Smartphone-based Qualitative Analyses of Social Activities During Family Time

Kunchay Sahiti
Department of Computer Science
Shiv Nadar University
Greater Noida, India
ks981@snu.edu.in

Lakshmi Manasa Kalanadhabhatta
Department of Computer Science
Shiv Nadar University
Greater Noida, India
lm160@snu.edu.in

Suman Sankar Bhunia
School of Computing
National University of Singapore
Singapore
dcsssb@nus.edu.sg

Akshit Singhal
Department of Computer Science
University of Texas, Arlington
Texas, USA
akshit.singhal2@mavs.uta.edu

Rahul Majethia
Department of Mathematics
Shiv Nadar University
Greater Noida, India
rahul.majethia@snu.edu.in

ABSTRACT

With the evolution of nuclear families and diverse career options, families as social groups are spending lesser time together than in the past decades. In this work, we study both quantitative as well as qualitative aspects of time spent with family members through a smartphone-based pervasive study on a sample of 12 families over 14 days. Further, we also examine the perception of 78 millennials on what they feel about, and expect from, the time they spend with their families, however long it may be. We aim to identify the key parameters that shape family life in this day and age, along with examining the participation of individuals of various roles within the family in activities such as conversations, workout sessions, eating together and other social interactions. Among all activities detected to be performed by families reporting high satisfaction with familial life, *Eating Together* and *Using Smartphones Together* emerged as the most prominent ones. We discover a greater disparity among the habits of family members, especially millennials, staying away from each other as compared to those staying together.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Social and professional topics** → **User characteristics**; • **Applied computing** → *Sociology*;

KEYWORDS

Social Activity, Smartphone Sensing, Pervasive Studies, Human-centered Computing, Behavioral Trends

1 INTRODUCTION

One of the most common structures of social interaction is that among the members of a modern-day nuclear family. Hence, it is essential to study the collective behavior of a family – herein loosely defined as a group of people with blood relations staying together, under ordinary circumstances, in one home – in relation to their individual interactions with each other and with ubiquitous computing devices in the home environment. While the effect of technological overuse and the consequent distraction on interpersonal relationships of different natures has been studied previously[19], we undertake an ideologically different behavioral study. In this paper, we propose a minimally invasive methodology to gain insights into the nature of interactions between members of a family. We undertook a *two-part* study - the first monitoring families as a whole, and the second as a standalone survey on millennials. In the first part of the study, we performed a smartphone-based data collection and Ecological Momentary Assessment (EMA)[17] study, spanning 2 weeks, on a set of 12 families with varying size and member roles. Secondly, we conducted a survey of 78 millennials aged between 18-25 with detailed questions on both quantitative as well as qualitative aspects of their family time when they are at home. We primarily focus on answering the following questions with respect to these interactions:

- How do people in various familial roles spend time with their family, and more precisely, what social activities do they perform together?
- What is the nature of the interactions among family members? How satisfied are they with these interactions?
- Are families losing out on spending quality time together with each person being engrossed in their own smart devices?

In this work, we specifically evaluate the feasibility of answering the above mentioned questions from data streams collected from the smartphones of each family member. To this end, we collect various data points (described in 3.3) unobtrusively from the Android smartphones owned by each member of our representative families using our data collection application. We also invite users to log subjective indicators such as their mood and emotional satisfaction. We use this data to recognize the social context of the user and model the group behavior of a family. The results of both the data-based family study as well the responses from our survey of millennials regarding social activities and smartphone usage patterns during family time exhibit interesting findings. While constant interaction with one's smartphone during family time is becoming a norm with millennials, eating together is still one of the deciding social activities of the happiness barometer within the families monitored. The reflection of a mixture of old traditional sayings ("*The family that eats together stays together - Matthew 24:14*") in the data study, and the process of acclimatization to the smartphone being an active member during family time, intrigues and motivates deeper analysis, some of which we have attempted to present in this paper.

The rest of the paper is organized as follows. Section 2 outlines some of the related work in social activity mining and psychological studies about families as social groups. Section 3 explains in detail the methodology behind both the data collection study on families as well as the qualitative survey on millennials, and acknowledges the demographic limitations of the present work. Section 4 presents a preliminary analysis of, and corroboration between, the data collected and what individuals opined about their interaction with family. Finally, Section 5 provides a roadmap to resolve current limitations and achieve deeper interpretation of abstract parameters such as remote interactions and emotional closeness between family members.

2 RELATED WORK

2.1 Quantifying effects of Social Activities

Understanding and interpreting human behavior and activities and utilizing ubiquitous sensing techniques to achieve the same has gained much traction in the recent past with the emergence of interest in quantifying and improving individuals' mental state and well being. Rabbi et al. in [14] demonstrated assessment of physical and mental wellbeing through smartphone sensors; a similar concept was also proposed in [11]. Ishimaru et al. in [9] presented the concept of the 'Thermometer for the mind' - a platform that estimates the mental state of an individual through sensing their social and physical activities. Such work has been improved upon by targeting specific interest groups, such as students, or the elderly, so that certain social activities and their effect on mental well being can be effectively studied, such as in [20] and [2]. Considering families as another specific type of group, we are optimistic about being able to integrate familial behavior with existing models of social well-being via the study conducted.

2.2 Activity Mining in a Social Context

Social activities have also been mined with respect to significantly larger bodies of individuals, such as groups, communities and crowds. The Reality Mining Project [7] made significant contribution to the field of social activity mining through the usage of mobile phones, paving the way for contextual analysis of social behavior through the usage of smartphones. Weppner et al. have analyzed crowd density using smartphones in [21] and [22]. Crowd analysis contextualizes the usage of methods such as crowdsourcing as a means of social data analysis, but behavior analysis requires individual or group identification within crowds. Sen et al. in [16] presented a platform for identifying and monitoring groups in urban spaces with 97% accuracy. Further, Jayarajah et al. in [10] analyzed user behavior in groups, showing significant differences when contrasted to user behavior in an individual context, highlighting interactions as a function of group dynamics. We wish to combine the motivations of researchers with prior work in this field, and augment upon the same by focusing on the effect of an identified group's (family) dynamics upon a specific social activity and vice versa, shedding light on the interactions that form the basis for the healthy functioning of a group, while simultaneously attempting to understand the contributions of social activities to these interactions.

2.3 Families as Social Groups

"As the family goes, so goes our civilization", as said famously by Reagan [15]. Families, both extended and nuclear, serve as one of the fundamental structures of the society [12]. The functions of family as a social group are vast, but essentially boil down to maintaining social stability. Bengtson's [3] work on nuclear families highlights the importance of looking beyond the apparent in order to glean the importance of underlying interactions and relationships. Burgess [5, 6], the pioneer of familial sociology proposed a fundamental shift in the function of a family - moving from an element of social structure to a system of relationships that supported an individual's social and emotional needs. The 'decline' of the nuclear family has been attributed to various factors that are bringing about a formative change in the way that individuals perceive families. The advent of legalization and increasing social acceptance of homosexuality, higher rates of divorce[1, 4], and consequent single parent households, has led to significant economic and social changes in the family. In such a socially dynamic context, it becomes increasingly important to investigate the interactions that constitute functional families. In order to begin to improve an individual's state of wellbeing, it is essential that one investigates an individual's state within a family, and the interactions that make it thus. In doing so, we build on the preliminary work by Spruijt-Metz et al., wherein the eating dynamics of families are monitored using an array of sensors throughout the home [18]. However, our work also diverges from the multi-sensor model to use only off-the-shelf smartphones and minimally invasive Bluetooth Low Energy (BluetoothLE or BLE) beacons. Our work tackles these fundamental interactions and examines their effect on the individual, and by large, the society.

3 METHODOLOGY AND SYSTEM DESIGN

3.1 Interpersonal Relation Cognizance

A crucial component of our study is the ability of our application (described in 3.3) to recognize and monitor the interactions between

Families surveyed	12 (2-4 members each)
Age range	18 to 60 years
Gender	46% male, 54% female
Individual millennials surveyed	78
Age range	18 to 25 years
Gender	55.12% male, 44.88% female

Table 1: Demographic Information of Participants

different members of a family while both individually identifying them and taking into account the nature of each interpersonal relationship. For the purpose of this study, we assigned each of our target families a unique *familyID*, which the members enter in the Welcome Form on installing the application. Subsequently, each member of a particular family is asked to select the nature of their relationship with the other members – the possible options being *Partner or Spouse*, *Child*, *Parent* and *Sibling* – as and when a new member with the same *familyID* registers with our application. An addition to the family results in an added relation between all the existing members and addition of new relations or an update of existing relations. These renewed relationships are stored and subsequently utilized in order to filter queries on the basis of relations.

3.2 Proximity Determination

The behavior of various families that participate in the aforementioned study is primarily quantified and defined using data from a smartphone application built for the Android platform, in conjugation with BluetoothLE beacons installed in the homes of said families. The data collection application measures and captures various parameters that optimally reflect the family's collective behavior.

Firstly, to sense familial group behavior within a home, we install BluetoothLE beacons in rooms where most communal interactions among family members usually take place. These rooms are identified through a preliminary observation as well as specific inputs from family members. To locate individuals in these rooms, we utilize their smartphones' Bluetooth capability to scan for these beacons, and determine their distance from each of them by recording the respective Received Signal Strength Intensity (RSSI) values. A free-space path loss model is assumed to model RSSI propagation. We then employ trilateration to position individual family members on a 2-dimensional plane, and proceed to determine the collective participation of the family (or a subset thereof) in a common activity within proximity of one another. We define the family (or a subset of said family) to be within proximity of one another when there is at most a 3 meter distance between the members. This metric was realized through continuous ground truth collection of whether the family members believed that they were in physical proximity of one another.

An important facet of family time is the collective involvement in activities outside the home. Therefore, we also define group behavior among family members outdoors through a slightly different approach. While none of the BluetoothLE beacons associated with the family's living spaces are found in the vicinity of the smartphone, we assume that the individual is not presently at home.

If, in this situation, his/her smartphone scans a family member's smartphone, we assume that they are together in the same locale.

3.3 Smartphone Data Collection

We now describe the collection of activity data using our smartphone application. We obtain the activity being performed by a certain family member through Google's ActivityRecognitionAPI, which recognizes and classifies a wide range of activities such as Still, Running, Walking, In Vehicle, etc. Using these labels, we also classify activities that members engage in as a group (i.e., when they are in proximity to one another). To this end, we identify *Conversation/Watching TV* as the event wherein all members are reported to be Still, *Traveling* when they are together In Vehicle, *Working out/Exercising* when they are Running or Walking for a continuous period, and *Eating* when they are together and Still at previously self-reported meal timings. We validate these activities, along with any identified family members in proximity, by sending EMA notifications requesting feedback to the smartphones of the members identified as engaging in said activity. An example of such a notification is presented in Figure 1.

In order to recognize the growing trend of using smartphones in the presence of family, we classify smartphone interaction by the family members within proximity of one another as another common activity that is pursued collectively by said members. We define smartphone interaction as an event wherein the device's screen is turned on for a duration longer than 1 minute (in order to take into account the brief turning on of screens due to notification arrival).

Furthermore, to assess the mood of individual family members and their level of satisfaction with their current familial interaction, we also prompt users to log the same by pushing EMA notifications as shown in Figure 2. As opposed to opportunistic querying at physical activity breakpoints as suggested in [13], our application delivers EMA prompts on the basis of interaction breakpoints, i.e., after a user has been identified as having spent at least 5 minutes in proximity to one or more of his family members. The responses logged at this time give us a fair indication of the effect that interacting with family member(s) might have on the user's mood.

The analysis of the data collected by the aforementioned application takes place after it has synced with the database, an activity that occurs once at the end of every day-session. A daily summary of personalized interaction statistics is also sent to each participating family member. An example of the same is shown in Figure 3. The daily statistics are meant to allow the individual to reflect on their day-to-day patterns of interaction and adjust their routine to spend time with their family members in a more productive manner in the upcoming days.

We examine the collected data to infer knowledge regarding the family dynamics in various contexts, the results of which are reported in Section 4. We recognize the efficiency and power consumption constraints that might arise while implementing such an application, which prompts the implementation of smart sampling strategies, elucidated upon in subsection 3.5.
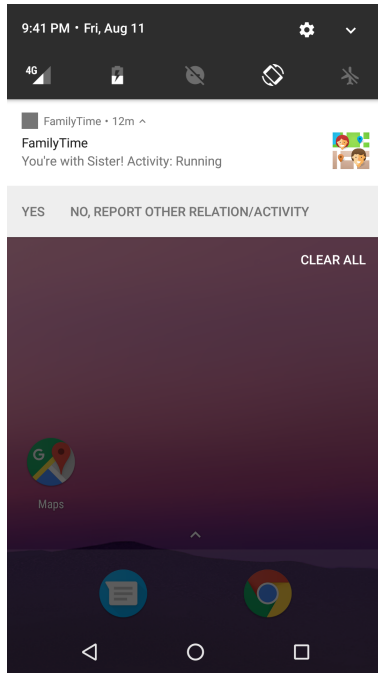
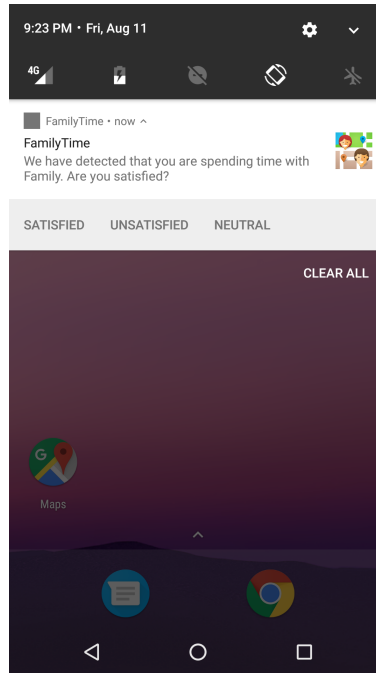**Figure 1: EMA to validate family members in proximity and activity**

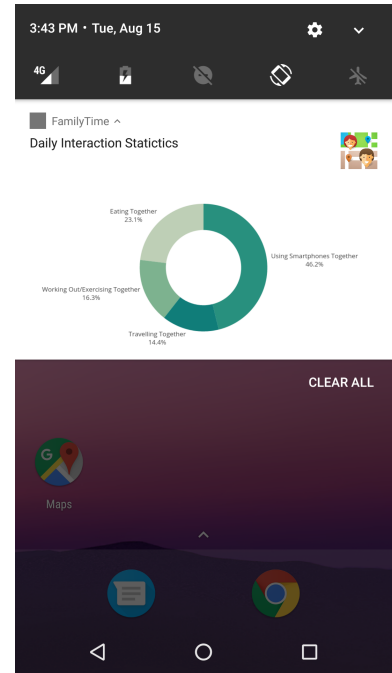**Figure 2: EMA notification with satisfaction survey**

Figure 3: Daily familial interaction summary notification

3.4 Monitoring Diverse Families

To best understand how families interact in today's interconnected social environment, it is essential to study diverse families across different cultural and geographical domains, as well as across various social strata. The demographic spread of our target group, all residing in India, is shown in Table 1. The participants of our study belong to 19 different states of India. We recognize that while it is beyond the scope of the present work, the study needs to be extended to families from diverse income backgrounds living in homes that could be of varying sizes (to account for proximity thresholds), and to families from other location demographics so as to account for differing expectations with respect to one's family across cultures.

3.5 Sampling strategies

To make our data collection application more optimal while retaining efficiency, we adopt a set of sampling strategies while collecting sensor data. As part of the preliminary survey, our participants are required to self-report their usual sleeping schedules. These are then utilized to turn off sensing activities during the night when interpersonal interaction is minimal. This is done by applying an exponential back-off strategy [8] starting at the participant's reported sleeping time, which can only be overridden by continuous and considerable change in either the phone state, physical activity or device proximity. After continuously sampling at a chosen minimum frequency for 20 minutes, the app stops collecting sensor data for the night and uploads the day's data to the server. Sampling at usual rate resumes once more at the reported waking time of the user. Moreover, to further conserve battery, Bluetooth scans

for identifying nearby devices also follow an exponential back-off scheme when no other family members' devices are located within the proximity range defined in subsection 3.3.

4 PRELIMINARY RESULTS

4.1 Intra-family Interactions

In this subsection, we present the insights gained from our quantitative application-driven study targeting Indian families. We also put forward the evidence substantiating the same, collected through our post-study survey. The study itself involved deployment of our data collection application among members of 12 participating families, which consisted of 2 (couples) to 4 members (nuclear). Preliminary analysis of the observations obtained through the data collection application and the follow-up survey revealed that families that reported being *Extremely Satisfied* to *Satisfied* with their family life partook in the following activities together (not mutually exclusive, as the respondents could partake in more than one activity): *Eating/Dining* (59.25%), *Working Out/Exercising* (14.81%), *Watching TV* (40.7%), *Traveling* (29.6%), and *Engaging with Smartphones* (74.08%). Further, the aforementioned activities were undertaken with a greater mood defined investment (i.e., while participating in these activities, the mood of the individuals ranged from *Happy* to *Amicable*).

In order to gain additional insights into social activity in the familial context, we segregated the family into subunits – *Children*, *Parents*, and *Couples* – based on mutual relationships. As can be observed from Figure 4, within families reporting high satisfaction, *Eating Together* emerged as the most prevalent activity among *Children* and *Couples*, with 80% and 81.81% subunits of families
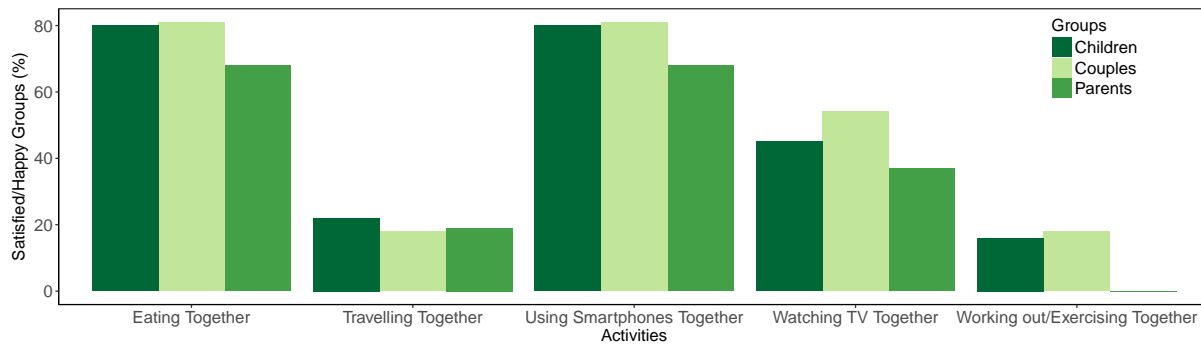
Figure 4: Social Activity Distribution of Sub-units of Families Reporting High Satisfaction During Time Spent Together

respectively reporting a high satisfaction rate with their familial engagement in this activity. Surprisingly, *Smartphone Usage* emerged as an equally prevalent group activity across all subunits (80% for *Children*, 81.88% for *Couples*, and 68.75% for *Parents*) among said families, subtly reinforcing the fact that smartphones are materializing into the social institution of the family.

Further, a gender based analysis was conducted among family members and the percentages of female and male familial population reporting high rates of satisfaction among the performed and detected activities were examined. It was observed that the highest percentages of both male and female members report high satisfaction in the time spent with family members while *Eating Together* (64.7% & 68.42% for Female and Male respectively) and *Using smartphones together* (64.7% & 68.42% for Female and Male respectively), while *Working out/Exercising together* (11.76% & 5.26% for Female and Male respectively) had the least amount of individuals from either genders reporting a high satisfaction rate. The activities in which the highest difference of proportion of individuals reporting high satisfaction rates were observed among the sexes were *Working out/Exercising together* (6.5% difference) and *Traveling together* (7.74% difference), with lower male family members reporting high satisfaction rates in both activities.

4.2 Familial Expectations Among Millennials

In addition to the families studied, we invited students through a University mailing list to respond to a survey on family time while visiting home. In doing so, we collected qualitative results from 78 individuals (43 male and 35 female, age group 18 to 25 years), who were not part of the initial study on families. The responses of these participants provide insights into the millennial generation's interaction habits with their family, as well as their satisfaction with the quality of time they spend with their family members.

Figure 5 is a comparison of the collective participation in various activities among families who live together and families of millennials who normally live separately. As opposed to 50.5% of the participants staying with their families who reported having similar sleep schedules to their family members, over 70% of millennials admit that their sleep timings are strikingly different from those of their relatives. Similarity of workout schedules is also low among the younger generation (around 9.3%) as compared to families living together (18.97%). Nearly a third of the millennials surveyed

(32.64%) opine that their habits and schedules are contrary to those of their families, suggesting the possibility of differences in habits developing over time with family members living apart.

It is intriguing to observe that only 5.4% of the total respondents said they dedicate their complete attention to their family while with them, whereas almost 28.38% prefer to multi-task between their phone and family. Only 15.3% of the participants felt that their phone was a source of distraction. Surprisingly, people who admitted that they usually spent time on their smartphones while interacting with their families did not seem to think this affected the quality of family time. Among the 22 respondents who said they multi-task between phone and family, 12 (54.54%) reported that the general environment at their homes was "mostly pleasant and cheerful". 10 of them also expressed being extremely satisfied with the quality of family time, while very few people (only 2 respondents) said they were extremely dissatisfied. Whether this is a bias from a millennial perspective or a culture of increasing acceptability of the phone as a ubiquitous presence during familial social activities needs to be understood in depth.

Similar to the analyses performed on familial interaction data, a gender based analysis was also performed on millennial interactions. *Eating Together* (68.42% & 66.67% for Female and Male respectively) and *Using Smartphones Together* (68.48% & 66.7% for Female and Male respectively) emerged as the predominant activities performed by individuals reporting to be Happy/Satisfied. *Working Out/Exercising Together* reported a lower percentage of Happy/Satisfied millennials (15.7% & 11.12% for Female and Male respectively).

5 CONCLUSION AND FUTURE WORK

In this paper, we report the findings from our study on the levels of satisfaction observed in families that engage regularly in various social activities. We observed that a majority (59.25%) of respondents reporting high satisfaction with their familial interactions regularly dined with their families. Interestingly, 74.08% of these individuals also spent considerable time on their smartphones while with their families, cementing our belief that the smartphone has become an indispensable part of social life, at least in a familial setting. We also studied the variation of activity participation habits among
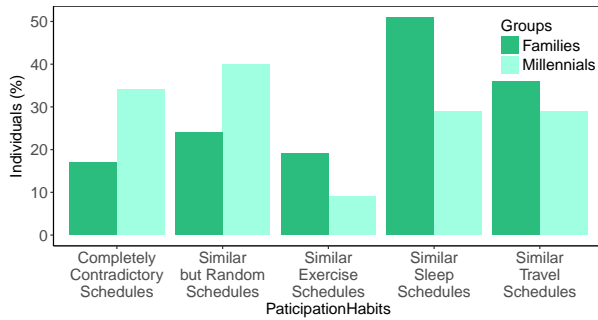
Figure 5: Collective Activity Participation Habits Among Families and Millennials Living Separately

different subunits of families and among male and female members of families.

Further, we surveyed a group of millennials in the 18 to 25 year age range to understand their views on family time as well as their satisfaction with the quality of the same. Around a third of the millennials living away from home report schedules disparaging from those of their families (while visiting), as opposed to very few family members living together. This suggests a divergence of habits coming about over a considerable period of living apart. Moreover, while only 5.4% of respondents claimed to dedicate their full attention to their families while spending time with them, most reported satisfaction with the quality of family time.

While we gained numerous insights into the social activity of family time through this work, we acknowledge the limitations of this paper and elucidate upon them herein. Firstly, there is an undeniable need to inclusively account for the behavior of varied and complex familial groups such as extended families, flat-mates etc. Also, it is important to replicate this study across populations from different demographics, as social pressures and expectations with respect to one's family may differ across cultures. Thus, the norms of familial interactions and closeness also tend to differ, as discussed in subsection 3.4.

Another avenue that can be explored to obtain contextually better results is the investigation of mood during activities in a minimally invasive or non-invasive manner, following which social behavior can be more naturally quantified. Additionally, since preliminary surveys indicated that the average size of rooms affects conversational distance between members, we plan to dynamically define proximity thresholds in the future with the help of deep learning models. We also plan to extend interaction detection to study their impact on individual members within a family, understand interactions among members while they are not in physical proximity, and determine the emotional closeness of an individual with other members in order to identify his/her support system.

REFERENCES

[1] Paul R Amato and Alan Booth. 2001. The legacy of parents' marital discord: consequences for children's marital quality. *Journal of personality and social psychology* 81, 4 (2001), 627.

[2] Gerald Bauer and Paul Lukowicz. 2012. Can smartphones detect stress-related changes in the behaviour of individuals?. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2012 IEEE International Conference on*. IEEE, 423–426.

[3] Vern L Bengtson. 2001. Beyond the nuclear family: The increasing importance of multigenerational bonds. *Journal of marriage and family* 63, 1 (2001), 1–16.

[4] Larry Bumpass, James Sweet, and Teresa Castro Martin. 1990. Changing patterns of remarriage. *Journal of Marriage and the Family* (1990), 747–756.

[5] Ernest Watson Burgess. 1926. *The family as a unity of interacting personalities*. American Association for Organizing Family Social Work.

[6] Ernest Watson Burgess and Harvey James Locke. 1945. The family: from institution to companionship. (1945).

[7] Nathan Eagle and Alex Sandy Pentland. 2006. Reality mining: sensing complex social systems. *Personal and ubiquitous computing* 10, 4 (2006), 255–268.

[8] Jonathan Goodman, Albert G Greenberg, Neal Madras, and Peter March. 1988. Stability of binary exponential backoff. *Journal of the ACM (JACM)* 35, 3 (1988), 579–602.

[9] Shoya Ishimaru and Koichi Kise. 2015. Quantifying the mental state on the basis of physical and social activities. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*. ACM, 1217–1220.

[10] Kasthuri Jayarajah, Youngki Lee, Archan Misra, and Rajesh Krishna Balan. 2015. Need accurate user behaviour?: pay attention to groups!. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 855–866.

[11] Nicholas D Lane, Mu Lin, Mashfiqui Mohammod, Xiaochao Yang, Hong Lu, Giuseppe Cardone, Shahid Ali, Afsaneh Doryab, Ethan Berke, Andrew T Campbell, et al. 2014. Bewell: Sensing sleep, physical activities and social interactions to promote wellbeing. *Mobile Networks and Applications* 19, 3 (2014), 345–359.

[12] David M Newman. 2009. *Families: A sociological perspective*. McGraw-Hill Higher Education.

[13] Mikio Obuchi, Wataru Sasaki, Tadashi Okoshi, Jin Nakazawa, and Hideyuki Tokuda. 2016. Investigating interruptibility at activity breakpoints using smartphone activity recognition API. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM, 1602–1607.

[14] Mashfiqui Rabbi, Shahid Ali, Tanzeem Choudhury, and Ethan Berke. 2011. Passive and in-situ assessment of mental and physical well-being using mobile sensors. In *Proceedings of the 13th international conference on Ubiquitous computing*. ACM, 385–394.

[15] Ronald Reagan. 1984. Address before a Joint Session of Congress on the State of the Union - February 6, 1985. *Washington, DC, January* 25 (1984).

[16] Rijurekha Sen, Youngki Lee, Kasthuri Jayarajah, Archan Misra, and Rajesh Krishna Balan. 2014. Grumon: Fast and accurate group monitoring for heterogeneous urban spaces. In *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*. ACM, 46–60.

[17] Saul Shiffman, Arthur A Stone, and Michael R Hufford. 2008. Ecological momentary assessment. *Annu. Rev. Clin. Psychol.* 4 (2008), 1–32.

[18] Donna Spruijt-Metz, Kayla de la Haye, John Lach, and John A Stankovic. 2016. M2FED: Monitoring and Modeling Family Eating Dynamics. In *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM*. ACM, 352–353.

[19] Catherine Steiner-Adair and Teresa H Barker. 2013. *The big disconnect: Protecting childhood and family relationships in the digital age*. Harper Business.

[20] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T Campbell. 2014. StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 3–14.

[21] Jens Weppner and Paul Lukowicz. 2011. Collaborative crowd density estimation with mobile phones. *Proc. of ACM PhoneSense* (2011).

[22] Jens Weppner and Paul Lukowicz. 2013. Bluetooth based collaborative crowd density estimation with mobile phones. In *Pervasive computing and communications (PerCom), 2013 IEEE international conference on*. IEEE, 193–200.