Chapter 4
Measuring Moral Values with Smartwatch-Based Body Sensors

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Abstract In this research project we predict the moral values of individuals through their body movements measured with the sensors of a smartwatch. The personal moral values are assessed using the Schwartz value theory, which proposes two dimensions of universal values (open to change versus conservative, self-enhancement versus self-transcendence). Data for all variables are gathered through the Happimeter, a smartwatch-based body-sensing system. Through multilevel mixed-effects generalized linear models, our results show that sensor and mood factors predict a person's values. We utilized three methods to investigate the relationship between the Big Five personality traits (OCEAN: openness, conscientiousness, extraversion, agreeableness, and neuroticism) of a person and their Schwartz values. This research highlights the use of recent technological advances for studying a person's values from an integrated perspective, combining body sensors and mood states to investigate individual behaviour and team cooperation.

Introduction

Human behaviour is driven by conflicting emotions. To better understand the interaction of different human emotions, researchers have started using sensors for automatic recognition of individual traits, including happiness, physical/psychological health, satisfaction, and so forth [16]. Yet little research so far has addressed how to predict values through the lens of sensing technology. We know that values are

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee with the Helsinki declaration and its later amendments or comparable with ethical standards.

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linked to behaviours, encouraging individuals to act in accordance with their values [25], and body sensors are the most honest way to pick up behaviours. In this regard, this demonstrates the feasibility of predicting values of a person with data that are collected by sensors.

In this study, we aim to advance an integrative view to study a person's values in terms of openness to change versus conservation, and self-enhancement versus self-transcendence, based on the Schwartz theory of human values (SHV) [21]. We explore the relationships between a person's values with (1) body sensors, (2) mood states, and (3) an individual's personality. Using the Happimeter system that has been developed since 2017 [8], we collected the necessary data from 2017 until now combining three channels: First, the sensor and mood data are collected through the Happimeter application using smartwatches. Second, the same application on mobile phones enables data to be transferred to the server. Third, the Happimeter website collects the value data and personality data based on the Schwartz value survey and NEO FFI test for personality [1]. The body sensors used in this research project include three categories: body movement, physiology, and context/environmental features, which are collected automatically by the Happimeter. The mood data focusses on the pleasance and activation level, which is based on users' self-report several times a day. By applying multilevel analysis to our dataset, our analysis reveals reliable support for the correlations between sensor/mood variables and values. When supplementing our framework with individuals' personality variables, we cannot find important insights based on our dataset.

The remainder of this article is organized as follows: In section "Theoretical Background", we provide a brief overview of the literature on related research. We then describe the methodology of the analysis we conducted and our findings, concluding with a discussion of our results and some future work suggestions.

Theoretical Background

Schwartz Value Theory

Many studies have utilized the Schwartz value theory. Schwartz [21] puts forth that 10 basic values, including universalism, benevolence, tradition, conformity, security, power, achievement, hedonism, stimulation, and self-direction, could be useful for understanding how people around the world think and behave. These subordinate values can be clustered into four higher order value constructs, which constitute two bipolar dimensions: openness to change versus conservation and self-enhancement versus self-transcendence [5].

The "openness to change" value dimension is defined as having autonomous thoughts and actions, and receptivity to novel experiences, while "conservation" is characterized as compliance with traditional values and customs. The first dimension captures the conflict between values that emphasize the independence of thought, action, and feelings and readiness for change and the values that emphasize order, self-restriction, preservation of the past, and resistance to change. Self-enhancement values are defined as placing importance and concern on self-interests and personal enrichment of status, while self-transcendence is operationalized as the concern for the welfare of others including those who have been marginalized. The values address egocentric desires (the pursuit of one's own interests, relative success, and dominance over others) and altruistic values (concern for the welfare and interests of others) [5, 21, 24].

Value Prediction

Figure 4.1 displays our framework, highlighting how predictors obtained from body movement combined with external influences can be applied to predict individuals' values in terms of the two bipolar dimensions: "openness to change versus conservation" and "self-enhancement versus self-transcendence". Predictors from body sensors contain three aspects: body movement, physiology, and environment feature. A second set of predictors are the mood states, which are divided into pleasance and activation. We supplement our theoretical framework with individuals' personalities, hypothesizing that they might improve the predictive quality of an individual's values.

Body Sensor and Value

A sensor generally refers to a device that converts a physical measure into a signal that is read by an observer or by an instrument. Currently, three general categories of sensors can be used for measuring physical activity in humans: movement sensors, physiological sensors, and contextual sensors [3].

Movement sensors can be used to measure human physical activities, including pedometers, gyroscopes, and accelerometers. Among these devices, accelerometers are currently the most widely used sensors for human physical activity monitoring. Physiological sensors monitor heart rate, blood pressure, temperature (skin and core body), heat flux, and so on. To date, heart rate monitoring remains the most common

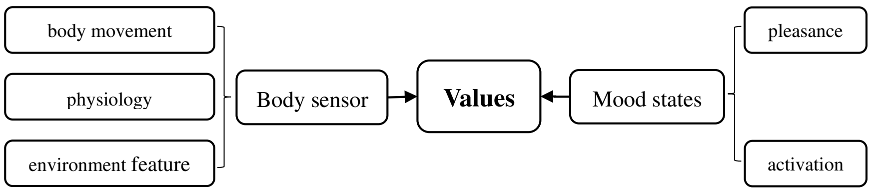

Fig. 4.1 Theoretical framework

sensor for physiological monitoring. Contextual sensors assess the context or environment in which the physical activity is being performed. Compared to motion and physiological sensors, contextual sensors are relatively new and have great potential to help describe the relationship between physical activity and various environmental features.

Using the Happimeter application, we collect data in the above-mentioned three dimensions. Bardi and Schwartz [2] demonstrated that each of the Schwartz values correlates significantly with a set of everyday behaviours. For example, power values correlate most positively with power behaviours and most negatively with benevolence behaviours. It is plausible to assume that the sensor data we collected reflects at least some causal influence of values.

We assume that people's sensors serve as predictable guides to their values related to openness to change, conservation, self-enhancement, and self-transcendence. While some sensor features are more associated with openness to alternative lifestyles and the acceptance of goals pursued by others (openness to change values), and support of justice for others (self-transcendence values), others may be more strongly influential for people who embrace authority, conformity, and traditional conceptualizations of family and society (conservation values), and pursue status and prestige (self-enhancement values) and in general are, for instance, less tolerant of homosexuality.

Mood States and Value

The second set of predictors are the mood states calculated by the Happimeter [8]. They are based on the circumplex model of affect theory, which proposes that each emotion of human beings can be understood as a linear combination of two dimensions: "valence" and "arousal" [20]. While valence is a pleasure–displeasure continuum, measuring how positive or negative an emotion is, the dimension of arousal reflects whether an emotion is exciting/agitating or calming/soothing [13]. Figure 4.2 shows the locations of different emotions which show the degree of valence and arousal each emotion presents (adopted from Lee et al. [27]). "Delighted", for example, is conceptualized as an emotional state that is associated with positive valence or pleasure together with moderate activation in the arousal dimension. Affective states other than "delighted" likewise arise from the same two dimensions but differ in the degree or extent of activation.

Emotions, by their very nature, express a personal, polarized, and biased perspective. Thus, emotion has been viewed as biasing one's evaluations, cognitions, and moral thought. The role of emotions in moral psychology has long been the focus of philosophical dispute [12]. However, all these disputes reach agreement that our mood states serve a primary role in value detection. For example, Horne and Powell [11] show that emotions are not simply experienced alongside people's judgments about moral dilemmas, but that our affective state plays a central role in determining those judgments. Eisenberg's [6] focus on guilt and sympathy shows that these higher-order emotions might motivate moral behaviour and play a role in its development

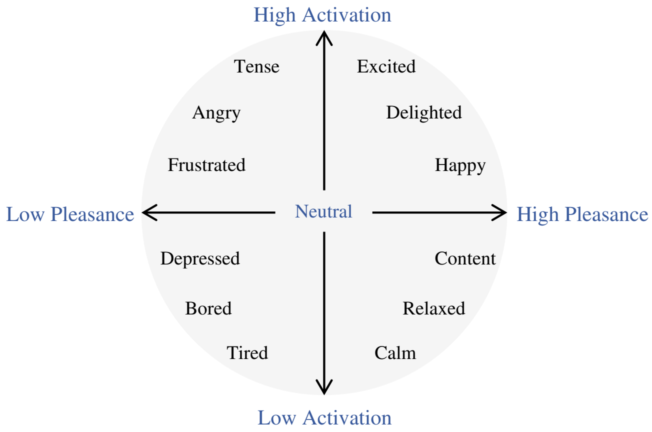

Fig. 4.2 The circumplex model of affect. *Note* The figure is adopted from Yu et al. [27]

and in moral character. Therefore, we add these two dimensions of mood states (pleasance and activation) into our experiment design. We polled users of the Happimeter system to report their levels of pleasance and activation while their sensor data was collected by the Happimeter system automatically.

Additional Tests of the Influence of Individual's Personality

Pre-tests by machine learning showed that the accuracy of Schwartz value prediction was significantly improved when users' personality variables were added into the model. In addition, there is a large extant body of literature that has explored the relationship between personality and values and verified the existence of the link between them (for instance, [7, 19, 26]. Parks-Leduc et al. [17] report a meta-analysis of 60 studies on the relations between personality traits and Schwartz values. Their findings show that openness has the most significant relationship with values. Openness correlates mostly and positively with self-direction. Moreover, openness correlates positively with stimulation and universalism, and negatively with tradition, conformity, and security. Agreeableness also has several strong associations with values, particularly and positively with benevolence. Further, agreeableness correlates positively with universalism, conformity, and tradition and negatively with power. Extraversion and conscientiousness have some moderate associations with values. However, anxiety, as a facet of neuroticism, has been associated with security [1].

Following prior literature, we used personality characteristics based on the five-factor inventory (FFI) model (neuroticism, extraversion, conscientiousness, agreeableness, and openness to experience) [4]. According to Costa and McCrae [4], neurotic people are typically distressed, depressed, impulsive, and vulnerable, and they monitor themselves closely. In turn, people characterized by openness are creative, inventive, sensitive, and open-minded. Extraverted people are social, assertive, talkative, and active, whereas those characterized by agreeableness are good-natured, compliant, and modest. Agreeable individuals are also friendly and cooperative. Finally, conscientious people are typically cautious, careful, responsible, and systematic. Personality traits are related to differences between individuals in their stable patterns of thought, emotions, and actions [14].

Data and Model

Data

The final dataset for value analysis includes 30 people who answered the Schwartz value survey at different times from 2017 to 2019; the participants include graduate students, researchers, and faculty members. Of the users who reported demographics, 37% reported their genders as male. The total number of Happimeter sensor data records for all these users is 7679. The sensor variables are directly recorded by the Happimeter application running on users' phones and smartwatches, while mood data is self-reported by users through smartwatches. Personality variables are collected through a responsive website. Only 20 of the users in our dataset could be matched with personality data. The variables list is shown in Table 4.1. Sensor and personality are continuous predictors while mood data are ordered categorical variables ranging from 0 to 2. All sensor data was standardized to facilitate interpretation of the effects.

Model

Multilevel Analysis

We use multilevel analysis to predict Schwartz values based on the sensor and mood data. The variability in the outcome can be thought of as being either within a user or between users. The data records level observations are not independent, as within a given user, data records are more similar. Figure 4.3 shows a sample where the dots are records within users, and each user is represented as a larger circle.

Mixed models incorporate fixed and random effects. A fixed effect is a parameter that does not vary, while a random effect is a parameter that varies according to the grouping variable (user), which makes it possible to explore the difference between effects within and between users. As shown in Fig. 4.4, within each user, the relation between predictor and outcome is negative. However, between users, the relation is positive. Multilevel analysis allows us to explore and understand these effects.

Table 4.1 Variables list

	Category	Variables	Definition
Values	The first dimension	Open	The sum of hedonism, stimulation, and self-direction subscores
		Conser	The sum of tradition, conformity, and security subscores
	The second dimension	Enhan	The sum of power and achievement subscores
		Trans	The sum of universalism and benevolence subscores
Sensor variables	Physiological sensors	Avgbpm	The average number of heart beats per minute
		Varbpm	The variance of heartrate per minute
	Contextual sensors	Avgnoise	The average noise level of the environment per minute
	Movement sensors	Nostep	The number of steps per minute
		Avgacc	The average of acceleration of user's movement in the physical space per minute
		Varacc	The variance of acceleration of user's movement per minute
Other variables	Mood states	Pleasance	Self-reported scores for pleasance, range from 0 to 2 (from low to high)
		Activation	Self-reported scores for activation, range from 0 to 2 (from low to high)
	FFI personality	o	Score of user's openness to experience aspect of personality
		c	Score of user's conscientiousness aspect of personality
		e	Score of user's extraversion aspect of personality
		a	Score of user's agreeableness aspect of personality
		n	Score of user's neuroticism aspect of personality

Regression Procedure

Multilevel mixed-effects generalized linear regression, using the stata mixed procedure [9, 18], was performed with 7179 data records (Level 1) across 30 individuals (Level 2) to control for the nested data structure. The models of each step are shown in Table 4.2.

Fig. 4.3 Multilevel dataset sample

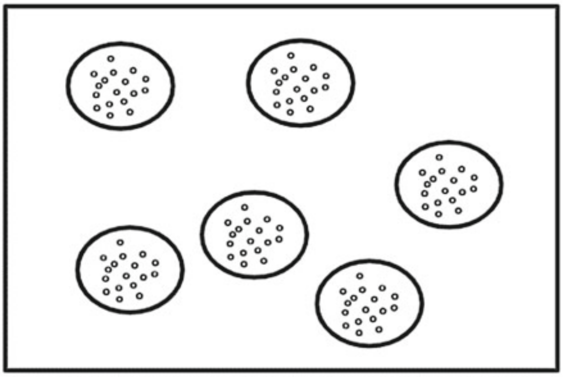

Fig. 4.4 Difference between and within groups

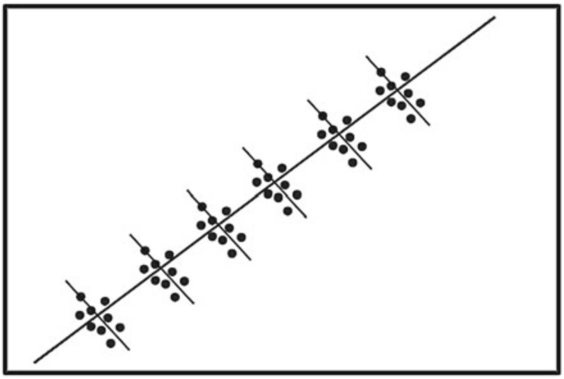

Table 4.2 Models for each step

1. Random intercept model	$V_{ij} = \gamma_{0j} + \varepsilon_{ij}$
2. Fixed sensor and mood predictors with randomly varying intercepts	$V_{ij} = \gamma_{0j} + \beta_1 S_{ij} + \beta_2 M_{ij} + \varepsilon_{ij}$
3. Fixed sensor, mood, and personality predictors with randomly varying intercepts	$V_{ij} = \gamma_{0j} + \beta_1 S_{ij} + \beta_2 M_{ij} + \beta_3 P_{ij} + \varepsilon_{ij}$

Note V = value, S = sensor predictors, M = mood predictors, P = personality predictors

Step 1 was specified as a null (baseline) model, by permitting random intercepts only, to determine whether mean scores in different dimensions of values were significantly discrepant across all users. This model was used to compute the intraclass correlation (ICC), an indication of the extent that sensor data of the same user were similar on their value scores relative to the total variation in sensor data among all users. A high ICC value beyond the null hypothesis of 0.00 signifies that sensor data units are not statistically independent within a certain user, and therefore the nested design should be considered by using a multilevel model.

Step 2 involved random intercepts with fixed-effect predictors. It builds on the previous model by including the fixed-effect predictors at the data records level (sensor variables and mood variables). Thus, Step 2 controlled for the nested structure by permitting intercepts to vary, while estimating fixed effects of the relevant variables.

Building on Step 2, Step 3 incorporated the user-level personality variables. They were added into the models to test the relationships between personality variables and Schwartz values.

Results

Descriptive information for all variables is presented in Table 4.3. Following the manual of the Schwartz value survey [23], we centred the score of each questions by the average score of each user. Then the four values were calculated based on the centre-scored results of all 10 value questions. From Table 4.3 we see that the mean value of openness is larger than that of conservation, while the averages of self-transcendence are larger than self-enhancement, which means that in our dataset

Table 4.3 Descriptive analysis of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Open	7,679	0.928	1.583	−4.9	8.1
Conser	7,679	−1.621	2.396	−7.2	4
Enhan	7,679	−1.574	2.843	−7	4.4
Trans	7,679	2.267	2.412	−2.6	6.8
Pleasance	7,679	1.463	0.555	0	2
Activation	7,679	1.183	0.58	0	2
Std avgbpm	7,679	0	1	−2.09	4.876
Std varbpm	7,679	0	1	−1.083	8.737
Std nostep	7,679	0	1	−0.459	7.788
Std avgnoise	7,679	0	1	−0.883	9.885
Std varnoise	7,679	0	1	−0.697	8.74
Std avgacc	7,679	0	1	−4.926	5.082
Std varacc	7,679	0	1	−1.839	6.95
o	6,186	0.585	0.0829	0.375	0.733
c	6,186	0.685	0.0884	0.521	0.767
e	6,186	0.684	0.0614	0.55	0.783
a	6,186	0.582	0.0678	0.375	0.683
n	6,186	0.471	0.0913	0.271	0.683
Gender	7,679	0.324	0.468	0	1

Table 4.4 Intraclass correlation of null models

Values	ICC	Std. Err.	95% Conf.	Interval
Open	0.946	0.0147	0.908	0.968
Conser	0.735	0.0604	0.602	0.836
Enhan	0.531	0.0791	0.378	0.679
Trans	0.617	0.0745	0.465	0.749

people tend to regard themselves as open to change and self-transcendent instead of conservative or self-enhancing. The correlation matrix of all predictor variables is presented in Table 4.5. It reveals that multi-collinearity exists between different indexes of personality, which is taken into consideration for the regression analysis. In addition, the correlations between avgacc and varacc, avgnoise, and varnoise are also higher than the rule of thumb (0.7), thus we removed varacc and varnoise from our final models.

Random Intercept Model

We hypothesized that characteristics attributed to the user level would explain variation in values. Based on the null model, the results (Table 4.4) reveal significant ICCs 94.6, 73.5, 53.1, and 61.7% for all dimensions, signifying that over 50% of the variance in one's value is explained exclusively by variations across users. This provided sufficient evidence that a multilevel regression model was warranted [9, 18].

Fixed Sensor and Mood Predictors with Randomly Varying Intercepts

Models 1–4 in Table 4.6 tested the fixed-effect for sensor and mood predictors at level 1. The results show that:

(1) Sensor-level variables are significantly related to the four aspects of the Schwartz values. Specifically, the average of heartrate is positively associated with conservation and self-transcendence, while negatively related to openness, which indicates that people who are open to change and who focus on self-development tend to have a relatively lower heart beat than people who are conservative. Regarding the variance of heartrate, we note that self-enhancing individuals tend to have low heartrate variability. For activity-related variables, neither the number of steps nor the average of acceleration is correlated with the Schwartz values of users; however, the standard deviation of all activity-related variables

is correlated with most Schwartz values; in general, the higher the standard deviation, the more open and the less conservative people are (Table 4.5). Regarding environmental attributes, for the noise level we found that people who are open to change and focus on transcendence are more likely to be in a quieter environment, whereas those who are conservative and pay attention to self-development seem to be in noisier environments.

(2) Mood variables are also related to the values of people. We find that pleasance and activation vary in the way they relate to the Schwartz values. Figure 4.5 shows the spectrum of Schwartz values for a person across our sample users. Open and self-enhancing people have higher tendency for pleasance but lower activation. This is somewhat surprising, as we commonly tend to regard self-transcendent people as happy and satisfied. It could be that in our sample self-transcendent people are more critical and questioning against themselves, which might reduce their happiness at times.

Looking at gender, we find that in our sample women tend to be less open and more conservative than men (gender has been coded as male = 1, female = 0).

Table 4.6 includes the results of the regressions for the four Schwartz values using fixed sensor, mood, and personality predictors with randomly varying intercepts.

Using FFI Personality as Additional Predictors or Moderating Variables

As the correlation matrix in Table 4.5 shows, high relative coefficients exist among the five personality variables. Taking this into consideration, we conducted further analysis using different methods to test the relationships between FFI personality and Schwartz values.

First, we add agreeableness, neuroticism, extraversion, and conscientiousness into our models while removing the openness personality variable. According to Table 4.5, severe multi-collinearity only exists between the personality variable openness and other personality variables (with agreeableness 0.84, neuroticism 0.70, agreeableness 0.69, and extraversion 0.50). After removing the openness variable, none of the other correlated coefficients is higher than the threshold of 0.7, which is used as a rule of thumb in literature. However, the models with dependent variables in the first dimension of value (openness to change and conservation) do not concave when adding the four personality variables to the models. For the second dimension (self-enhancement and self-transcendence), including the personality characteristics into the regression also does not lead to reliable results. Encouraged by existing studies (i.e., [10]) we were looking for a better fit by adding one personality variable into the models at a time to avoid the multi-collinearity problems. Unfortunately, that did not work with our dataset neither. Finally, we also unsuccessfully tested indirect or moderating effect of users' personality on the Schwartz values. In conclusion, no solid evidence was found with the above methods to support the relationship between FFI personality and Schwartz values based on our dataset.

Table 4.5 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Open	1																		
2	Conser	−0.50*	1																	
3	Enhan	−0.28*	−0.31*	1																
4	Trans	0.17*	−0.30*	−0.69*	1															
5	Pleasance	0.04*	0	0.03*	−0.05*	1														
6	Activation	−0.03*	0.01	−0.06*	0.08*	0.26*	1													
7	Std avgbpm	−0.01	0.11*	−0.08*	−0.01	−0.01	0.04*	1												
8	Std varbpm	0.09*	−0.01	−0.04*	0	0.04*	0.01	0.12*	1											
9	Std nostep	0.14*	−0.16*	0.05*	0.01	−0.03*	−0.04*	0.22*	0.14*	1										
10	Std avgnoise	−0.05*	0.16*	0.07*	−0.20*	0.06*	−0.03*	0.19*	−0.13*	−0.02	1									
11	Std varnoise	0.01	0.17*	−0.06*	−0.11*	0.02	0	0.10*	−0.08*	−0.04*	0.53*	1								
12	Std avgacc	−0.08*	0	0.04*	0	−0.01	−0.04*	−0.05*	−0.15*	0.03*	0.07*	−0.06*	1							
13	Std varacc	0.10*	−0.05*	−0.02	0.01	0.02	0.05*	0.36*	0.16*	0.28*	0.12*	0.09*	−0.67*	1						
14	n	−0.38*	0.41*	0.21*	−0.46*	0.09*	0.09*	0.03*	−0.09*	−0.25*	0.18*	0.11*	−0.03*	−0.03*	1					
15	e	−0.14*	0.54*	−0.34*	−0.03*	0.02	0.09*	0.12*	0.11*	−0.03*	−0.05*	0.04*	−0.07*	0.07*	0.45*	1				
16	o	−0.15*	0.63*	−0.34*	−0.12*	0.07*	0.13*	0.11*	−0.02	−0.30*	0.16*	0.18*	−0.04*	−0.03*	0.70*	0.50*	1			
17	a	−0.34*	0.64*	0.04*	−0.49*	0.07*	0.05*	0.03*	0.01	−0.23*	0.12*	0.17*	0	−0.07*	0.51*	0.17*	0.69*	1		
18	c	−0.15*	0.55*	−0.11*	−0.32*	0.08*	0.09*	0.11*	0.09*	−0.18*	0.14*	0.13*	−0.04*	0.01	0.62*	0.62*	0.84*	0.58*	1	
19	Gender	0.19*	−0.54*	0.20*	0.18*	−0.01	0.06*	0.01	0.17*	0.17*	−0.17*	−0.13*	0	0.04*	−0.46*	−0.15*	−0.28*	−0.27*	0.04*	1

*$p < 0.1$

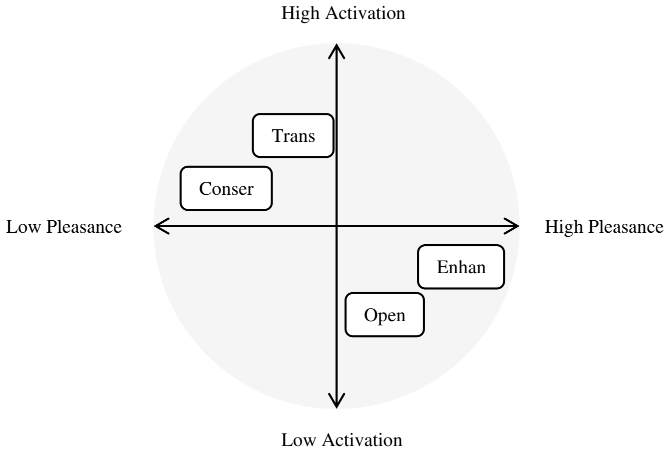

Fig. 4.5 Relationships of mood states and values

Table 4.6 Regression results

	Model 1	Model 2	Model 3	Model 4
Variables	Open	Conser	Enhan	Trans
Avgbpm	−0.014**	0.261***	−0.236***	0.003
Varbpm	0.068***	0.112***	−0.252***	−0.013
Nostep	−0.000	−0.233***	0.062**	0.054**
Avgacc	−0.016**	−0.027	0.016	0.028
Avgnoise	−0.085***	0.241***	0.445***	−0.536***
Pleasance	0.028**	−0.112***	0.180***	−0.138***
Activation	−0.045***	0.154***	−0.343***	0.317***
Gender	0.841	−2.660***	1.575***	0.515***
Constant	0.733***	−0.733***	−1.773***	1.742***
Observations	7,679	7,679	7,679	7,679
Number of groups	30	30	30	30

Note Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Discussion

The ethical values of individuals have captured the interest of researchers, practitioners, social critics, and the public at large [15]. Schwartz [22] defined values as reflected in the course of action in an individual's life. However, prior literature mainly focuses on measuring people's values via surveys. The advent of sensing technology provides a powerful solution to the challenge of detecting an individual's values. Smartwatch sensors provide a simple way of passively detecting the body signals and the environment a user is encountering, also reducing the burden of self-reporting. Through our unique Happimeter mood sensing system, we were able to gather data about body signals and environmental features sensed by the smartwatches, self-reported pleasance and activation levels, in combination with personal data about Schwartz values, FFI personality, and morals entered through a survey on a website. We found that a person's values are reflected by their body sensors and mood states. What's more, body language also has a strong relationship with a person's personality. By using multilevel regressions, we showed a link between sensor/mood variables and people's values, while no evidence was found to show a moderating effect of FFI personality characteristics on Schwartz values, at least in our dataset.

This article contributes to both the theoretical and practical sides. With respect to furthering the state of research literature, we see our study having two contributions. First, we provide a novel method of detecting people's ethical values based on sensing technologies, going beyond traditional survey methods. Prior research acquires the value of an individual mainly by questionnaire, and this study fills the academic gap and indicates the potential of applying a sensing system for value detection. Second, we propose an integrative framework of using body signals, mood states, and environment features to study ethical values. We highlighted that the body signals that a person displays, the environment that people live in, and the mood states of people may be consistently associated with their perceptions and behaviours, and thus have psychological implications and clear links to a person's values.

Our findings also provide important insights for the real world. First, by applying sensing technology, individuals become more aware of their values, which helps them to make choices with which they feel comfortable. They can also become more aware of how they come across to others. Self-awareness is a first step in any change. They would know if they need to make moves based on their image of themselves. Second, pairs working in a team that might have had difficulties working well together can better identify the cause of blockages or conflict, which might be related to values. The better knowledge of individuals' values can help us design better teams and manage the relationships in teams more effectively.

However, our study inevitably has some limitations. First, this study only focusses on a set of limited variables (mainly heartrate, acceleration, noise level, and pleasance). As technology continues to develop and research continues to identify new predictors that are psychologically meaningful, future work will be able to investigate the collective and interactive effects of these additional factors on people's values. For instance, researchers could integrate stress level, light level, and other relevant variables into their models. Second, the combination of mood states and smartwatch sensing allowed us to collect large amounts of within-person data in the current work. However, the number of participants in our dataset is limited. Further analysis will have to be done with larger numbers of participants.

In sum, we have identified novel links between body postures and body language, emotions, and ethical values, showing that how one behaves really tells who he/she is.

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