Using Feedback on Computer States to Improve Power Management Behaviors

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Abstract Computer power management settings can potentially save substantial energy by putting computers into low-power modes when not being used. However, previous research shows that sleep settings are often disabled in office desktops. The Power Management User Interface (PMUI) feedback app was designed to give users feedback on their computer idle states and to encourage enabling of sleep settings. Unlike current energy feedback devices, PMUI is a standalone free software application that does not require installing additional equipment. PMUI was field tested in 407 computers (303 treatment subjects and 104 control subjects), with a minimum 1-month baseline period and 2-month treatment period for each subject. At baseline, only 13% of computers had computer sleep settings enabled, but 56% of subjects reported the settings were enabled. Findings suggests user confusion about settings that is correlated to lack of use and lack of knowledge. Subjects exposed to the PMUI application were significantly more likely than control subjects to enable their computer sleep settings and to reduce the delay time. Treatment subjects' computers subsequently spent less time idle and more time in sleep mode than control subjects' computers. Overall, these results provide strong evidence that feedback on computer states can effectively induce desktop users to improve their power management settings and thus save energy, without the need for separate plug meter devices to measure energy usage.

1 Introduction

Many feedback interventions have been designed to change users' behaviors with the goal of reducing energy demand at home and at the workplace, with varying degrees of success [1–5]. The current study focused on behaviors toward one specific device: the desktop computer. Desktop computers are less prevalent than portable computers, but their contribution to energy consumption continues to be high.

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P. Bertoldi (ed.), *Energy Efficiency in Domestic Appliances and Lighting*, Springer Proceedings in Energy, https://doi.org/10.1007/978-3-030-79124-7_19

A recent study estimates the installed base in the US of desktop computers to be 72 million, compared to 122 million for portable computers. However, the higher energy consumption for desktop computers results in an estimated annual electricity consumption of 18 TWh compared to only 5.1 TWh for portable computers [6]. Desktop computers are major contributors of wasted "idle" energy use in homes and businesses [7]. Current ENERGY STAR® guidelines estimate average power consumption for desktops at 2.3 W in sleep mode compared to 48.1 W in idle mode [8]. In one case study, desktops with sleep settings enabled (regardless of delay time) spent an average of 12% of the week in idle mode, compared to 68% for those without sleep enabled [9]. The solution is simple to conceive but difficult to implement: ensure that desktops spend as much time in sleep mode and as little time idle as possible.

Unfortunately, despite having power management options available, most desktop users are not applying them. Physical audits and monitoring studies in commercial and university buildings have found that in practice a high percentage of computers were left on unnecessarily when not being actively used, and that substantial energy savings could be possible with better power management practices [e.g., 10–13].

In contrast to research observing computers directly, most surveys show high rates of users reporting that their computer sleep settings are engaged [14]. Some of the discrepancy between self-reports of enabled sleep settings and observations of idling computers appears to be due to user confusion about sleep settings [15]. One study that linked self-report to research observations for the same subjects found that although 86% of subjects had reported their computer sleep settings enabled, only 30% of those subjects actually had their settings enabled [16]. Furthermore, those who rated themselves as more knowledgeable about computers were more likely to be accurate about their settings. This suggests that educating users about sleep settings and giving them feedback about their current power management settings and the computer's sleep behavior may be an important step to saving energy.

Previous studies have tried encouraging office workers to save energy with their computers and other equipment by providing advice and feedback to employees about the power consumption of their workstations, covering a range of plug load devices [17–19] or the whole office [20]. A few feedback studies focused on computer states and energy use [21, 22] or provided the user or researchers with usage information disaggregated for specific devices [23, 24]. Few feedback studies have examined user behavior in connection with computer states and power modes [21, 22]. However, most studies suffer from small sample sizes or were not able to utilize an experimental randomized control trial design. More studies are needed to assess the potential of feedback on influencing computer users' behaviors.

One approach to improving computer energy efficiency in commercial enterprises is centralized IT control, in which a company's IT department uses a software application or service to remotely control its employees' computers, including their power management settings. This works well for many companies and can save substantial energy. However, it is not appropriate in many situations, such as residential computer use and small companies with limited IT resources. Also, even where centralized IT control is already used to facilitate updates and backups, a policy of mandatory sleep settings can face resistance from IT personnel and employees [22, 25]. Thus, a method for encouraging voluntary improvements in energy-saving computer behaviors could be useful in many circumstances.

To address this problem, the research team at University of California, Irvine developed a software application, the Power Management User Interface (PMUI), designed to encourage voluntary use of automatic sleep settings. PMUI was developed based on design principles established by prior research on using feedback to motivate behavior, which describe the importance of giving timely feedback [26–28], offering specific, actionable tips [28, 29], presenting data in multiple, simple to understand graphs and figures [26, 30, 31], comparing users' current outcomes to previous outcomes [32, 33] or to an ideal standard or goal [5, 34], rewarding the desired behavior with happy face emoticons [35], appealing to common norms by using pro-environmental messages [36, 37], and engaging the user with interactive features [27, 30].

This paper presents the results of a field test of the PMUI interface, with 407 staff members of a major university. The overall research question asks whether the PMUI interface encourages subjects to improve their sleep setting behaviors, relative to the baseline period, and whether this behavior change is significantly better than for the control group, who are only reminded how to access their standard sleep settings.

The primary research question is whether use of the PMUI application can positively affect subjects' behavior: specifically, encouraging them to improve their automatic sleep settings by either enabling them (if they were disabled) or reducing the delay time (if they were already enabled). This behavior is assessed at two time points. First, it is hypothesized that initial exposure to the PMUI application will result in more treatment subjects improving their computer sleep settings than control subjects, who are exposed only to their standard sleep settings interface. If this were the only effect of PMUI, it would indicate that PMUI is more effective as an informational tool than simply reminding subjects to check their standard sleep settings. Second, it is hypothesized that the PMUI application has an ongoing and persistent effect past the initial effect, as indicated by larger improvement in sleep settings between initial exposure and the end of the study (2 or more months later) compared to the control group. If PMUI is shown to have an effect over time in addition to the initial exposure effect, it would indicate that ongoing feedback and encouragement had an important role.

Although the PMUI application does not offer feedback to users on display settings, possible improvements in display settings are also examined.

2 Methods

2.1 *The Power Management User Interface Feedback Application*

The Power Management User Interface (PMUI) application was designed to encourage users to better utilize their computers' existing sleep settings by (1) providing a clear, simple sleep settings interface for computer and monitor/display, (2) providing consistent cues about the importance and desirability of reducing idle time; (3) providing clear advice about how to reduce idle time; (4) providing multiple types of feedback reports on how much time the computer spends idle, including comparisons to previous time periods and to a "target" profile; and (5) using multiple types of encouragement, including environmental impact measures and smiling versus sad emoticons. To simplify the interface, the PMUI application did not provide feedback to users on the idle time of their monitors. PMUI sends a weekly pop-up reminder for users to check their usage report for the week (see Fig. 1). Users can access the application using a tray icon, which opens onto the sleep settings page (see Fig. 2). A laboratory pretest walked 22 subjects through the use of every feature and asked open-ended questions to assess their comprehension and interpretation. Pretesting was staggered so that later subjects were presented with revisions based on earlier subjects' responses to confirm that the changes were effective. Other details about the software are presented elsewhere [38, 39].

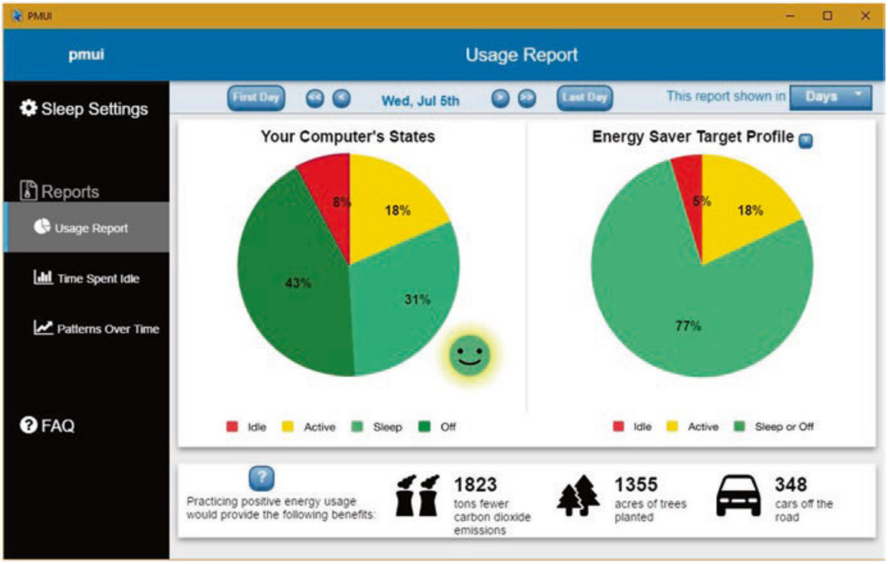

Fig. 1 PMUI usage report page

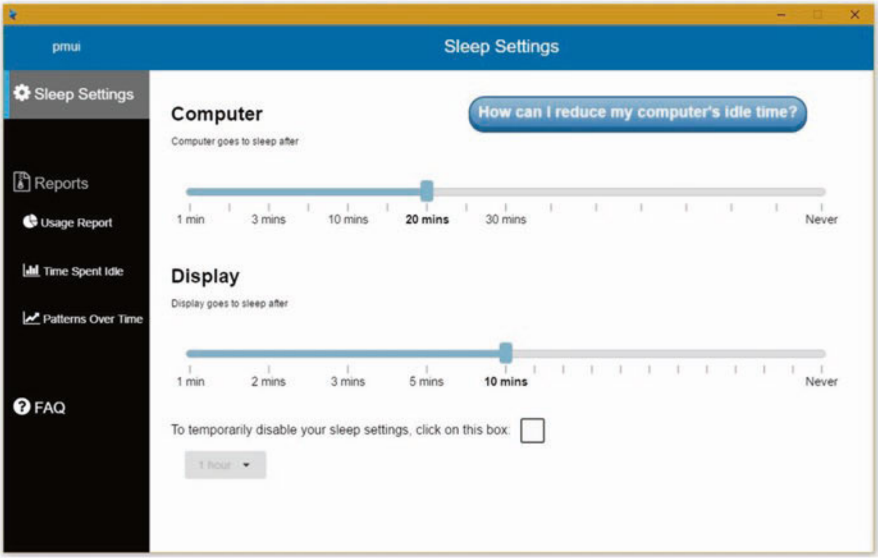

Fig. 2 PMUI sleep settings page

2.2 *Data Collection*

All schools and other units on campus who might be eligible for inclusion were identified. Recruitment began with the administrative units whose computers were managed by the Office of Information Technology. Other units were added in waves, focusing on those with substantial numbers of staff, and limited to those where the unit did not have a sleep setting policy in place and where the IT manager, director, dean, or other representative approved the use of the software. The participating units represent a wide range of staff on campus, including humanities, physical sciences, administration, and facilities management. Data collection lasted from March 2017 to May 2018.

Once a unit was chosen, staff contact information was obtained from the university directory or from the unit itself. The IT manager sent an email alerting staff that the recruitment email was not a scam and that participation was voluntary. Potential subjects were then emailed a recruitment letter detailing the study, including a link to the consent form. If interested, they filled out an online form verifying their eligibility and asking for potential times to schedule their first appointment. The public name of the study shown to subjects was "[University Name] Computer Energy Study" to reduce introducing bias by mentioning power management or sleep settings in the initial materials.

Individuals were eligible if they were university staff, aged 18 or older, who were the sole users of a desktop computer on campus and had the ability to change their own sleep settings.

Student research assistants (RAs) conducted three research visits per subject. Subjects were given a $25 Amazon gift card at each of the three visits, for a total of $75. At the first research visit (T1), the RA went over the informed consent document and obtained the subject's signature before proceeding. The RA installed the PMUI software on the desktop, set to observation-only mode. The RA also plugged the computer and its monitor(s) into a power strip, which was plugged into a power monitor. The specially programmed power monitors transmitted real-time energy consumption data to the study's secure servers. Baseline data on computer sleep settings and on energy use was collected for a minimum of 4 weeks, subtracting vacations, university holidays, and other leaves.

After T1, subjects were assigned to the control or experimental condition, at a one-to-three ratio. This process was not entirely random, but depended on the order in which the Access database sorted new cases. In addition, a few cases were reassigned at or before T2 (e.g., cases where a researcher accidentally mentioned the PMUI app to a control subject).

At the second research visit (T2), subjects filled out an online survey on the RA's tablet. For the treatment group, RAs activated the PMUI GUI and showed the subject how to access the app. For the control group, RAs showed the subject how to access their computer's standard computer settings. Included in the extensive training the RAs received was how to manage this last step without implying that the subject didn't already know.

The final research visit (T3) was conducted a minimum of 8 weeks after T2. Subjects filled out another online survey, including questions asking them to evaluate their standard computer sleep settings and, for the treatment group, to evaluate the PMUI app. At this visit, the RA removed all hardware and software.

2.3 Subjects

The final sample consisted of 407 subjects, all university staff. This included research and administrative staff and post-doctoral scholars, but not faculty or students. The majority were women (68%). Almost half (45%) of subjects identified as white, with 28% identifying as Asian or Pacific Islander, 11% identifying as Hispanic or Latino, 8% identifying as more than one race or ethnicity, and less than 5% identifying with any other group. Compared to Census estimates for California, the sample is less white (versus 72.4%), less Hispanic (versus 37.2%) and more Asian (versus 15.2%). However, the state race and ethnicity data is for people of all ages and education, whereas staff members who use computers at a university (and at other similar enterprises) are likely to be of working age and more highly educated than average. Indeed, all but 11% of the sample are college-educated: 53% have a bachelor's degree, 28% have a master's degree, 1% have a different professional degree, and 6% have a doctorate. By contrast, the Census shows that for the overall population in the state, only 32% of persons 25 and older have a bachelor's degree or higher. Subjects were asked to identify which official Census occupation category fit them best. The majority were professionals, administrative support, or higher-level administrators. Almost all (98%) reported working full-time, defined as at least 30 h/week, or a 75% appointment. These demographic differences from the overall state averages are to be expected with a sample focused on office workers in administrative and professional settings, who comprise most users of office desktop computers.

The majority of desktops in the study (92%) used the Windows operating system, most using Windows 7 (77% of the sample) or Windows 10 (15% of the sample). The other 8% used Mac operating systems, mostly the most recent build at the time, macOS Sierra (19 of the 31 Mac computers, and 5% of the sample).

Multiple monitors were common: at the beginning of the study, 37% of subjects had one monitor, 62% had two monitors, and six subjects (less than 2%) had three or four. Seven subjects changed the number of monitors they had over the course of the study, but the percentages in each group stayed the same. Twenty-five desktops (6%) were all-in-one computers; these were all Apple computers, although two of them were running Windows operating systems. All-in-one computers were coded as having one monitor; nine of them were also connected to a second monitor.

As planned, three in four subjects were in the treatment group (303, or 74.5%). The treatment and control groups did not differ significantly on any of the demographic characteristics measured, nor on the operating system of their computer or the number of monitors.

2.4 Measures

The sleep settings for the PMUI app are the same as those in the standard sleep settings, that is, those that come with the Windows or Mac OSX operating system. Only sleep settings for the computer and monitor/display are assessed (not, for instance, hard drive sleep, hybrid sleep, or hibernation). Sleep settings that are set to "never" are considered "disabled" while sleep settings set for a delay time (e.g., 20 min until sleep) are considered "enabled." A shorter delay time indicates that the subject reduced the number of minutes of idle before the computer or monitor goes into sleep mode, while a longer delay time indicates the opposite.

The hypotheses are tested by looking at changes in the sleep settings over the course of the subject's study period, particularly whether the sleep settings at the end of the study period (T3, about 2 months after the intervention at T2) differ from the settings observed at the end of the baseline period (T2). The current analysis thus does not capture subjects who made multiple changes and ended with the same setting. For instance, those who initially enabled their sleep settings but did not persist—that is, went back to disabling their settings—are considered as "no change" in the end.

3 Results

3.1 Initial Computer Sleep Settings

Consistent with prior research, only a minority of subjects (14%) had their computer sleep settings enabled at the first research visit. Of those computers, the most common sleep delay time was 30 min (the default), with almost equal proportions of others exhibiting higher and lower delay times. Far more computers had display sleep settings enabled at baseline (83%). Almost all of them had delay times set at 30 min or less, with a substantial minority at 15 min or less. Only nine subjects changed their settings during the baseline period, suggesting the lack of a Hawthorne effect. Four subjects enabled computer sleep and two disabled it, while three subjects enabled display sleep and two disabled it (two subjects changed both computer and display sleep).

At the end of the baseline period, the control group had a slightly higher proportion of computers with computer sleep enabled (17% vs. 14% in the treatment group) and a slightly lower proportion with display sleep enabled (81% vs. 84%), but neither difference was statistically significant.

3.2 Changes to Sleep Settings

As the primary goal of PMUI is to encourage users to enable their sleep settings, the first analysis is whether the group using the PMUI application were more likely to enable their sleep settings than the control group. As shown in Fig. 3, the main effect of PMUI on behavior is clear and substantial. Among subjects who had their computer sleep settings enabled prior to the intervention at T2, slightly more treatment subjects retained them, but the difference is not significant. However, among those with disabled computer sleep settings, treatment subjects were much more likely to enable them than control subjects (59% versus 15%, $p < 0.0001$).[1] The results are similar, if not as strong, for those who began with their display settings disabled, with 56% of treatment subjects versus 30% of control subjects enabling them ($p = 0.0484$).

Clearly, exposure to the PMUI application is more effective at encouraging energy-saving settings than reminding subjects of their normal sleep settings. The next set of analyses assess whether this effect occurs mainly upon first exposure to the information, or if it is amplified by more extended, longer-term feedback and encouragement.

[1] All the analyses in this paper use bivariate chi-square tests to compare results for treatment versus control groups; no other variables were controlled for.

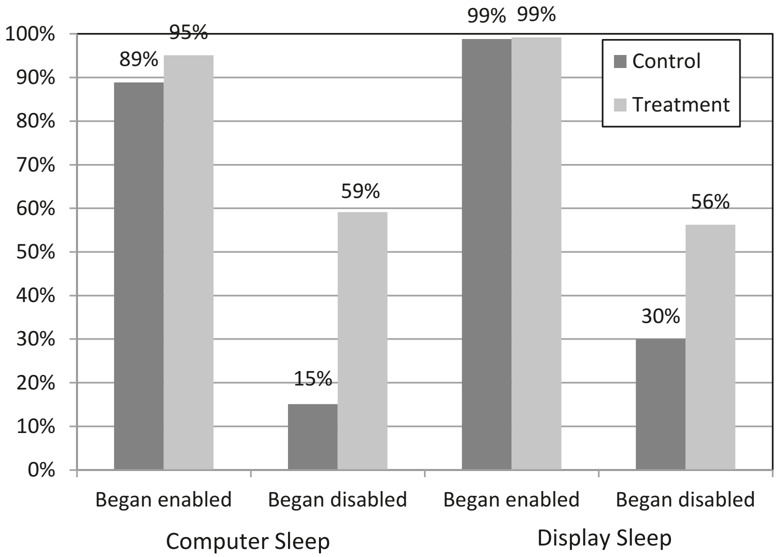

Fig. 3 Percentage of computers with sleep settings enabled at T3 by experimental group and initial settings at T2

Table 1 Change in computer sleep settings after initial intervention (T2), by condition

Status at T2	Change after T2	Control group #	Control group Percent	Treatment group #	Treatment group Percent
Disabled	No change	71	83	186	71
	Enabled sleep	15	17	76	29
	N	86		262	
Enabled	No change	16	89	31	76
	Disabled sleep	0	0	1	2
	Increased sleep delay	1	6	0	0
	Decreased sleep delay	1	6	9	22
	N	18		41	
Total		104		303	

3.2.1 Immediate Response to Intervention

As it is possible that the subject experimented with changing during or shortly after the research visit at T2 and then reverted to the previous settings, these analyses examine the change in status (if any) from the end of the day prior to T2 to the end of the day after T2 occurred. The possible subject actions following the intervention at T2 depend on whether the computer sleep settings were already enabled; they are listed in Table 1. Among subjects who had computer sleep disabled prior to the intervention, subjects in the treatment group were significantly more likely to enable sleep than those in the control group (29% versus 17%, $p = 0.0342$). Among subjects who already had computer sleep enabled, a larger proportion of treatment subjects decreased (that is, improved) the sleep delay (22% versus 6%); however, this is not statistically significant, likely because of the small sample size. Overall, this suggests that subjects were more motivated to improve their sleep settings by looking at the PMUI program than by looking at their standard settings, even though the two interfaces displayed the same basic information.

Immediate effects of the intervention on display sleep settings are shown in Table 2. The observed relationship is in the same direction as with computer sleep settings. More subjects in the treatment group than in the control group enabled display sleep or decreased the delay time, but the difference is not statistically significant.

3.2.2 Long-Term Changes over the Experimental Period

The next analysis assesses the relationship between the subjects' initial response after T2 and the eventual outcome, that is, whether continued use of PMUI had an additional effect on the outcomes shown at the end of the study. For the control subjects who began with disabled computer sleep settings, those who did not change them during T2 were highly unlikely to change them later in the study (only 1%), while 20% of those who enabled their sleep settings during T2 had disabled them again by the end of the study (see Table 3). By contrast, of the treatment subjects who did not enable their settings during T2, almost half (45%) enabled their computer settings later in the intervention period and kept them enabled until T3. Also, almost all of the treatment subjects who enabled their settings at T2 still had them enabled at the end of the study (95%). All the treatment subjects with enabled sleep settings who did not change them at T2 still had them enabled at T3; the other cells in the table are too small to produce reliable percentages. In short, the continued positive changes for the treatment group after the change at T2 suggest the effectiveness of the ongoing intervention of the PMUI feedback.

Table 2 Change in display sleep settings after initial intervention (T2), by condition

		Control group		Treatment group	
Status at T2	Change after T2	#	Percent	#	Percent
Disabled	No change	16	80	30	63
	Enabled sleep	4	20	18	38
	N	20		48	
Enabled	No change	74	88	208	82
	Disabled sleep	0	0	1	0
	Increased sleep delay	0	0	1	0
	Decreased sleep delay	10	12	45	18
	N	84		255	
Total		104		303	

Table 3 Relationship of change in computer sleep settings after initial intervention (T2) to outcome at end of study (T3), by condition

		Control group			Treatment group		
Status at T2	Change at T2	#	Sleep disabled at T3 (%)	Sleep enabled at T3 (%)	#	Sleep disabled at T3 (%)	Sleep enabled at T3 (%)
Disabled	No change	71	99	1	186	55	45
	Enabled sleep	15	20	80	76	5	95
Enabled	No change	16	13	88	31	0	100
	Disabled sleep	0			1	0	100
	Increased sleep delay	1	0	100	0		
	Decreased sleep delay	1	0	100	9	22	78
Total		104			303		

Table 4 Relationship of change in display sleep settings after initial intervention (T2) to outcome at end of study (T3), by condition

		Control group			Treatment group		
Status at T2	Change at T2	#	Sleep disabled at T3 (%)	Sleep enabled at T3 (%)	#	Sleep disabled at T3 (%)	Sleep enabled at T3 (%)
Disabled	No change	16	88	13	30	67	33
	Enabled sleep	4	0	100	18	6	94
Enabled	No change	74	0	100	208	0	100
	Disabled sleep	0			1	0	100
	Increased sleep delay	0			1	0	100
	Decreased sleep delay	10	10	90	45	2	98
Totals ($N = 407$)		104			303		

The same analysis for display sleep settings is shown in Table 4. As most subjects had their display sleep settings enabled for the entire study, there are not many differences by experimental condition. In both control and treatment groups, all of the subjects who already had display sleep enabled and made no change at T2 still had display sleep enabled at the end of the study, as did most of the subjects who enabled display sleep at T2. Among subjects with disabled settings who did not enable them at T2, treatment subjects were more likely than control subjects to later enable them, but this relationship is not statistically significant. A small number of subjects who decreased the display delay time at T2 later disabled display sleep.

3.2.3 Changes in Delay Times for Computer and Display

Although enabling sleep settings has the largest impact on how much time the computer or monitor spends idle, reducing the delay time for sleep settings also saves energy. Table 5 shows the proportion of subjects in each group who already had sleep settings enabled before the intervention at T2 who either increased or decreased their delay time. Subjects in the treatment group were somewhat more likely than control subjects to reduce the delay time for their computer sleep settings, but this relationship only approached the level of significance (39% versus 11%, $p = 0.0532$). The difference for the larger number of subjects who began with display sleep settings is more pronounced, with 47% of treatment subjects reducing their display delay time compared to 13% of control subjects ($p < 0.0001$).

4 Discussion

The field test results presented here suggest that users can be encouraged to save substantial amounts of energy on desktop computers, if given clear feedback on how their decisions affect the energy consumption of the devices. A substantial minority of control group subjects (15%) enabled their sleep settings after being shown the standard settings page, and left those settings enabled for at least another 2 months. This is an interesting result in itself, as it suggests that many computer users are honestly unaware that their sleep settings are disabled, and are willing to enable them without any additional feedback or encouragement.

Table 5 Change in sleep setting delay times over intervention period, by condition

	Control group		Treatment group	
	Number	Percent	Number	Percent
Computer sleep settings				
Delay time at T3 versus T2				
Same	13	72	23	56
Shorter	2	11	16	39
Longer	1	6	0	0
Disabled	2	11	2	5
N	18		41	
Display sleep settings				
Delay time at T3 versus T2				
Same	71	85	122	48
Shorter	11	13	120	47
Longer	1	1	11	4
Disabled	1	1	2	1
N	84		255	

Outcomes for the treatment subjects are even more dramatic: 59% of those with disabled sleep settings enabled them after using the PMUI app. This is more than three times higher than the effect for the control group. Also, those subjects who already had their settings enabled were more likely to reduce the delay time for their computer sleep and for their monitor sleep if they were exposed to the PMUI app.

Subjects might be more likely to pay attention to the information relayed by PMUI than by their standard sleep settings, given that PMUI is new to them and includes engaging, colorful reports. If so, this could result in a stronger response for the treatment group at the T2 research visit, but no discernable additional long-term effects. However, additional analyses indicate that PMUI had additional effects over the course of the experimental period, suggesting that its effect is not solely due to information provided at the intervention visit.

One limitation is the length of the study period, as treatment subjects were only observed about 2 months after first encountering the PMUI app at T2. For behavioral change interventions, persistence is a serious concern. For in-home energy feedback devices or behavioral modification devices (e.g., Fitbit step counters), if subjects stop accessing the feedback after a few weeks or months, or otherwise appear to lose interest, their behaviors are likely to revert to their previous level. It is worth stepping back to consider the types of energy-saving behaviors most programs encourage, which are usually divided into investment decisions versus curtailment behaviors. For investment decisions, the focus is on convincing users to buy more energy-efficient appliances. Once that purchase is made, the energy savings (for that device, at least) are locked in, and the user need not persist in thinking about it. By contrast, curtailment behaviors (such as remembering to turn lights off, choosing the "no dry" option on the dishwasher, or hanging up laundry instead of using clothes dryers) must be repeated on a regular basis, and thus require longer-term commitment and persistence.

A third type of energy-saving behavior gets less attention, which is changing settings. This behavior change is similar to investment behavior, in that the user may adopt more energy-efficient settings for, say, their thermostat, after which they do not need to persist in thinking about it. However, this behavior resembles curtailment to some extent also. As the user's experience is altered by the setting, it may be noticeable and even onerous enough to feel like curtailment, possibly leading to the user reverting the setting to the earlier, less energy-efficient level. Enabling sleep settings on a computer is conceptually much the same as thermostat settings. Simply enabling the settings once does not guarantee that sleep will remain enabled. Subjects who experience computer delays or other problems after enabling sleep (for example, complications when trying to remote into their work desktops from home), whether or not actually related to sleep, may decide that the cost of dealing with the problem is not worth the benefits, and disable sleep again. This may have happened to some proportion of the treatment subjects, who ended up with disabled sleep settings at T3. However, 2 months may be a reasonable period for measuring persistence in sleep settings, especially for subjects who changed their settings early on in that period. These subjects work full-time and most use their campus computers every day. If they have their sleep delay set for 30 min (the default) or less, they would return to a sleeping computer several times per day. This provides many repeated experiences of computer sleep over time, and it seems plausible that anyone who would be annoyed enough to disable sleep after 3 months would already be annoyed enough to do so after a few weeks. Later in-depth analyses of the timing of changes and the number of subjects who changed their minds about enabling sleep will hopefully shed more light on this, as will analyses of the reasons given for not using sleep settings, and the qualitative comments subjects made about problems with engaging sleep.

Another limitation is that the study focused on a specific population: staff members at a university. However, compared to many other organizations, a university provides a wide and diverse range of subjects, working in varied fields and with varied occupations and tasks. They are more highly educated than the average worker, but perhaps no more so than the average worker whose job involves regular use of a desktop computer. Still, the results cannot be assumed to apply to employees of small businesses or to home users of desktops. Additional field tests would be needed to assess the utility of the PMUI app in these other settings.

Overall, these results are strong, and bode well for future use of feedback interventions for saving energy on office computers and other plug load devices by encouraging more pro-environmental behavior among individual users.

In summary, these results are promising, and offer strong support for the idea that giving users engaging feedback and actionable information can encourage meaningful pro-environmental behavior change. The current results are specific to office desktop computers, but could reasonably be applied to other home or office devices for which power management settings and the energy impacts of user behavior may be misunderstood.

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