

Toward Social Role-Based Interruptibility Management

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Pervasive and ubiquitous computing facilitates immediate access to information in the sense of always-on. Information, such as news, messages, or reminders, can significantly enhance our daily routines but are rendered useless or disturbing when not being aligned with our intrinsic interruptibility preferences. Attention management systems use machine learning to identify short-term opportune moments, so that information delivery leads to fewer interruptions. Humans' intrinsic interruptibility preferences—established for and across social roles and life domains—would complement short-term attention and interruption management approaches. In this article, we present our comprehensive results toward social role-based attention and interruptibility management. Our approach combines on-device sensing and machine learning with theories from social science to form a personalized two-stage classification model. Finally, we discuss the challenges of the current and future AI-driven attention management systems concerning privacy, ethical issues, and future directions.

When the coronavirus emerged from a local outbreak to a worldwide pandemic in March 2020, mobile phones, smartwatches, and laptops were a driving factor that enabled work-from-home regulations. While individuals were working remotely at home, they often experienced stress, frustration, and even conflicts with family members.¹ The potential of pervasive and ubiquitous computing for work and private life-related conflicts results from their ability to overcome and breach peoples' preferences and boundaries. People establish preferences and boundaries to structure their work, and private-related demands.² Interruptions imposed by work-related emails, phone calls, or reminders are potential manifestations that breach individuals' preferences and boundaries—especially in the after-hours.³ According to a recent study with 67 participants, higher levels of

exhaustion are reported, particularly when participants had valued work over private matters and were using their private smartphone while working.⁴

Attention and interruption management systems aim to support individuals in maintaining their interruptibility preferences.⁵ They try to mitigate the net effects of interruptions, such as prolonged primary task completion,⁶ increased rates of self-interruptions,⁷ or errors within primary task execution. However, to date, interruptibility management is focused on particular contextual descriptors associated with events and the expectation that short-term opportunities for interruptions arise when users, for example, finish particular tasks or make transitions between physical activities.⁸ Even though research in social and behavioral science promotes the idea of distinguishing interruptions for work and private domains concerning individuals' preferences,^{3,4,9} attention management is still in its infancy when it comes to supporting individuals' holistic preferences. For example, applications, such as Apple's Focus mode or Android's do-not-disturb mode either aim to block communication entirely, do not provide support

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for social roles and life domains, or still need manual configuration.¹⁰ Consequently, there is a need for human-centered AI-driven approaches and systems that support individuals' interruptibility on a broader scale. Such approaches would complement approaches based on particular events, locations, or short-term opportunities.

In this article, we build upon this idea and present our research findings on social role-based interruptibility management that focuses on the respective user—putting their social roles and preferences in the spotlight. Thus, we first discuss role theory and boundary management representing the basic principles of our approach. We then describe our mobile sensing study with 16 participants for five weeks. In this study, we captured participants' social roles, interruptibility preferences, and other contextual information in a multidevice environment. Personalized classification models to identify individuals' interruptibility preferences and social roles are then evaluated and combined to form our vision toward social role-based interruptibility management. Finally, we investigate the challenges of multidevice settings in detecting social roles for interruption management before discussing implications regarding privacy, ethics, and future AI-driven attention management systems using our approach.

ROLE THEORY AND BOUNDARY MANAGEMENT

Our vision is to integrate theories on human behavior into a human-centered attention management system. From the data captured in our mobile sensing and experience sampling method (ESM) study, we extract information on social behavior and related individual interruptibility preferences. This kind of information then serves to support users in their interruptibility. Theories on social roles and boundary management provide the theoretical background to our approach. Further, these theories guide us through our study design, the questionnaires, and the extracted features we used to model individuals' interruptibility.

Role Theory

People establish physical, temporal, or cognitive boundaries to shape their domains.² Domains are mental constructs that sort and maintain similar and associated events according to their meaning. For instance, individuals might establish the domains of work and private and characterize each of the domains with colleagues, friends, and demands on the domain. Within and across domains, people enact

various social roles.² Social roles are defined as characteristic social behavior,¹¹ or expected behavior associated with a social position where each position has its rights and obligations.¹²

Boundary Management

Role boundaries limit the perimeters of associated social roles.² Boundaries are flexible and permeable to facilitate transitions from one social role to another. Based on the findings of Nippert-Eng's work¹³ stating that individuals tend to segment their domains, Ashforth et al. suggested that roles can be aligned on the continuum from high segmentation to high integration.² The continuum results in three different role preferences: 1) segmentation, 2) integration, and 3) combination. Whether a person is interruptible depends on their social role and preferences. While positive effects of concurrent roles on individuals' well-being have been found, the net effect of interactions and interruptions contradicting demands is detrimental.⁹ The adverse effects on individuals due to frequent breaches of preferences in pervasive and ubiquitous computing motivated us to build a system that focuses on its users.

CAPTURING SOCIAL ROLES AND INTERRUPTIBILITY PREFERENCES

There is a need of *in situ* social role and interruptibility data to investigate the importance of social roles in attention and interruptibility management. To fulfill this need, we implemented two applications—a cross platform application for Windows and macOS and a separate mobile application for Android. Both applications feature experience sampling and continuous background sensing, and were used in an in-the-wild study to capture participants' self-reported social roles, interruptibility preferences along with their locations and device usage.

Procedure

Experience sampling within our applications is based on two different approaches inspired by Berkel's work.¹⁵ The first approach is based on a fixed schedule of 90 minutes, asking participants about their current social role and interruptibility preferences. These questionnaires are only scheduled between 7 a.m. and 10 p.m. The second approach is event based, showing additional questionnaires after participants interact with their phones for more than 10 minutes. We set a minimum time of 30 minutes between event-based questionnaires. When a questionnaire is issued, individuals can select between two social roles, namely work and private, as they represent the main domains differing between being at work

TABLE 1. Overview of extracted features. our target variables are denoted with (+). Information marked with (*) have been manually reported via questionnaires.

Context	Features
Computer (Windows and macOS)	
Application stream	number of unique applications, count vectorization (CV), term frequency (TF), term frequency-inverse document frequency (TF-IDF) on application sequences
Keyboard	number of pressed keys {chars, control keys}, interaction {true, false}
Mouse	number of pressed buttons {left, right}
Interaction	the total time spend with applications prior to an ESM
Smartphone (Android)	
Application stream	number of unique applications, CV, TF, TF-IDF on application sequences
Location	Pluscodes {8 and 10}, most frequent and last pluscodes
Physical activity	number of unique activities—Google API
Ringer mode	ringer mode changes, last ringer mode
Screen state	number of states {on, off}
Notification	number of {notifications received, unique applications with notification}
	number of notifications received from {family, friend, work},
	number of notifications received from contacts with hierarchical relation {same, above, below}
Contact	hashed contact and/or group name extracted from notification titles
Application genre	number of different application genres
Interaction	the total time spend with applications prior to an ESM
Temporal	
Time	part of the day {morning, noon, afternoon, evening, night}
Day of week	number of day within week {0–6}
Weekend	{yes, no}
Self reported	Description
Social relationship*	Information about family, friends, colleagues and contacts with no relationship
Task*	The task the participants had progressed the most in the last 90 minutes ¹⁴
Social role ⁺	The social role the user was in the last 15 minutes: {private, work, both}
Interruptibility ⁺	Interruptibility preferences for the last 15 minutes: {private-only, work-only, both, none}

and private-related behavior. Private comprises home and social, including interactions with, e.g., the parents, the partner, pursuing hobbies.¹³ Contrary to this, work represents all work-related activities, such as being at work or communicating with a colleague. As individuals may encounter difficulties when choosing between work and private, we added both as the third selection in our questionnaires. When being asked about their current social role, individuals can also choose between four different interruptibility preferences: interruptible for 1) private, or 2) work-related interruptions, for 3) both, or 4) none. Finally, we issue questionnaires on peoples'

relationships and—if applicable—their hierarchical relationship to a contact. These questionnaires are shown to participants as soon as they receive at least five notifications from their contacts.

Each application features background services that, if available, keep track of location updates, physical activities, interactions with applications, notifications, and the device's state (e.g., screen status or ringer modes). The captured data are regularly uploaded to our university server through an encrypted channel. A list of captured information and target variables is shown in Table 1.

TABLE 2. Distribution of participants' ESM answers per device and class. In total, we received 3255 valid questionnaires answers.

Device	No. ESM	Interruptibility				Social role		
		Private	Work	Both	None	Private	Work	Both
Smartphone	2344 (72.01%)	40.57%	14.46%	31.14%	13.82%	56.31%	28.29%	15.40%
Computer	911 (27.99%)	15.70%	36.66%	24.48%	23.16%	26.68%	55.32%	18.00%

Dataset

Data collection was carried out for five weeks. The participants received information on using our applications, their rights (e.g., erasing their collected data on request), and privacy protection measures. Our privacy officer and ethics committee approved consent forms and data collection procedures. Overall, we captured data from 16 participants—13 male and three female. At the time of our data collection, participants were between 19 and 41 years old ($M = 31.44$ and $SD = 5.17$ years). The study population comprised junior and senior academics and technical staff members. Their major tasks involved experiments, writing research papers, proposals, and the documentation of technical matters. Participants lived in five different countries on two different continents. We captured data from 14 Android, 12 Windows, and two macOS devices. In total, 3255 out of 10,701 questionnaires (answering rate = 30.41%) were answered. The overall answering rate is comparable to other ESM-based studies within the field of interruptibility.¹⁶ A distribution of ESM answers per device and class is shown in Table 2.

Feature Engineering and Classifiers

Table 1 shows the list of features we used to train and validate our machine-learning models. We extracted features within periods of 15 minutes before an ESM questionnaire. The features encompass temporal, location, and application-based features, commonly used in attention management systems.⁵ We further computed features based on self-reported information—for example, the relationship to a contact. We also extracted application streams—long sequences of application usage prior to an ESM. The motivation behind extracting application streams is that they might contain unique patterns related to a particular social role. To form homogeneous application streams across devices, we first grouped applications within the application stream. As some applications appear in every application stream, we removed applications containing less or no information about the device interaction. Such applications included launchers, system updates, or home screens. All remaining applications preceding a ESM questionnaire were assigned to a unique sequence with a self-reported social role and interruptibility preference.

Application sequences are textual representations. Such representations need to be transformed into sparse matrices for machine learning. Common approaches to transform textual representations into sparse matrices are TF, TF-IDF, CV, or neural networks, such as Word2Vec (W2V). After a preliminary investigation, we chose CV that extracts the number of application occurrences within sequences. In addition to application-based features, we extracted features related to keyboard and mouse events.

Classifiers

We chose popular classifiers from the field of attention and interruption management.⁵ In particular, we evaluated multi-layer perceptron (MLP), K -nearest neighbors (KNN), logistic regression, ridge classifier, and decision tree. To extend our evaluation, we integrated ensemble-based learning, namely, AdaBoost and random forest (RF). We used a classifier that predicts the most frequent class as the baseline. To provide a unified representation to our classifiers, we decided to apply a binary encoding scheme to self-reported roles and interruptibility preferences. In particular, we encoded interruptibility to fall in the categories: 1) interrupt-private—{yes, no}, and 2) interrupt-work—{no, yes}. Consequently, the interruptibility of both and none are encoded as interrupt-private and interrupt-work as {yes, yes} and {no, no}, respectively. The same encoding was performed for social role answers. Note that the evaluation of our models was carried out on the original classes. We chose the weighted F1-score to evaluate our personalized classification models. This metric combines both precision and recall with the support of each class. Classifiers are trained on a randomized train and test split.

INTERRUPTIBILITY AND SOCIAL ROLE CLASSIFICATION

In this section, we report on the results of our interruptibility and social role models. People may not use their phones during work or their work computer while being private. In such situations, we cannot collect interactions with both devices at the same time. Therefore, we trained our classifiers separately as we

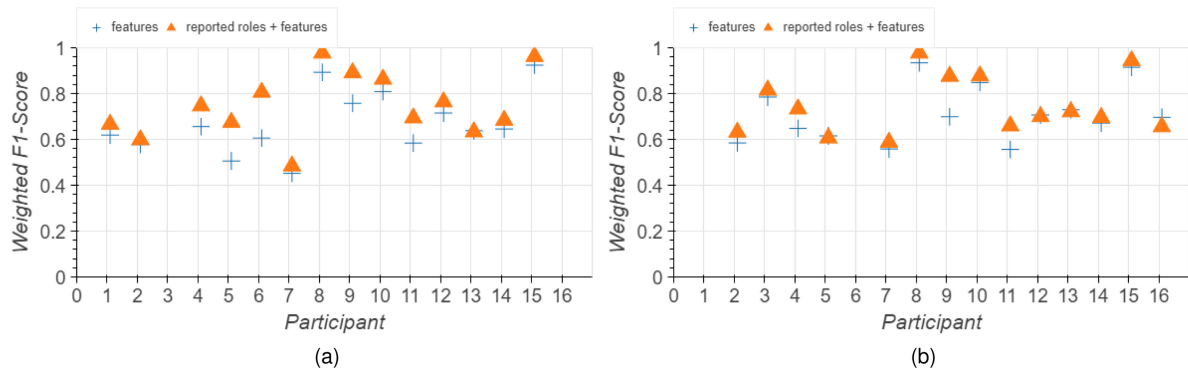


FIGURE 1. Weighted F1-scores of the RF classifier for inferring individuals' interruptibility. (a) Phone-based features. (b) Computer-based features.

were interested in whether our models would be comprehensive enough to detect social roles and individuals' interruptibility under these circumstances. We first investigate the performance for classifying four different interruptibility preferences, namely work, private, both, and none. We then move on and report on our social role classification models.

Classifying Individuals' Interruptibility

We built interruptibility models on common temporal and location-based features used in previous studies.⁸ Furthermore, we added the number of unique applications, physical activities, pressed keys, or the currently selected ringer mode to the feature set. Before we detail the results per device and participant, we present general classification performances computed over all participants and devices. We computed the 25th, 50th, and 75th percentiles and the mean of weighted F1-scores of all participants and classifiers. All classifiers outperformed the baseline. The median interquartile F1-score of all classifiers ranged from 0.58 to 0.67 (baseline 0.44). The KNN and Adaboost classifier showed outliers below the 25th percentile, whereas the logistic regression and ridge classifier achieved lower minimum and higher maximum F1-scores. Overall, the RF showed the most stable results with a median interquartile F1-score of 0.67.

To investigate whether incorporating social roles within interruptibility models enhances the classification performance of individuals' interruptibility, we added participants' self-reported roles to our machine-learning models. The classification performance of all classifiers is improved by adding self-reported roles. The most significant improvement was observed for the ridge classifier. A conducted paired t-test confirms a statistically significant improvement

of the RF classifier. By setting the significance level α to 0.05, we note that the classification of individuals' interruptibility preferences based on features only ($M = 0.70$, $SD = 0.13$) improves significantly by adding information on self-reported social roles ($M = 0.74$, $SD = 0.13$) as an additional feature ($t = -4.37$, $p \leq 0.05$). The improvement has a medium effect size with a Cohen's d metric of -0.36 . Figure 1 shows the classification results of the RF classifier per participant with and without self-reported social roles. We note individual differences in the improvement when incorporating self-reported social roles. As shown in Figure 1(a) and (b), participant 15 shows a comparable performance but no improvement. However, the classification performance for participant 5 improves when including self-reported social roles on phone-based but not for desktop-based features. The results indicate the importance of incorporating social roles within interruptibility classification.

Classifying Individuals' Social Roles

To augment future interruptibility models with individuals' enacted roles, we first need to extract their social roles through machine learning. Therefore, we trained and tested the same classifiers as above on all features (see Table 1) to extract social roles—private, work, and both. We first present classification performances computed over all participants and devices. We then detail classification results per device. Analog to our interruptibility classification results, we computed the 25th, 50th, and 75th percentiles and the interquartile mean of obtained F1-score.

We note that all classifiers perform better than the baseline. The median interquartile of the evaluated classifiers ranged from 0.76 to 0.83. The

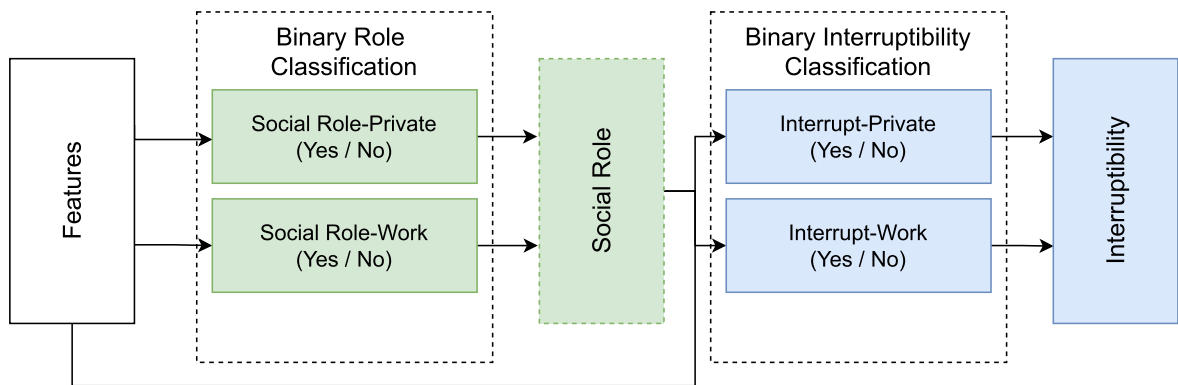


FIGURE 2. Two stage binary classification approach for inferring roles and interruptibility preferences.

baseline classifier achieved a median interquartile F1-score of 0.45. The logistic regression showed a maximum of 0.93 and a corresponding minimum of 0.59 weighted F1-score. Over all participants, the RF achieves the highest median F1-score of 0.83 for inferring social roles. The mean classification accuracy was 0.81. Considering the performance for each class, we note that private and work achieved a recall of 0.83 and 0.65 when training the models on phone-based features only. For desktop-based features, we achieved a recall of 0.84 and 0.71. In both cases, the performance of the social role both with a recall of 0.32 and 0.25 was underwhelming. A potential explanation is that both represents the combined role of private and work and, therefore, is harder to detect.

TOWARD SOCIAL ROLE-BASED INTERRUPTIBILITY CLASSIFICATION

The results from our interruptibility and social role classification models motivated us to combine both models. Therefore, we designed a social role-based interruptibility classification approach. This approach focuses on individual social behavior and related preferences to infer individuals' interruptibility. It is based on individuals' intrinsic interruptibility preferences—established for and across different social roles. The design of our social role-based interruptibility classifier is shown in Figure 2. Individuals' private- and work-related roles are classified in the first stage. This newly gained information is added to the available feature set from Table 1 and fed to the binary interruptibility classifier in the second stage. Our two-stage model uses the RF classifier, which showed promising results in our previous models. The interruptibility models in the second stage then perform binary classification of

individuals' interruptibility preferences. The binary result is then decoded to represent our former four interruptibility preferences—private, work, both, and none. Figure 3 shows the results of the social role-based interruptibility classifier per participant and device. We note that the biased classified social role still improves the classification of individual interruptibility preferences. As shown in Figure 3(a), all participants except participant 15 achieve higher F1-scores for detecting their individual interruptibility preferences if using social role-based interruptibility models. When using computer-based features, all participants achieve higher or at least equal F1-scores for social role-based interruptibility models compared to traditional models, as shown in Figure 3(b).

We conducted a paired t-test to investigate if our two-stage interruptibility classification model performs differently than those interruptibility models that have been trained on temporal and application-based features. Our social role-based interruptibility models ($M = 0.73$, $SD = 0.13$) perform better than traditional interruptibility models ($M = 0.70$, $SD = 0.13$) setting $\alpha = 0.05$ ($t = -5.21$, $p \leq 0.05$). The effect size is small to medium with a Cohen's d metric of -0.23 . There were no statistical differences between interruptibility models evaluated on classified or self-reported social roles.

MULTIDEVICE CLASSIFICATION

In this section, we investigate the impact of multidevice data on social role and interruptibility classification. We conducted multiple paired t-tests and set α to 0.05. Further, we use the RF classifier, which showed promising results. As shown in Table 3(a), we note that the combination of features from phones and computers ($M = 0.78$, $SD = 0.08$) significantly improves the classification for the private role compared to using

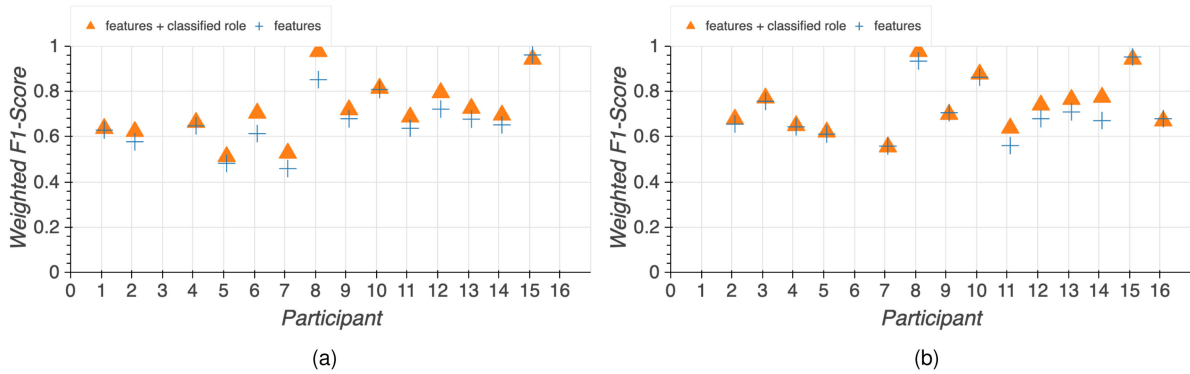


FIGURE 3. Weighted F1-scores of the RF classifier for social role-based interruptibility classification. (a) Phone-based features. (b) Computer-based features.

only phone-based features ($M = 0.76, SD = 0.12$). The effect is significant ($t = -2.63, p \leq 0.05$). The same observation applies to the work role where phone and

TABLE 3. Impact of devices on the classification of social roles and interruptibility preferences.

(a) Phone versus combination				
Variable	Phone	Combination	t-statistic	α
Social role				
Private	$M = 0.76$	$M = 0.78$	-2.63	$\leq .05$
	$SD = 0.12$	$SD = 0.08$		
Work	$M = 0.78$	$M = 0.83$	-5.32	$\leq .05$
	$SD = 0.12$	$SD = 0.07$		
Interruptibility				
Private	$M = 0.69$	$M = 0.74$	-2.97	$\leq .05$
	$SD = 0.20$	$SD = 0.17$		
Work	$M = 0.43$	$M = 0.45$	-0.89	0.39
	$SD = 0.37$	$SD = 0.37$		
(b) Computer versus combination				
Variable	Desktop	Combination	t-statistic	α
Social role				
Private	$M = 0.79$	$M = 0.78$	1.67	0.10
	$SD = 0.08$	$SD = 0.08$		
Work	$M = 0.84$	$M = 0.83$	1.11	0.27
	$SD = 0.06$	$SD = 0.07$		
Interruptibility				
Private	$M = 0.75$	$M = 0.74$	0.75	0.46
	$SD = 0.17$	$SD = 0.17$		
Work	$M = 0.46$	$M = 0.45$	0.15	0.87
	$SD = 0.42$	$SD = 0.37$		

computer-based features improve the classification performance ($t = -5.32, p \leq 0.05$). Further, the combination of both devices only improves the interruptibility inference for private-related matters. No significant effect is observed for the interruptibility preference work. Considering the classification of social roles and interruptibility preferences using only computer-based features [see Table 3(a)], we note that the mean classification performance for being interruptible for private related matters ($M = 0.75, SD = 0.17$) as well as for work ($M = 0.46, SD = 0.42$) is comparable to the results of the combination of computer and phone-based features. The same observation applies to the mean classification results for the private and work social role. To investigate these observations further, we applied a fixed-effects multinomial logistic regression to analyze dependencies between interruptibility preferences and social roles. We modeled interruptibility preferences as dependent variables (DVs) and social roles as independent variables (IVs).

Further, temporal features from our feature set were added as time-varying covariates—leading to four different models. Significance levels and estimated coefficients remained stable—even after integrating time-variant variables in our models. Our results indicate that participants engaged in a private role were more willing to be interrupted by private-related matters. In contrast, participants were either more interruptible for work-related matters or not interruptible while working. Furthermore, the dependencies of interruptibility preferences and roles primarily suggest a within-role interruptibility. Participants are more interruptible for events originating from the role they are currently enacting than from different roles, indicating a tendency toward segmenting matters of their private and work-related roles.

DISCUSSION

Although our results indicate that information on individuals' enacted social roles can improve interruptibility classification, there are still open challenges to be considered. Our results are based on a mobile sensing study with 16 participants over five weeks. Features extracted on application usage, contacts, and the relationship to these contacts are subject to each participant. Therefore, it is challenging to generalize our results. Still, our classification results align with research findings in social and behavioral science showing that interruptions breaching individuals' preferences have adverse effects on their well-being,⁴ and concepts are needed to negate them.¹⁷ Further, the target variables we used within the classification were biased among the study population. Individuals frequently selected private or work as a social role when asked on their smartphone or computer, respectively. Under these circumstances, our classification performance showed robust results regarding the F1-score as a combination of precision and recall. Classification models, in addition, outperformed the baseline classifier that predicted each individual's most frequent interruptibility preference. However, the distribution of our target variables might explain the multidevice t-test results in Table 3. As participants frequently selected work as a social on their computers, the classification performance for work increases when combining features taken from both devices—as computer-based features might contain more descriptive features for work.

IMPLICATIONS

Our results suggest that the classification of social roles can enhance interruption management systems by covering individuals' life domains. Our approach is a complementary addition to well-established techniques based on breakpoints⁸ or mental workload.¹⁸ In the future, social role-based attention and interruption management can be combined with short-term-based approaches in a staged system. Such a staged system can infer individuals' enacted social roles and related interruptibility preferences while identifying short-term moments for immediate interruptions. In the first stage, the system provides information on users' receptivity toward interruptions related to their more general preferences. If users are segmenting demands, they may not be interruptible by notifications from friends or reminders from private-related applications while working. Relevant interruptions can be identified by mapping the origin of interruptions to individuals' current roles. If individuals' preferences and interruption origin coincide, short-term-based approaches further identify opportune moments for supporting individuals'

fine-grained interruptibility. Interruptions might then be deferred to breakpoints or moments with a low mental workload and handled according to common strategies—negotiated, scheduled, immediate, mediated.¹⁹

Our experimental results might prove helpful in future work environments and organizations where work- and private-related interruptions are prevalent. While working, a social role-based interruption management system enforcing an individual's segmentation preferences can defer private-related interruptions to when employees start enacting their private role again. The system might also allow interruptions for an employee's private roles when applying an integration preference. Therefore, the system provides a means for organizations to employ regulations and policies to support their employees' work-life balance and well-being by reducing unwanted interruptions.⁴

Ethics and Privacy

There is an imminent risk of misuse and abuse of information on social roles for workplace surveillance and productivity assessments. These risks multiply as soon as detailed and fine-granular roles (e.g., parent, student, supervisor, or colleague) become available. With such a fine granularity, detailed profiles on social identities become practicable, including how people structure and organize demands in their environment. Consequently, the risk and chances of social role-based interruption management systems have to be weighted.

A socio-technical design approach could mitigate risks related to misuse and workplace surveillance. A key concept of socio-technical design is that the performance of a to-be-designed system depends on the joint optimization of technical and social subsystems. Social subsystems include employees' and employers' interests and requirements that have to be weighted and equally considered in a workplace environment. The risk of misuse and workplace surveillance would then be addressed by system design. The use of multidevice data to build meaningful machine learning models bears additional privacy issues. To protect the exploitation of sensitive information, privacy-preserving machine learning models and methods related to differential privacy²⁰ might help. Furthermore, we propose processing the data anonymously and in compliance with GDPR directly on the user's device.

CONCLUSION

Pervasive and ubiquitous computing facilitates immediate access to information in the sense of always-on, including notifications and interruptions. Attention

management systems aim to address the challenge of defining short-term opportune moments for interruptions using machine learning and AI so that information delivery leads to fewer distractions. This work investigated the applicability of social role-based interruption management systems centered on the human being. Based on role theory and boundary management findings, we investigated the influence of social roles on the two-stage classification of four different interruptibility preferences.

A paired t-test confirmed that information on individuals' current social roles—private, work, both—significantly improves conventional interruptibility models. We combined social role and interruptibility classification in a novel two-stage classification model based on this finding. In the first stage, individuals' private- and work-related roles are classified to improve the recognition of the individual interruptibility preference (private-only, work-only, both, and none) in the second stage. Our results suggest that individuals' intrinsic interruptibility preferences—often established for and across different social roles and life domains—improve existing interruptibility approaches.

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