Buddy System: An Adaptive Mental State Support System Based on Active Inference and Free-Energy Principles

Motoko Iwashita and Makiko Ishikawa

Abstract—**To support a healthy human mental state, controlling the environment is one of the best-known solutions. However, it is difficult to design an environmental control system because of the uniqueness of individual preferences and mental state fluctuations. Here, we propose "Buddy system" as an adaptive mental state support solution that controls devices in the environment, depending on the recognized user's mental state at the time and how it could be improved, serving a role similar to a "buddy" to individuals. The recognition of mental states and the locus of actions to control one's surrounding environment are implemented on the basis of a brain-derived theory of computation known as active inference and free-energy principles, which provide biologically plausible computations for perceptions and behavior in a changing world. For the generation of actions, we modify the general calculations of active inference to adjust to individual environmental preferences. In the experiments, the Buddy system sought to maintain the participants' concentration while a calculation task was conducted. As a result, the task performance for most of the participants was improved through the aid of the Buddy system. The results indicated that the Buddy system can adaptively support to improve the mental states of individual users.**

Index Terms—**Active inference, human–system interaction, mental support system.**

I. Introduction

RECENT advances in technology have made many aspects of human life easier. For instance, working conditions for many may permanently shift to telework, aided by information technology, given the sudden demand in the wake of the COVID-19 pandemic. Even though information technology improves the Quality of Life (QoL), a study showed that the stressors associated with telework can lead to a reduction in well-being [1], eventually diminishing work performance. Thus, a mental support system is necessary to maintain well-being, but it should not be limited to one's working situation and should hold the potential to be extended to everyday life to improve the QoL.

A mental support system requires two functional features, namely, the recognition of a person's mental state, and the capacity to positively affect it, which underpins key technologies in terms of human–computer interactions.

To recognize mental states, researchers have utilized deep-learning techniques [2] and sophisticated brain scanning technologies [3]. However, both techniques possess unresolved problems. The main problem with the former technique is their accuracy, which is highly demanding on the learning data sets. Especially for mental recognition by facial expressions, some commercially available algorithms showed that the accuracies differed among different data sets. When the Acted Facial Expressions in the Wild data set, containing close to natural facial expressions, was tested, the accuracies were ~0.2–0.6, while when Surrey Audio–Visual Expressed Emotion data set, acquired from nonprofessional actors in laboratory settings, was tested, it increased to ~0.4–0.7 [4]. The results indicated that current techniques still needed to be improved for high accuracy with more natural facial data. In contrast, the primary issue with the latter technique is the stability of brain patterns. In other words, brain patterns exhibit differential variations among individuals that the system must account for. Even in the same individual, there can be differences depending on the situation. The nature of these fluctuations in complex mental state dynamics results in difficulties in applying them for real-time mental detection [5].

The other key component of a mental support system is the capacity to control the mental state and navigate it to a desired one. So far, many biofeedback schemes have been developed and utilized to improve mental states by informing users of their current heart rate and blood pressure [6], [7]. Some biofeedback technologies entail users to learn how to voluntarily control their involuntary physiological responses to enhance their mental states. Although such technologies have performed well, learning to control physiological processes requires considerable time and effort on the part of users [7]. Alternative methods for controlling the mental state include the use of the physical environment. Environmental factors, such as room temperature and sound volume, can indirectly affect the mental state for short periods [8]. Moreover, making use of environmental factors does not require efforts by the user and can work in real time [9].

Manuscript received 15 February 2021; revised 29 June 2021; accepted 1 August 2021. Date of publication 6 August 2021; date of current version 9 September 2022. *(Corresponding author: Motoko Iwashita.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by DENSO CORPORATION under Application No. 20-001.

Motoko Iwashita is with the AI R and I Division, DENSO CORPORATION, Nisshin 4700111, Japan (e-mail: moko0927@gmail.com).

Makiko Ishikawa is with DENSO CORPORATION, Tokyo 1080075, Japan.

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TCDS.2021.3102993.

Digital Object Identifier 10.1109/TCDS.2021.3102993

Overall, both the recognition and improvement of mental states by controlling the environment in real time are required to develop an effective mental support system. Although most previous researchers have separately developed these technologies, combining them into a single system appears to be challenging. With the existing methods for real-time mental state recognition, the recognition models/classifiers are adjusted to the statistical average spanning many people [10], [11], assuming that it is difficult to control environments in accordance with individual proclivities through the models/classifiers. Until now, few approaches have been devised that combine the recognition of mental states and control of the environment in real time for improving mental status [12].

In this study, we propose to apply a recent neurobiological theory called free-energy principles (FEPs) and a derived scheme called active inference [13], [14] to develop a mental support system that is able to recognize and improve a person's mental state by controlling the environment while conforming to individual users. Active inference offers adaptive real-time perception and behavior control within a singular scheme [15]. Until recently, FEP and its extended form of active inference were evaluated and discussed in the context of simulated environments [16], [17]. However, active inference schemes are just starting to be adopted in the robotics field to develop the capacity to estimate and control adaptive states, which are needed by robots operating in dynamically changing and noisy real-world setting [18], [19]. These studies have shown the advantages of utilizing active inference to adapt to dynamically changing and noisy environments. In accordance, the mental state is also dynamic and fluctuating, and therefore, the free-energy framework would have advantages in a mental support system. Herein, we call our mental support solution the "Buddy system." The Buddy system is designed to adaptively support the improvement of the mental state in individuals with a similar architecture for perception and behavioral control as a human.

The contribution of this study is the development of a mental support system in which FEP and active inference are applied. In our system, the method for adaptive controlling of the environment to the individual user was developed and implemented in an active inference scheme. For recognition of the mental state levels, we only used a simple linear function with a single input. However, we accounted for how to overcome this simplicity to generate an effective environmental control and to be functioning in real time, and then presented a proof of concept for the Buddy system.

Section II describes the general mathematical formulas of FEP and active inference for perception and action. Section III then describes the structure and algorithm incorporated by the Buddy system. In Section IV, the experimental evaluations are described. Finally, in Sections V and VI, the relevance of the Buddy system to mental support tools is discussed and conclusions are drawn.

II. FEP Framework

FEP is an account of how biological organisms adaptively perceive and interact with their environments [13], [14]. According to this theory, organisms must minimize the variational free energy to keep themselves in a restricted and limited state within the varying environment. The active inference is an extended form of FEP that accounts for actions [14]. The general concept of FEP and active inference are described here.

A. FEP

The underlying idea of the FEP framework is that agents possess a probabilistic generative model of their environments and seek to minimize the occurrence of atypical observations (sensations), i.e., they aim to minimize surprises. Agents measure the environment by encoding beliefs about environmental causes (hidden states) to inform their sensations. Such beliefs correspond to the posterior probability of the causes attributed to the sensations. Thus, perception is regarded as a Bayesian inference that refers to optimizing belief about hidden states through maximizing the Bayesian evidence (and minimizing the free energy) [20], [21].

Accordingly, perception of the hidden state χ is formulated using the observed sensory inputs ρ as follows:

$$p(\chi|\rho) = \frac{p(\rho|\chi)p(\chi)}{p(\rho)} \tag{1}$$

where $p(\rho|\chi)$ is the likelihood of the sensory input ρ being caused by the hidden state χ, and $p(\chi)$ is the prior probability corresponding to the belief about hidden states before receiving sensory observations (observed sensory input) ρ. The likelihood $p(\rho|\chi)$ is usually parameterized by θ, described as $p(\rho|\chi;\theta)$, but is omitted for the simplicity of description. The joint density $p(\rho,\chi;\theta) = p(\rho|\chi;\theta)p(\chi)$ of the sensory input ρ and hidden states χ, parameterized by θ, is called a generative model [θ is omitted in (2) and (3) but described as needed]. To calculate the posterior probability $p(\chi|\rho)$, we must evaluate $p(\rho)$. However, $p(\rho)$ includes a hard integral, and hence, a variational Bayes method is introduced in the FEP to approximately determine $p(\chi|\rho)$. In the variational Bayesian method, the approximated distribution of $p(\chi|\rho)$, which is substituted by the recognition density $q(\chi)$, is determined by minimizing the Kullback–Leibler divergence *DKL* between the true posterior $p(\chi|\rho)$ and $q(\chi)$ [20]. *DKL* is written as follows:

$$\begin{aligned}\mathrm{DKL}(q(\chi)||p(\chi|\rho)) &= \int d\chi q(\chi) ln \frac{q(\chi)}{p(\chi|\rho)} \\ &= F + \ln p(\rho)\end{aligned} \tag{2}$$

where F, defined as the free energy, is expressed as follows:

$$F = \int d\chi q(\chi) ln \frac{q(\chi)}{p(\chi,\rho)}. \tag{3}$$

Thus, minimizing the free energy F allows the recognition density $q(\chi)$ to be close to the true posterior.

The Kullback–Leibler divergence *DKL* is always greater than zero, and so the following is derived as follows:

$$F \geq -\ln p(\rho) \tag{4}$$

where $-\ln p(\rho)$ is the negative logarithmic model evidence (i.e., surprise). Thus, minimizing the free energy F also contributes to a minimization of surprise.

In the variational approach, it is common to approximate the recognition density $q(\chi)$ as a Gaussian distribution $N(\chi|\mu, \Sigma)$, which is called the Laplace approximation and it peaks at its mean value μ with variance Σ [22], [23]. The mean μ represents the internal belief about the χ. Under the Laplace approximation, μ is optimized by minimizing F. F can be simplified as

$$F \approx -\ln p(\rho, \chi; \theta)|_{\mu} - \frac{1}{2}\ln 2\pi \Sigma. \tag{5}$$

As in [21], a simpler derivation could be to assume that the variance of recognition density Σ tends to zero by approximating $q(\chi)$ by means of Dirac delta. Then, F can be further simplified as

$$F \approx -\ln p(\rho, \chi; \theta)|_{\mu} = -\ln p(\rho, \mu; \theta). \tag{6}$$

The optimized belief is calculated by updating μ through a gradient descendant method

$$\dot{\mu} = -\kappa \frac{\partial F}{\partial \mu} \tag{7}$$

where κ is the learning rate.

B. Active Inference

The active inference is a framework that asserts that natural agents act so as to sample preferred observations and fulfill prior beliefs about their preferred world with less surprise. Thus, under active inference, action results from minimizing free energy F [24], [25].

The action does not explicitly appear in the FEP formulation F, but the sensory input can be changed by actions to minimize F. Thereafter, using the relationship for the action and sensory input, $\rho = \rho(a)$, and the chain rule, the gradient of F with respect to the action was described as follows:

$$\frac{\partial F}{\partial a} = \frac{\partial \rho}{\partial a}\frac{\partial F}{\partial \rho} \tag{8}$$

where a represents the action's value.

Therefore, in the dynamic system, the action value is calculated by the gradient descendant scheme as follows:

$$\dot{a} = -\kappa_a \frac{\partial \rho}{\partial a}\frac{\partial F}{\partial \rho} \tag{9}$$

where κ_a is the learning rate.

C. Learning Generative Model Parameters

Minimizing the free energy F with respect to the parameters of the generative model can better account for the sensory input [26]. The learning could be regarded as a parameter inference (i.e., the optimizing parameter) within the Bayesian inference framework.

The generative model parameters are then optimized by updating them thorough the gradient descendant method as shown in [20], [21]

$$\dot{\theta} = -\kappa_\theta \frac{\partial F}{\partial \theta} \tag{10}$$

where κ_θ is the learning rate.

III. Buddy System With Active Inference and Laplace Approximation

The Buddy system is designed to feature the same architecture for perception and behavior control as a human and is expected to support mental states in an adaptive way for individuals. In this section, we outline greater details regarding the Buddy system's formula.

A. Problem Formulation

The Buddy system improves a given mental state, for instance, concentration or relaxation. A relevant mental state is scaled here as numerical mental level.

A schematic of the Buddy system is depicted in Fig. 1. The green oval contains the user's mental state processing. The red oval contains the Buddy system's processes. It can be seen that the Buddy system estimates the user's mental state level μ with sensory input ρ of the user's biological signals collected from a sensor (the pink dotted box) by minimizing the free energy F, which comprises the prediction error between ρ and the predicted sensory input ρe. The estimated μ is biased to μd, which is the desired state, and hence, the predicted sensory input ρe always differs from the sensory inputs ρ, and therefore, the prediction error is always produced unless the mental state level reaches the desired one. To minimize the prediction error (=minimizing F), actions a, control orders for environmental devices are generated. The white boxes are functions of the general active inference scheme, whereas the yellow boxes are those we specifically modified or added the function to adapt the fluctuating nature of the user's mental state and preferences.

The Buddy system infers the user's mental state level μ from a single sensory input ρ and executes actions a to control the various environmental devices, leading the sensory inputs to being close to the preferred ones and fulfilling prior beliefs regarding the desired mental state level.

The Buddy system receives the user's biological signals as single sensory input $\rho \in R$. The reason for using a single sensory input is for the sake of simplicity, so that the system can work in real time (see Section III-D for further details). Here, biological signals comprise autonomic nervous activity, whose relationship to mental state has been extensively studied [27] and many commercial sensors to collect data on it are available. The belief of the mental state level, which underwent optimization during the mental state estimation process, encoded in the system is $\mu \in R$. To describe the agent's belief regarding the dynamics of the mental state level, μ' is also encoded in the generative model. Action $a \in R^n$ is a vector for n environmental devices $(a_1, a_2, a_3, \ldots, a_n)$ to be controlled by the Buddy system.

B. Generative Model

The system encodes the likelihood $p(\rho|\mu)$ and prior $p(\mu'|\mu)$ as a generative model for the sensory inputs. Here, the likelihood $p(\rho|\mu)$ determines how the mental state level μ induces the sensory input ρ, and the prior $p(\mu'|\mu)$ is a belief in the user's dynamic mental state level. The likelihood $p(\rho|\mu)$ is

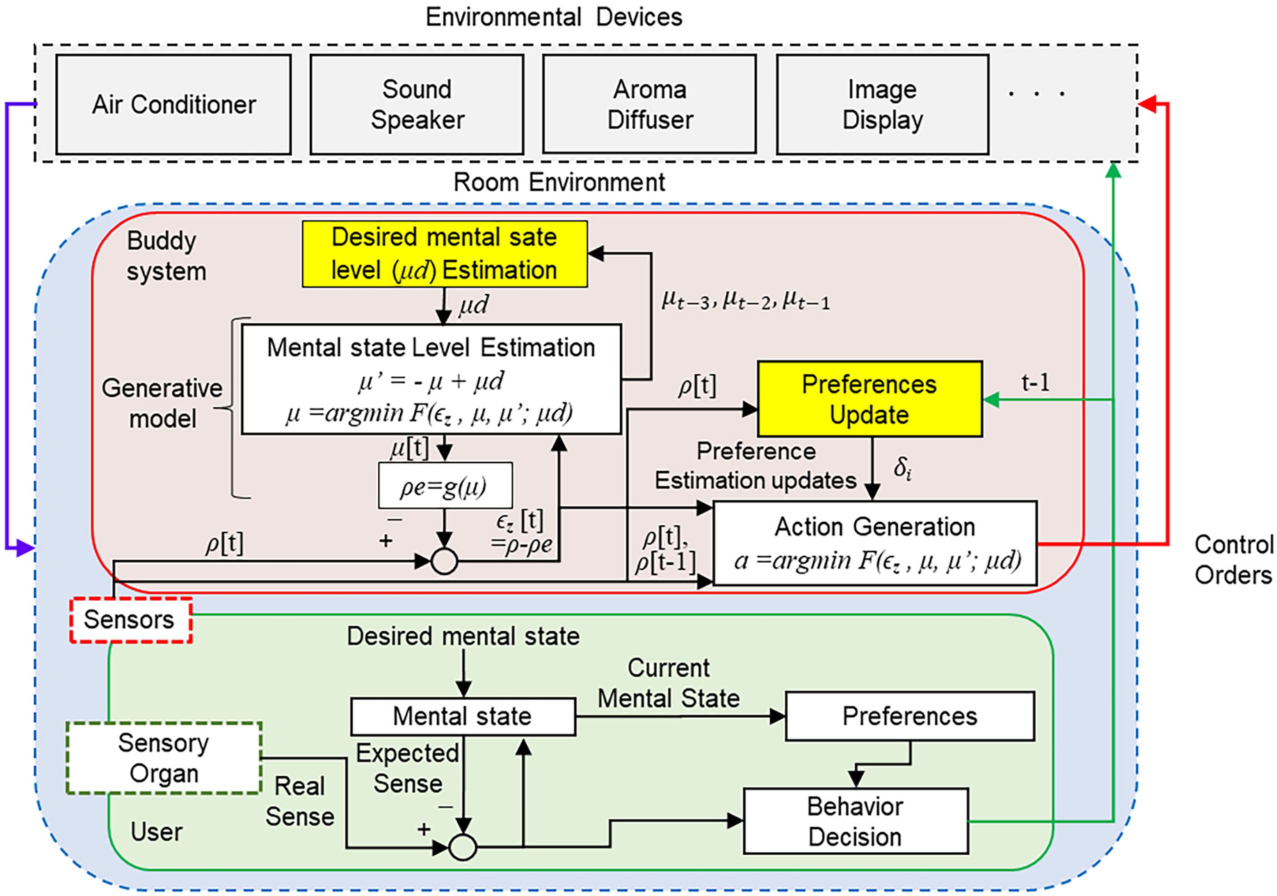


Fig. 1. Structure of the Buddy system equipped with active inference.

defined as follows:

$$p(\rho|\mu) = f(\rho; g(\mu; \theta), \ \Sigma_z) \tag{11}$$

where $f(\rho; g(\mu; \theta), \ \Sigma_z)$ denotes the density of a normal distribution with mean $g(\mu; \theta)$ and variance Σ_z. $g(\mu; \theta)$ is a generative mapping between the mental state level μ and expected single sensory input ρe, parametrized by θ. The mental state level μ is translated into the expected sensory input ρe via $g(\mu; \theta)$. Here, we adopted a simple linear function for $g(\mu; \theta)$ as $g(\mu; \theta) = \alpha\mu + \beta$, $\theta = (\alpha, \beta)$ for the sake of simplicity with a few parameters so as to function in real time (see Section III-D for further details on why the linear model was adopted).

The dynamics of belief of the user's mental state level μ were defined so that the user's mental state level was evolving to be stable around the desired mental state level μd. Accordingly, we defined the dynamics of the mental state level up to the third order, following the example described in [20], as follows:

$$\begin{aligned} \mu' &= \frac{d\mu}{dt} = h(\mu) + \omega = -\mu + \mu d + \omega \\ \mu'' &= h^{\prime(\mu)} + \omega'' = -\mu' + \omega'' \\ \mu''' &= h''(\mu) + \omega''' = \omega''' \end{aligned} \tag{12}$$

where $h(\mu) = -\mu + \mu d$ and ω, ω'', and ω''' represent the Gaussian noise.

Usually, μd is a static value, for instance, the target position of the robot arm manipulator [18], [19]. However, considering the human mental state, the desired mental state level should flexibly change for the following reason. For instance, when people wish to concentrate, they usually do not try to enter deep concentration immediately and rather initially spend some time in shallow concentration, i.e., focused on a reachable target, whether consciously or not. After achieving the reachable target, they update their next reachable target and repeat the process until the true goal of deep concentration has been attained. We implemented this mental process in the Buddy system, wherein the desired mental state level μd was updated at every sampling cycle by taking the maximum value from the last three mental state levels, adding random noise, which is as described in

$$\mu d = \max\{\mu_{t-3}, \mu_{t-2}, \mu_{t-1}\} + \text{noise} \tag{13}$$

where t is the current time and the *noise* is a portion of a standard deviation between μ_{t-3}, μ_{t-2}, and μ_{t-1}.

The prior $p(\mu'|\mu)$ is described as follows:

$$p(\mu'|\mu) = f(\mu'; h(\mu; \mu d), \ \Sigma_\omega) \tag{14}$$

where $f(\mu'; h(\mu; \mu d), \Sigma_\omega)$ denotes the density of a normal distribution with mean $h(\mu; \mu d)$ and variance Σ_ω [for $h(\mu; \ \mu d)$; see (12)].

C. Perceptual Inference of the Mental State Level

Given the generative model, the free energy F (6) is calculated as follows:

$$F = \frac{1}{2}\left[\frac{1}{\Sigma_z}(\epsilon_z)^2 + \frac{1}{\Sigma_\omega}(\epsilon_\omega)^2 + \frac{1}{\Sigma_{\omega'}}(\epsilon_{\omega'})^2\right] \tag{15}$$

where $\epsilon_z = \rho - \rho e$, $\epsilon_\omega = \mu' - h(\mu)$, and $\epsilon_{\omega'} = \mu'' - h'^{(\mu)}$. ϵ_z, ϵ_ω, and $\epsilon_{\omega'}$ are prediction errors, where ϵ_z is the error obtained between the sensory input ρ and estimated sensory input ρe, and ϵ_ω and $\epsilon_{\omega'}$ represent the differences between the expected μ' and μ'' from each prior belief, respectively.

Using the gradient descendant method for estimating the mental state level in a dynamical system, following the example described in [20], the updating μ', μ'', and μ''' are described as follows:

$$\begin{aligned}\dot{\mu} &= \mu' - \kappa_\mu\left[-\frac{\epsilon_z}{\Sigma_z} + \frac{\epsilon_\omega}{\Sigma_\omega}\right]\\ \dot{\mu}' &= \mu'' - \kappa_\mu\left[\frac{\epsilon_\omega}{\Sigma_\omega} + \frac{\epsilon_{\omega'}}{\Sigma_{\omega'}}\right]\\ \dot{\mu}'' &= -\kappa_\mu\frac{\epsilon_{\omega'}}{\Sigma_{\omega'}}\end{aligned} \tag{16}$$

where κ_μ is the learning rate.

D. Learning of the Generative Model

Here, we adopt a linear function for the generative model $g(\mu;\theta)$, a mapping between the expected sensory input ρe and the mental state level μ. Typically, the biological signal is not simple but rather noisy and fluctuating in a context-dependent manner, and therefore, a linear function for the generative model $g(\mu;\theta)$ seems to be too simple to be valid. To precisely describe the generative model $g(\mu;\theta)$, it is best to determine all of the factors affecting the mental state and implement these factors' effects in the generative model. In that case, multiple sensors would be required to accurately determine the state through the generative model $g(\mu;\theta)$. However, to use multiple sensory inputs, a more complex formula for $g(\mu;\theta)$ is required, yielding the increasing time needed for the turning/learning parameters and making it difficult to work in real time. Therefore, a smaller number of sensors and consequently simpler models are better. Although the simple linear model easily loses the accuracy of calculating the sensory input, frequent updating of the linear generative model based on the current data could offer a locally better estimation of the sensory input from the estimated mental state level. Therefore, we utilized the frequent online learning of the parameters θ of $g(\mu;\theta)$ in every sampling cycle. Using (10), the updated equations of the parameters $\theta = (\alpha, \beta)$ are defined as follows:

$$\begin{aligned}\dot{\alpha} &= -\kappa_\alpha\frac{\partial F}{\partial \alpha} = -\kappa_\alpha\frac{\rho - \alpha\mu - \beta}{\Sigma_z}\\ \dot{\beta} &= -\kappa_\beta\frac{\partial F}{\partial \beta} = -\kappa_\beta\frac{\rho - \alpha\mu - \beta}{\Sigma_z}\end{aligned} \tag{17}$$

where κ_α and κ_β are the learning rate.

E. Active Inference for Action Control

The Buddy system was designed to be capable of utilizing several environmental devices to improve the mental state. Some of these, such as sound, lighting, and temperature, are known to influence the mental state [8], [28]–[30]. Therefore, action a of the Buddy system represents the environmental devices with controllable values, such as the sound volume, light color, and temperature. Under active inference, how the sensory input ρ changes by action a, described as $\rho = \rho(a)$, must be defined in order to determine action a. Here, we adopt the inverse U-shaped function for $\rho = \rho(a)$ for the following reasons. The sensory input (i.e., the user's biological signals) ρ changes depending on environmental conditions. For instance, loud sounds increase the activity of the sympathetic nerves. However, too low or too high settings do not effectively improve mental states. Such relationships are described as the inverse-U function, which is conceptually similar to the Yerkes–Dodson law, which states that performance peaks in the middle range of the arousal level [31]. We then implemented the inverse-U-shaped knowledge in the relationship between ρ and a, that is, extremely low and high control values for environmental devices, such as too loud and too low sound volume, do not positively affect the sensory input (the user's biological signal). In mathematic formulaic terms, the optimized/desired sensory input is peaked in the quadratic function. Then, the $\rho = \rho(a)$ is defined as

$$\rho = \gamma\left\{\begin{array}{c}(a_1+\delta_1)^2 + (a_2+\delta_2)^2\\ +\cdots+(a_n+\delta_n)^2\end{array}\right\} + \rho d \tag{18}$$

where γ is the negative value of the coefficient and $(-\delta_1, -\delta_2, -\delta_3, \ldots, -\delta_n,\ \rho d)$ is the vertex of the formula, and ρd is the expected sensory input when the status attains the desired state level μd; i.e., $\rho d = g(\mu d)$. Here, multiple environmental devices were assumed to be additive effects.

Given (18), the free energy F with respect to action a using (8) is described as follows:

$$\begin{aligned}&\frac{\partial F}{\partial a_i} = \frac{\partial \rho}{\partial a_i}\frac{\partial F}{\partial \rho} = \frac{2\gamma\alpha(a_i+\delta_i)(\rho-\mu)}{\Sigma z}\\ &i = 1, 2, 3, \ldots, n.\end{aligned} \tag{19}$$

Here, calculating $\partial F/a_i = 0$ to minimize F yields optimized actions a_i^* as shown in

$$a_i^* = -\delta_i. \tag{20}$$

Therefore, the vertex values for action a_i^* of (18) indicate optimized action values.

The update rule for the action is described, using (19), as follows:

$$\dot{a}_i = -\kappa_a\frac{\partial F}{\partial a_i} = -\kappa_a\frac{2\gamma\alpha(a_i+\delta_i)(\rho-\mu)}{\Sigma z} \tag{21}$$

where κ_a is the learning rate.

In general, in the FEP, $\rho = \rho(a)$ is not updated, because the relationship of the sensory input and action is stable. For instance, in robotics, the relationship of the arm velocity observed by the sensor and arm's movement has a stable relationship. However, in terms of the sensory input of biological signals, the relationship between the sensory input and action is not stable because the user's biological activities of the autonomic nervous system are not only affected by environmental factors but also by the ongoing statuses of the internal organs and brain [32], [33]. Again, because we only utilize a single sensory input, the relationship between actions and the sensory input is susceptible to the other factors, and therefore easily deviates from the true one. However, instead of detecting all signals from the internal organs and brain and having a sophisticated formula for $\rho = \rho(a)$, we adopted a strategy of utilizing the simple quadratic function described above [formula (18)] and updating the parameters every cycle. In the presence of undefined factors that influence the sensory input (i.e., the user's biological signal), the same actions could change the sensory input in the opposite fashion. For instance, with the same sound volume, sympathetic nervous activity sometimes increases and decreases. As a mathematic formula, this corresponds to that the axis of the symmetry of the quadratic function relative to the current point (a, ρ) differs in the presence of the other factors, such as the ongoing states of internal organs and brain. To adjust the axis of symmetry $(a_1^*, a_2^*, \ldots, a_n^*, \rho d)$ denoted in (18) and (20), the current point $(a_{1,t}, a_{2,t}, \ldots, a_{n,t}, \rho_t)$ and the most recent point $(a_{1,t-1}, a_{2,t-1}, \ldots, a_{n,t-1}, \rho_{t-1})$ are used. Here, depending on whether or not the sensory input ρ_t is increased with the given environmental changes, $\Delta a_i = a_{i,t} - a_{i,t-1}$, a_i^* relative to $a_{i,t}$ is determined by the conditions below, fulfilling passage of the point $(a_{1,n,t}, \rho_t)$

$$\begin{aligned}
&\text{if } \Delta a_i > 0 \text{ and } \rho_t > \rho_{t-1}, \text{ then } a_i^* > a_{i,t}\\
&\text{if } \Delta a_i < 0 \text{ and } \rho_t < \rho_{t-1}, \text{ then } a_i^* > a_{i,t}\\
&\text{if } \Delta a_i > 0 \text{ and } \rho_t < \rho_{t-1}, \text{ then } a_i^* < a_{i,i}\\
&\text{if } \Delta a_i < 0 \text{ and } \rho_t > \rho_{t-1}, \text{ then } a_i^* < a_{i,t}.
\end{aligned} \tag{22}$$

The parameter γ is held constant.

F. Personal Adaptation of the Function for Mapping the Sensory Input and Environmental Device Control Actions

We hypothesize that the user changes the environment in a manner that s/he believes is best for achieving his/her desired mental state. The combination of the environmental devices controlled by the user reflects the affective sets of devices and their values to attain the desired mental state; in other words, the preference of the user's environmental settings for achieving the desired state. For instance, some people modulate the sound volume, and others want to change the lighting conditions in order to concentrate on a task. Implementing these user preferences in the $\rho = \rho(a)$ helps the Buddy system to generate more effective actions to decrease the need for user control.

In our formula and calculation method for action generation (see Section III-E), when the current environmental settings are far from optimized, the environmental changes are large and when the settings are close to the optimized value, the environmental changes are small. Therefore, the extent to which environmental devices are changed depends on how great the differences are between the current setting a_i and optimized setting a_i^*. To implement the user's preference in our action generation scheme, we updated the values, $-\delta_i (i = 1, 2, \ldots, n)$, which are the vertex values representing the optimal action values $a_i^* (i = 1, 2, \ldots, n)$ [see (20)], so that the Buddy system could exert substantial change to devices, with which the user made change in large amounts. In practice, we updated $-\delta_i (i = 1, 2, \ldots, n)$ using a rate bias R_i calculated from the most recent manipulation history of the user. R_i is defined as follows:

$$R_i = \frac{|\Delta a_i|}{\sqrt{\Delta a_1^2 + \Delta a_2^2 + \cdots + \Delta a_n^2}} \tag{23}$$

where $\Delta a_i (i = 1, 2, \ldots, n)$ are the most recent modulations of the environmental devices' values under the user's control.

Given the current action and sensory input $(a_1, a_2, \ldots, a_n, \rho)$ and the most recently changed amounts Δa_i, we then updated the $-\delta_i$ to accommodate the following equation. Note that the determination of the exact value for $-\delta_i$ was performed by the rule described in (22)

$$|-\delta_i - a_i| = R_i r \tag{24}$$

where $r = \sqrt{(\rho - \rho d)/\gamma}$ represents the radius of the n-sphere [see (18)]. In this updating rule, when the user changes the intensity of the device significantly, it results in a large difference between the current setting a_i and the optimized setting a_i^*. At this point, the Buddy system can enact significant changes in relevant devices, corresponding to the user's change.

IV. Experimental Evaluations

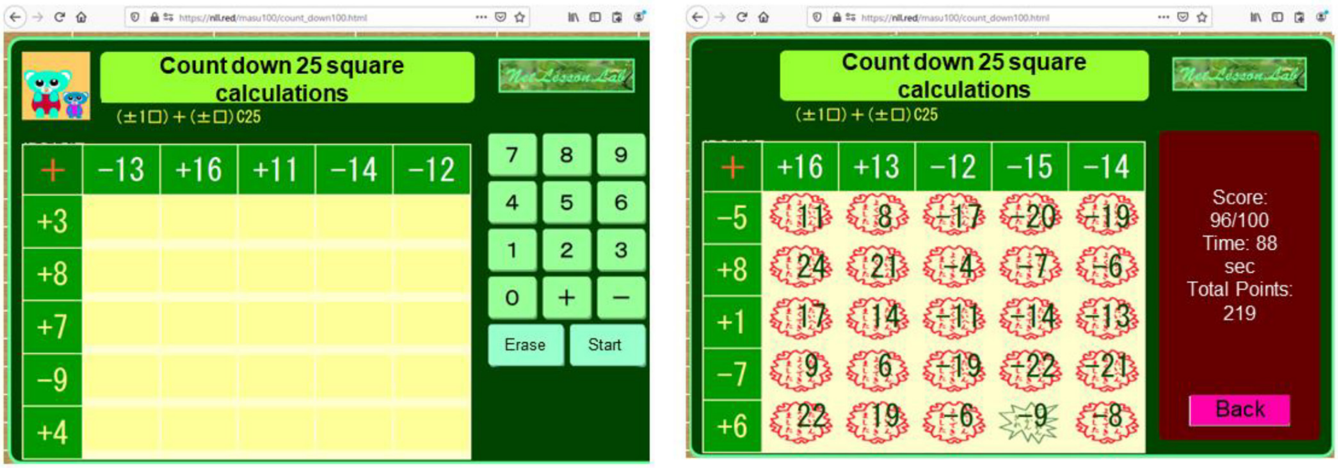
The Buddy system was evaluated through experiments with nine participants, in which the desired mental state was concentration. Participants were asked to perform the countdown 25 square (C25S) game for 45 min in an environment with three devices, namely, sound speaker, aroma diffuser, and lighting while sympathetic nervous activity was measured.

In this section, the Buddy system settings for the concentration task are first described, followed by the experimental tasks, setup, design, and statistical methods, respectively. This is followed by the results and discussion.

A. Buddy System Settings

The Buddy system was installed to improve the participants' concentration, which was numerically scaled as a mental state level. The Buddy system inferred the participants' concentration level μ from their sympathetic nervous activity, which changes in relation to the task that requires concentration [34]. The sympathetic nervous activity [35] was measured via the nasal temperature ρ as detailed in [36], and actions $a_i (i = 1, 2, 3)$ were performed to control the environmental devices to sample the preferred nasal temperature, which fulfilled prior beliefs regarding the desired level of concentration. Here, actions $a_i (i = 1, 2, 3)$ included sound volume, aroma volume, and illumination color, which influence the sympathetic nerve activity [37]–[39].

The Buddy system first inferred the current mental level μ_t by means of the averaged nasal skin temperatures ρ_t that were recorded for 2 min. The nasal skin temperature was normalized by subtracting the forehead temperature. The normalized nasal skin temperature was observed to decrease when the sympathetic nervous activity increased [36]. Next, if the current normalized nasal skin temperature ρ_t was higher than 98%



(a) (b)

Fig. 2. C25S calculations game. (a) Calculations begin when the start button is clicked. A question is answered by clicking the number on the right-hand panel. (b) Answer should be given within 5 s; otherwise, a loss is registered. When 25 calculations of the game are completed, the score, elapsed time, and total points are shown on the right-hand panel.

of the latest ρ_{t-1}, the system generated the actions for controlling the devices in order to change the environment. If not, the system did not generate any actions. Thus, the generation of actions depended on the changes in the normalized nasal skin temperature ρ, which was expected to avoid causing annoyance to the participants due to too many environmental changes. The series of procedures described above were performed every 2 min in cycles. 2 min is enough time that sympathetic nerve activity would be reflected in the nasal skin temperature [36], [40].

B. Experimental Tasks

To evaluate the system for concentration, a long-term task (45 min) that requires concentration but causes boredom or distraction without sleepiness is desirable because this would allow us to evaluate the efficacy of the proposed system on concentration. Before the experimental trials, a preliminary experiment was conducted with three other participants to confirm that C25S did not cause moderate or heavy sleepiness. The C25S calculation shown in Fig. 2 is one of the tasks. C25S is a PC game/educational-free application consisting of simple 25 summation or subtraction calculations. Participants completed a questionnaire regarding their sleepiness at the end of each experiment, and we confirmed that C25S did not cause moderate or heavy sleepiness.

C25S is available at https://nll.red/masu100/index_S.html. We obtained permission from the developer to use it. Once a participant started the game by clicking on the start button, s/he then had to calculate an equation, which was randomly selected by the system from 25 possible calculations, and to then input the answer value by clicking the number displayed on the right side of the screen [Fig. 2(a)] within 5 s. If the participant could not answer correctly within 5 s, it was counted as a "fail" and the next equation was randomly selected. After calculating all 25 equations (i.e., a game ends), participants repeated the game by clicking the start button again until the 45 min total had elapsed. The content of the game was refreshed each time by clicking the start button. Participants were allowed to perform shoulder and arm stretches between game sessions to reduce the fatigue caused by long-term mouse operation. The score of each game was termed the "Points" [Fig. 2(b)] and calculated with the following equation, considering the time elapsed per game and the correct answer rate:

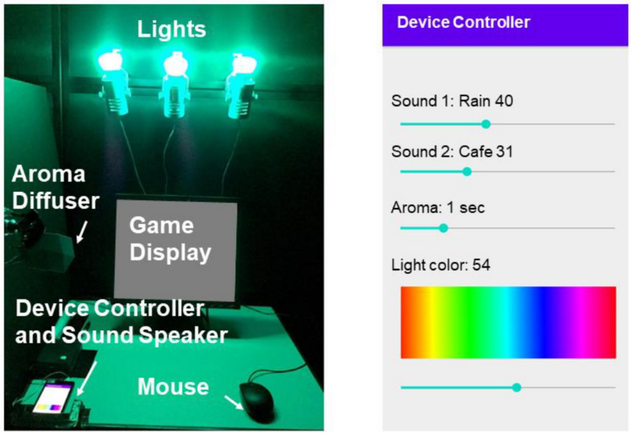
$$\text{Points} = C/25 * 100 + 108507/T \tag{25}$$

where C is the number of correct answers and T is the time (in sec) elapsed per game.

C. Experimental Setup

Nine healthy males aged 18–42, who were all employees of DENSO CORPORATION, participated in the experiment. The experiment was approved by the local ethics committee at the DENSO CORPORATION. After receiving detailed written and oral instructions, participants provided their informed written consent to participate in the study.

Fig. 3 displays the experimental setup. The environmental devices that were manipulated by both participants and systems were a natural sound speaker (a smartphone application), an aroma emitter (by Aroma Join Corporation), and three smart light bulbs (by PHILIPS). The participants selected two of five natural sounds (wave, rain, café, village, and magma) as preferences beforehand. The two natural sound volumes, the aroma intensity, and the light color were controlled by the device controller application [Fig. 3(b)]. The sound volumes were scaled as 0–100, corresponding to about 15–70 dB. The volumes of the two sounds could be separately specified. The aroma intensity was scaled as 0–5, representing the spray time from 0 to 5 s, increased by 1 s. The light color was scaled as 0–100, corresponding to red to purple.



(a) (b)

Fig. 3. Experimental setup and device controller display. (a) Experimental setup equipped with sound speakers, aroma diffuser, and three smart lights. (b) Device controller implemented on a smartphone. (a) and (b) are reused with permission from Front. Comput. Sci. 3:702069.

The Buddy system's output was a_1 as the sound volume of a larger one, a_2 as the aroma intensity, which was converted to a 0–100 scale from a 0–5 scale displayed on the controller [Fig. 3(b)], and a_3 as the light color. The smaller sound was determined by a_1 with the volume ratio of two sounds. The volume ratio was based on the volumes set by the participants at the beginning of the experiment. When the participants changed the sound volume during the experiment, the volume ratio was also changed, accordingly.

Both the nasal and forehead skin temperatures were measured using Polymate I, a biological signal recorder (by Miyuki Giken Corporation).

D. Experimental Design

The participants played the C25S calculations game for 45 min under three different conditions, with or without the aid of the Buddy system (see below for the three conditions). During the first 8 min, the participants played the game under the initial environmental settings of the three devices, which were set by the participants based on their preferences just before first C25S calculations were begun. For the remaining time, participants played the game under one of three conditions: 1) under user-only control (User); 2) under random control (With Random); and 3) in conjunction with the Buddy system (With Buddy). Under the condition User, environmental changes were all controlled by participants' manipulations, without the aid of any system. Under the condition With Random, the system's actions were randomly determined. The actions were set to execute with a 50% chance rate across all action determination timings (every 2 min, which was the same as with the Buddy system) and the degree of changing values of the devices were randomly selected. Under the condition With Buddy, the Buddy system controlled the environment based on the normalized nasal skin temperature, as described in Section IV-A. Under the condition With Random and With Buddy, the participants could control the environmental devices whenever they wanted, as in the User condition. Participants had priority for control of the environmental devices, even if the system attempted to control them at the same time. Under all conditions, the participants could only manipulate the controller before starting each round of the game.

The participants partook in three experiments under three different conditions at three different morning hours. Every experiment was executed at least one day apart. When the participants finished all three experiments, they ranked their preferences for each day. Here, the execution order of the three conditions was randomized for each participant. Participants were neither informed about the functional detail of the three different conditions nor which condition was to be executed on each day. However, the participants were only informed of whether or not the system automatically controlled the environment in the relevant experimental sessions for the sake of reducing their surprise with respect to the automatic changes in the environment during the sessions.

The sample size of $n = 9$ was estimated using the freeware G*Power (ver 3.1.9.7) [41] with the following parameters: paired Wilcoxon test, effect size $(dz) = 1.0$, alpha error probability $= 0.05$, and detection power $= 0.80$ under one-tail test (enhanced performance was expected based on the preliminary experiment).

E. Statistical Methods

To evaluate the task performance, a time series of each participant's game points were fitted to the linear model and the slope of the trend line was calculated. The task performance was then analyzed by means of a statistical comparison among the three conditions (User, With Random, and With Buddy) using a nonparametric repeated method (Freidman test) and Wilcoxon's signed-rank tests. The *post-hoc* Bonferroni correction was then applied.

To evaluate the functional effect of the system on the sensory input, we specifically noted all of the events where the normalized nasal temperature was increasing in 2 min, because the Buddy system was designed to execute environmental changes when the nasal temperature increased in 2 min. The degree of change in the nasal temperature in the 2 min was added up and compared among the three conditions. Statistical analyses using Wilcoxon's signed-rank tests to compare the temperature increases among all conditions were then performed.

To analyze the subjective evaluation of system preferences, differences in preference ranking data among the three conditions were tested by means of ordinal logistic regression, which is a statistical test used to predict a single ordered categorical variable.

F. Results and Discussion

As for the results, under the With Buddy condition, seven out of nine participants improved their game points during the experiment. One participant from the nine improved his game points under the User condition. The result indicates that our proposed system was able to support most participants in maintaining their concentration during the 45 min.

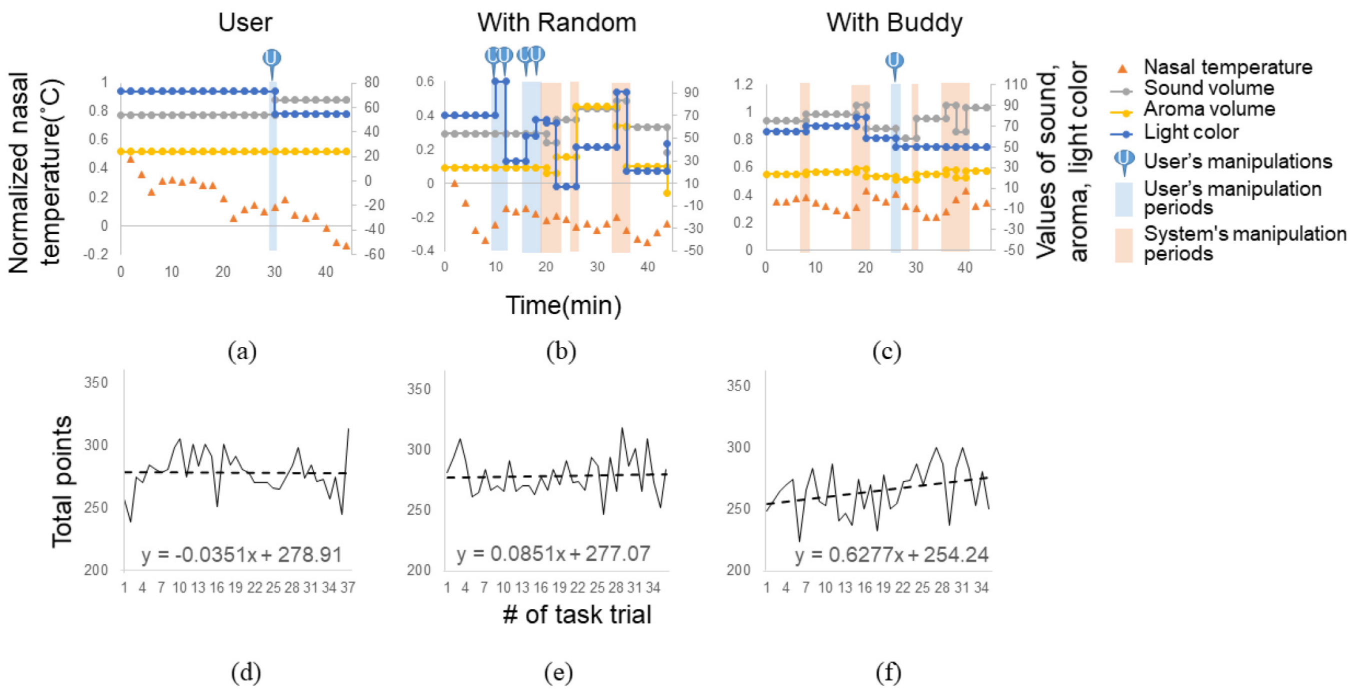


Fig. 4. Example of a participant's results of time courses for nasal temperature, environmental manipulations, and task performance. (a)–(c) Time courses for the nasal temperature and environmental manipulations for the sound volume, aroma volume, and light color under three conditions (User, With Random, and With Buddy). (d)–(f) Time courses for the task performances measured by points in each C25S game. The trend lines (the dotted line) and approximation formulas are also shown. (a)–(f) are reused with permission from Front. Comput. Sci. 3:702069.

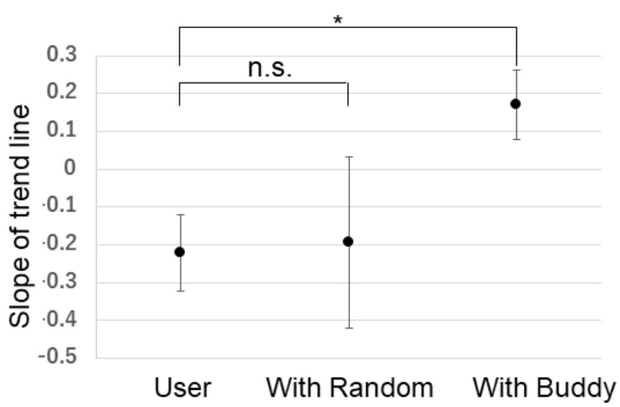


Fig. 5. Effects of the three conditions on task performance. The error bars represent the standard error of the mean (SEM) of the slope of the trend line.

The results of each statistics are discussed as follows.

1) Evaluation of the Buddy System Against Participants: As an example, the sensory input and environmental change results of a participant are shown in Fig. 4(a)–(c), whereas the task performance of the C25S calculations is shown in Fig. 4(d)–(f).

The task performance was evaluated by the slope of the trend line of the time series of game points. The points tended to increase under the condition With Buddy but not under the other conditions [Fig. 4(d)–(f)]. Fig. 5 shows the averaged slope of the trend line of the points for all participants under the three conditions. The differences between the conditions were statistically significant, as determined by the Freidman test [Chi-square (df $= 2$) $= 6.2$, $P = 0.0446$]. Under the condition With Buddy, the slope value was significantly high compared to that of the User condition (Wilcoxon test, $Z = 2.3, P = 0.0391$, adjusted by the Bonferroni correction, Effect size dz $= 1.35$). Under the With Random condition, the slope value was not significantly different compared to the User condition (Wilcoxon test, $Z = 0.7, P = 0.5703$, adjusted by Bonferroni correction). Typically, people expect to be able to efficiently control environmental devices to attain the desired mental state level. The experimental result shows the opposite though, suggesting that people do not know themselves as well as they might expect. Overall, the Buddy system successfully improved the task performance, which required concentration, suggesting the Buddy system was beneficial for improving it.

Next, we analyzed the functional effect of the system on nasal temperature to see whether the Buddy system could contribute to diminish the increase in the nasal temperature. Fig. 6 shows the summation of the changes in the nasal temperature, which increased over 2 min. Although not statistically significant, the nasal temperature under the condition With Buddy better diminished with the increasing trend than the other conditions [Freidman test: Chi-square (df $= 2$) $= 1.6$, $P = 0.4594$].

Fig. 7 shows the evaluation of the participants' preferences for each of the conditions. The participants were asked to rank their preferences regarding the three conditions. The With Buddy condition was mostly ranked first or second. The With Random condition was mainly ranked as first or third. The User condition was primarily ranked as second or third. These results show that the preference tended to be high in the use of the Buddy system (ordered logit: Chi-square (df $= 2$) $= 5.0$,

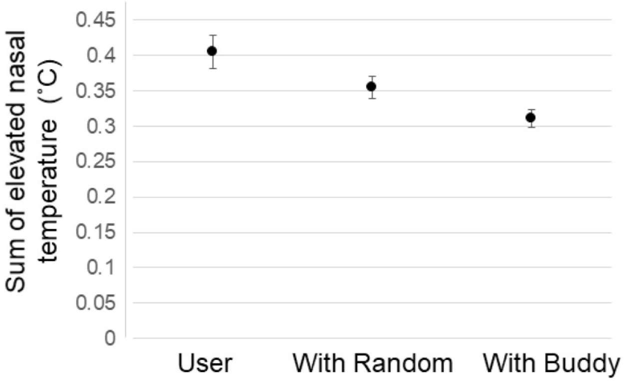


Fig. 6. Effects of the three conditions on nasal temperature. The error bars represent the SEM of the sum of the elevated nasal temperature.

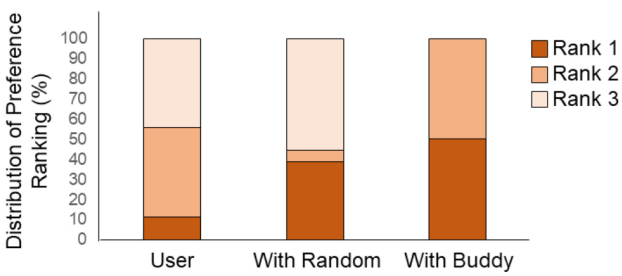


Fig. 7. Preferences of the three conditions.

$P = 0.0819$). The With Random condition had a mixed rank, which suggests that the random controls sometimes appeared to be good and bad for participants.

On the basis of the experimental results outlined above, the improvements in task performance were most prominent in the With Buddy condition. However, as is shown in Fig. 8, some examples featured less improvement in task performance under the condition. The slope of trend line 0.0457 under the With Buddy condition is indicative of less improvement in the later period of the experimental session. However, when we compared the slope of the trend line under the User condition, the slope of the trend line under the With Buddy condition was greater by more than 0.2. Therefore, the Buddy system still contributed to improved task performances. Overall, it successfully improved the participants' concentration.

In future works, we will aim to extend to a larger and more diverse sample size than that in the present study.

2) System Dynamics: As for the desired mental state level, the Buddy system was designed to update it depending on the mental state-level history, as described in [13]. As is shown in Fig. 9(a), the desired state level was always somewhat larger than the recent mental state levels. Therefore, the Buddy system functioned as desired.

As for the actions relating to environmental control, the Buddy system controlled the environmental devices in order to reduce the nasal temperature when the nasal skin temperature rose. The action values were calculated by the mapping function between the environmental settings and the nasal skin temperature $\rho = \rho(a)$. As described in Section III-E, each optimized action value a_1^*, a_2^*, and a_3^*, which are also values of the symmetrical axis of $\rho = \rho(a)$ [see (18) and (20)], was updated whenever the latest environmental manipulation by the Buddy system was not effective for decreasing the nasal skin's temperature. Fig. 9(b)–(d) shows an example of the time courses of the optimized action values under the Buddy system for control. For instance, when the latest action $a_{1,t-1}$ was an increase of the sound volume but the nasal skin temperature did not decrease, the axis of symmetry a_1^* was flipped around the current value $a_{1,t}$, and then the new action $a_{1,t}$ was to decrease the sound volume. The updating of a_1^* continued as long as the nasal skin temperature was increasing [indicated in the second and fourth red shaded boxes in Fig. 9(b)–(d)].

$\rho = \rho(a)$ was also designed to update in accordance with the participants' preferences. By making use of the participants' device manipulation histories, $\rho = \rho(a)$ was updated through the rule described in (24). As is shown in Fig. 9(b)–(d), after the participant manipulated the devices of sound and light after around 30 min [indicated as the blue-shaded box in Fig. 9(b) and (d)], the Buddy system changed the sound volume and light color and the aroma volume less significantly [as indicated by the fourth red shaded box in Fig. 9(b)–(d)] while updating the axis of symmetry of $\rho = \rho(a)$ in accordance with the participant's manipulations.

Overall, the experiments showed that the Buddy system technically functioned in the way it was designed for.

V. Discussion

Herein, we applied the FEP/Active inference scheme to the so-called Buddy system we designed, which is intended to improve human mental states by controlling the environment based on individual preferences. Within this framework, the Buddy system features a probabilistic model of the user's mental state. One of the benefits of having a probabilistic model is the capacity to perform perceptual inferences with little biological sensory input. Typically, a few sensors make it difficult to gain an accurate and complete generative model of mental states; however, the functional aim of the active inference framework described here is to make adaptive actions rather than utilizing a complete generative model [15]. The internal model of the Buddy system is not designed to feature an entire complex model but is enough to model the vicinity of the current state by frequently updating the model's parameters, and enough to generate appropriate actions online. Our experimental results showed that the environmental settings controlled by the Buddy system reduced participants' overall nasal skin temperature, suggesting that the Buddy system was able to undertake appropriate actions in terms of control of the environmental devices, and led participants' mental states to the desired condition. While with the current generative model, the evolution of belief of the mental state level μ is defined arbitrarily to be stable around the desired level μd [see (12)]. Therefore, the evolution of belief regarding the mental state level is not modeled for its true in humans. Therefore, the current system is unable to predict true future mental state levels. If the system had a dynamic model close to the true mental state level's evolution instead of having a model (12), it could

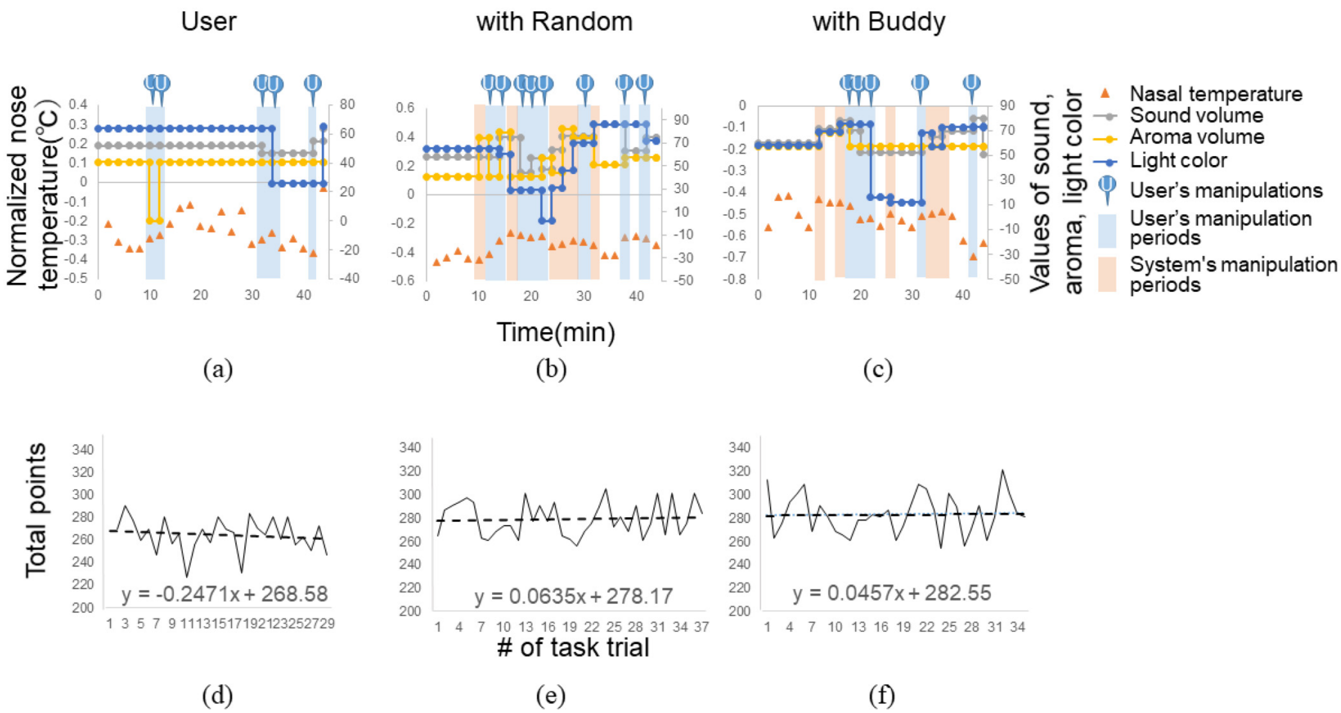


Fig. 8. Example of a participant's results of time courses for nasal temperature, environmental settings, and task performance. (a)–(c) Time courses for the nasal temperature and environmental manipulations for the sound volume, aroma volume, and light color under the three conditions (User, With Random, and With Buddy). (d)–(f) Time courses for the task performances measured by the point calculated in every CD25S game. The trend lines (the dotted line) and approximation formulas are also shown.

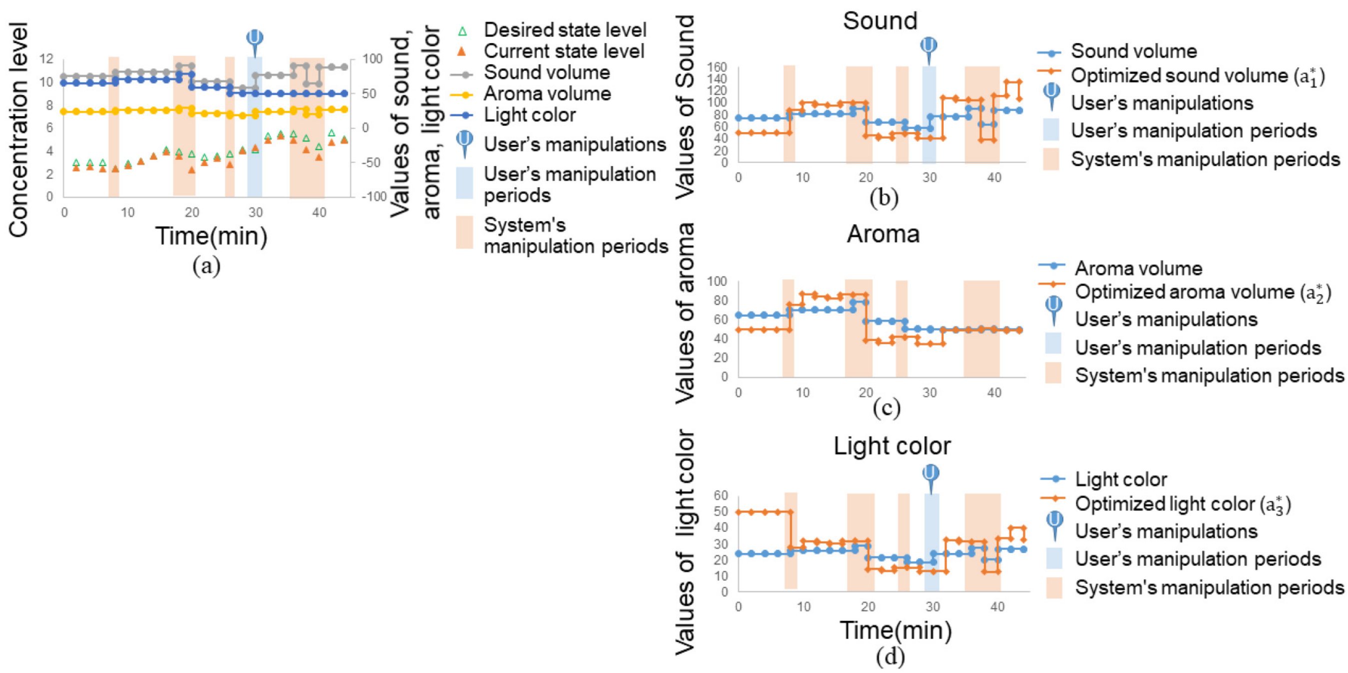


Fig. 9. Example of a participant's results for the time courses regarding a desired state level, current state level, and environmental manipulations, and those of the optimized action value with the Buddy system control. (a) Time courses for the desired mental state level, current mental state level, and environmental manipulations for the sound volume, aroma volume, and light color. (b)–(d) Time courses for the environmental manipulations of the sound volume, aroma volume, and light color, and their optimized values.

predict true future state levels and use them to generate more effective actions. Future work will develop a system that can predict true future mental states and generate more effective actions by minimizing the future free energy F [42]. Then, by strengthening future state prediction, the system will be able to behave proactively with respect to the user's mental state, which may also enhance their preference to use the Buddy system.

With the Buddy system, personalized action generation is implemented by fitting the sensory-action mapping function $\rho = \rho(a)$ to individuals, taking into account that optimal environmental settings differ among individuals. For instance, a high sound volume that is favorable to one may not always have the same effect on another. Therefore, personalized action generation is expected to enhance the effectiveness and preferences regarding the use of our proposed system. Here, $\rho = \rho(a)$ is modeled as a multivariate quadratic function to express the inverse-U shape, taking into account the knowledge that suboptimal environmental settings, such as too much or too little sound volume, are not conducive to the desired mental state, but the middle value is the most optimal. The value of the vertex of the quadratic function will then be adjusted to individuals based on the relationship between how they changed the environment and how the sensory input changed (see Section III-F). Finally, the experimental results indicated higher task performance and higher preference under the With Buddy condition.

In order to increase the effectiveness and preference of using the system more, the addition of more environmental devices such as air temperature controls could be helpful. The Buddy system could easily accommodate such an increase in the number of devices. The sensory-action mapping function $\rho = \rho(a)$ could still be formulated as a multivariate quadratic function (18) with more devices, and therefore adjusting it to individuals is merely a matter of adjusting the value of the vertex of the quadratic function using (23) and (24) while referring to a user's manipulations of devices in the environment. Therefore, the proposed system could easily add environmental devices to its control interface to more effectively improve the user's mental state.

VI. Conclusion

This article presented a biologically inspired framework for a mental state-supportive system, namely, the Buddy system. We adopted the FEP/Active inference scheme for the Buddy system for the sake of gaining adaptive control for mental states, which innately fluctuate. Based on the general FEP/Active inference scheme, we modified two of its functions. One was that the desired mental state level μd expressed in the prior probability of generative model was designed to be changeable depending on recent mental state levels. Similar to the human dynamics of improving their mental state levels step by step, the Buddy system was designed to appropriately update the desired mental state level based on the user's current and recent mental state levels. The other modified function of the Buddy system is its online updating of the sensory-action mapping function $\rho = \rho(a)$ to meet individuals' preferences. The experimental results reported here provide a proof of concept for the Buddy system, by which task performance was improved, the sensory data was optimally controlled, and the preferences of the Buddy system were high.

Acknowledgment

The authors would like to thank Enago (www.enago.jp) for their English language reviewing services.

References

[1] M. Molino *et al.*, "Wellbeing costs of technology use during Covid-19 remote working: An investigation using the Italian translation of the technostress creators scale," *Sustainability*, vol. 12, no. 15, pp. 1–20, 2020, doi: 10.3390/SU12155911.

[2] D. Demekas, T. Parr, and K. J. Friston, "An investigation of the free energy principle for emotion recognition," *Front. Comput. Neurosci.*, vol. 14, pp. 1–17, Apr. 2020, doi: 10.3389/fncom.2020.00030.

[3] K. A. Lindquist, T. D. Wager, H. Kober, E. Bliss-Moreau, and L. F. Barrett, "The brain basis of emotion: A meta-analytic review," *Behav. Brain Sci.*, vol. 35, no. 3, pp. 121–143, 2012, doi: 10.1017/S0140525X11000446.

[4] M. Mariya, M. Artemyev, A. Belyaev, and O. Perepelkina, Overview of the Advancements in Automatic Emotion Recognition: Comparative Performance of Commercial Algorithms. *PsyArXiv*, 2019, doi: 10.31234/osf.io/x7bvd.

[5] F. Lotte, "A tutorial on EEG signal processing techniques for mental state recognition in brain-computer interfaces," in *Guide to Brain-Computer Music Interfacing*. London, U.K.: Springer, 2014, pp. 133–161.

[6] A. P. Sutarto, M. N. A. Wahab, and N. M. Zin, "Resonant breathing biofeedback training for stress reduction among manufacturing operators," *Int. J. Occup. Safety Ergon.*, vol. 18, no. 4, pp. 549–561, 2012, doi: 10.1080/10803548.2012.11076959.

[7] D. L. Frank, L. Khorshid, J. F. Kiffer, C. S. Moravec, and M. G. McKee, "Biofeedback in medicine: Who, when, why and how?" *Mental Health Family Med.*, vol. 7, no. 2, pp. 85–91, 2010.

[8] K. T. Ferguson and G. W. Evans, "The built environment and mental health," in *Encyclopedia of Environmental Health*, vol. 80. Amsterdam, The Netherlands: Elsevier, 2019, pp. 465–469, doi: 10.1016/B978-0-12-409548-9.11009-7.

[9] G. Becerra and R. Kremer, "Ambient intelligent environments and environmental decisions via agent-based systems," *J. Ambient Intell. Humaniz. Comput.*, vol. 2, no. 3, pp. 185–200, 2011, doi: 10.1007/s12652-011-0056-0.

[10] R. El Kaliouby and P. Robinson, "Real-time inference of complex mental states from facial expressions and head gestures," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Workshop*, vol. 10. Washington, DC, USA, Jan. 2004, p. 154, doi: 10.1109/CVPR.2004.427.

[11] R. Richer, N. Zhao, J. Amores, B. M. Eskofier, and J. A. Paradiso, "Real-time mental state recognition using a wearable EEG," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Honolulu, HI, USA, 2018, pp. 5495–5498, doi: 10.1109/EMBC.2018.8513653.

[12] A. Rodrigues, L. Lopes, C. Costa, and D. Cabral, "LightStress: Targeting stress reduction through affective objects," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput. Int. Symp. Wearable Comput.*, 2019, pp. 191–193. [Online]. Available: http://doi.acm.org/10.1145/3341162.3343773

[13] K. Friston, "The free-energy principle: A unified brain theory?" *Nat. Rev. Neurosci.*, vol. 11, no. 2, pp. 127–138, 2010, doi: 10.1038/nrn2787.

[14] K. J. Friston, J. Daunizeau, J. Kilner, and S. J. Kiebel, "Action and behavior: A free-energy formulation," *Biol. Cybern.*, vol. 102, no. 3, pp. 227–260, 2010, doi: 10.1007/s00422-010-0364-z.

[15] A. Tschantz, A. K. Seth, and C. L. Buckley, "Learning action-oriented models through active inference," *PLoS Comput. Biol.*, vol. 16, no. 4, pp. 1–30, 2020, doi: 10.1371/journal.pcbi.1007805.

[16] L. Pio-Lopez, A. Nizard, K. Friston, and G. Pezzulo, "Active inference and robot control: A case study," *J. Roy. Soc. Interface*, vol. 13, no. 122, 2016, Art. no. 20160616, doi: 10.1098/rsif.2016.0616.

[17] B. Millidge, "Implementing predictive processing and active inference: Preliminary steps and results," *PsyArXiv*, 2019, doi: 10.31234/osf.io/4hb58.

[18] C. Pezzato, R. Ferrari, and C. H. Corbato, "A novel adaptive controller for robot manipulators based on active inference," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 2973–2980, Apr. 2020, doi: 10.1109/LRA.2020.2974451.

[19] G. Oliverz, P. Lanillosz, and G. Chengz, "Active inference body perception and action for humanoid robots," 2019. [Online]. Available: arXiv:1906.03022.

[20] C. L. Buckley, C. S. Kim, S. McGregor, and A. K. Seth, "The free energy principle for action and perception: A mathematical review," *J. Math. Psychol.*, vol. 81, pp. 55–79, Dec. 2017, doi: 10.1016/j.jmp.2017.09.004.

[21] R. Bogacz, "A tutorial on the free-energy framework for modelling perception and learning," *J. Math. Psychol.*, vol. 76, pp. 198–211, Feb. 2017, doi: 10.1016/j.jmp.2015.11.003.

[22] K. J. Friston, N. Trujillo-Barreto, and J. Daunizeau, "DEM: A variational treatment of dynamic systems," *Neuroimage*, vol. 41, no. 3, pp. 849–885, 2008, doi: 10.1016/j.neuroimage.2008.02.054.

[23] K. Friston, "Hierarchical models in the brain," *PLoS Comput. Biol.*, vol. 4, no. 11, 2008, Art. no. e1000211, doi: 10.1371/journal.pcbi.1000211.

[24] K. Friston, T. FitzGerald, F. Rigoli, P. Schwartenbeck, and G. Pezzulo, "Active inference: A process theory," *Neural Comput.*, vol. 29, no. 1, pp. 1–49, Jan. 2017, doi: 10.1162/NECO_a_00912.

[25] K. Friston, Q. Square, and J. Kilner, "Action understanding and active inference," *Biol. Cybern.*, vol. 104, no. 1–2, pp. 137–160, 2011. [Online]. Available: https://doi.org/10.1007/s00422-011-0424-z.

[26] K. Friston, "Learning and inference in the brain," *Neural Netw.*, vol. 16, no. 9, pp. 1325–1352, 2003, doi: 10.1016/j.neunet.2003.06.005.

[27] S. D. Kreibig, "Autonomic nervous system activity in emotion: A review," *Biol. Psychol.*, vol. 84, no. 3, pp. 394–421, 2010, doi: 10.1016/j.biopsycho.2010.03.010.

[28] P. Valdez and A. Mehrabian, "Effects of color on emotions," *J. Exp. Psychol. Gen.*, vol. 123, no. 4, pp. 394–409, 1994, doi: 10.1037/0096-3445.123.4.394.

[29] J. A. Benfield, B. D. Taff, P. Newman, and J. Smyth, "Natural sound facilitates mood recovery," *Ecopsychology*, vol. 6, no. 3, pp. 183–188, 2014. [Online]. Available: https://www.liebertpub.com/doi/10.1089/eco.2014.0028

[30] S. Warrenburg, "Effects of fragrance on emotions: Moods and physiology," *Chem. Sens.*, vol. 30, no. s1, pp. 248–249, 2005, doi: 10.1093/chemse/bjh208.

[31] J. D. Dodson, "The relation of strength of stimulus to rapidity of habit-formation in the kitten," *J. Anim. Behav.*, vol. 5, no. 4, pp. 330–336, 1915, doi: 10.1037/h0073415.

[32] J. B. Furness, "The organisation of the autonomic nervous system: Peripheral connections," *Auton. Neurosci. Basic Clin.*, vol. 130, no. 1–2, pp. 1–5, 2006, doi: 10.1016/j.autneu.2006.05.003.

[33] R. P. Dum, D. J. Levinthal, and P. L. Strick, "Motor, cognitive, and affective areas of the cerebral cortex influence the adrenal medulla," *Proc. Nat. Acad. Sci. U. S. A.*, vol. 113, no. 35, pp. 9922–9927, 2016, doi: 10.1073/pnas.1605044113.

[34] Z. B. Moses, L. J. Luecken, and J. C. Eason, "Measuring task-related changes in heart rate variability," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Lyon, France, 2007, pp. 644–647, doi: 10.1109/IEMBS.2007.4352372.

[35] B. G. Wallin, "Sympathetic nerve activity underlying electrodermal and cardiovascular reactions in man," *Psychophysiology*, vol. 18, no. 4, pp. 470–476, 1981.

[36] A. Nozawa and M. Tacano, "Correlation analysis on alpha attenuation and nasal skin temperature," *J. Stat. Mech. Theory Exp.*, vol. 2009, no. 1, 2009, Art. no. P01007, doi: 10.1088/1742-5468/2009/01/P01007.

[37] S. Koelsch and L. Jancke, "Music and the heart," *Eur. Heart J.*, vol. 36, no. 44, pp. 3043–3048, 2015, doi: 10.1093/eurheartj/ehv430.

[38] M. J. Ross, P. Guthrie, and J.-C. Dumont, "The impact of modulated, colored light on the autonomic nervous system," *Adv. Mind Body Med.*, vol. 27, no. 4, pp. 7–16, 2013.

[39] T. Hongratanaworakit, "Physiological effects in aromatherapy," *Songklanakarin J. Sci. Technol.*, vol. 26, pp. 117–125, 2004.

[40] T. M. B and Y. Kume, "Development of a glasses-like wearable device to measure nasal skin temperature," in *Proc. Int. Conf. Hum. Comput. Interact.*, vol. 1, 2015, pp. 727–732, doi: 10.1007/978-3-319-21380-4.

[41] E. Erdfelder, F. Faul, A. Buchner, and A.-G. Lang, "Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses," *Behav. Res. Methods*, vol. 41, no. 4, pp. 1149–1160, 2009, doi: 10.3758/BRM.41.4.1149.

[42] K. Friston, F. Rigoli, D. Ognibene, C. Mathys, T. Fitzgerald, and G. Pezzulo, "Active inference and epistemic value," *Cogn. Neurosci.*, vol. 6, no. 4, pp. 187–214, 2015, doi: 10.1080/17588928.2015.1020053.