Hedonism and the choice of everyday activities

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Edited by Marcia K. Johnson, Yale University, New Haven, CT, and approved June 29, 2016 (received for review October 12, 2015)

Most theories of motivation have highlighted that human behavior is guided by the hedonic principle, according to which our choices of daily activities aim to minimize negative affect and maximize positive affect. However, it is not clear how to reconcile this idea with the fact that people routinely engage in unpleasant yet necessary activities. To address this issue, we monitored in real time the activities and moods of over 28,000 people across an average of 27 d using a multiplatform smartphone application. We found that people's choices of activities followed a hedonic flexibility principle. Specifically, people were more likely to engage in mood-increasing activities (e.g., play sports) when they felt bad, and to engage in useful but mood-decreasing activities (e.g., housework) when they felt good. These findings clarify how hedonic considerations shape human behavior. They may explain how humans overcome the allure of short-term gains in happiness to maximize long-term welfare.

hedonism | emotions | motivation | decision making | happiness

What will you be doing in an hour? Working? Doing your laundry? Having a beer with a friend? Behind this simple question lies one of the most important decisions we face in our lives, namely, how to spend our time. On average, people live about 600,000 h, and whether we decide to spend a greater or lesser number of these hours working, sleeping, socializing, or watching television has crucial consequences for our mental and physical health (1–3).

There are many factors that influence our everyday activities—from financial considerations to social norms to political constraints—yet most theories of motivation have highlighted the crucial role played by negative and positive affective states (4–6). In particular, human behavior is believed to be guided by the hedonic principle, according to which our choices of activities aim to minimize negative affect and maximize positive affect (7).

The hedonic principle has been tested empirically through laboratory studies that have used a wide variety of mood induction techniques (e.g., writing about negative or positive life events, watching sad or happy movies) and then asked individuals to choose among various activities. Results have largely supported the hedonic principle: when they feel bad, most people try to decrease their negative emotions by choosing to engage in activities that make them feel better (e.g., eating comfort food, seeking social support) (8–12); when they feel good, most people try to maintain or even maximize their positive emotions (e.g., playing, engaging in various social, physical, and leisure activities) (13–15)—at least when positive emotions are not considered inappropriate due to social norms or utilitarian concerns (16–18).

Do these laboratory findings generalize to our everyday decisions? Although widely supported in the laboratory, the hedonic principle, without further specification, does not explain much of people's everyday behavior: if we always try to improve our moods, when are we motivated to do the dishes, wait in line at the post office, or even go to work?

One possibility is that our choice of activities is mostly determined by the demands and constraints of everyday life. In the face of these constraints, the "hedonic opportunism hypothesis" suggests that we try to maximize our mood whenever an opportunity arises. A second possibility is that the hedonic principle applies mainly when people's affective states are salient (19). According to this "hedonic salience hypothesis," we are concerned with maximizing our mood when we feel very bad or very good, and we undertake less pleasurable—yet necessary—activities when we are in a more neutral affective state. A third possibility—suggested by Herbert Simon (20) half a century ago—is that people have multiple simultaneous goals, from seeking short-term rewards (e.g., increasing one's mood state) to pursuing longer-term rewards (e.g., working hard toward a promotion), and affective states help to prioritize among these goals. According to this "hedonic flexibility hypothesis," whereas negative affect may drive people to seek solace in short-term rewards, positive affect should lead people to shift their priorities toward less pleasant activities that might be important for their longer-term goals (21).

These three hypotheses make different predictions regarding how mood should be related to people's subsequent choices of activities. The hedonic opportunism hypothesis suggests that mood should not predict the type of activities that people engage in. The hedonic salience hypothesis suggests that extreme mood states should predict a higher propensity to engage in pleasant activities, whereas neutral mood states should predict a higher propensity to engage in useful but unpleasant activities. Finally, the hedonic flexibility hypothesis suggests that negative mood states should predict a higher propensity to engage in pleasant activities, whereas positive mood states should predict a higher propensity to engage in useful but unpleasant activities.

To test which specification of the hedonic principle is best able to explain choices of everyday activities, we conducted a large experience-sampling study, monitoring in real time the activities

Significance

Decisions we make every day about how to invest our time have crucial personal and societal consequences. Most theories of motivation propose that our daily choices of activities aim to maximize positive affective states but fail to explain when people decide to engage in unpleasant yet necessary activities. We tracked the activities and moods of over 28,000 people in real time and demonstrated that people seek mood-enhancing activities when they feel bad and unpleasant activities when they feel good. These findings clarify how emotions shape behavior and may explain how humans trade off short-term happiness for long-term welfare. Overcoming such trade-offs might be critical for our personal well-being and our survival as a species.

Author contributions: M.T. and J.Q. designed research; M.T., J.Q., and J.J.G. performed research; M.T. and J.Q. contributed new reagents/analytic tools; M.T., J.Q., Y.-A.d.M., and M.D. designed the mobile application and acquired data; M.T., J.Q., and J.J.G. analyzed data; and M.T., J.Q., Y.-A.d.M., M.D., and J.J.G. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1519998113/-/DCSupplemental.

and moods of over 60,000 people across an average of 27 d using a multiplatform smartphone application (www.58sec.com), totaling over half a million samples. Participants were presented with questionnaires at random times throughout the day and asked to rate their current mood on a scale from 0 (very unhappy) to 100 (very happy) and to report what they were doing from a standard list of 25 non-mutually exclusive choices (1). Using a Bayesian regression model and selecting participants who answered two consecutive questionnaires or more within a range of 12 h ($N_{participants} = 28{,}212$; $M_{age} = 28.1$, $SD_{age} = 9.0$; 66% women; $N_{questionnaires} = 245{,}006$), we examined simultaneously how people's current mood (mood *t*) related to the type of activity they would be engaging in a few hours later (activity *t* + 1) and the relationship between that activity and their subsequent mood (mood *t* + 1), controlling for what people were previously doing (activity *t*), time of the day, day of the week, and amount of time elapsed between the two measurement times. This approach allowed us to compute whether one's current mood changes the odds of subsequently engaging in each of the 25 activities (i.e., what people decide to do) and how engaging in each of the 25 activities changes one's future mood (i.e., how people feel as a result).

Results

The results of our analyses are depicted in Fig. 1, and they reveal two key findings. First, people's daily decisions to engage in one activity rather than another are related to how they currently feel: participants' mood at time *t* significantly predicted what they would be doing at time *t* + 1 for 15 out of 25 activities (posterior probability <0.005; color bars in Fig. 1*A*), a finding that is inconsistent with the hedonic opportunism hypothesis. The effects of mood on people's choice of activities were stronger for pleasant than unpleasant activities. As depicted in Fig. 1 *C* and *D*, although mood at time *t* significantly predicted people's propensity to engage in five unpleasant activities at time *t* + 1 (i.e., commuting, working, housework, sleeping, and waiting), these activities were more strongly predicted by the day of the week or the time of the day (as measured by the proportion of deviance explained by each degree of freedom of the corresponding variable). In contrast, of the 10 pleasant activities significantly predicted by mood at time *t*, two activities (i.e., eating and childcare) were better predicted by mood than by the day of the week, three activities (i.e., nature, leisure, and culture) were better predicted by mood than by the time of the day, and three activities (i.e., sport, chatting, and drinking) were better predicted by mood than by either day or time. In other words, if you wanted to predict how likely a random stranger whom you meet is to be working, cleaning the dishes, or sleeping a few hours from now, knowing what day or time it is would be more informative than knowing her current mood. If, however, you wanted to predict how likely that person is to exercise, chat with friends, or have a drink in the next few hours, knowing her current mood would give you more information than knowing that it is Saturday or that it is 7:00 PM.

Second, the interplay between mood and choices of activity followed a very specific pattern. In line with both the hedonic salience and hedonic flexibility hypotheses, when participants were in a bad mood, they were more likely to engage in activities that tended to subsequently boost their mood. For instance, if people's current mood decreased by 10 points, they were more likely to later engage in doing sport [adjusted odds ratio (OR_{adj}) = 1.129], going out into nature (OR_{adj} = 1.092), leisure (OR_{adj} = 1.074), chatting (OR_{adj} = 1.068), cultural activities (OR_{adj} = 1.065), drinking (OR_{adj} = 1.046), playing (OR_{adj} = 1.044), eating (OR_{adj} = 1.029), or taking care of children (OR_{adj} = 1.021), and all of these activities were in turn associated with a subsequent increase in mood (Fig. 1*B*, red bars). Contrary to the hedonic salience hypothesis, however, and consistent with the hedonic flexibility hypothesis, when people were in a good mood, they were more likely to engage in activities that tended to subsequently dampen their mood. Specifically, if people's current mood increased by 10 points, they were more likely to later engage in doing housework (OR_{adj} = 1.036), commuting (OR_{adj} = 1.037), resting (OR_{adj} =

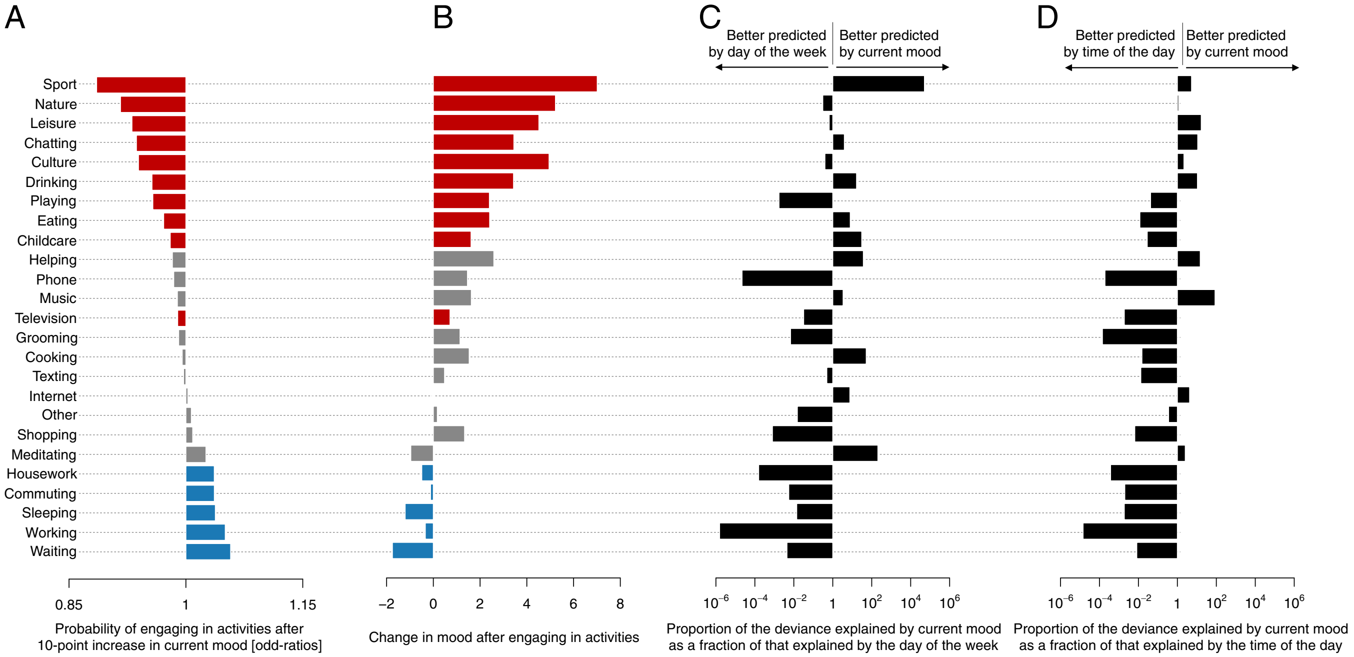

Fig. 1. The association between daily mood and choice of activities follows a hedonic flexibility principle. (*A*) Relationship between people's current mood (mood *t*) on their subsequent choice of activities (activity *t* + 1). (*B*) Relationship between people's choice of activities (activity *t* + 1) on their subsequent mood (difference between mood *t* and mood *t* + 1). The red and blue (vs. gray) bars depict statistically significant relationships with a posterior probability <0.005. (*C*) Proportion of the deviance of choice of activities (activity *t* + 1) explained by people's current mood (mood *t*) relative to the deviance explained by the day of the week. (*D*) Proportion of the deviance of choice of activities (activity *t* + 1) explained by people's current mood (mood *t*) relative to the deviance explained by the time of the day.

1.038), working ($OR_{adj} = 1.051$), or queuing ($OR_{adj} = 1.057$), and all of these activities were in turn associated with a subsequent decrease in mood (Fig. 1*B*, blue bars). Our pattern was robust and replicated in 10 random splits of the sample. To illustrate these ORs and the magnitude of the hedonic flexibility principle with a concrete example, imagine an average individual deciding what to do on a Sunday afternoon. If that person was particularly unhappy in the morning (scoring 10 on the mood scale), she would be twice as likely (4.32% vs. 2.08%) to go for a walk in nature in the afternoon than if she was particularly happy that morning (scoring 90 on the mood scale). Likewise, if that person was particularly happy in the morning, she would be about 30% more likely (5.64% vs. 4.43%) to clean up her apartment in the afternoon than if she was particularly unhappy that morning.

Our findings suggest that mood shapes the decisions people make about which activities to undertake in the next few hours and that, in turn, these activities influence how they feel. However, two alternative explanations of the interplay we observed between activities and mood are possible. The first is that the succession of activities in everyday life might follow a systematic pattern or "rhythm" (e.g., people typically eat breakfast then go to work rather than the other way around). The second is that mood might follow a natural rhythm [e.g., people typically feel in a better mood in the morning than just before lunch (22)].

If activities followed a natural rhythm that was not affected by mood but caused corresponding changes in moods (e.g., eating breakfast makes people happy, working makes people unhappy, and people typically eat breakfast before going to work), then one might expect to observe similar associations between mood and activities as the ones we observed, even if mood actually does not cause any change in people's choice of activities. In that case, mood at time t would not be a valuable predictor of activity at time $t+1$. To rule out this alternative explanation, we computed, for each activity, the Akaike information criterion (AIC) of a model in which mood at time t was removed from the set of independent variables. These analyses revealed that our findings could not be explained by the natural rhythm of activities ($P < 0.004$).

If mood follows a natural rhythm that is not affected by the activities that people are currently doing but causes corresponding changes in choices of subsequent activities (e.g., people are happier at 8:00 AM than at 11:00 AM, and being happy in the early morning increases the odds they work a few hours later), one might expect to observe similar associations between mood and activities as the ones we observed, even if the choice of activity actually did not cause changes in people's mood. In that case, the change in mood between times t and $t+1$ would solely be predicted by current mood and not by activities at $t + 1$. To rule out this alternative explanation, we compared the AIC of two models predicting the change in mood ($\Delta M = M_{t+1} - M_t$) from either current mood alone or current mood and activities at time $t+1$. This analysis revealed that our finding could not be explained by the natural rhythm of mood ($P < 0.0001$). Taken together, these findings offer further support for the hedonic flexibility hypothesis.

Discussion

Deciding what to do with one's time is one of the most fundamental choices humans face every day—a choice that has crucial consequences both for individuals and society at large. Our findings demonstrate that people's everyday decisions regarding which activities to undertake are directly linked to how they feel and follow a remarkably consistent pattern. People seek mood-enhancing activities when they feel bad and engage in unpleasant activities that might promise longer-term payoff when they feel good. Although our data cannot directly tell us whether regularly engaging in unpleasant activities predicts psychological and social adjustment 5 or 10 y down the line, a large body of work has consistently demonstrated the importance of sleeping (23), employment (24), and living in a reasonably clean and organized home (25, 26) on mental and physical health.

The present research shows robust associations between affective states and choices of activity: people's current mood meaningfully changes (sometimes doubling or tripling) the probability they later engage in certain types of activity, and mood sometimes predicts what people will be doing in the next few hours better than knowing what day or time it is. However, it is important to note that, owing to the study design, our examination of the effect of mood on choice of daily activities was limited to a standard subset of assessed activities. Future research should examine the pervasiveness of the hedonic flexibility principle with a wider range of activities (e.g., via open-ended responses). In addition, further work is needed to examine the underlying mechanism through which affective states relate to choices of activities. For instance, it is possible that indirect effects, such as the impact of mood on people's concentration or fatigue levels, influence the relationship that we observed. Likewise, the present work has focused on the relationship between mood and people's choices on average. However, it is very likely that important individual differences exist in the extent to which affective considerations guide people's daily choices. Investigating the hedonic flexibility principle across various groups of individuals and cultures represents an exciting avenue for future work. Finally, experimental research is needed to establish the causal impact of affective states on daily decisions. One could, for example, manipulate mood by sending positive or negative stimuli on people's phone and measuring how this impacts their subsequent choices of activity.

Opportunities to indulge in short-term pleasure are all around us—from our favorite hobbies to our favorite ice cream. Our personal well-being and survival potential as a species might crucially depend on our ability to overcome the allure of short-term happiness gains to maximize long-term welfare. The hedonic flexibility principle may explain how humans have and continue to overcome such trade-offs in their everyday life.

Materials and Methods

Participants and Experience Sampling. Participants volunteered for the study by downloading *58 seconds* (www.58sec.com), a free francophone mobile application for iPhone and Android phones dedicated to measuring various aspects of users' well-being through short questionnaires presented at random times throughout the day. The project received significant media coverage in France. At initial signup, participants answered several questions about themselves, including age, gender, and country of residence (see Table S1 for detailed information on the composition of the sample). Next, participants were asked which days of the week and within what time windows they wished to receive questionnaire requests (default = 7 d/wk from 9:00 AM to 10:00 PM). Participants could also customize the number of daily questionnaire requests they wanted to receive (default = 4, minimum = 1, maximum = 12). The application algorithm then divided each participant's day into a number of intervals equal to the number of samples to be requested, and a random time was chosen within each interval. The minimum time between two questionnaires was set to 1 h to avoid large artifactual autocorrelations between answers to the same question in consecutive tests. The random sampling was ensured through a notification system that did not require users to be connected to the Internet. New random times were generated each day, and the times were independently randomized for each participant. At each of these times, participants received a notification on their mobile phone informing them that a new questionnaire was available (Fig. S1*A*). They then had the possibility to take the questionnaire, snooze it (i.e., delay it by 9 min), or reject it (Fig. S1*B*). The two questions asked to participants were "How do you currently feel?" (Fig. S1*C*) and "What are you currently doing?" and were always presented in that order (i.e., mood then activity). The frequency of recorded results as a function of time and day is reported in Fig. S2. In the present paper, we refer to activities that are associated with positive changes in mood (compared with the previous mood level) as pleasant activities and activities that are associated with negative changes in mood as unpleasant activities.

This study has been approved in written form as part of a broader project on emotions in everyday life by The Ethics Committee of the University of Groningen, The Netherlands. The study method was carried out in accordance with the approved guidelines. All study protocols were approved by the

PSYCHOLOGICAL AND COGNITIVE SCIENCES

aforementioned committee. At initial sign-up, participants provided their written informed consent.

Regression Model. To assess whether people's current mood impacts their decision to later engage in an activity, we related these variables in a regression model. Because current and future moods are likely to be correlated and because future mood is also likely to be correlated to future activities, we incorporated future mood as a covariate in the regression model. This guarantees that associations between current mood and future activities are not merely mediated by future mood. Specifically, we let M_t and M_{t+1} denote the mood at time t and $t+1$, respectively, and we let A_t^j and A_{t+1}^j be dichotomous variables denoting whether the participant was engaged in the jth activity ($j = 1,\ldots, 25$) at time t and $t+1$, respectively. If $A_t^j = 1$, then the participant is engaged in the jth activity at time t, whereas the opposite is true if $A_t^j = 0$. Using a logistic regression, we can link M_t and M_{t+1} to the probability $P(A_{t+1}^j)$ that participants engage in the jth activity. The generic regression model has the following expression:

$$\text{logit } P\left(A_{t+1}^j\right) = \beta_0^j + \beta_c^j M_t + \beta_f^j M_{t+1} + \sum_{k=1}^{K} \beta_k^j X_k,$$

where β_0^j is the intercept, β_c^j is the coefficient related to the current mood, and β_f^j is the coefficient related to the future mood. The terms in X_k are a set of possible covariates that need to be controlled for. We consider the following covariates: the day of week (e.g., people are more likely to be working on a weekday than during the weekend), the time of day (e.g., people are more likely to be eating at noon than at 10:30 AM), and latency effects (e.g., some activities span a period that is longer than the time between two measurements). Preferences based on the day are expressed by adding a categorical variable D specifying whether the day of the measurement is a weekday, a Saturday, or a Sunday. Because no prior functional variation (e.g., linear or quadratic) of the activity with respect to the time of day can reasonably be expressed, we represent the time of day as a categorical variable H by binning the time in 12 periods of 2 h (from 0:00 AM–1:59:59 AM to 10:00 PM–11:59:59 PM). Finally, the latency effect can be represented by adding the dichotomous variable A_t^j indicating whether one was already engaged in the jth activity at the previous measurement.

Selecting which predictors are relevant is a model selection problem and the AIC is a widely used and efficient method to achieve model selection (27). This criterion is as follows: $\text{AIC} = 2N - \log L$, where N is the number of parameters of the model and L is the maximum value of the model likelihood (i.e., its likelihood after the coefficients of the model have been optimized). By trading off between the goodness of fit of the model ($-\log L$) and its complexity, AIC measures the relative qualities of different models. Lower AIC indicate better-suited models. In order for more complex models to be selected, the increase in their log-likelihood term must outweigh the cost associated with additional parameters. We investigated the following six models (**1**–**6**) and computed their AIC for each of the 25 activities:

$$\text{logit} P\left(A_{t+1}^j\right) = \beta_0^j, \quad [1]$$

$$\text{logit} P\left(A_{t+1}^j\right) = \beta_0^j + \beta_f^j M_{t+1} + \beta_h^j H + \beta_d^j D + \beta_a^j A_t^j, \quad [2]$$

$$\text{logit} P\left(A_{t+1}^j\right) = \beta_0^j + \beta_c^j M_t + \beta_f^j M_{t+1}, \quad [3]$$

$$\begin{aligned}\text{logit} P\left(A_{t+1}^j\right) = {} & \beta_0^j + \beta_c^j M_t + \beta_f^j M_{t+1} \\ & + \beta_h^j H + \beta_d^j D + \beta_a^j A_t^j,\end{aligned} \quad [4]$$

$$\begin{aligned}\text{logit} P\left(A_{t+1}^j\right) = {} & \beta_0^j + \left(\beta_c^j + \alpha_c^j \frac{1}{\Delta t}\right) M_t + \beta_f^j M_{t+1} + \beta_h^j H \\ & + \beta_d^j D + \left(\beta_a^j + \alpha_a^j \frac{1}{\Delta t}\right) A_t^j,\end{aligned} \quad [5]$$

$$\begin{aligned}\text{logit} P\left(A_{t+1}^j\right) = {} & \beta_0^j + \left(\beta_c^j + \alpha_c^j \frac{1}{\Delta t}\right) M_t + \beta_f^j M_{t+1} + \beta_h^j H \\ & + \beta_d^j D + \sum_{k=1}^{25} \left(\beta_a^k + \alpha_a^k \frac{1}{\Delta t}\right) A_t^k.\end{aligned} \quad [6]$$

Model **1** is the null baseline model that has no predictor. Model **2** assumes that current mood has no effect on the decision to later engage in an activity. Model **3** assumes that no covariates are required to express the relation between mood and the decision to engage in activities. Models **4** and **5** include all covariates described above. Model **5** includes additional interaction terms to express the influence of the actual time elapsed between two reports (Δt). This model is based on the assumption that, if current mood has an effect on the decision to later engage in an activity, then this effect must be stronger if the actual time difference between two measurements, Δt, is smaller. The same applies to the latency effect. Finally, model **6** includes the dichotomous variables of all of the previous activities at time t and not just the jth activity.

The resulting AIC (computed using the aic function from R, version 3.1.0) for all activities and all models are summarized in Table S2. For readability purposes, we normalized each AIC by the maximum AIC among all models. This does not alter our conclusions because we are only interested in the identity of the model that leads to the smallest AIC. Model **6** is the most appropriate model for all 25 activities. Consequently, we used model **6** throughout our analyses.

Statistical Analyses. To assess whether people's current mood significantly predicts their future decision to engage in an activity, we computed the probability that the coefficient β_c^j in model **6** is larger than 0 for all 25 activities. If that probability is very large (i.e., close to 1), then an increase in current mood is almost certainly associated with an increase in the odds to engage in the jth activity. Conversely, if this probability is very small (i.e., close to zero), then a decrease in current mood almost certainly leads to an increase in the odds to engage in the jth activity. If the current mood does not reliably predict the odds to engage in the jth activity, then this probability ought to be around 0.5, reflecting our ignorance of changes in future odds beyond chance level (50%). This posterior probability is estimated in a Bayesian approach and can be interpreted as the Bayesian equivalent of conventional P values, which assess whether the coefficients are significantly different from zero. Specifically, we estimated the parameters of model **6** using the inference method implemented as the bayesglm function from the arm package (28) (version 1.7-05) in R (version 3.1.0), using the default parameters. This function returns estimates for the posterior mean (μ) and SE (σ) of β_c^j. Assuming that the posterior distribution of β_c^j can be approximated by a Gaussian distribution, we computed the probability that $\beta_c^j > 0$ as follows:

$$P\left(\beta_c^j > 0\right) = 0.5 + 0.5\,\text{erf}\left(\frac{z_c^j}{\sqrt{2}}\right), \text{ where } z_c^j = \frac{\mu}{\sigma}.$$

Activities are deemed to be significantly predicted by the current mood if the probability $P(\beta_c^j > 0)$ is either larger than $1 - 10^{-4}$ (blue bars on Fig. 1) or lower than 10^{-4} (red bars on Fig. 1). In the former case, the reported posterior probability ($<10^{-4}$) is taken as $1 - P(\beta_c^j > 0)$, so that small probabilities always indicate that the decision to engage in activities was significantly predicted by the current mood (similarly to small P values indicating a coefficient that is significantly different from zero).

The coefficients β_c^j were reported as adjusted ORs expressing the impact of an increase/decrease in current mood on the probability to later engage in a particular activity. These adjusted ORs were reported for a difference arbitrarily set to 10 points in current mood ($\Delta M_t = 10$) and were calculated as follows: $\text{OR}_{\text{adj}}^j = e^{\beta_c^j \Delta M_t}$. Fig. 1*A* represents the OR_{adj} for each activity.

To assess the association between activities and changes in mood, we computed, for each activity, the mean difference between future and current moods. In other words, for each activity j, we computed the average difference in mood $\Delta M_j = M_{t+1} - M_t$ for all entries presenting with $A_{t+1}^j = 1$. Note that ΔM_j should not be confused with ΔM_t used above. ΔM_j represents an observed change in mood between time t and time $t+1$ when the participant is engaged in the jth activity at time $t+1$, whereas ΔM_t represents some difference in mood at time t that is arbitrarily fixed to some value (fixed to 10 for the visualization in Fig. 1*A*) to observe the impact that such a difference in mood would have on the subsequent likelihood to engage in an activity.

We analyzed the proportion of explained deviance (equivalent to the proportion of variance for generalized linear models) using the function anova in R. We compared the proportion of deviance explained by the mood at time t to that explained by the day of the week and the time of the day. Because the day of the week adds 2 degrees of freedom to the model and is therefore more likely to explain more deviance due to chance alone, we report it as the proportion of explained deviance per degree of freedom by dividing its explained deviance by 2, and similarly for the time of day, which has 11 degrees of freedom.

Interpretation of ORs. In *Results*, we provided an example of the impact of current mood on an average participant's likelihood to later either go out to nature or to do housework. The result of this example can be obtained as follows. The OR of engaging in a particular activity is given by the product of adjusted ORs for all independent variables (current activities, current mood, time of day, etc.) as described by logistic regressions. All other factors being equal, the impact of a difference in current mood on the OR to later engage in a specific activity amounts to multiplying the average OR of that activity by the adjusted OR $e^{\beta_c^j \Delta M_t}$. The frequency of times that participants in our study went out in nature on a Sunday between 2:00 PM and 3:00 PM was 3%, and the frequency of times that they did housework at that time was 5%. The corresponding baseline OR [$\mathrm{OR} = P/(1-P)$] were 0.0309 and 0.0526, respectively. Assuming a baseline mood of 50, the OR for an individual scoring 90 on the mood scale is simply obtained by multiplying the baseline OR by $e^{\beta_c^j \times 40}$ and that for an individual scoring 10 on the mood scale is simply obtained by multiplying the baseline OR by $e^{-\beta_c^j \times 40}$. Using the value of β_c^j corresponding to nature and housework, we obtain the ORs for going out in nature as follows:

$$\mathrm{OR} = 0.0309 \times 0.6856 = 0.0212 \text{ for } \Delta M_t = 40, \text{ and}$$

$$\mathrm{OR} = 0.0309 \times 1.4585 = 0.0451 \text{ for } \Delta M_t = -40,$$

and those ORs for doing housework as follows:

$$\mathrm{OR} = 0.0526 \times 1.1352 = 0.0597 \text{ for } \Delta M_t = 40, \text{ and}$$

$$\mathrm{OR} = 0.0526 \times 0.8809 = 0.0464 \text{ for } \Delta M_t = -40.$$

These ORs can be transformed back to the probability of engaging in these activities by using the inverse formula for ORs: $P = \mathrm{OR}/(1 + \mathrm{OR})$.

Robustness Analyses. To test the robustness of our results, we randomly split the dataset in 10 subsets, each containing the data from 2,822 subjects except for the 10th subset containing the data from 2,814 subjects. We estimated the parameters of model **6** in each of these subsets independently. Results were found to be virtually identical across the 10 samples.

Ruling Out Explanations by Natural Rhythms. To rule out the alternative explanation that the rhythm of activities in everyday life might account for our findings, we computed, for each activity, the AIC of the following model **7** (which is similar to our original model **6** except that mood at time t was removed from the set of independent variables):

$$\mathrm{logit}P\left(A_{t+1}^j\right) = \beta_0^j + \beta_f^j M_{t+1} + \beta_h^j H + \beta_d^j D + \sum_{k=1}^{25}\left(\beta_a^k + \alpha_a^k \frac{1}{\Delta t}\right) A_t^k. \quad [7]$$

These analyses revealed that the AIC of model **7** was higher than that of model **6** for 20 of 25 activities, which under the null hypothesis that both models are equivalently good would occur less than once in 250 times (two-tailed binomial test: $P < 0.004$). Furthermore, the five activities for which model **7** had a lower AIC than model **6** were those for which mood at time t did not significantly predict activity at time $t+1$ so that, in these cases, mood had low predictive value. These results cast doubts on the hypothesis that natural rhythm of activities could explain our pattern of results. All AIC for models **7** can be found in Table S3.

To rule out the alternative explanation that the rhythm of mood in everyday life might account for our findings, we computed the AIC for the following two models:

$$\Delta M = \beta_0 + M_t, \quad [8]$$

$$\Delta M = \beta_0 + M_t + \sum_{j=1}^{25} \beta_m^j A_{t+1}^j. \quad [9]$$

This analysis revealed that the AIC of model **9** was lower than that of model **8** by over 4,000 points, which rejects the null hypothesis that model **8** is as good or better than model **9** in terms of information loss ($P < 0.0001$). These results cast doubts on the hypothesis that natural rhythm of mood could explain our pattern of results.

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