An Exploratory Study to Detect Temporal Orientation Using Bluetooth's sensor

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Abstract: Mobile sensing technology is allowing us to investigate human behaviour while performing day-to-day activities. In study we examined temporal orientation, which refers to the capacity of thinking or talking about personal events in the past and future. We utilize mk-sense platform that allow us to use experience-sampling method in daily life. Individual's thoughts and their relationship with smartphone's Bluetooth data is analysed to understand in which contexts people are influenced by social environments, such as the people they spend the most time with. As an exploratory study and based on previous work, we analyse social condition influence through collection of Bluetooth data and survey information from participant's smartphones. Preliminary results show that people are likely to focus on past events when interacting with close-related people, and focus on future planning when interacting with stranger. Similarly, people experience present temporal orientation when accompanied by known people. We believe that these findings are linked to emotions since in its most basic state, emotion is a state of physiological arousal combined with an appropriated cognition. In this contribution, we envision a smartphone application for automatically inferring human emotions based on user's temporal orientation by using Bluetooth sensors, we briefly elaborate on the influential factor of temporal orientation episodes and conclude with a discussion and lessons learned from this exploratory analysis.

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An Exploratory Study to Detect Temporal Orientation Using Bluetooth's sensor

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ABSTRACT

Mobile sensing technology is allowing us to investigate human behaviour while performing day-to-day activities. In study we examined temporal orientation, which refers to the capacity of thinking or talking about personal events in the past and future. We utilize mk-sense platform that allow us to use experience-sampling method in daily life. Individual's thoughts and their relationship with smartphone's Bluetooth data is analysed to understand in which contexts people are influenced by social environments, such as the people they spend the most time with. As an exploratory study and based on previous work, we analyse social condition influence through collection of Bluetooth data and survey information from participant's smartphones. Preliminary results show that people are likely to focus on past events when interacting with close-related people, and focus on future planning when interacting with stranger. Similarly, people experience present temporal orientation when accompanied by known people. We believe that these findings are linked to emotions since in its most basic state, emotion is a state of physiological arousal combined with an appropriated cognition. In this contribution, we envision a smartphone application for automatically inferring human emotions based on user's temporal orientation by using Bluetooth sensors, we briefly elaborate on the influential factor of temporal orientation episodes and conclude with a discussion and lessons learned from this exploratory analysis.

CCS CONCEPTS

• **Human Computer Interaction (HCI)** → Ubiquitous and mobile computing

KEYWORDS

Mobile sensing, Temporal orientation, Social environment, Human behaviour, Bluetooth.

1 INTRODUCTION

In psychology research, temporal orientation refers to relatively stable individual differences in the relative emphasis one places on the past, present, or future [1]. Temporal orientation has been widely examined in relation to personality traits [2], academic outcomes [3], risky behaviours [4], and health outcomes [5]. For instance, researchers have found that future-oriented thinking tends to reflect students' higher grades [1], [3], drink less alcohol, smoke less tobacco [4], [6], [7] and have a better financial planning [6]. Other findings involve demographic characteristics, such as gender [7], [8] and age, suggesting that as people age they tend to think less about the present and more about the future [8]–[10]. Consider three pairs of emotions: (a) regret and nostalgia, (b) boredom and joy, and (c) dread and hope. In each pair, emotions are opposed in valence but similar in orientation toward the past (a), present (b), or future (c) [11]. Overall, cognition capacity and sensibility to emotions offers the opportunity to humans for mental projection, allowing individuals to recall experiences from the past and simulate possible future events [12].

In this context, retrieving quality data associated with day-to-day scenarios is a challenge for the ubiquitous computing community due to unexpected technical and human-related behaviours [13]. Nonetheless, it is being rapidly developed due to the increasingly growing spread of mobile devices and their diversity of embedded technology. Sensor modalities available in modern smartphones consist of motion, thermal, sound, image, location, and proximity sensors, enabling the opportunity to intuitively obtain environmental context data [14].

Temporal orientation has been studied in relation to personality traits [2], academic outcomes [3], risky behaviours [4], and health outcomes [5]. In this regard, and considering that much of human behaviour and cognition occurs in social settings [15] we explore the possibility of analysing the temporal orientation of individuals' thoughts and conversations in real life by using nonintrusive technology. The study takes a set of data-analysis from a previously conducted pilot study, which was led by an interdisciplinary project entitled "Thought and Life Logging (Tholilo)" [16]. This paper builds upon the assumption that temporal orientation analysis is connected to affective behaviour [17]. Hence, by identifying person's temporal orientation, we hypothesise (to some extend) could unobtrusively detect person's emotional state, by using Bluetooth sensor.

This study aims to explore the feasibility of a smartphone application as a complementary tool to other techniques which could lead to a better comprehension of an individual's temporal orientation in social interactions. Hence, we examine the relationship between smartphone's Bluetooth sensor and the characterization of people that surround and accompany the participants (*e.g.*, co-workers, family, friends, strangers) with the participant's thoughts (*i.e.*, past, present, future). In contrast to the methodology reported by the related work [18], [19] which exclusively used proximity technology, we adopt smartphone surveys as a mechanism to capture participants' thoughts.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 presents the study conditions to collect data. Section 4 describes the different data analyses, and Section 5 briefly describe discuss a mobile application to illustrate the adoption of this study's findings. Section 6 summarizes the paper by providing a conclusion, and challenges.

2 RELATED WORK ON TEMPORAL ORIENTATION'S TRADITIONAL AND COMPUTATIONAL APPROACHES

Temporal orientation is traditionally assessed by self-reports and experience-sampling methods, such as the Zimbardo Time Preference Inventory, which is normally used to model student's academics achievement, risk-taking, drug use, and burnout [1]. The Future Consequences Scale, which provides tools to show the extent to which an individual's behaviour is influenced by hypothetical further outcomes, it's commonly used in contexts such as subjective well-being, social relations, health preventive behaviour and post-traumatic stress disorders [20], [21]. The Balanced Time Perspective Scale focuses on measuring the extent to which an individual exhibits positive and negative time perspectives [22].

As far as the authors are aware, there is only one study on temporal orientation adopting computation approaches. Park et al. [21] have presented a methodology to automatically measure temporal orientation through messages expressed on social media, concluding that language-based assessment can complement and extend existing measurements by providing an alternative approach and adding insights into language and personality relationships [11]. Understanding the factors that affect human behaviour is an important topic that has being explored by multidisciplinary research teams. For instance, Fiemke *et al.*, developed a computational model to analyse the benefits of exercising on mood regulation, that can be further utilized to develop tools to monitor an individual's sedentary life [23]. Other examples involve the use of a smartphone's Bluetooth feature as a proximity sensor to recognize social patterns in daily user activity, to infer relationships, and identify socially significant locations to understand individual behaviour [24]. The Reality Mining project uses Bluetooth sensors in combination with call data records and cellular-tower to detect social network structures and recognize an individual's social patterns [25]. To map human interaction, some projects use physical activity data from smartphone sensors to model the relationship between mood regulation and depression levels, and to predict the health status of individuals by estimating causality between physical symptoms and mental health [26], [27].

More recently, Takano K *et al.*, has investigated the moderating role of depression symptoms within daily activities and ruminative thinking. They examined situations and conditions in which ruminative self-focus is likely to occur among daily life activities [28] check ref. Guide A. *et al.*, used audio recording samples from smartphones by analysing running speech calls, in which voiced segments are featured to (*posteriori*) identify mental disorders, such as bipolarity [29]. And Mohino-Herranz *et al.*, assess mental fitness by using a customized wearable device to collect electrocardiogram signals. Then they considered different scenarios to evaluate people's mental conditions and the connection between physical activities with mental states and mental load [30].

The project described in this paper leveraged the use of embedded sensor capacities within smartphones and Bluetooth technology. We use smartphone surveys to collect participant's thoughts, so that our approach can complement other techniques towards helping researchers to conduct larger-scale studies in naturalistic conditions.

3 DATA COLLECTION USING M^K-SENSE PLATFORM

In this study we used Tholilo, which is a software package built upon the m^k-sense platform [31] that allowed us to use the experience-sampling methodology which involves repeated sampling of the same individual's thoughts, feelings and behaviours over time in natural contexts. Additionally, sensor modalities and survey notifications (*e.g.*, sampling frequency, duty cycle) were set up to monitor participant's data completeness [32].

A. Study

In order to collect participant's thoughts and feelings, participants were asked to enable the Tholilo package (available within the m^k-sense application), followed by a training session to appropriately fill out the experience-sampling surveys. In the conducted study, sensor data were collected in periodic time intervals to reduce battery consumption. The Tholilo package was configured to collect Bluetooth scan data (scans for devices every 5 minutes), GPS data (every 30 minutes), Accelerometer data (sampled with a frequency according to the user's device configuration at intervals of 10 seconds every 5 minutes), information on apps currently executing, and screen on / off states.

The first question in the survey was "Were you talking right before receiving the notification?". If the user answered Yes, they were automatically directed to the "talking survey". However, if they responded No, they were taken to the "thinking survey". These two surveys slightly varied, but each survey consisted of several questions to be answered by scrolling a bar, and by entering free input (*i.e.*, texting or audio recording). When for some reason the user ignored one survey, we provided a one-question survey in which the user could explain the reason for the previous omission.

Surveys are based on a previous study conducted at the University of Zurich [33]. Each participant was notified seven times a day at random time intervals to fill out the survey. Two example questions are shown in Figure 1.

B. Population

As part of the inclusion criteria, participants were required to install the Tholilo package on Android smartphones (temporarily borrowed) and carry their devices as usual. A total of 38 participants were involved in the study (22 males and 16 females) with an average age of 22.52 years old (σ = 6.64 years). Five participants (3 males and 2 females) were excluded from the data analysis due to lack of surveys filled out. Participants signed a consent letter to participate within the study; they were compensated with 50 Swiss Francs.

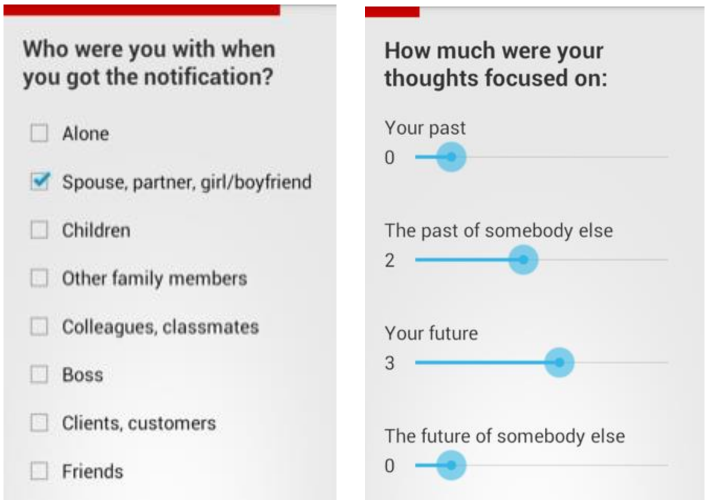

Figure 1. Interfaces of first and second page of the survey showing checkbox (left side) and 7-point Likert scale options to answer questions (right side).

A total of 512 talking surveys, 1,299 thinking surveys, and 349 missed surveys were collected during the seven-day period of the study.

4 SURVEY'S ANSWER AND BLUETOOTH'S SENSOR DATA ANALYSIS

Participants' surveys were associated to Bluetooth sensor data collected in the same interval of time, thus, answers could be mapped to smartphone sensors. We adopted Bluetooth as proximity sensor to infer person's presence [34], and participant's answer and temporal orientation self-report were linked to Bluetooth's sensor data utilizing Bluetooth's MAC address.

In this section we present the results in three categories: the first category elaborates on the number of devices around each participant. The second category uses logistic regression analysis by combining sensor and survey data, and in the last category we examine questionnaire-related data regarding social conditions that could influence participant's thoughts and utterances when experiencing temporal orientation (*i.e.*, thinking or talking about past, present, and future events).

A. Findings from average number of devices around the participant

In this section, three different scenarios are explored, when the participant is (1) accompanied with a known-person which includes (but is not limited to) people the user is familiar with, such as partner, relatives, friends, and colleagues; (2) surrounded by strangers; or (3) when the participant is alone.

As presented in Figure 2, the average number of devices around the participant is always smaller when accompanied by known persons compared to being surrounded by strangers. This is true for all time segments and for both talking and thinking surveys as shown in Figure 3. Moreover, note that results from the third category (*i.e.*, alone) show that no devices were detected, since by definition participants could not be talking while alone.

Thus, these results can be interpreted as the fact that when someone is with known people, he / she is usually in a more private environment (*e.g.*, home, office) with fewer people around.

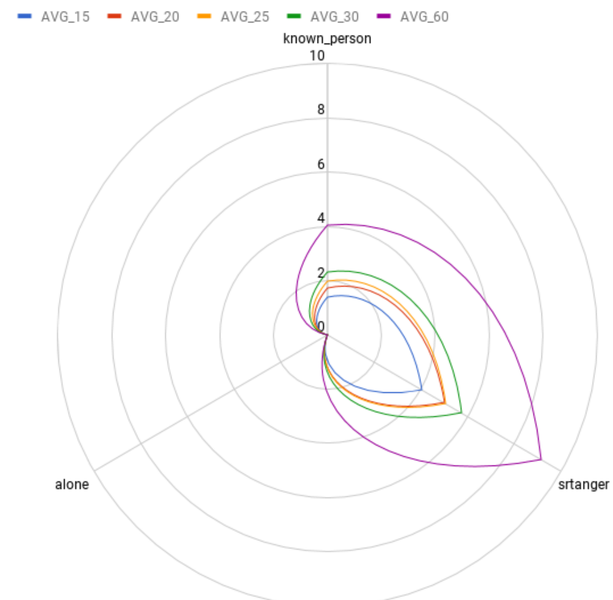

Figure 2. Average amount of unique Bluetooth devices detected by participants, while reporting to be talking. Each category represents a different time segment, for example 15, 20, 25, 30, and 60 minutes from the time the survey was receive by the participant.

During thinking, the average number of devices in proximity is always the smallest when being alone compared to being accompanied by known persons or strangers, as presented in Figure 3. The relevance of this results relies on the convergence between the data automatically collected by the smartphone and the information reported by the participant, which can be interpreted as that people tend to increase their mental effort when they perceive themselves as alone. This is true for all time segments.

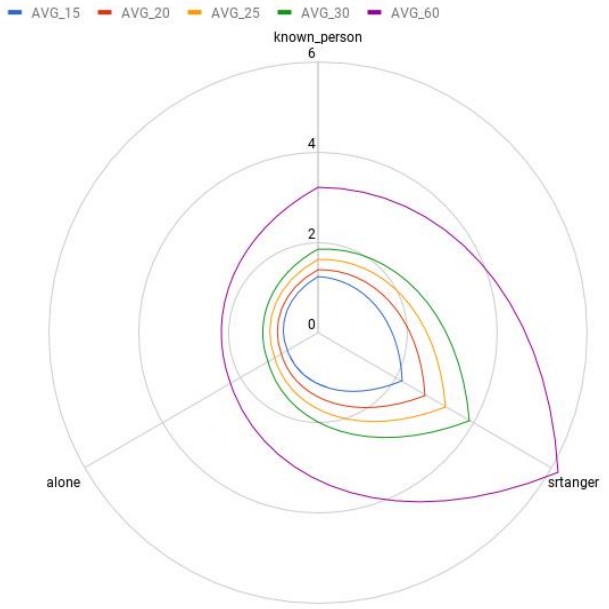

Figure 3. Average amount of unique Bluetooth devices related to people around the participant, while reporting to be thinking.

B. Findings from logistic regressions

Our interest in this section is the association between the amount of people the participant was exposed to, along different periods of time, and their relationship with those people, as presented in Table 1.

Table 1. Logistic regression based on unique Bluetooth devices, where the time clause represents a threshold in minutes that covers a segmentation before and after receiving respective survey.

Logistic Regression Model	Logistic Regression (B), values in the time segments in minutes				
	15	20	25	30	60
1. Talking survey when participants are surrounded by strangers (17) vs known people (471)	-	--	-	-	-
2. Thinking survey when participants are surrounded by strangers (168) vs known people (381)	--	--	--	--	--
3. Thinking survey when participants are alone (719) vs accompanied by known and unfamiliar people (549)	++	++	++	++	++

Previous label code is described next:
- represents B < 0, p < 0.05
-- represents B < 0, p < 0.01
+ represents B > 0, p < 0.05
++ represents B > 0, p < 0.01

The logistic regression model shows a simple association by stressing relevant findings based on unique Bluetooth devices, such as:

1. Number of Bluetooth devices is significantly lower when accompanied by known persons during talking.
2. Number of Bluetooth devices is significantly lower when accompanied by known persons during thinking.
3. Number of Bluetooth devices is significantly higher when accompanied by someone during thinking.

Results are consistent across time-segments for each of the three models analysed. Importance of this findings relies on the evidence that depict a relationship between the number of Bluetooth unique identifiers with the self-report made by the participants.

C. Findings from questionnaire data analysis

Influence of social partners on participants' behaviour.

This section is driven by the interest in exploring whether there is a relationship between who is around the user (*i.e.*, alone, not alone, work, family, or friends) and their reported behaviour (*i.e.*, thinking or talking).

As presented in Table 2, when participants reported to be surrounded by strangers, they were thinking 91% of the time and talking only 9% of the time. In contrast, when the participant was surrounded by friends, they were talking 73% of the time.

Table 2. Relationship that shows a cross tabulation analysis for the two different surveys (i.e., thinking and talking). Where header code stands for: R: Relative, P: Partner, F: Friend, A: Acquaintance, C: Colleague, S: Stranger.

	R	P	F	A	C	S
Thinking	46	40	27	21	58	91
Talking	54	60	73	79	42	9
TOTAL (%)	100	100	100	100	100	100

Note that blue versus orange findings have the opposite pattern: With partner, friends and acquaintances, people are more likely to talk, whereas with colleagues and strangers, they are more likely to be thinking. The relative column is white because its percentages are almost 50:50, so there is no larger difference between thinking and talking.

Overall, this finding, report a first study to evidence a novel unobtrusive approach towards relating a smartphone's user temporal orientation status and their relationship with people who accompany them.

5 ENVISIONED MOBILE APPLICATION

Due to the close relationship between thoughts and emotions [17], [28], [30], we believe that Bluetooth sensor data can be utilized as a method for emotions detection based on the identification of people that accompanied us.

For instance, a mobile application can implement a repository of Bluetooth's identifiers detected unobtrusively while the user carries his / her smartphone. As soon as the app identifies a relevant Bluetooth identifier (*e.g.*, given by a factor based on the number of samples collected and interval of time), the app could ask the user for details about the people surrounding at a particular moment. Inputs of the user will start building a directory of familiar people commonly accompany him/her. Given the uniqueness of Bluetooth identifiers, the user will eventually stop been requiring user's inputs. Therefore, detecting the relationship of the user's accompanier could be non-intrusiveness, objective, and automatic.

6 CONCLUSION AND CHALLENGES

We explored the relations between the socialization degree; interpreted in this study as the amount of unique Bluetooth devices detected by the participant's smartphone. We have presented findings on Bluetooth and survey answers correlated to participants' thinking and talking events while being accompanied by known people and strangers. Furthermore, we explored the association between previous factors towards time-episodes such as past, present, and future.

Based on the presented results and recognizing the limitations of this study in terms of its sample size (n = 33), it is speculated that for some population it can be deduced that they are actively sharing ideas and / or having thoughts about their past while a small number of people are nearby, implying a more private environment. In contrast, people are equally to talk about their future when surrounded by strangers. Furthermore, people are likely to think about the present while accompanied by known people.

We connect this study with emotion detection by building upon the assumption that temporal orientation analysis is connected to affective behaviour [17]. Hence, by identifying person's temporal orientation, we hypothesise (to some extend) could unobtrusively detect person's emotional state, by using Bluetooth sensor.

As part of our vision and based on our exploratory results from Section 4, we introduce a vision to design a mobile application to link up people's thoughts and conversations towards past, present, or future scenarios, which can help to better understand how social circumstances influence people emotions / behaviour.

As future work, we will work on complementary analysis results upon extensively validate the connection between detecting human emotions by identifying user's relationship of people that surrounded.

A. Challenges and limitations

Results of the pilot study show correlations between Bluetooth sensor data to talking and thinking events. However, there are two key limitations and challenges we will overcome in our future studies as presented below.

Daily surveys. In order to avoid loss of participant's insight, we need to better understand the circumstances in which participants are not willing to fill out the survey. In the pilot study, we already asked the participants to provide us with reasons when they did not fill out a survey. We still need to analyse participant's feedback.

Bluetooth devices. We used the number of Bluetooth devices as a marker of people nearby the participants on the study. However, individuals might carry multiple Bluetooth devices such as headphones, mobile phone, tablets. Thus, we cannot guarantee that each device corresponds to one person.

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