be different if the user is in a public place or a private place. The perception might also be different if the user is interested in detaching from the people around her or not. When defining the Perceived Privacy variable, we rely on definitions of privacy in spatial environments, which reflect the freedom of an individual to carry out any type of behavior in a given place [23]. This concept should not be confused with the more current prevalent concept of informational privacy, which reflects the control of the individual over their online information.

To evaluate the model, we expect the following hypotheses to hold:

- **H1** Users perceive interruptions from their devices as more disturbing for the environment if more people are around (based on [24, 26, 50])
- **H2** Users perceive interruptions from their devices as more disturbing for the environment if they perceive the place as public. We will accept this hypothesis if this factor impacts disturbance independently than the size of the crowd in the territory (based on [58])
- **H3** Users perceive interruptions from their devices as more disturbing for the environment if they believe they have less privacy in the territory (based on [28])
- **H4** Disturbance is correlated with the activity carried out in the place (based on [45, 51, 71])
- **H5** Disturbance is correlated with the activity carried out on the device (based on [28])

4 METHOD

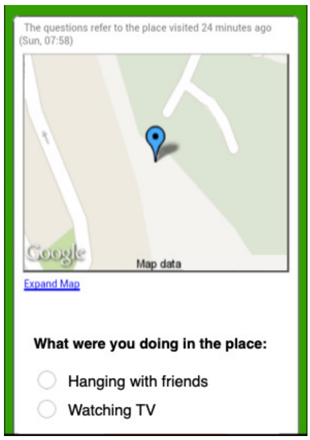
To answer the research questions, we have uses a mixed-method approach, combining experience sampling and data collection on mobile phones. The data gathering was based on **Smart-Spaces**, a dedicated application developed for this experiment, which combines mobile phone tracking with experience sampling [67]. Data gathering was carried out for three weeks among 51 adult subjects. Before the study has started, participants were interviewed by a research assistant, answering questions about definitions of places. After three weeks, participants were interviewed again and were asked to remove their Smart-Spaces application.

4.1 Smart-Space: The Research Application

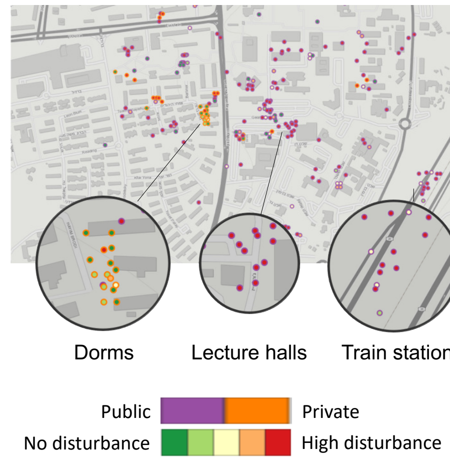
Smart-Spaces is implemented as an Android application, installed on the participants' own phones (see a screenshot in Figure 1a). The data collection included the location of the phone, using the phone's built-in positioning services (GPS, Wi-Fi and cellular triangulation), as well as recording the applications running on the phone at the time of the notification. Participants were notified about the availability of the questionnaire, where they answer a short survey in the context of their recent location. The survey was presented along with a map, as depicted in Figure 1a.

Smart-Spaces was designed to balance user burden and coverage of times and location. Limiting user burden is essential to maximize response rate by reducing the cost of filling a survey [67]. Therefore, the surveys were displayed based on an algorithm that tried to cover as many of the places visited by the participant while minimizing the number of surveys per day. To maximize coverage of locations, if the location was already surveyed more than two times by Smart-Spaces, the application would defer the survey. We defined a similar location as a location which is at most 20 meters from an existing one. To reduce the user burden, the algorithm was adjusted to leave at least 5 hours between two consecutive surveys and to avoid surveying a location that was already surveyed at least two times. To further reduce the burden, the algorithm only surveyed "static" locations, i.e., locations in which the participant was present for more than 10 minutes, rather than places in transit. To reduce the inconvenience to participants, Smart-Spaces did not use the noise alert after 22:00.

Survey notifications are presented using the default sound, vibration, and icon on Android for several minutes. We have utilized expiry time, suggested by van Berkel et al. to fight experience sample response fatigue [68]. If the participant had dismissed the notification, then Smart-Spaces would show the notification again after 15 and 30 minutes, giving the participant another chance to



(a) A screenshot of Smart-Spaces, the mobile experience sampling and tracking research application.



(b) A map of the surveyed places, colored according to the level of disturbance (inner color) and the publicness of the place (the outer color).

Fig. 1. A screenshot of Smart-Spaces (left) and a map produced from the dataset (right)

answer the questionnaire about the same location. If the participant had ignored these notifications, Smart-Spaced would randomly choose another time to show the survey. This length of expiry time is perceived as sufficient in similar experience sampling studies [67].

4.2 Participants

Participants were compensated for their study by gift vouchers worth roughly $40, $15 at the beginning of the study, and $25 at the end of the study. All of the subjects, but one, had persisted through the whole duration of the study. Participants were recruited from the university population using fliers and posters, and the study itself took part during the school year. Of the participants, 27 were males and 24 were females. The median age of the participants was 25, with the youngest participant being 22 and the oldest being 32. Most of the participants were living either in the city or in its immediate suburbs (and commuting to the city), and therefore were visiting a diverse set of places through their daily routine. The institutional ethics review committee approved the form and the experimental procedure.

4.3 Variables

The dataset included information about the location and time of a sampled point, which corresponds to the time of the notification. Table 1 presents the factors: the answers to six questions related to the participant's perceptions and a factor which was sensed automatically. As the space in the online questionnaire is very limited, the application included short stubs of the questions, which were presented and explained in full by the research assistant at the beginning of the study.

The participants were asked to provide answers to all the questions that were collected through the questionnaire. To portray disturbance we have asked about a voice calls. We have used this language because phone calls are more standard across phones makes and styles of usage. Participants were guided by the research assistant to answer the question about perceived privacy with regard to the people around them and in their immediate physical surroundings. In Activity, the participants

Table 1. Factors from the Smart-Spaces dataset and the features that comprise them.

Factor	**Features**	**Collection**
Activity	Hanging with friends, watching T.V., learning, working, eating, using my smartphone, other	Questionnaire
Number of People	The number of people in the place (alone, 1, 2, 3-5, 6-10, 11+)	Questionnaire
Perceived disturbance	To what extent will it disturb your surroundings if you will accept a voice call in this place? (Likert 1-5)	Questionnaire
Perceived privacy	To what extent does your smartphone provides you with privacy in this place? (Likert 1-5)	Questionnaire
Publicness	Whether the participant considers the place as public (yes or no)	Questionnaire
Location	The physical location of the participant's phone	GPS and Wifi Position
Running applications	The applications that were actively used by the participant 15 minute prior to the time of the survey	Phone OS

were asked to select from a list of locations that were selected from an experience sampling study that had used a similar methodology [64] and was adapted to the student population.

To produce the list of the running applications, we accessed the list of applications running on the phone using the Android API, requesting all the applications that were actively used by the participant 15 minutes prior to the time of the survey. A research assistant categorized the applications based on the classification provided by [11]. These categories included the following: browser, communication (phone voice use), games, launcher, multimedia, news, productivity, social applications, travel, and multimedia.

4.4 Pre-Processing and Analysis

The 50 valid participants answered a total of 1912 location questionnaires. Our participants had provided answers for an average of 2.23 surveys per day, with a standard deviation of 1.3 surveys. Before analyzing the results, we carried out several pre-processing operations. The data were cleaned for two types of mistakes: partially fulfilled surveys and wrongful location information. Of the 1912 surveyed places, the questionnaire for 64 locations (3%) were partially fulfilled and were therefore discarded. Of the surveyed places, 40 (2%) were discarded because participants had marked the location as erroneous.

To validate the model, we used an Ordinal Mixed Model regression, which uses the perceived disturbance as the dependent variable and the participant ID as the random effect. The method allowed us to manage the assumption of data point independence. We used the non-parametric Spearman rank correlation test to measure the degree of the similarity between context variables (e.g., publicness and number of people) or between perceptions and context (e.g., perceived privacy and publicness). We have tested the relationship for the monotonic assumption. To analyze the relations between the context variables, we applied one-way ANOVA, which was found to be a robust enough to test hypotheses even when the data is not normally distributed [9].

5 RESULTS

5.1 Models of Disturbance

To characterize the effect of multiple context properties on mobile device disturbance, we have applied ordinal mixed model regression to create several models of perceived disturbance (Table 2). To test the impact of different sets of variables, we use a theory-based gradually evolving set of models. The models were selected based on our theoretical research questions, helping us isolate the contribution to several groups of variables, as suggested by [8]. We start with a model that only contains the number of people around (model 1), and end with a model that contains all variables (model 5). We have tested for interaction effects (Table A).

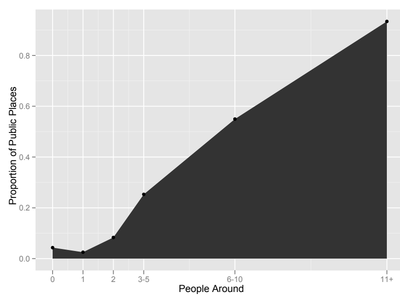
Table 2. Ordinal mixed models regression for perceived disturbance. Each The cells contain estimates and the corresponding 95% CI in brackets. Significance levels are noted by: $p < 0.0001$ '***'; $p < 0.001$ '**'; $p < 0.05$ '*'.

Factor	Model 1		Model 2		Model 3		Model 4		Model 5	
Intercept	-0.43	(-0.63–0.25)	0.12	(-0.47–0.64)	1.56	(1.13–2.09)	1.47	(0.95–2.04)	5.69	(2.83–9.00)
Number of People	0.135***	(0.11–0.16)	0.17***	(0.11–0.25)	0.07***	(0.04–0.10)	0.09**	(0.05–0.13)	0.34***	(0.17–0.54)
Non-public place			-0.94***	(-1.51– -0.47)	-0.46***	(-0.71– -0.24)	-0.39**	(-0.66– -0.12)	-1.60***	(-2.75– -0.44)
Privacy					-0.39 ***	(-0.50– -0.31)	–0.46***	(-0.58– -0.35)	-1.73***	(-2.51– -1.02)
Activity										
Watching T.V.							-0.56**	(-1.01– -0.20)	-2.00**	(-3.77– -0.54)
Learning							0.55***	(0.30–0.84)	2.12***	(0.87–3.37)
Working							0.51***	(0.19–0.89)	1.84***	(0.65–3.27)
Eating							0.06	(-0.28 – 0.40)	0.33	(-0.93–1.84)
Other							0.48***	(0.19–0.73)	1.74***	(0.67–3.02)
Device										
Browsing									1.92***	(0.59–3.79)
Communication									-1.22**	(-2.14– -0.11)
Gaming									-1.47	(-4.71–1.71)
Multimedia									-1.74*	(-3.86–0.18)
News									1.37	(-0.59–3.4)
Productivity									-0.95	(-2.50–0.46)
Social networks									-0.16	(–2.2–1.31)
Travel									-0.49	(-3.02–1.84)
DIC	**4018.79**		**3361.77**		**3815.25**		**2025.94**		**628.61**	

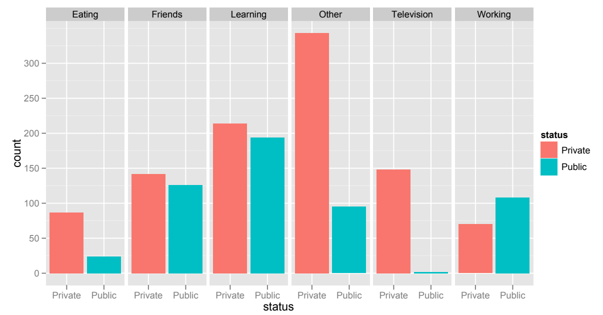
To intuitively understand the impact of the social and spatial context on phone disturbance, we can look at Figure 1b, which presents a map with different surveyed locations, each with the level of disturbance and whether the place is considered private or public. Overall, the map reflects a high correlation between publicness and disturbance: participants perceive most public locations as locations in which phones are more disturbing. However, we can see some exceptions: disturbance can be higher in some private locations, and it can be lower in some public locations. Therefore, in this analysis, we answer the research questions and statistically analyze whether the factor influence disturbance independently.

5.2 Disturbance and Number of People

We characterize the territorial context according to the number of people, publicness, and activity carried out at the place. In 33.7% of the surveyed locations, participants classified the place as public, and in 66% of the places were classified as private. As Figure 2a shows, the proportion of places that are defined as public by the participants is generally strongly correlated with the number of people around ($r = 0.723, p < 0.0001$.)



(a) The relation between publicness and number of people.



(b) The number of places according to publicness categories and activities carried out in that place

Fig. 2. Basic statistics of the dataset.

The ordinal mixed model regression show that all of the social contexts are correlated with disturbance even with cross-correlations. The phone is perceived as being more disturbing when there are more people around. The number of people around the participant has a consistently significant positive effect on disturbance, ranging between 86% when it is the only predictor to around 5% when it is one of the multiple predictors. As the measure is significant even when combined with other predictors, we conclude that hypothesis H1 is confirmed.

The results confirm the intuitive observation that a phone call creates a greater disturbance when there are more people around. In all of the models, the number of people has a positive effect on the disturbance. Figure 4a shows the strong positive correlation between disturbance and the number of people around (Spearman test $\rho = 0.46, p < 0.0001$). Note that the scale starts at 1 because the questions referred to the people around the participants. The impact of the number of people remains significant even when we add other variables, which are highly correlated with the number of people around, such as the publicness or the activities carried out in the place.

5.3 Disturbance and Publicness

Publicness is another significant factor: the norms governing the place are also meaningful. As Table 2 shows, if a place is considered non-public, a phone call will be perceived as less disturbing at about 22% to 10%, depending on other predictors (confirming hypothesis H2). Figure 4b clearly shows, the disturbance is consistently higher for public places than in private places. A one-way ANOVA indicated that the number of people around the participant is significantly higher in places defined as public by the participant than in places defined as private $F(245, 5) = 603, p < 0.001$ with an average of $8.99 \pm 3.4511.80 \pm 2.058$. The strong correlation between publicness and number of people points to a consensus between participants regarding how to define a place as public, which provides further validation of our results. In Table A we show the results of the regression models, controlled for the interaction of publicness and number of people. The significance levels and effects were similar to the models without the interaction, which means that in some of the sampled locations, given a similar number of people, disturbance would be perceived differently, based on the perceptions of the social norm of the place.

5.4 Disturbance and Perceived Privacy

Participants have expressed varying degrees of perceived privacy based on the spatial-social properties of the place. Figure 4a depicts the perceived privacy based on number of people around

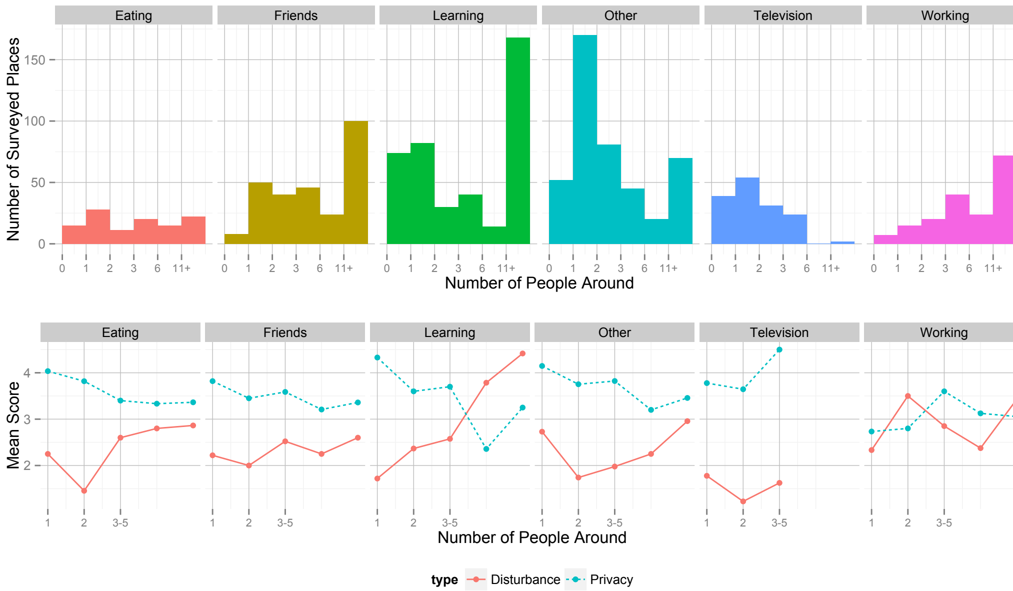


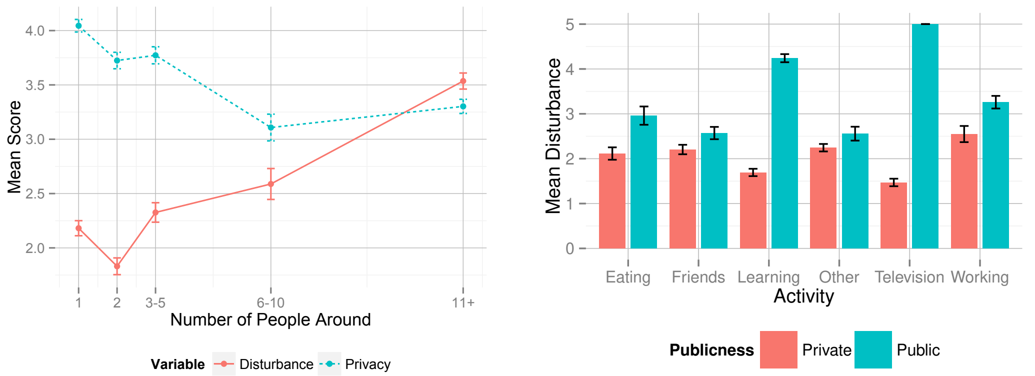
Fig. 3. An analysis of disturbance and perceived privacy according to activity. The top diagram is a histogram of the number of people around the participant during different activities. The bottom diagram depicts the average values of the perceived privacy and the perceived disturbance in places where participants were not alone based on the activity and the number of people around the participant.

the participant. On average, the device provides the highest level of privacy when the participant is with another person, and the perceived privacy decreases with increasing numbers of people around. Paradoxically, when the participant is surrounded by a larger crowd (more than 5 people), the phone provides less privacy than in situations when the participant is surrounded by a small number of people. Perceived privacy is negatively correlated with the number of people around ($\rho = -0.27, p < 0.001$).

The perception of privacy in the place is also a significant factor in the perception of disturbance. If the participants believe that the phone provides a higher level of privacy, they also believe that it is less disturbing. The effect is consistently significant in all models, standing around 30%-15 of the intercept, regardless additions of other factors (confirming hypothesis H3). In contrast, perceived privacy is negatively correlated with perceived disturbance (Spearman test $\rho = -0.375, p < 0.0001$). Publicness (whether the place is perceived as public) is highly correlated with the perceived privacy ($\rho = 0.23, p < 0.001$).

5.5 Disturbance and Activity

Figure 3 depicts the types of activities that were reported by participants and the distribution of the number of people per activity. The activities carried out by the participant impact perceived privacy ($F(5, 1498) = 5.292, p < 0.001$). Specifically, 'Working' is associated with a decrease of the perceived privacy in comparison to 'Watching T.V.', 'Learning', 'Eating' and 'Other' activities. Some activities, such as 'watching T.V.', are carried out mostly alone or amongst a small number of people. Other activities, such as 'learning', are performed either alone, in small groups or amongst a large crowd (most likely in a classroom). Most activities occur in both public and private spaces



(a) Disturbance and perceived privacy by number of people around he user.

(b) Disturbance while carrying out different activities. Error bars depict ±1 standard error.

Fig. 4. Two breakdowns of the disturbance measure

but in different social contexts. Figure 2b displays the proportion of public and non-public places per activity. For example, 'Learning' is carried out in private spaces in solitude or in small groups, whereas in public spaces, it occurs in a crowd.

Some activities are also shown to have an impact on phone disturbance. When participants are learning, working, or doing unclassified activities ("Other"), they significantly perceive a phone call as more disturbing. When adding the interaction of activities and number of people to the ordinal mixed model regression, 'Learning' and 'Watching TV' are still significant (estimates of 1.11 and 0,74 respectively). However 'Working' is not and its effect is wholly due to the number of people around. In three other activities, the estimates were not strong enough to be considered. However, because of the number of activities and the estimated strength, we can conclude that hypothesis H4 stands for several important activities. As publicness is also dependent on the activity, the activity carried out by the participant at the time of the survey is also significant in our model ($F(5, 1515) = 9.442, p < 0.001$). On average, the perceived disturbance was significantly higher for 'working' (mean 0.51) or 'Learning' (mean 0.55) than for any other activity.

The combined effect of activities and publicness on disturbance is depicted in Figure 4b. The activities had different effects on the phone call disturbance in public and private spaces $F(5, 1511) = 19.132, p < 0.001$. We can see that for activities such as 'Learning', there is a considerable difference in disturbance between private and public places. In public (and crowded) spaces, disturbance is significantly higher than in private (and sparse) spaces. A similar effect can also be observed for 'Watching T.V.', but due to the small number of samples in which television was watched in public, the results are statistically insignificant. Table A in the Appendix describes the interactions between activities and publicness, and demonstrates that . These results hold even when controlling for the interaction between publicness and activities in the ordinal regression models.

To gain a deeper look into the relation between places and disturbance, we extended the self-reported information provided by participants with more general categories of places using Foursquare categories. Foursquare categories provide definitions regarding the type of the location, with a larger scope than the particular room the participants were asked about [40]. To produce the categories, we used a method similar to [46], categorizing the place based on the categories of nearby Foursquare venues (e.g., food, shop and service, residence, travel and transport, arts and entertainment). For each surveyed location, we retrieved the categories of the Foursquare venues in the vicinity of 200 meters and choose the category with the largest number of instances as the category of the location, normalized based on the overall number of locations nearby. Generally, the Foursquare place category is determined to significantly affect the perceived disturbance ($F(9, 1511) = 5.148, p < 0.001$). When adding the category to the mixed model regression, only 'University' was found to be significant with an estimate of $3.83(0.69 - 7.70)$, with an intercept of 6.27.

5.6 Device Interaction and Activities

The use of a number of applications is shown to be correlated with different perceptions of the phone disturbance. The models show that 'Browsing' (e.g., using the mobile device browser), 'Communications' (talking on the phone or texting), and 'Multimedia' (watching videos) are significantly correlated with perceived disturbance. Using communication and multimedia applications is correlated with a significant decrease of the perceived disturbance. On the other hand, browsing is correlated with a significant increase. Therefore, we can say that that hypothesis H5 is supported for these particular applications.

6 DISCUSSION

The findings presented in this study demonstrate how the spatial and social environment plays a role in the user experience of mobile computing devices. We show that perceptions regarding the potential disturbance of mobile devices rely to a very large extent on the social environment and that multiple factors form a spatial-social context. Our findings can explain some of the reasons that studies that took groups in disturbances studies have achieved higher accuracy taking into account the number people in the vicinity of the user [31] or about location [25, 43]. Our study confirms some of the results of three vignette studies that suggested that location is related to interruptibility preferences [24], interruptibility modality [26], and social interruptibility [32]. Our longitudinal experience sampling study provides additional ecological validity to their conclusions, while also adding new dimensions to the spatial-social contexts.

The considerations people make in perceiving disturbance cannot be reduced to a single factor, such as the activity carried out at the location or number of people. Our findings show that when we attempt to unpack the effect of spatial-spatial contexts, we see a rich picture, in which there are complex relations between the factors, without clear hierarchies. Our most important conclusion is that subjective perceptions and social norms are at least as important (if not more important) than the basic properties of the place. The publicness of the place and the perceived privacy are consistently strong predictors in all of our regression models, accounting together for about 20% of the variability. The number of people around the user (a property that was used in [50]) explains only 17% of the variability in the perceived disturbance in Model 1. However, Model 3, which includes publicness and perceived privacy, explain 27% of the variability. These normative judgments are very different in nature. Most of our participants agree on the publicness of the place: a coffee shop is almost always considered public, and a private residence is almost always considered private. In contrast, perceived privacy is a subjective judgment call, and it depends on the current activity of the user and their own personal approach.

Our findings provide additional empirical evidence to the effect of mobile computing on perceptions of space and social relations. Mobile computing creates an elastic boundary between the public and the private and between the personal and the collective [23]. In the user study, we describe the properties and the limits of this elasticity. We can think of the perceptions of users as reflecting a portable private-personal territory (PPPT) around them: a representation of the way personal space and territory are redefined using mobile devices [28]. The effects of place, activity and number of people on physical privacy strengthen the assertion that PPPT is a socio-spatial construct. Using certain applications on the phone can lead users to be more susceptible to disturb their environment. The results also allow us to start to portray some of the multidimensional sets of relations defined by events and interactions that characterize the territory, namely the crowd, the norms, and the device.

The dynamic nature of disturbance – the fact that it changes with the perceptions of the user – led us to think about it as a process. We tend to think of disturbance as the consequence of an event: disturbance follows an event such as a phone ring [39]. The outcome of a disturbing event is the result of an underlying negotiation process between the user and the surrounding environment about how an interruption will be perceived. Our results cannot help characterize properties of this negotiation process, but the fact that the perceived privacy and social norms affect disturbance provide some evidence for its existence. Device disturbance is tied to how "disciplined" a place is. We saw a difference in situations in which the user cannot use the smartphone freely (e.g., when 'Working' with other people around) and between undisciplined situations in which the attention of others still allows the user to use the smartphone. For example, when 'Hanging with friends', we see that disturbance is stable with the number of people.

While urban studies are focused mainly on analyzing public spaces [19, 58], our results show that the impact of devices on perceived privacy is stronger in private spaces than in public spaces. For example, one of the situations in which smartphones provide the highest level of privacy is when the user is watching television with one to two other people (Figure 3). We contextualize this result in the studies of [54] and [13], which contradict the Aristotelian definition of private spaces as spaces controlled by the person. Our study participants were mostly students, who in most cases live with their parents on with roommates and who do not always exercise full control over their physical environment. The smartphone performs as a "poor person's private home", allowing users to focus their attention elsewhere, engage in private communication through messaging, and to negotiate the relation with their environment. The interpretation of this result is open for debate: scholars who claim that mobile devices are drawing people apart, such as [65] and [15], may look at the results as evidence for this growing trend. Other scholars, such as [19] and [13], may argue that mobile devices serve as a necessary and adaptive interface to spaces.

Our findings lead us to ask how mobile technology can be designed to address the norms that surround behavior in public and private places. Physical spaces, and especially urban environments, are increasingly embedded with mobile and pervasive technologies [36]. We argue that the design of these technologies should take into account the social norms. On a basic level, we can ask that technologies would be aware and respect social norms. For example, mobile devices can use context awareness to silence themselves when in a place where the potential for disturbance is high.

6.1 Limitations

Our study has several important limitations. First, the quickly changing norms related to mobile technologies and physical spaces pose a major limitation of our study. Naturally, because these norms are rapidly changing, the reader should be careful when judging the longitudinal validity of this research. We do not know if the results will be relevant to technologies that will emerge years from now or to the social norms that surround them. Additionally, our sample is not representative of the general population. Our study consisted of mainly young and educated participants with strong self-selection towards technology literacy. To generalize the results to the entire population, further studies and comparisons would have to be carried out with a more heterogeneous population. Disturbance might also be highly correlated with perceptions of personal space, which differ considerably between cultures [5].

Our research method also holds several limitations which are typical to experience sampling [67]. The frequent surveys might distract the participants and cause them to deviate from their immediate perceptions. We have tried to control for this bias by limiting the number of surveys per day. Also, we measured a small number of spatial contexts, missing some interesting questions for the sake of reducing user burden. The limited number of activities the user could select from and the various scopes in which locations can be defined is another limitation. Future work might add further semantics to our dataset, for example by categorizing the locations to the type of building. Another limitation is the within-subject design, which does not condition the actual use of the technology or measure its impact on privacy. Therefore, we cannot conclude that smartphone technology is responsible for changes in people's behavior. We believe that experimental approaches and between-subject design might help us understand. We hope to further test other types of context, for example, whether the user is surrounded by strangers or by acquaintances.

7 CONCLUSION

Our paper explores the factors that are related to the way social disturbance is perceived by users. Social disturbance is related to the social context of the place, including the number of people around the user, how public the place is perceived, as well as the activity carried out in the place. The norms and the perceptions of a place are at least as important (if not more important) than the its functional properties (such as the number of people in the place). Factors that are related to the user's own activities also play a role: perceptions of privacy and the activity carried on the phone. Overall, these results point to ways in which mobile interruption management systems, including both applications and operating systems, might be designed differently to help support devices that try to respect the social norms around the users and to reduce social tensions. This might involve sensors that are more aware of what other people are doing in this space, as well as opportunities to externalize and communicate these norms. Our methodology can serve as a case study for investigating the use of various mobile technologies, quickly collecting information grounded within a physical context, and guiding the development of technologies that are more sensitive to the physical contexts or urban environments that are geared towards mobile technologies.

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A INTERACTION EFFECTS

Ordinal mixed regression models for perceived disturbance with interaction effects. Each The cells contain estimates and the corresponding 95% CI and the p values.

	No interaction effects				publicness * number of people				All interaction effects			
Factor	Estimate	5% CI	95% CI	p	Estimate	5% CI	95% CI	p	Estimate	5% CI	95% CI	p
(Intercept)	11.53848	3.26552	19.64067	<0.001	11.93912	2.96311	20.38572	<0.001	3.58837	1.05218	6.25884	<0.001
numPeople	0.68259	0.19351	1.16744	<0.001	0.53452	0.09284	0.97881	0.002	0.16461	0.03812	0.31183	<0.001
Non-public Place	-3.09091	-6.26091	-0.5738	0.002	-4.49882	-8.77324	-0.6688	<0.001	-0.05713	-1.42729	1.40598	0.958
Privacy	-3.51014	-5.8139	-1.22113	<0.001	-3.34142	-5.50564	-1.00843	<0.001	-1.14871	-1.87515	-0.46771	<0.001
Watching T.V.	-4.21084	-8.77666	-0.87691	0.008	-3.74663	-7.51812	-0.45417	0.004	79.71057	3.27171	159.82471	0.002
Learning	4.22169	1.08482	7.63268	<0.001	4.2021	0.98016	7.56581	<0.001	4.13822	1.65637	6.89773	<0.001
Working	3.67426	0.6509	7.15333	0.002	3.44858	0.66731	7.11147	0.002	1.5506	0.37265	3.21931	<0.001
Eating	0.59259	-1.74293	3.85898	0.63	0.60901	-1.89447	3.67938	0.636	0.66541	-0.78742	2.61691	0.414
Other	3.44596	0.83002	6.6205	<0.001	3.43113	0.79857	6.87614	<0.001	0.86174	-0.17967	2.22326	0.102
Browsing	3.98038	0.7093	7.92838	0.008	3.70188	0.20515	7.52868	0.006	1.16076	0.04762	2.55887	0.006
Communications	-1.99756	-4.6191	-0.18319	0.026	-1.82035	-3.98655	0.07904	0.038	-0.60162	-1.3577	0.05063	0.044
Games	-2.91679	-10.21642	2.99775	0.328	-3.28658	-10.42992	2.28538	0.268	-1.04585	-3.68684	0.99878	0.354
Multimedia	-3.41898	-8.40024	0.01072	0.044	-3.40642	-7.905	0.20756	0.05	-0.77024	-2.20688	0.60767	0.222
News	3.44439	-0.8865	8.44248	0.076	3.4734	-0.268	8.15027	0.06	1.23005	-0.15292	3.1535	0.082
Productivity	-1.76712	-5.34233	1.10155	0.204	-1.89174	-5.05315	0.69767	0.14	-0.74856	-2.20123	0.22667	0.14
Social networks	-0.50723	-4.34888	3.1666	0.81	-0.16697	-3.82677	3.78885	0.932	0.10288	-1.15039	1.33397	0.866
Travel	-1.09105	-6.19103	3.62417	0.628	-0.98964	-5.92926	4.04955	0.636	-0.42708	-2.38539	1.13469	0.63
Number of people * Non-public Place					0.30693	-0.14691	0.87453	0.152	0.09303	-0.05876	0.28442	0.22
Non-public Place * Watching T.V.									-82.1633	-162.56271	-3.81647	<0.001
Non-public Place * Learning									-5.14768	-8.57936	-1.90876	<0.001
Non-public Place * Working									-0.08368	-2.01508	1.316	0.95
Non-public Place * Eating									-1.18962	-3.44181	0.82478	0.194
Non-public Place * Other									-0.10985	-1.63147	1.09498	0.88

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