

Chapter 1

“No Pain No Gain”: Predicting Creativity Through Body Signals



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Abstract Creative people are highly valued in all parts of the society, be it companies, government, or private life. However, organizations struggle to identify their most creative members. Is there a “magic ingredient” that sets the most creative individuals of an organization apart from the rest of the population? This paper aims to shed light on a part of this puzzle by introducing a novel method based on analyzing body language measured with sensors. We assess an individual’s creativity with the Torrance Tests of Creative Thinking, while their body signals are tracked with the sensors of a smartwatch measuring heart rate, acceleration, vector magnitude count, and loudness. These variables are complemented with external environmental features such as light level measured by the smartwatch. In addition, the smartwatch includes a custom-built app, the Happimeter, that allows users to do mood input in a two-dimensional framework consisting of pleasance and activation. Using multi-level regression, we find that people’s creativity is predictable by their body sensor readings. We thus provide preliminary evidence that the body movement as well as environmental variables have a relationship with an individual’s creativity. The results also highlight the influence of affective states on an individual’s creativity.

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Introduction

Creative thinking is the foundation for art, science, and technology. It is at the core of societal advancement [1, 3], leading to products, ideas, or processes that are novel and useful [14]. However, what kind of features do highly creative individuals display that sets them apart from the rest of the population? Is there an automated way to distinguish them from others? Current best practices to identify the most creative individuals are based on surveys and cognitive assessments [19]. In this paper we investigate the research question if the body language of a person might also predict her/his creativity.

Based on the rapid growth of mobile computing and sensor technology, we introduce a novel way to predict creativity through data collected from a variety of wearable sensors. In this study, we aim to advance an integrative view of a person's creativity through the lens of body sensors, mood states, and external environment features. Using commercially available smartwatches, we built a body sensing system called "Happimeter" [6] that collects data in three broad categories for objectively measuring physical activity: body movement, physiology, and context information. We explore the associations between these factors and the five constructs of their creativity obtained from the Torrance Test of Creative Thinking: Fluency, Originality, Elaboration, Abstractness of Titles, and Resistance to Premature Closure [23, 25]. We also investigate how pleasantness and activation levels [9] collected by the Happimeter app will influence the five aspects of a person's creativity.

Theoretical Background

The Measurement of Creativity

Creativity of a solution to a problem is characterized by assessing the novelty (e.g., solutions have less frequent features) and utility (i.e., solutions satisfy precise needs) of the solution [21]. A broad set of theories and models are discussed in the research literature on cognitive psychology [11], revealing different ways to measure an individual's creativity. In this paper, we use the Torrance Tests of Creative Thinking (TTCT). Researchers have employed the Torrance Tests of Creative Thinking (TTCT, [22, 23, 25]) for more than four decades, and this measure continues to dominate the field when it comes to the testing of individuals' creativity from kindergarten through adulthood.

The TTCT contains two parts, the verbal part and the figural part. It consists of five activities, some of which need to be answered by drawing, while others are answered in writing. As is common with such tests, it has to be completed under time pressure. The current form of the TTCT includes scores for Fluency, Originality, Elaboration, Abstractness of Titles, and Resistance to Premature Closure (see [10], for details).

Table 1.1 Five dimensions of creativity in TTCT

Aspects	Definition
Fluency (flu)	The number of relevant ideas; shows an ability to produce a number of figural images
Originality (origin)	The number of statistically infrequent ideas; shows an ability to produce uncommon or unique responses
Elaboration (elab)	The number of added ideas; demonstrates the subject’s ability to develop and elaborate on ideas
Abstractness of titles (abs)	The degree beyond labeling; based on the idea that creativity requires an abstraction of thought
Resistance to premature closure (res)	The degree of psychological openness; based on the belief that creative behavior requires a person to consider a variety of information when processing information and to keep an “open mind”

The five subscales and information about scoring and the content measures are shown in Table 1.1.

Torrance [24] discouraged interpretation of scores as a total score or a static measure of a person’s ability and warned that using a composite score might be misleading because each subscale score has independent meaning. Instead, Torrance encouraged the interpretation of subscale scores separately. We followed these instructions in our study by using the five constructs of creativity instead of a composite score. While some individuals were wearing the watch over extended periods of time, we restricted analysis of the sensor readings to a time window of three days around the time when the individuals took the test. Some participants only wore the watch for a few days around the time when taking the test, while others had been wearing it for years.

Factors Influencing Creativity

Prior studies reveal that factors which influence creativity can be broadly classified as either domain- and creativity-relevant factors or affect and external factors [7]. The Torrance Test of Creative Thinking aims to predict creative performance in general, outside of a given domain (for a discussion, see [18]). Thus, in this article, domain-relevant skills are not our focus. Also, Hennessey and Amabile [7] argue that there are factors on seven levels that will influence a person’s creativity, ranging from the biological basis to affect/cognition/training, from the environment to culture and society. Here we focus on the biological, affective, and environmental differences between individuals to reveal their creativity by using data from sensor devices and answers from users.

Three general categories of sensors can be used for measuring parts of the above-mentioned information: movement sensors, physiological sensors, and contextual

sensors [2]. Movement sensors can be used to measure human physical activities. Among these devices, accelerometers are currently the most widely used sensors for human physical activity monitoring. Physiologic sensors include measurement of heart rate, blood pressure, temperature (skin and core body), heat flux, and so on. To date, heart rate monitoring remains the most common sensor for physiologic monitoring and is used in our research. Contextual sensors are concerned with assessing the context of the environment in which the physical activity is being performed. Compared to movement and physiological sensors, contextual sensors are relatively new and have great potential to help describe the relationship between physical activity and various environmental features. We obtain the light information of the imminent environment by our “Happimeter” sensor system which combines smartwatches and smartphones. With regard to affective states, we implement our analysis based on the two dimensions pleasance and activation, according to the Circumplex Model of Affects [9]. We explored other models of emotion such as the six-dimensional model of Plutchik.

There is evidence that highly creative individuals have a tendency to be physiologically overactive [13]. Moreover, a large body of literature has investigated affective impact on creativity. For instance, Isen et al. [8] found that participants performed better on creative problem-solving tasks when they experienced positive affect than participants in a negative or neutral affective state. Thus, they argue that positive affect fosters creativity. Similarly, Murray et al. [16] also found that positive affect increased creativity. However, instead of highlighting that positive affective state is better than negative affect for fostering creativity, George and Jing [5] found that negative affect can help identify when a conscious effort is needed to refine and improve creative outcomes. This contradiction in scientific evidence about the relationships between affect and creativity is also addressed in our article. As for the influence of the external environment, we argue that features of the surroundings might modify the performance of generating novel and useful solutions to creative problems. We also investigated the influence of light, more specifically, the level of illumination. Some studies show that a darker environment is better for out-of-the-box thinking since bright lights give people the impression that they are under surveillance, and thus less free to take risks. But other scholars also posit that low-light conditions discourage the eye from focusing on details, leaving people free to get involved in abstract mental processing of creative thinking [19].

To the best of our knowledge, less work has investigated the utility of sensing devices for modeling creativity. For instance, Muldner and Burleson [15] applied machine learning to data from eye tracking, a skin conductance bracelet, and an EEG sensor to predict creativity. They found reliable differences in sensor features characterizing low versus highly creative students. As this is an emerging field, more work is needed to explore how to apply body sensors to creative problem-solving. Our research provides a step in this direction.

The theoretical framework is shown in Fig. 1.1.

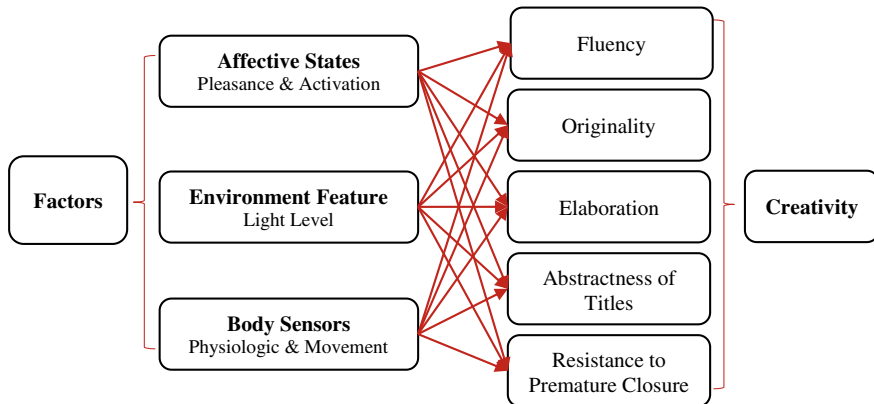


Fig. 1.1 Theoretical framework

Methodology

Participants

Participants were members of the 2017 Collaborative Innovation Networks (COINs) conference that took place in Detroit, USA from September 14 to 17, 2017, and of two student block seminars held in Bamberg and Cologne, Germany, from October 10 to 17, 2017. They completed the TTCT using paper and pencil. The participants wore smartwatches provided by our research group and downloaded the Happimeter app from the Google Play or iTunes store, and installed it on their smartphones and smartwatches. The analysis reported here includes all users who provided data on all dependent and independent variables required for this analysis. Some users had technical problems connecting the smartwatch to their phones, or to install the app, these users were excluded from the analysis.

A total of 50 users' creativity tests are collected (23 from the conference and 27 from the seminar) and their creativity score is graded by three raters according to our research design. To demonstrate consistency among observational ratings provided by these coders, the assessment of inter-rater reliability (IRR) is necessary for verifying the reliability of our data. IRR analysis aims to determine how much of the variance in the observed scores is due to variance in the true scores after the variance due to measurement error between coders has been removed. The results of IRR are shown in Table 1.2.

In addition, we obtained the creativity score from their TTCT results, and combined it with momentary self-reports of affective mood states and sensor data collected by the Happimeter. The Happimeter app trains mood prediction system by repeatedly asking two questions: [1] How pleasant do you feel? [2] How active do you feel? The user chooses his affective states levels with a scale of 0–2, where 0 represents low pleasant or activation, while 2 corresponds to high pleasant or

Table 1.2 Inter-rater reliability

Dimensions of creativity	IRRs for conference	IRRs for seminars
Fluency	0.983	0.956
Originality	0.852	0.790
Elaboration	0.957	0.841
Resistance	0.828	0.65
Abstractness	0.759	0.479

activation. After matching affective states data, sensor data, and TTCT scores and doing data filtering, we got a total of 8339 records with sensor data for 37 users, among whom 57% are male and 43% are female. Given that these users may or may not have provided their affect information at the same frequency as their sensor data, the analyses described in the results section uses an average level of pleasantness and activation on each day to match with the sensor data records. The majority of the participants (62%) are from Europe, and 16% each from Asia and North America.

Model

Variables

The predictor measures are shown in Table 1.3. As some users did not report their age, we did not include it into the analysis. This is supported by the results of Lee and Kyung [12], who found that age was not an influential factor of creativity.

Multilevel Analysis

We use multilevel analysis with levels sensor and user. The variability in the outcome can be thought as being either within a user or between users. The sensor data level observations are not independent, which means that for a given user, sensor data records are related to each other. The multilevel mixed-effects generalized linear model, using the Stata mixed procedure, was performed with 8339 sensor data records (Level 1) across 37 individuals (Level 2) to control for the nested data structure. The independent variables pleasantness and activation were collected through experience-based sampling [6] by polling users at random times per day on the smartwatch by asking them the questions “how active do you feel?” and “how pleasant do you feel?”, and the user could then enter this information using a slider shown on the touchscreen of the watch.

Table 1.3 Variables

	Category	Variables	Definition
Dependent variables	Five aspects of creativity	Flu	The standardized score of <i>Fluency</i> derived from TTCT results
		Origin	The standardized score of <i>Originality</i> derived from TTCT results
		elab	The standardized score of <i>Elaboration</i> derived from TTCT results
		abs	The standardized score of <i>Abstractness of Titles</i> derived from TTCT results
		res	The standardized score of <i>Resistance to Premature Closure</i> derived from TTCT results
Independent variables	Affective states	pleasance	Self-reported scores for pleasance, range from 0 to 2
		Activation	Self-reported scores for activation, range from 0 to 2
	Physiologic sensors	avgbpm	The average number of heart beats per minute (standardized)
		varbpm	The variance of heart rate within a day (standardized)
	Contextual sensors	avglight	The light level of the environment (standardized)
		varlight	The variance of light level within a day (standardized)
	Movement sensors	VMC	The vector magnitude counts of the user (standardized)
		avgacc	The magnitude of the acceleration of the user’s movement in the physical space (standardized)
		varacc	The variance of acceleration of the user’s movement within a day (standardized)

(continued)

Table 1.3 (continued)

	Category	Variables	Definition
Control variables	User profile	Gender	Gender = 1, male, otherwise, female
	User location	Continent 1	Continent 1 = 1 if the user is from Asian, otherwise, 0
		Continent 2	Continent 2 = 1 if the user is from Europe, otherwise, 0
		Continent 3	continent 3 = 1 if the user is from North America, otherwise, 0
		Continent 4	Continent 4 = 1 if the user is from Oceania, otherwise, 0
		Continent 5	continent 5 = 1 if the user is from South America, otherwise, 0

Results

Table 1.5 presents correlations for all explanatory variables along with descriptive statistics, which indicates that multicollinearity should not pose a problem. No value is higher than the threshold of 0.7 that is used as a rule of thumb for collinear relationships. We also checked the variation inflation factors (VIFs) and found that the VIFs for all principal variables are below the rule-of-thumb cutoff of 10 (the average of VIFs is 2.08), indicating no serious problem with multicollinearity [17]. Our last test was to check for heteroscedasticity in the data using the Breusch-Pagan test. Results indicate that heteroscedasticity is not a problem with the data.

With the null model (permitting random intercepts only), we calculate the intra-class correlations (ICCs) of all creativity dimensions, which are shown as Table 1.4. ICC is an indication of the extent to which sensor data of the same user are similar on their value scores relative to the total variation in sensor data of all users. An ICC value of 0 signifies complete observation independence within a user, while an ICC

Table 1.4 Interclass coefficients of null models

	ICC	Std. err.	95% conf.	Interval
Fluency	0.368	0.0762	0.234	0.525
Originality	0.31	0.0726	0.188	0.467
Elaboration	0.397	0.0783	0.257	0.555
Abstractness	0.442	0.0813	0.293	0.602
Resistance	0.464	0.0804	0.314	0.62

value of 1 indicates that differences in the outcome variable are completely dependent on the grouping variable. Therefore, ICC is used to verify if the nested design is suitable using a multilevel model. A review of the ICCs of our model shows that multilevel regression is a good method for our data and analysis since the ICCs of these creativity dimensions varies from 0.3 to 0.5, meaning that significant similarities exist in each group (user). For all dimensions, 30–50% of the creativity variance can be explained by the differences between users, while 50–70% can be accounted for by variables on the sensor data level.

Second, we test the predictive effects of body sensors, external environment feature, and affective states on creativity. We build on the previous model by adding random intercepts and fixed-effect predictors from level 1 or/and level 2 into our regressions. Table 1.6 provides regression results. Models 0–4 serve as baseline models that include only control variables (also level 2 variables). As shown in our sample, females tend to be more creative than men in all dimensions: Fluency, Originality, Elaboration, Abstractness of titles, and Resistance to premature closure. As for the continental difference, only taking continents with large samples into consideration, the conclusion can be made that Europeans (continent 2) are the most creative people, while Asian (continent 1) people are the least creative. The creativity scores for individuals from North America (continent 3) are in-between. As the sample size for the South American and Oceania participants is too small, they are not included in this analysis.

Models 5–9 test the predictive and influential power of body sensors, environmental feature, and affective states on five subscores of creativity. The results support that all three groups of variables are significantly related to creativity but vary in the degrees and directions of the influence they exert on.

The results show that sensor features can reliably distinguish high creativity individuals from the low creativity ones. The average of heartbeat (standardized heartbeat average) negatively influences fluency and elaboration subscores of creativity but is positively related to abstractness. The variance of heart rate within a day is mostly positively related to the five dimensions of creativity, with positive coefficients for fluency, originality, abstractness, and elaboration but negatively related to resistance. As for acceleration and VMC (vector magnitude counts), we also find partial support for their relationships with creativity.

Table 1.5 Descriptive statistics and correlations

	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10
1 avgbpm	79.49	19.06	40	200	1.00									
2 varbpm	247	102.1	0	466.6	0.13**	1.00								
3 avlight	1.612	0.992	-1	4	0.00	-0.05**	1.00							
4 varlight	11.93	6.383	0	22.02	0.04**	0.10**	0.35**	1.00						
5 avgacc	888.8	138.3	22.98	1299	-0.04**	0.01	0.01	-0.05**	1.00					
6 varacc	282774	213845	15.07	1569000	0.06**	0.05**	0.05**	0.12**	-0.48**	1.00				
7 vmc	2202	2119	0	15938	0.29**	0.07**	-0.05**	-0.01	-0.19**	0.24**	1.00			
8 varvmc	30444	11035	0	47452	0.07**	0.67**	0.01	0.44**	-0.03**	0.11**	0.10**	1.00		
9 pleasance	1.36	0.443	0	2	-0.03*	-0.06**	0.12**	0.03**	0.03**	0.00	-0.04**	-0.19**	1.00	
10 activation	0.74	0.381	0	2	0.03**	-0.23**	0.04**	0.23**	-0.04**	0.07**	0.00	-0.08**	0.30**	1.00
11 gender	0.677	0.468	0	1	-0.07**	0.23**	-0.08**	-0.20**	0.04**	0.01	0.01	-0.05**	-0.08**	-0.10**

Note: ** p<0.01, * p<0.05

Note ** p < 0.01, * p < 0.05

Table 1.6 Results of multilevel regressions

Variables	Model0 flu	Model1 origin	Model2 abs	Model3 elab	Model4 res	Model5 flu	Model6 origin	Model7 abs	Model8 elab	Model9 res
Gender	-11.13***	-11.06***	-11.47***	-3.102***	-14.42***	-12.22***	-10.84***	-15.10***	-5.727***	-11.46***
Continent 1	-61.62***	-43.19***	-74.14***	-49.60***	-50.95***	-56.55***	-32.72***	-54.88***	-42.77***	-70.38***
Continent 2	-46.91***	-29.42***	-39.02***	-38.81***	-30.40***	-42.60***	-22.49***	-26.61***	-33.00***	-48.36***
Continent 3	-52.14***	-38.25***	-52.17***	-47.12***	-47.07***	-47.47***	-29.74***	-31.43***	-38.24***	-58.96***
Continent 4	-22.45***	-16.16***	-39.26***	17.31***	7.371***	-25.59***	-18.84***	-33.92***	15.17***	-0.846
o.continent5	-	-	-	-	-	-	-	-	-	-
Pleasance						-8.743***	-3.598***	-6.113***	-13.34***	-10.49***
Activation						5.977***	-1.762***	-5.542***	7.883***	0.664
stdavgbpm						-1.222***	-0.212	0.430***	-0.726***	-0.14
stdvarbpm						2.438***	2.297***	6.116***	4.161***	-2.873***
stdavglight						1.438***	1.638***	1.476***	1.096***	1.165***
stdvarlight						-5.255***	-4.697***	-2.933***	-5.451***	6.743***
stdavgacc						0.618***	0.530***	0.2	-0.00364	-0.0807
stdvaracc						-0.0959	0.0374	0.702***	0.0211	-0.305*
stdvmc						0.351**	0.274	-0.0919	0.324***	0.441***
stdvarvmc						-3.648***	-4.625***	0.810***	-2.268***	0.163
Constant	151.8***	136.6***	148.3***	136.4***	139.8***	156.2***	136.1***	150.1***	144.9***	166.9***
Observations	8.339	8.339	8.339	8.339	8.339	8.339	8.339	8.339	8.339	8.339
Number of groups	37	37	37	37	37	37	37	37	37	37

Note *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

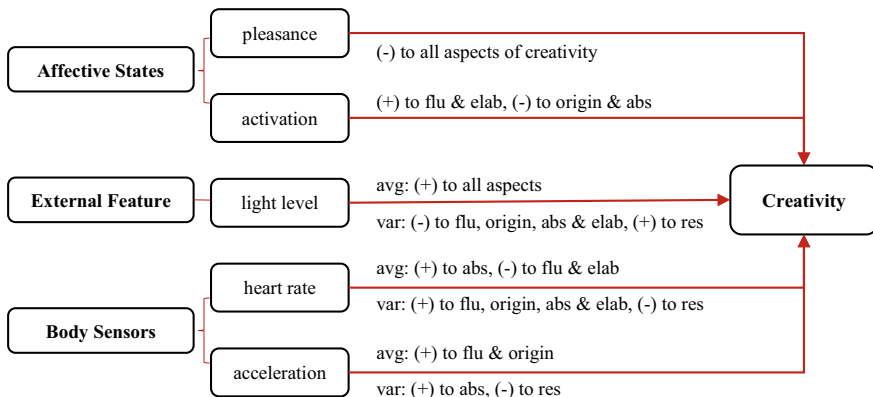


Fig. 1.2 Significant predictors of creativity

Another important finding is that the external light level has great impact on creativity (both the average light level and variance of light level within a day). While increasing light level will enhance all subscores of creativity, the variance of light will lead to the reduction of four dimensions of creativity (fluency, originality, elaboration, abstractness).

Moving on to the influence of affective states, both the scores of pleasance and activation play a prominent role regarding creativity. One interesting finding is that pleasance would actually impede a person’s creativity. Our results also provide evidence for the relationship between activation and creativity, while activation promotes fluency and elaboration, and it has adverse effects on originality and abstractness.

Figure 1.2 summarizes our results, with (+) referring to a positive relationship, while (–) indicates a negative one.

Discussion

Literature focusing on creative thinking can be divided into research about the creative product, process, person, and environment [4]. This study focused on creative thinking skills of a person, investigating the influence of body sensors, environmental features, and affective states. We find strong contributors from the biological, psychological, and environmental sides. Comparing the specific indexes, we find that while both the average and variance of heart rate, light level, and pleasance and activation have relatively stronger influences on creativity, accelerometer data (VMC and acceleration) has relatively small, almost negligible, effect size. We independently investigated the five aspects of creativity since the TTCT is an instrument used to measure different constructs and prior literature advised them being explored separately. Our results show distinct differences in the impact of body sensor, mental

states, and environmental features on difference subscores of the creativity measured by TTCT.

Also, on the individual level, similar to Lee and Kyung [12], we find gender difference in creativity, which reveals that females tend to score higher in different constructs than men. Moreover, the cultural differences revealed by Saeki et al. [20], which assessed cross-cultural creativity differences between American and Japanese students, are confirmed in our study. We identify regional inequalities of creativity between study participants from different continents, and find that Europeans are most creative, followed by North Americans, and Asians. This illustrates that creativity cannot be isolated from the socio-cultural context in which an individual lives and works.

This study contributes to literature about creativity by both supporting previous findings and providing new insights. We provide evidence for the gender and region difference in creativity. By new insights, we refer to the introduction of a novel method to measure individuals' creativity based on analyzing body language, environmental feature, and mood states. We also demonstrate how technology, specifically sensor-based systems like the Happimeter, might be used to collect personality characteristics in a non-intrusive way, without the need to fill out surveys. However, this study also has some limitations. First, the dataset is quite small, with 37 participants. Future research is needed to replicate the findings related to the five constructs of creativity with a larger size group of people. Second, this study only pays attention to a set of limited variables related to body sensor, affective states, and environmental feature. As there is rapid development in this field, it is desirable to collect in future research data from different types of sensors. For instance, researchers could integrate latest results on analyzing stress levels by adding more psychology-related variables, or more variables describing types of noise in the environment. This research did not explore group problem-solving or an actual creative solution. Rather it was a correlational analysis of independent variables with a standardized creativity assessment. Future research may explore creative teams on real-world problems. With the current work we have barely scratched the surface of this exciting new area of research.

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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