

Moti-Meter: A System for Visualizing Personal Learning Motivation

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Abstract. In recent years, e-learning systems have been introduced and used at many educational institutions. However, because of difficulty in maintaining student motivation in classes that use these systems, e-learning systems for self-study may foster user dropout; more precisely, because users are isolated during self-study, they may be highly motivated to engage in e-learning initially, but this motivation may gradually decline over time. In this study, we introduce “Moti-Meter,” a system intended to support the maintenance of user motivation and avoid psychological reactance by enabling users to visualize their own motivation. Estimation of users’ motivation is done using regression analysis of data collected from non-invasive sensor devices, such as smartphones and wearable devices. Visualizing one’s motivation has potential for applications in a range of other fields as well, for instance in healthcare.

Keywords: E-learning · Motivation · Wearable device

1 Introduction

In the first decade of the twenty-first century, e-learning systems have been introduced and used at many educational institutions [1, 2]. In Japan, too, the Ministry of Education decided to formally adopt digital textbooks in elementary and junior high schools [3]. However, because of difficulty in maintaining student motivation in classes that use these systems, e-learning systems for self-study may foster user dropout; more precisely, because users are isolated during self-study, they may be highly motivated to engage in e-learning initially, but this motivation may gradually decline over time. For these reasons, the current study examines how motivation may be maintained when using e-learning systems.

2 Relevant Studies

Narumi and colleagues [4] investigated the “Sotsuron-Watch” (*sotsuron* is the Japanese word for a graduation paper at university), a tool that collects and shares information about students’ progress toward finishing their graduation papers [4]. This system succeeded in helping students maintain the motivation to write their graduation papers.

However, users' motivation may decline if they use e-learning inappropriately. This concept, called "psychological reactance" [5] refers to the adoption or strengthening of a view or attitude contrary to what was intended, which also increases resistance to persuasion [5]. Asao [6] provided evidence for the importance of psychological reactance for e-learning through his questionnaire entitled "Feelings of Usefulness of Information Transfer in Interactive Mathematical Web Materials for Teenagers." Some student respondents said that the help function of the system they used was meddling, and that more appropriately functions should exist [6]. The study showed that psychological reactance could be minimized, and motivation maximized, by providing users with timely help.

In this study, we introduce "Moti-Meter," a system supporting user motivation in relation to studying by enabling users to visualize their own motivation. Estimation of users' motivation is then done using data collected from non-invasive sensor devices such as smartphones and wearable devices. This system aims to maintain users' motivation and avoid psychological reactance.

3 Utilization of Wearable Devices

In this study, we estimate the motivation of users using data collected from wearable devices. In chapter, we summarize today's studies in this field.

Nowadays, miniaturization and price reduction have improved the performance of various wearable devices such as smartphones. Thanks to these devices, many studies have been launched, for example, in the health field, on using bio-information, or registering and sharing Lifelog and healthcare support services. Yonekura et al. [7] investigated a system forecasting user motivation in mental health care using data collected from wearable devices alongside other data collected by answering a questionnaire, for example on weather favorability, time spent on relaxing activities such as sports or video games, or time spent on necessary daily commitments such as students' classes or jobs [7]. The experiment conducted in this study show that this method enables to forecast motivation with high accuracy, over a long period.

4 How to Visualize Motivation

4.1 Method

In this study, we use lifelog data such as activity data by having participants use wearable devices. We also got data on, for instance, weather favorability, by answering the questionnaire. From these data, we propose a system which visualizes motivation for studying: the "Moti-Meter" (Fig. 1).

We asked our participants to study English every day during the experimental period. Before studying, they manually entered a self-assessment of their motivation to study into the Moti-Meter.

Models of user motivation are estimated using regression analysis of the manually entered motivation ratings along with the following data collected from non-invasive

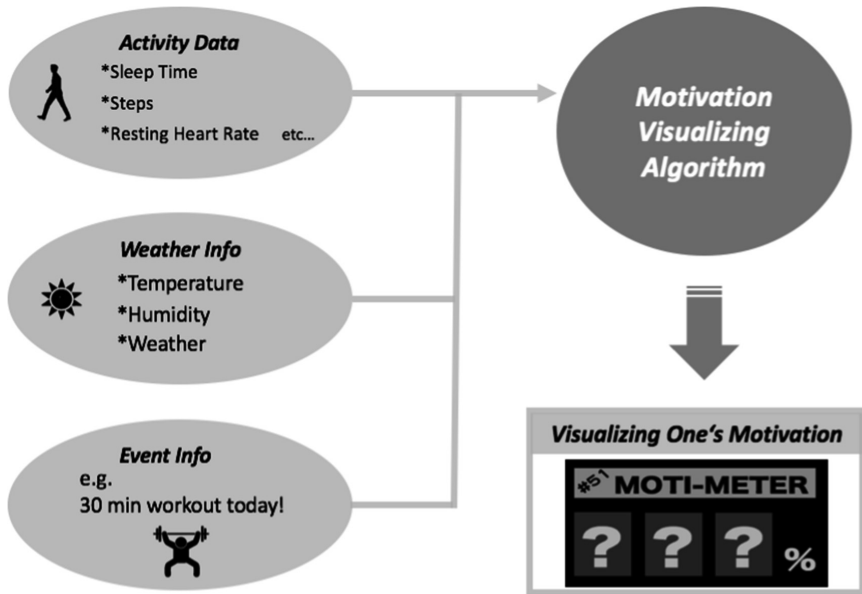


Fig. 1. General view of our method.

sensor devices such as smartphones and wearable devices: sleep time; resting heart rate; active time (as defined by Fitbit); steps; calories burned; and other data collected by answering the questionnaire: weather favorability; time spent on relaxing activities; time spent on necessary activities.

4.2 Acquisition of Activity Data and Weather Information

To get physical activity data, we use the Fitbit Charge HR (Fitbit, Inc.), wristband-shaped wearable device (Fig. 2) [8]. The Charge HR has various sensors, including a heartbeat sensor, GPS, acceleration sensor, etc. In this study, participants were always wearing the Charge HR, yielding activity data.

We also gave the participants a questionnaire to get weather favorability, additional data we could not gather through the Charge HR.

4.3 Acquisition of Event Information

Yonekura and colleagues classify each event in terms of the categories of “relaxing” or working on a “task” [7]. According to them, a task is an event in which one participates and which one must respond to even against one’s will, such as going to class or going to one’s part-time job, while relaxing is action that follows one’s will, such as sports or playing video games.

In this study, we event information following the Yonekura et al. definition, by distributing a questionnaire to the participants and have them answer with time values, like “Today I had a 30-min workout!”



Fig. 2. Fitbit Charge HR.

5 Experiment: Estimating a Model of Studying Motivation

5.1 Objects of This Experiment

To develop the motivation visualizing system, Moti-Meter, we first have to experiment to estimate it, which we will endeavor to do so by percentage.

5.2 Experimental Method

Participants were required to do classwork using the e-learning system for TOEIC (Test of English for International Communication) every day for 15 days. The system was produced by Newton Inc. During the period of the experiment, participants always wore the Fitbit Charge HR except when impossible, for example while taking a bath.

We made participants evaluate their own subjective motivation for studying before they had the chance to during the experimental period. We also made them answer questionnaires (Fig. 3) to get event information and weather favorability every day.

Date	Task min	Relax min	Weather (-2 ~ +2)	Humidity (-2 ~ +2)	Temperature (-2 ~ +2)	Today's Motivation	Notes
9/Dec	360	70	1	1	1	60	
10/Dec	360	150	-1	1	1	40	
11/Dec	120	90	2	1	1	30	

Fig. 3. Questionnaire to get some data.

The parameter to estimate the motivation model is summarizing in Table 1.

Table 1. Parameters for estimating motivation visualizing model.

Dependent variable	Motivation for studying (subjective value)
Explanatory variable 1	Yesterday's sleep time
Explanatory variable 2	Resting heart rate
Explanatory variable 3	Active time*
Explanatory variable 4	Steps
Explanatory variable 5	Calories burned
Explanatory variable 6	Weather favorability (subjective value)
Explanatory variable 7	Humidity favorability (subjective value)
Explanatory variable 8	Favorability (subjective value)
Explanatory variable 9	Time for relaxing
Explanatory variable 10	Time for task

“Active Time” is an activity indicator defined by Fitbit, using the MET (Metabolic equivalents). Based on the point of view that “10 min of exercise at a time is fine,” which is mentioned by CDC (Centers for Disease Control and Prevention), Fitbit defined “Active Time” as exercising more than 3 MET for over 10 min [9].

5.3 Analytic Method

Based on the hypothesis that the “Dependent variable and the Explanatory are linear,” We adopted the linear multiple regression analysis for the analyses. We tried to derive a regression model of motivation for studying, and a visualizing algorithm.

5.4 Results and Analysis

We succeeded in getting 82 days' worth of data from 6 participants' 15-day data. Participants were all college students in their 20 s. We did the linear multiple regression analysis, and Table 2 is a summary of the results.

Table 2 shows that the parameters of Weather and Relaxing Time were significant and that of Temperature, marginally significant. However, Temperature has very little coefficient (-0.0307), meaning that it has little relation to one's motivation for studying.

Other parameters were not significant, and adjusted multiple correlation coefficients (R-squared value) were very small (0.08). This result means the model is not linear.

5.5 Discussion

Improvement of the motivation estimating model

The result of regression analysis yield a correlation between Measured and Estimated Motivation (Fig. 4).

Table 2. Results of linear multiple regression analysis.

	Coefficient	Standard deviation	t	P-value
Intercept	50.186	36.913	1.360	0.178
Sleep time	-0.918	1.331	-0.690	0.493
RHR	0.229	0.618	0.370	0.712
Active time	-0.078	0.162	-0.484	0.630
Steps	0.000	0.001	0.395	0.694
Calories burned	-0.003	0.012	-0.245	0.807
Weather	6.200	2.546	2.435*	0.017
Temperature	-5.154	2.840	-1.815*	0.074
Humidity	2.904	3.038	0.956	0.342
Relaxing time	-0.037	0.018	-2.023*	0.047
Task time	-0.020	0.020	-0.968	0.337

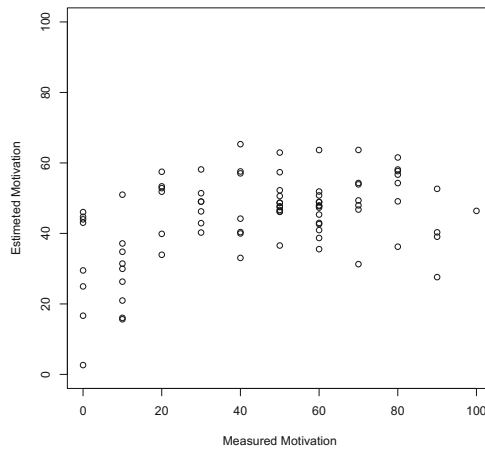


Fig. 4. Correlation between measured and estimated motivation.

As Fig. 4 shows, this relationship does not have a tendency to monotonic increase. That is why we conclude that the model is not linear. In our future work, we are going to try to conduct analogous analyses using nonlinear modeling, GA (genetic algorithm), or other methods to yield the most optimum motivation estimating model.

The Influences of Seasonal Factors

Based on the results of multiple regression analysis, the parameters Weather and Temperature were significant. This means that motivation for studying has a generous correlation with weather favorability. The experiment was held in December 2016, when the weather is very cold and stormy in Japan. Because of this seasonal factor of Weather, we guess that the motivation for studying has been affected.

Before the Experiment whose results are presented in this section, we conducted a preparatory Experiment in October 2016, when the weather is better. In the pilot, parameters related to weather favorability do not have any big correlation with motivation for study. These results should be compared with those of studies in other seasons, for reliability and validity.

6 Conclusion and Future Work

We conducted an experiment to get a regression model of motivation for studying. The results failed to yield a significant regression model. However, parameters related to weather favorability had a generous correlation with motivation for studying.

In our future work, we are going to try other methods of analysis, such as nonlinear modeling and GA, to support the findings; reflect the findings in the “Moti-Meter” algorithm, and test them.

We also intend to develop a “Moti-Meter” application for Android smartphone. Storing active data from Fitbit’s API (application programming interface) to throw it into the algorithm will help us better measure user motivation.

In this study, we assumed that e-learners study on their own, and tried to visualize their motivation. However, we certainly did not investigate all potentially relevant variables, such as diet. This methodology can be applied to such cases to flesh them out also.

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References

1. Kodama, S., Azuma, S., Sato, T., Sawaguchi, T., Tatsumi, Y.: An empirical study on the effect of e-learning in teaching exercises for undergraduate macroeconomics. *J. Educ. Appl. Inf. Commun. Technol.* **14**(1), 16–20 (2011)
2. Sato, O.: Research for e-learning performance in universities. *J. Jpn. Soc. Inf. Manag.* **29**(4), 3–11 (2009)
3. Ministry of Education, Culture, Sports, Science, and Technology of Japan. <http://www.mext.go.jp/>
4. Narumi, T., Tanikawa, T., Hirose, M.: Visualization and vitalization of research activity using gamification. In: *The 29th Annual Conference of the Japanese Society for Artificial Intelligence*, pp. 1–4 (2015)
5. Brehm, J.: *Explorations in Cognitive Reactance*. Academic Press, New York (1966)
6. Asao, A.: Questionnaire research on feelings of usefulness of information transfer in an interactive mathematical web material for teenagers. *Rep. Jpn. Assoc. Educ. Technol.* 183–190 (2012)
7. Yonekura, S., Okamura, S., Kajiwara, Y., Shimakawa, H.: Mood prediction reflecting emotion state to improve mental health. In: *FIT2015 (The 14th Forum of Information Technology)*, pp. 343–344 (2015)
8. Fitbit, Inc. <https://www.fitbit.com/jp>

9. Centers for Disease Control and Prevention. <http://www.cdc.gov/physicalactivity/basics/adults/index.htm>
10. Minolta, K.: https://www.konicaminolta.jp/runpro/running/sports_safety/004.html