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How to Foster the Adoption of Electricity Smart Meters? A Longitudinal Field Study of Residential Consumers

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Abstract: The objective of this research was to explore correlates and predictors that play a role in the process of adopting and withdrawing from using a smart metering information platform (SMP). The SMP supports energy monitoring behaviors of the electricity consumers. The literature review shows, however, that not every customer is ready to the same extent to adopt novel solutions. Adoption requires going through stages of readiness to monitor energy consumption in a household. In a longitudinal field experiment on Polish residential consumers, we aimed to see whether messages congruent with the stage of readiness in which participants declared to be at a given moment will be more effective in prompting participants to progress to the next stage than a general message or a passive control condition. We also tested the effect of attitude and knowledge about energy monitoring on phase changes. Our study reveals that what affects the phase change is the participation in the study. The longer the participants were engaged in the usage of SMP, the more willing they were to monitor their energy consumption in the future. This result sheds light on the future educational and marketing efforts of the authorities and energy suppliers.

Keywords: energy monitoring; electricity smart meters; smart metering information platforms; knowledge; longitudinal study; consumers

1. Introduction

Recently, many countries, for environmental and political reasons, have been striving to increase the energy efficiency of production, distribution, and consumption of energy. The goal of increasing energy efficiency is closely correlated with the new approach to the power system, namely the concept of smart grids (SG). Intelligent networks use modern communication technologies to exchange information between market agents (producers, market operators, and end users) to improve production efficiency and energy consumption [1–4]. One of the milestone steps in the transformation of the traditional power system to SG is the extensive implementation of the smart meters (SM) among electricity end users [5–7]. A smart meter is an electronic device that measures energy use and sends this information automatically over wireless networks to the energy supplier. The consumer can benefit from SM in multiple ways—firstly, by receiving a much more accurate billing; secondly, by gaining an opportunity to control one's energy consumption in real time. The information collected by SM can provide consumers with a feedback on current energy consumption and energy efficiency via an SM information system (platform, SMP) that is a website or mobile application connected with SM [4,8–10].

Global roll-outs of SM are usually initiated by pilot programs and local deployment of SM in a given region or city [11–15]. A good example of such practices is Wroclaw—a capital city of Lower Silesia in Poland, with nearly 630,000 inhabitants. Since 2015 Tauron Dystrybucja S.A., the local electricity distribution system operator (DSO) has been running a project AMIPlus Wrocław, which aimed at installing a smart meter at each household and enabling access to the SM platform (both an Internet website and a mobile app called e-licznik).

As SM is still a novelty on the Polish energy consumer market, and most of the electricity consumers are not fully aware of the potential of the installed devices [3,4], we have taken this opportunity to better understand the process of adopting novel electricity solutions. Our longitudinal field study was performed to explore individual variables that foster or hinder progression in the stages of readiness to adopt using a smart meter platform: e-licznik. The originality of this contribution relies on using the stage model approach, so far not explored thoroughly in the energy related studies.

The remainder of the paper is as follows. In Section 2, we provide the literature review of variables having an impact on SM and SMP adoption and energy monitoring. We also discuss the theoretical background of the study. Next, in Section 3, we present the methodology of the survey and its design. In Section 4, the obtained results are presented and discussed. Finally, in Section 5, the outcomes of the survey are concluded and some practical recommendations are provided.

2. Literature Review

2.1. Barriers in Using Smart Meter Platforms

The worldwide roll-outs of SM and the access to the information about the real-time energy consumption create some new opportunities for consumers and suppliers [12,16,17]. The literature provides a number of findings from the recent studies in which: (i) willingness to monitor energy in general, and by means of SMP is investigated [4,8,10,18–20], (ii) factors influencing the acceptance of SM and SMP by end-users are studied [3,6,15,21–25].

There is a great number of barriers to SM acceptance that limit users' willingness to use the enabling technologies, such as smart metering information systems (platforms, SMP) [26]. The barriers include among others distrust in the industry, lack of familiarity, a sense of procedural fairness, and concerns related to privacy and cost [7,23,25]. To focus on benefits of using SM, customers must be willing to accept this technology. Various aspects of community and social SM acceptance have been already explored [3,6,7,23–25,27–29]. As in the case of any other energy technology, the lack of acceptance may lead to slowing or a halting of the development [7,30]. Evidence from SM roll-outs run in various countries all over the world have shown that the widespread implementation of SM is unlikely to be successful unless it adequately addresses the perspectives and needs of the consumers [5,7,11,16,17,31].

Table 1 summarizes the most common incentives and barriers to SM and SMP adoption.

2.2. Monitoring of Energy Consumption

Many studies emphasize that the introduction of smart grids and a broader implementation of SM may open new perspectives for consumers in terms of their awareness and control of energy consumption [5,31,32]. The question is, however, if they are interested and ready to control energy consumption and, if yes, what motivates them most: savings, environmental attitudes, social influence, or maybe something else.

The impact of information and feedback about energy consumption on consumers' habits and behaviors have been already studied [17,33,34]. Especially computerized feedback, by means of SM devices, mobile apps, and smart metering platforms have been widely explored [8,9,18,35]. These studies reveal that computerized feedback may lead to some reduction of energy consumption by leading to habitual changes and/or prompting investments in smart and energy efficient home appliances and smart devices (e.g., smart plugs). At the same time, the user-friendliness and ease of access to the information is emphasized [18,36]. These are critical conditions that the computerized feedback must fulfill to engage consumers, especially as the general level of consumers' interest and knowledge is low [3,4,15,36].

Table 1. Incentives and barriers of SM and SMP adoption.

Factor	Description	References
Privacy concerns	These concerns originate from consumers' beliefs that using SM may lead to a loss of privacy by providing detailed information about household behaviors. Data collected by SM may reveal the activities of people inside of their home (i.e., their habits, usage, and type of home appliances they possess, etc.) In case of improper cyber security, SM data can be misused by authorized and unauthorized parties.	[7,25,37,38]
Procedural fairness	It refers to access to and control in the decision-making process. It indicates whether one has control over a certain process or procedure—in this case, SM data transmission and usage.	[7,39]
Trust	Both previous factors connect with the issue of trust in energy suppliers (whether they will secure the personal information and will not share it with third parties). Trust is especially vital in situations where familiarity with a technology is low, as it influences perceptions of risks and benefits.	[7,25]
Financial aspects	Some consumers are afraid that, due to SM installation, their cost of energy will increase (more adequate readings). On the other hand, some of them may expect immediate savings from SM, which is rather unrealistic.	[7,21,40,41]
Familiarity & knowledge	Familiarity of SM technology is still low. Consumers mistake SM with some other smart home devices. To some extent, knowledge and exposure to SM may be associated with increased concerns about negative attributes of these technologies. However, at the same time, it may increase interest and willingness to monitor energy consumption.	[8,21,22,42]
Environmental concern	The impact of environmental beliefs and concerns on SM acceptance is ambiguous. Generally, people who are aware of climate change are supposed to be more willing to accept SM as a useful and energy efficient technology.	[7]
Acceptance & engagement	There is some empirical evidence indicating an impact of SM acceptance on SM related behaviors, i.e., energy saving and monitoring.	[8,10]

The first step in monitoring energy consumption is its measurement [8], based on the traditional electricity bills and/or SMP. The second step includes observations of the measurements and its comparative analysis [4,8]. Energy monitoring behavior may increase the general awareness of one's energy usage, or the energy consumption of certain home appliances [43]. However, the possibility of monitoring energy by means of SMP may still not be enough to create a habitual behavior. Consumers may need some additional incentives, such as customized feedback [43], or some combination with demand side management and demand response tools, such as dynamic electricity tariffs [26].

2.3. Phase Changes of Behaviors

The acceptance and use of SM platforms is a phase process, as in the case of other eco-innovations, e.g., the use of ecological forms of transportation [44] or green energy [45]. Our study has been motivated and inspired by the stage model of self-regulated behavioral change (SSCB), proposed by Bamberg [46].

This model draws from a classic action phases model proposed by Heckhausen and Gollwitzer [47,48]. Accordingly, behavioral change, such as adoption of novel solutions, is a goal-directed and deliberate process in which individuals take gradual steps to the goal. In the first stage (pre-decisional), an individual has to choose a given behavior from competing options. In the second stage (pre-actional), an individual forms an intention to perform a behavior. He or she weighs the pros and cons of engaging in a certain behavior and specifies how the behavior will be performed. In the third stage (actional), an individual implements an intention. The fourth stage (post-actional) focuses on the evaluation of an action.

The model of innovation diffusion (DOI) proposed by Rogers [49] is another example of a phase model. The SSCB model refers to the diffusion stages of DOI, but it focuses more on individual determinants such social norms, attitudes, and perceived behavioral control as determinants of people's engagement in the following phases.

To illustrate four phases of behavior change in the context of using SMP, the example would be as follows: (1) Predecisional phase—when consumers choose to use SMP or to engage in an energy monitoring behavior; (2) Preactional phase—when consumers specify their intention to use SMP or to perform an energy monitoring behavior, (3) Actional phase—when consumers regularly use SMP or monitor energy consumption, and (4) Postactional phase—when consumers evaluate the satisfaction of using SMP or monitoring energy consumption [44,46]. As different phases of behavior change involve different psychological processes, past research has shown that consumers at different stages of the process need different methods to encourage them to move on to the next phase [44,46].

Literature shows that consumers' ecological behavior is strongly associated not only with professed values and opinions, but also with norms, barriers, and difficulties with accepting new behaviors, social norms, and legal regulations [31,50–53]. The SSCB model has been successfully used thus far to explore behaviors related to green public transportation [46]. In the context of energy market, phase models have not been widely used. Recently, one study applied the SSCB model and analyzed whether German SM platforms are properly designed so that, through their use, energy consumers can move from one decision-making phase to another [35]. The conclusions of this work show that the SSCB model is suitable for assessing consumer behavior related to energy saving.

2.4. Specific Research Goals

Although the acceptance of the SM and SMP acceptance and diffusion have already been studied, we still see a need to explore which factors are responsible for the transition from one behavioral stage to another, in the process of creating awareness, acceptance, and regular usage of SMP or energy monitoring behavior.

Hence, we aimed to see whether messages congruent with stages in which participants declared to be at a given moment will be more effective in prompting participants to progress to the next stage than a general message or a passive control condition. We also tested the effect of attitude and knowledge about energy monitoring on phase changes.

Based on the current knowledge on factors enhancing SM and SMP adoption, within our survey, we wanted to check what may enhance consumers' willingness to regularly monitor energy consumption by means of SMP. Hence, we checked the impact of the following issues such as: knowledge about the energy market, participation and engagement in the longitudinal study, environmental attitudes and behaviors, positive attitudes towards energy monitoring, and, finally, computer skills. In particular, we tested: (i) an impact of messages (interventions), (ii) an effect of an attitude towards energy monitoring, and (iii) an effect of knowledge about energy market on phase change of regular energy monitoring by means of SMP.

3. Methodology of the Study

3.1. Study Design

To address our research questions, we conducted a longitudinal experiment with six points of measurement: pretest (T0), posttests after interventions on Monday (T1), Wednesday (T2), Friday (T3), and Sunday (T4), and the follow-up (T5) and two control groups: one active (C1), one passive (C2), and an experimental group (Ex).

3.2. Procedure

The study was established on an Internet platform designed for the purpose of the project. The data were collected between July 2018 and July 2019. Participants were recruited by research assistants from the general population as well as from the initial, preliminary study conducted in March 2018 on a sample of adult inhabitants of Wroclaw (see [4], for more details). The inclusion criteria were living in the agglomeration of Wrocław—a large city in the southwest of Poland, having smart meters installed in the household, being over 18 years old, and being responsible for paying electricity bills.

In the first stage of the study, participants registered on the platform and completed the base measurement (T0) that is a questionnaire containing socio-demographic variables, knowledge about the energy market, various items measuring attitudes, and behaviors related to energy monitoring and environmental issues, and the declaration in which phase stage towards a smart metering platform—e-licznik—participants were (see Appendix A for a detailed description). E-licznik is a free mobile application and Internet widget developed by the energy supplier Tauron Dystrybucja S.A and broadly available to customers. The application provides data based on consumption metering from a smart electricity meter.

At least seven days after completion of T0, participants took part in the main study (T1–T4). On Monday, they received a message (text message or email) with a request to log on the platform. Then, they were asked to get acquainted with the instruction regarding the e-licznik platform. Subsequently, participants were asked to report on the platform the readings from the application regarding their energy consumption from the previous day and to complete short questionnaires measuring the behavioral stage that the respondents were in, and attitudes towards monitoring, environmental issues, and behaviors. The same procedure was repeated on Wednesday (T2), Friday (T3) and Sunday (T4). On the last day, the participants also completed a post-test questionnaire, identical to the T0 one. The study framework with a timeline is presented in Figure 1.

At T1, participants were randomly assigned either to a passive control group (C1), to an active control group (C2), or to an experimental group (Ex). In the passive control group (C1), participants completed the questionnaires at T1, T2, T3, and T4 without any help or reminders from the research assistants. In the active control group (C2), they received instructions on how to log to an e-licznik platform and were asked to do it and report their energy consumption. In the experimental group, participants additionally received text messages adjusted to their behavioral stage (F1–F4) reported in the last questionnaire. In particular, the following messages were sent to participants at T1, T2, T3, and T4:

- Group C2: ”Log into the https://inteligentnylicznik.pl and fill in information about your energy consumption.”
- Group Ex, Stage F1: ”Log into the https://inteligentnylicznik.pl. You probably think that monitoring energy consumption is time consuming, but it only takes 10 min.”
- Group Ex, Stage F2: ”Log into the https://inteligentnylicznik.pl. Load the attached instruction. It will help you start monitoring your energy consumption.”
- Group Ex, Stage F3: ”Log into the https://inteligentnylicznik.pl. Plan your day to find 10 min to monitor energy consumption. For example, after checking your email in the evening, log in to the e-licznik platform.”

- Group Ex, Stage F4: "Log into the https://inteligentnylicznik.pl. You can organize your time so that you can continue to regularly monitor energy consumption for at least a month."

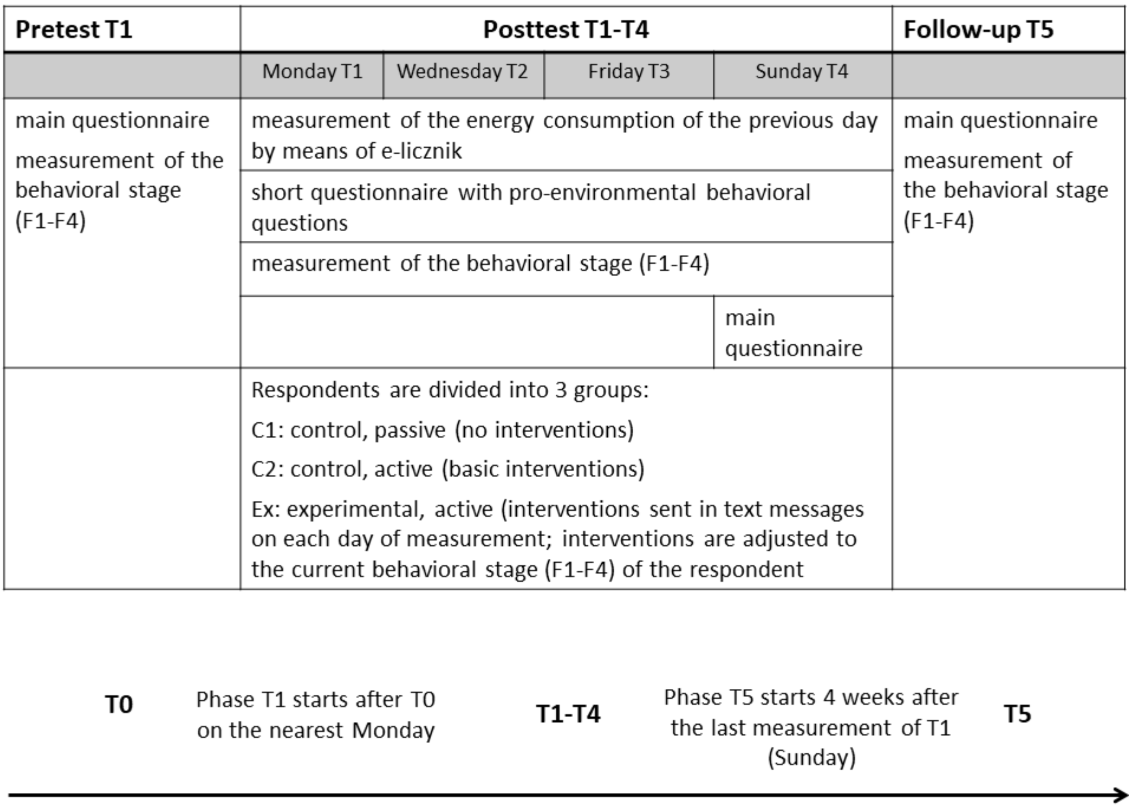

Figure 1. Survey framework with six measurement points: T0–T5.

Each behavioral stage (F1, F2, F3, F4) was measured with the following questions:

- pre-decisional stage F1: "I never use e-licznik web platform/application";
- pre-actional stage F2: "Currently, I sometimes use e-licznik web platform/application";
- actional stage F3: "My goal is to organize my week so that I can monitor my energy consumption regularly";
- post-actional stage F4: "I often monitor the energy consumption of my household using e-licznik platform/application".

Participants responded to these questions on a Likert scale from strongly disagree (1) to strongly agree (5).

In all groups apart from the control group C1, over the course of the study, participants were also receiving text messages and emails reminding them about the next measurement in the study. At least four weeks after the T4, in the last stage of the study (T5), we measured again the behavioral stage at which participants were at the moment. We also measured their satisfaction with using the e-licznik platform. Those participants who completed the whole survey were gifted with a smart plug or another small smart device worth ca. 50 PLN (c.a. 11 Euro).

4. Results of the Study

4.1. Statistical Analyses

The results section is organized as follows. First, we present descriptive statistics for the demographic and control variables. Second, we describe details on measures and materials used in a study, the measure of energy monitoring, the measures of an attitude towards environmental issues, and knowledge on the energy market.

Analyses were performed using statistical language R v. 3.4.3 (RCore Team, 2019) for logistic regression models and IBM SPSS Statistics v. 25 for the rest of the analyses performed. To construct measures of attitudes towards energy monitoring and pro-environmental issues, we reduced the number of the items into meaningful components by means of the Principle Components Analysis (PCA).

Then, we directly addressed stated hypotheses and explored whether the time of measurement (T0, T4, T5) and the experimental manipulation predicted phase changes (F1–F4). Next, we tested correlations between monitoring of energy consumption and attitude towards pro-environmental issues and a the level of education, and knowledge. All analyses were conducted in the frequentist approach with α-level set to 0.05.

4.2. Participants

In total, 289 respondents have been recruited to stage T0 and 142 (49%) completed all measurements (T0–T5). It is noteworthy that such an attrition rate is quite common in longitudinal studies, especially with strict inclusion criteria. The final sample's mean age was M = 35.5 years old (SD = 0.89). The sample was equally represented by men (50.7%) and women (49.3%) and over represented by participants with higher education (76.8%). Likely, the reason of such a distribution of age and education is that inhabitants, having access to e-licznik, need to have better computer skills and are more familiar with technology.

Participants were asked about their age, gender, income, the type of household, and the number of inhabitants in the household. Figure 2 presents demographics of the respondents who have completed the survey (all T0–T5 points of measurement). In terms of material situation, 10.5% of the respondents stated that it is lower than average, 57% that it is similar to average, and 26.8% that it is higher or much higher (1.4%) than average. Most of the respondents live either in blocks of flats or modern apartments, in families with 2 (35.9%), 3 (28.2%), or more (21.1%) members. Finally, the average monthly electricity bills did not exceed 50 PLN (11 Euro) in case of 5.6% of participants, were between 51–100 (12–22 Euro) PLN for 39.4%, between 101–200 PLN (23–45 Euro) for 41.5%, and are higher than 201 PLN (45 Euro) for 11.3%.

The majority of the respondents confirmed using a computer for at least an hour every day (95%, M = 4.68, SD = 0.59), using social media and applications for communication with friends and family (e.g., Facebook, Twitter, WhatsApp, Hangout, and others) (86%, M = 4.39, SD = 1.05), has at least one email address (97%, M = 4.67, SD = 0.62), can download a new application or program from the Internet to their computer or mobile phone (96%, M = 4.68, SD = 0.56).

Participants also indicated their attitudes towards SM and SMP. They expressed their willingness to receive information and reports on their current energy consumption in general and of individual electrical appliances in their household directly via the website or an application in their mobile phones. The lack of trust in the energy supplier appeared not to be an issue for participants. More than 75% of them believed that the energy consumption data collected by SM is safely stored by the energy supplier and will not be sold to third parties without consumer′ permission. Only 11% stated that the energy supplier had an excessive knowledge of their habits thanks to SM, and 13% were afraid that the data provided by SM was not sufficiently secured and that unauthorized persons may have access to them. Thanks to the installation of SM and access to the data on current energy consumption via SMP more than 60% of participants expected to have more knowledge about the energy consumption of individual electrical devices in their households, and 25% believed to be able to change their habits and use more electricity when it is cheaper.

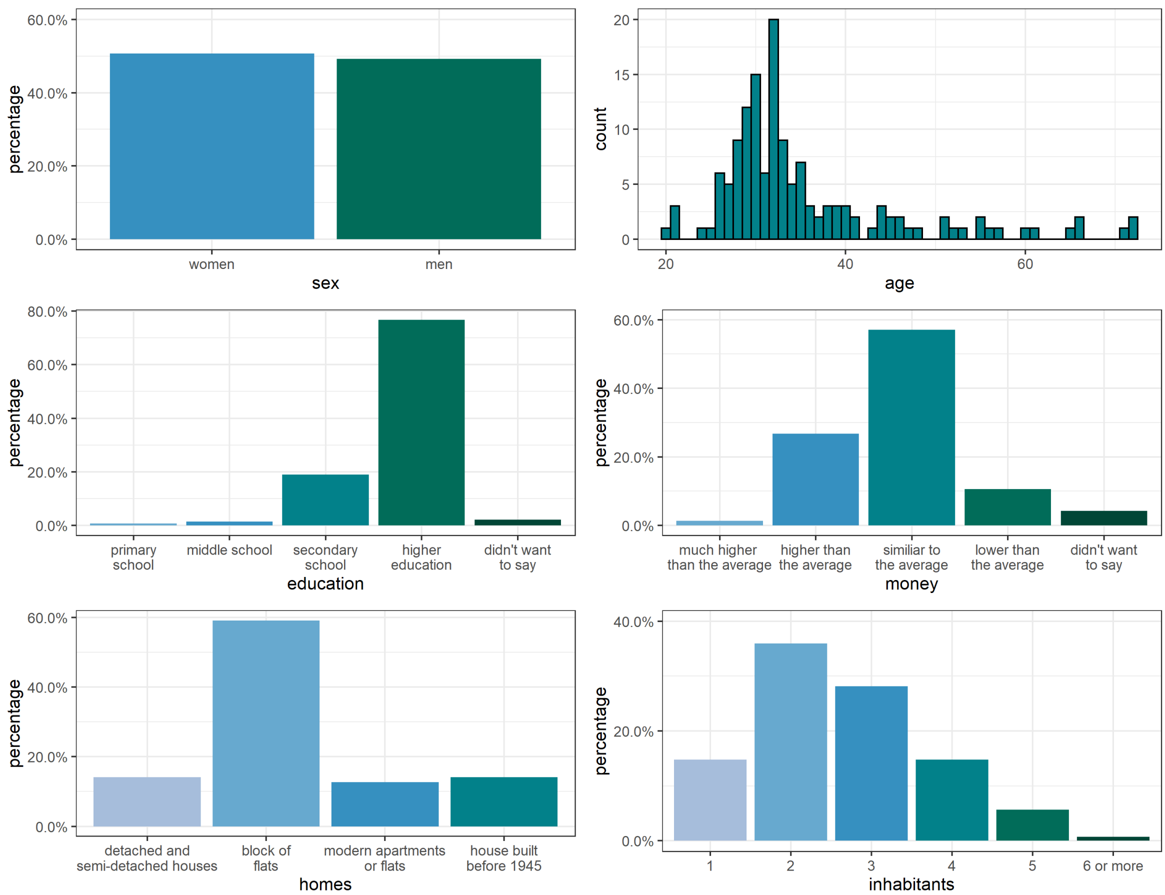

Figure 2. Frequencies of the demographics for participants who completed all measurement points of the study (n = 142).

Finally, we asked the participants what annual savings they expect thanks to the installation of SM in their household. Interestingly, 21% of them had no financial expectations. The rest of the participants expected a certain level of savings starting from 1–5% per year (21% of respondents), 6–10% (30%), 11–15% (12%), 16–20% (5%), 21–25% (5%), and more than 25% (6%).

4.3. Predicting the Phase Change

We applied multinomial logistic regression model from NNet package [54] to predict phase change (F1–F4) depending in which group a given person belonged to (C1, C2, or Ex), the time of measurement (T0, T4, T5), and the interaction of the group and the time of measurement. As a reference point, we took a null model with an intercept only and without any predictors entered. We performed null, group, time of measurement, and the interaction of group × time of measurement models, and we compared them against each other using AIC and ANOVA tests (Table 2).

Table 2. Model comparisons.

Model	AIC	Psuedo-R^2	df	LR	p-Value
Null	849.35	<0.01	-	-	-
Group	853.34	0.01	6	8.01	0.237
Time of measurement	838.16	0.03	6	23.20	<0.001
Group × Time of measurement	858.01	0.05	18	16.15	0.582

4.3.1. The Group Model

To test the effect of the manipulation (congruent vs. control messages) on phase changes, we included as predictors a passive control group (C1), an active control group (C2), and the experimental group (Ex) into the model. We performed the regression analysis, in which we compared these groups using the contrasts. Specifically, we compared C1 to Ex and C2 to Ex. Even though C1 and C2 had slightly different procedures, we also examined possible difference between joined control groups (C1 + C2) and the experimental group (Ex). The analysis yielded the following results. The omnibus group model was not significantly different from the null model, and the AIC value (853.54) was bigger than the value of null model (849.35). Based on these results, we inferred that experimental manipulation was not successful as assignments to the groups were not significant predictors of the phase change. Therefore, we do not report specific results for contrasts' analyses.

4.3.2. The Time of Measurement Model

To test the effect of the time of measurement, we entered T0, T4, and T5 measurements to the model (see 'time of measurement model' in Table 2). The reason for which we chose these three measurement points is that we were interested in possible long-term phase changes and not in day-to-day changes. Moreover, we wanted to keep the same number of points of measurement across most of the analyses performed. Once again, we set custom contrasts for the time of measurement model in which T0 was compared to T4, T0 to T5, and T4 to T5. The difference between the time of measurement model and the null model was statistically significant, and the AIC value for the time of measurement was lower (838.16) than that of the null model (849.35). It indicated that this model fits the collected data better than the null model.

The time of measurement model explained 3% of variance of the dependent variable (based on McFadden pseudo-R2). The outcomes of the Wald tests revealed that the difference between T0 and T4 and T0 and T5 for phase change from F1 to F2 were significant (see Table 3 for more details). More specifically, the change from T0 to T4 increased the odds of phase change from F1 to F2 by 1.37. In addition, the change from phase F1 to phase F2 was 1.48 odds higher on T5 when compared to T0. Similar results were obtained for change from phase F3 to phase F4. The significant predictors were contrasts between T0 and T4, and T0 and T5. Change from T0 to T4 increased the odds of phase change by 1.48, and change from T0 to T5 increased the odds by 1.86. The contrasts between the time of measurements did not predict the likelihood of changing from the phase F2 to the phase F3.

Table 3. Multinominal regression coefficients of the time of measurement model.

Odds	Effect	Estimate	SE	Wald	*p*-Value	Exp(β)
P(Y = F2)/P(Y = F1)	Intercept	0.60	0.17	3.45	<0.001	1.82
	T0–T4	0.31	0.13	2.37	0.018	1.37
	T0–T5	0.39	0.14	2.74	0.006	1.48
	T4–T5	0.08	0.15	0.54	0.588	1.08
P(Y = F3)/P(Y = F2)	Intercept	0.42	0.18	2.34	0.019	1.52
	T0–T4	0.04	0.13	0.32	0.750	1.04
	T0–T5	0.16	0.14	1.10	0.270	1.17
	T4–T5	0.12	0.16	.73	0.463	1.12
P(Y = F4)/P(Y = F3)	Intercept	0.13	0.19	0.69	0.489	1.14
	T0–T4	0.39	0.16	2.53	0.012	1.48
	T0–T5	0.62	0.16	3.86	<0.001	1.86
	T4–T5	0.23	0.16	1.46	0.145	1.25

4.3.3. The Interaction of the Group and the Time of Measurement

We compared the model with an interaction term (time of measurement × group) to the time of the measurement model. They were not significantly different. In conclusion, the best fitting model was the one with the time of measurement as the predictor of the phase change. It suggests that mere participation in the study independent of the group was the best predictor of changes from phase 1 (pre-decisional stage) to phase 2 (pre-actional stage) and from the phase 3 (actional stage) to phase 4 (post-actional stage), see Table 2.

4.4. The Effect of the Participation in the Study on Energy Monitoring and Attitude towards Environmental Issues

In the next step, we conducted three exploratory Principal Component Analyses (PCA), one for each point of measurement T0 (n = 274), T4 (n = 145), T5 (n = 142), for questions A1–A6 (pro-enviromental attitudes), B1–B5 (monitoring behaviors), and M1–M16 (attitudes towards monitoring) with the exclusion of items M1, M2, and M10 (see Table A1 in the Appendix A for a description of variables, their coding and scales used in the study). We excluded these items because they were referring to energy monitoring and environment protection at the same time, which caused ambiguity we wanted to avoid. Altogether, we included 24 items in conducted PCAs.

The results of Bartlett sphericity tests and KMO coefficients indicated that a reduction of dimensions may be useful with collected data (see Table 4 for details). We used eigenvalues above 1 as a criterion to select the number of components. In effect, for each measurement (T0, T4, and T5), the solution with two components best fitted the data. We based our selection of items for each component on item loading cut-off point, which was set to 0.3.

Table 4. Coefficients of Bartlett sphericity tests, KMO, eigenvalues, and percentage of explained variance for solutions with two components.

Measurement T	χ^2	df	p	KMO	Components	Eignevalue	%Variance
T0	2726.58	276	<0.001	0.86	1.EM	6.20	32.62
					2.EA	2.59	13.62
T4	1880.03	276	<0.001	0.86	1.EM	8.34	34.75
					2.EA	2.85	11.87
T5	1976.64	276	<0.001	0.88	1.EM	10.69	39.59
					2.EA	2.88	10.66

Note: df for Bartlett sphericity test are based upon the number of variables included in the analysis.

The first component was **energy monitoring (EM)**, which contained the following items: B1–B5, M4, M5, M6, M7, M8, M9, M11, M12, M13, M14, M15, and M16. This component explained respectively 32.62% (T0), 34.75% (T4), and 39.59% (T5) of variance. The exemplary items that best describe this component are: "I decided to use internet platforms/applications to monitor energy consumption in my household" (M11), "I check monthly energy consumption according to data from the electricity meter" (B2), "I believe that energy monitoring is good" (M9), "I feel bad when I don't control the energy consumption in my household" (M7).

In the second component, **attitude towards environmental issues (EA)**, we included items number A1, A2R, A3, A4, A5R, A6 (R—means negative loading). This component explained respectively 13.62% (T0), 11.87% (T4) and 10.66% (T5) of variance. The items that best describe this factor are: "In my opinion, reports about the ecological crisis are exaggerated" (A2R), "I am happy when the climate and environment protection plays an important role in politics" (A3), "In my opinion, every person has an impact on environmental protection through his own behavior" (A4), "Protecting the environment is particularly important to me (A1).

After exploring the results of PCA, we decided to remove item M3 from further analyses as it was causing problems with coherent components' interpretation. In T0, item M3 was loading the second component but did not suit it from the semantic point of view. In T4, component loading of M3 did not exceed 0.3, and, in T5, it was loading the first component. There was a small variance of item loadings between each point of measurement, hence we decided to apply the same two component solutions for each measurement.

Finally, we created two factors from 23 items and each factor was produced by calculating arithmetic mean scores, where high scores mean more favorable attitude towards environmental issues and more endorsement of energy monitoring. The reliability of these two components was examined using the Cronbach's alpha. Cronbach's alpha for each component at each time of measurement was at least on the level of 0.65. Internal reliability for monitoring of energy consumption was $\alpha = 0.90$ (T0), $\alpha = 0.92$ (T4), $\alpha = 0.93$ (T5) and for a pro-environmental attitude was $\alpha = 0.65$ (T0), $\alpha = 0.77$ (T4), $\alpha = 0.74$ (T5). These results indicate an acceptable consistency of the measurement items and construct reliability. Some more descriptive statistics and normality test for EM and EA at three points of measurement T0, T4, and T5 are presented in Appendix A in Table A2.

To explore the effect of the participation in the study on the energy monitoring and attitude towards environmental issues, we conducted a repeated measures ANOVAs with the group variable as a between group factor and time of measurement of energy monitoring as a dependent variable measured at T0, T4, and T5 (n = 142). The results of the analysis showed a statistically significant main effect of the time of measurement for energy monitoring, F(1.72, 242.09) = 14.74, $p < 0.001$, partial-η^2 = 10% see Table 5. The results of a post-hoc pairwise comparison with Sidak correction revealed that participants energy monitoring at T4 (M = 3.30, SD = 0.72) was significantly higher than in T0 (M = 3.16, SD = 0.71), $\triangle$ = 0.14, p = 0.009, and the energy monitoring at T5 (M = 3.39; SD = 0.75) was significantly higher than at T0 and T4, respectively $\triangle$ = 0.23, $p < 0.001$ and $\triangle$ = 0.09, p = 0.020. This outcome means that participants' energy Monitoring (EM) was increasing with each point of measurement. We also performed the same analysis with the attitude towards environmental issues (EA). However, we found no significant effects of participation in the study on participants' attitudes towards environmental issues (see Table 5 and Figure 3).

Table 5. Results of the repeated measures ANOVA for energy monitoring (EM) and attitude towards environmental issues (EA).

Variables	Greenhouse-Geiser ϵ	p-Value	F	df	p-Value	Partial-η^2
EM	0.86	<0.001	14.74	1.72, 242.09	<0.001	0.10
EA	0.88	<0.001	2.65	1.76, 249.98	0.080	0.02

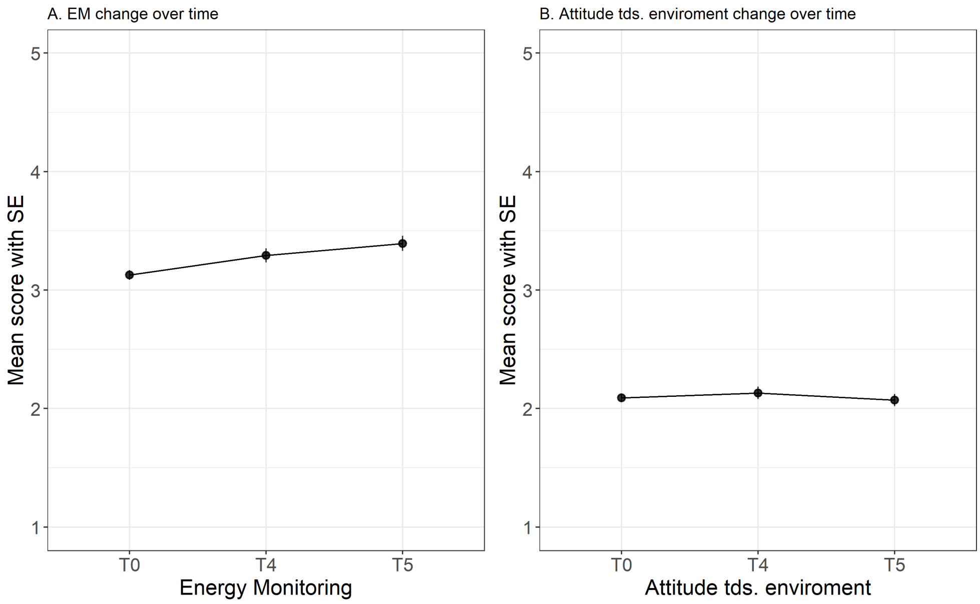

Figure 3. Mean scores with SE for repeated measurements of energy monitoring (EM) and attitude towards environmental issues (EA).

4.5. Knowledge and Education as Correlates of Energy Monitoring and Attitude towards Environmental Issues

In the last analysis, we explored relationships between energy monitoring (EM), attitude towards environmental issues (EA), and knowledge measured at T0, T4, and T5, as well as education level. To measure knowledge, we asked four questions (K1–K4) testing participant's familiarity with the following terms and issues: (K1) the concept of smart grid; (K2) the concept of smart metering; (K3) the opportunity to change the energy supplier; and (K4) the most energy-consuming home appliance. Each question had only one correct answer, so the sum of the collect answers might have ranged from 0 to 4. In the T5 point of measurement, the majority of respondents knew which of the home appliances is the most energy-intensive (91.5% correct answers). In addition, most of the respondents (83%) were aware that SM enables remote reading of energy consumption by the energy supplier. Less respondents were aware of who may change the electricity supplier or what smart grid means (62.7% and 30% of the correct answers, respectively).

We used the Spearman correlation coefficient as it is less susceptible to extreme cases, and allows for assessing the relationship for ordinal data (see Table 6). The results of the conducted analyses showed that energy monitoring (EM) at T0 was moderately negatively correlated with education level and positively correlated with knowledge at T0 and T4. Energy monitoring in T4 and T5 was positively correlated with knowledge in T0, T4, and T5. Surprisingly, we found no correlations with attitude towards environmental issues and knowledge or education.

Table 6. Correlation analysis coefficients for relationships between energy monitoring (EM), attitude towards environmental issues (EA), Education, and Knowledge in T0, T4, T5, and weekly attitude.

Variables	Coeff.	Education	Knowledge T0	Knowledge T4	Knowledge T5
EM in T0	rho Spearmana	−0.25	0.25	0.35	0.14
	p-value	<0.001	<0.001	<0.001	0.024
EM in T4	rho Spearmana	−0.16	0.34	0.31	0.26
	p-value	0.053	<0.001	<0.001	0.001
EM in T5	rho Spearmana	−0.15	0.31	0.35	0.28
	p-value	0.084	<0.001	<0.001	<0.001
EA in T0	rho Spearmana	−0.02	0.00	−0.07	−0.08
	p-value	0.716	0.940	0.411	0.212
EA in T4	rho Spearmana	0.03	−0.12	0.00	0.01
	p-value	0.743	0.156	0.959	0.925
EA in T5	rho Spearmana	0.06	−0.02	0.02	−0.05
	p-value	0.505	0.837	0.841	0.593

5. Discussion and Conclusions

Although the acceptance of smart meters has been studied in the literature, the consumers' readiness to use SM platform still warrants exploration.

Expecting that acceptance of SMP and involvement in energy monitoring is a phase process, we aimed to test whether messages congruent with behavioral stages in which participants declared to be are more effective in prompting participants to progress to the next stage than general messages or passive control conditions. Based on the current literature review, we have expected to observe that phase change as well as participants' attitudes to use SMP and monitor energy regularly will be affected by their environmental attitudes, energy monitoring behaviors, and knowledge on the energy market [18,36].

5.1. Summary of the Results

In summary, our results showed that the most important factor affecting phase change was the participation in the study. The longer the participants remained in the study, the higher was the chance that they progressed from the pre-decisional to pre-actional stage and from the actional to the post-actional stage. Moreover, the time of measurement affected energy monitoring.

We found no differences between the control groups and the experimental group. One explanation could be purely statistical, the power of the performed test was too low. That is, the effects we tested were too small to detect with the sample size we had. Another explanation, which seems more plausible, is that participation in such a demanding study even in the control group in which participants completed a number of questionnaires was an experience strong enough to affect changes. Numerous studies in psychology show that an investment of effort in some issues makes people value the given cause more [55]. In other words, effort invested could have given additional value to energy monitoring even in the control group. This interpretation could be additionally supported by the results showing that participants were more eager to engage in energy monitoring as the study progressed.

Participation in the study also affected attitudes towards environmental issues, but to a lesser extent. Thus, the participation in the study was more effective for a variable closer related to behaviors referring to the control of energy consumption.

Knowledge about energy market was correlated with participants' energy monitoring. This is quite an intuitive result as probably specific knowledge provided know-how for participants in the study. More surprising are the results that education was negatively related to energy monitoring. We may speculate that participants with higher education have more absorbing professional lives and spend more time in front of the computer. Therefore, they are less willing to control energy, using technology in their spare time.

For most of the participants, monitoring energy by means of SMP has similar pros and cons. The higher control over one's energy consumption and better energy management belonged to the biggest advantages of using SMP, whereas time consumption and low effectiveness in terms of financial savings were mentioned as the biggest disadvantages and barriers of regular SMP usage. For such consumers, the energy supplier should offer automatic transmission of e.g., daily reports on energy consumption or information on exceeding a given level of energy consumption (e.g., daily limit set by the energy consumer according to his own needs). Such services could increase the level of interest and engagement in SMP usage.

5.2. Limitations of the Study and Future Work

The main limitation of our study was a restricted sample size, relatively small, but also composed of volunteers. It is also possible that the study itself was overly time-consuming and difficult for our participants. This would explain why part of the participants resigned from the participation in the study.

Moreover, we focused on participants' declarations and not on real behaviors as indicators of energy consumption. We asked participants to report energy consumption, but we observed a large proportion of missing responses for this item.

Future work should focus on larger, more diverse samples and provide easier to use applications for participants. Ideally, some data could be collected directly from SMP and compared to survey data in collaboration with an energy provider.

Despite a few mentioned limitations, the originality of this contribution relies on using the stage model approach, so far not explored thoroughly in the energy related studies (see [35]). Moreover, we tested our hypotheses in a longitudinal field experiment, which allowed us to observe changes in the process.

5.3. Practical Recommendations

Based on our results, we may conclude that, while electricity smart meters are useful for the energy providers, they might not offer enough real benefits for the residential consumers. Even if SM are combined with smart metering information platforms, such as Internet widgets and mobile applications, their role in prompting energy monitoring is very limited. At the same time, we observed that mere participation in the study, independent on the group and getting acquainted with the e-licznik application, enhances the phase change and the readiness to monitor energy consumption. These findings suggest that using SMP without any prompts and instructions is unlikely to occur as there are no reasonable incentives that could convince respondents to monitor energy. Financial, social, or environmental benefits are probably too low and the effort too high to lead to a permanent behavioral change.

In conclusion, we believe that some good practices are needed. It is necessary to make monitoring of electricity consumption easy, intuitive and non time-consuming. Designers and suppliers of smart metering platforms should provide user friendly solutions. Smart meters should also be proposed with some additional enabling technologies, such as e.g., smart plugs or smart devices, as well some IT solutions enabling remote adjustment of energy consumption of home appliances or air conditioning to the current electricity prices. Moreover, to raise awareness, some educational campaigns would be helpful. Our results suggest, however, that the role of theoretical knowledge in the energy market should not be overestimated when it comes to energy monitoring and phase changes. Knowledge appears to affect attitudes on monitoring more than behaviors. Rather reasonable price polices, such as additional financial incentives for consumers to control energy consumption and to shift from pick to off-pick hours, would be more beneficial.

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Writing and editing the paper: A.K.-P., K.B., and J.S. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

SG	Smart grids
SM	Electricity smart meters
SMP	Smart metering platform (SM information systems)
DOI	Diffusion of innovation model
SSCB	Stage model of self-regulated behavioral change

Appendix A

Table A1. Definitions of the variables, coding, and description.

Variable	Code	Description
Demographics	**D1–D7**	
Gender	D1	2 categories (nominal)
Age	D2	integer (ordinal)
Education	D3	5 categories (nominal)
Housing	D4	4 categories (nominal)
Material situation	D5	5 categories (ordinal)
Range of electricity bill (in PLN per month)	D6	4 categories (ordinal)
Inhabitants in the household	D7	6 categories (ordinal)
Pro-environmental attitudes	**A1–A6**	
Environmental protection is especially important to me	A1	scale from 1 to 5
In my opinion, reports of the ecological crisis are exaggerated	A2	
I am glad that climate and environmental protection play an important role in politics	A3	
In my opinion, every person has an impact on environmental protection through their own behavior	A4	
As an individual, I do not have much influence on environmental protection	A5	
I would be willing to pay higher taxes in order to protect the natural environment better and more effectively	A6	
Energy monitoring behaviors	**B1–B6**	
I check monthly energy consumption according to data from electricity bills	B1	scale from 1 to 5
I check the monthly energy consumption according to the data from the electricity meter	B2	
I use a platform or web application to monitor energy consumption	B3	
I use an intelligent energy management system in my household (the so-called home area network)	B4	
I have an electronic device installed in my household and can see my current electricity consumption	B5	
Do you use other methods of monitoring energy consumption? (open question)	B6	
Attitudes towards monitoring	**M1–M16**	
To care for the environment and increase energy efficiency, everyone should monitor the energy consumption of their household	M1	scale from 1 to 5
Everyone can contribute to taking care of the environment by monitoring the energy consumed in the household using e.g., access to data from an energy meter	M2	
To reduce energy consumption, I turn off the lights, avoid leaving appliances on stand-by, only turn on the washing machine and dishwasher when they are full	M3	

Table A1. *Cont.*

Variable	Code	Description
Attitudes towards monitoring	**M1–M16**	
Regardless of what others may think, my own rules oblige me to monitor household energy use	M4	scale from 1 to 5
I know that some of my neighbors and friends reduce their energy consumption by regularly monitoring their energy consumption by accessing data from an energy meter. It motivates me to try to do the same	M5	
I feel good when I know I am in control of my energy consumption by regularly accessing consumption data from my energy meter, e.g., via a platform or web application	M6	
I feel bad not having control of the energy consumption in my household	M7	
I can see the possibility of regular energy monitoring, e.g., by accessing data from an intelligent energy meter via a platform/web application	M8	
I believe that monitoring energy consumption is good	M9	
I intend to contribute to the protection of the environment by regularly monitoring energy consumption, e.g., using a platform/web application	M10	
I have decided to use a web platform/application to monitor my household energy consumption	M11	
I have decided to use a web platform/application to monitor my household energy consumption	M12	
I foresaw possible problems that may arise and prevent me from carrying out regular monitoring of energy consumption via the platform/web application	M13	
I have developed a way to avoid problems and obstacles in the implementation of regular monitoring of energy consumption and how to flexibly adapt the monitoring to a given situation	M14	
For the next 7 days, I am going to monitor energy consumption via the platform/web application	M15	
I intend to continue using the web platform/app to monitor my energy consumption even when it is inconvenient	M16	
Computer skills	**S1–S4**	
I use my computer for at least an hour every day	S1	scale from 1 to 5
I use social media and applications to communicate with friends and family (e.g., Facebook, Twitter, Whatsapp, Hangout, and others)	S2	
I have at least one email address	S3	
I can download a new application or program from the Internet to my computer or mobile phone	S4	
Knowledge about energy market	**K1–K4**	
How do we call an energy system that integrates the activities of all participants in the generation, transmission, distribution and use processes (1) smart metering; (2) smart grids; (3) advanced metering infrastructure; (4) I do not know	K1	selection test (one answer is correct)
For energy consumers who have an intelligent energy meter installed, it is possible to: (1) Individual appointments of a collector to read energy consumption; (2) Remote reading of energy consumption by the seller and monitoring of energy consumption through the web portal; (3) Settlements based on forecasts of electricity consumption, made by the electricity supplier on the basis of (4) I do not know	K2	
What is true: (1) In Poland, every energy consumer has the right to change the electricity supplier; (2) In Poland, only industrial and institutional customers have the right to change the electricity supplier; (3) In Poland, changing the electricity supplier requires the consent of the President of the Energy Regulatory Office; (4) I do not know	K3	
The most energy-intensive household electronics and household appliances include: (1) computer; (2) refrigerator; (3) home lighting; (4) I do not know	K4	

Table A1. *Cont.*

Variable	Code	Description
Preferences towards SM	**P1–P3**	
Access to information from e-licznik would be most useful to me for	P1	selection test (option to choose one answer)
My confidence in the energy supplier regarding data security is best described by the sentence	P2	
Thanks to the installation of an intelligent energy meter and access to data on my current energy consumption, I expect	P3	
Behavioral stages	**F1–F4**	
I never use e-licznik web platform /application	F1	scale from 1 to 5
Currently, I sometimes use e-licznik web platform /application	F2	
My goal is to organize my week so that I can monitor my energy consumption regularly	F3	
I often monitor the energy consumption of my household using e-licznik platform/application	F4	

Note: Likert scale from 1 (fully disagree) to 5 (fully agree).

Table A2. Descriptive Statistics with the Shapriro–Wilk normality test for EM and EA at T0, T4, and T5.

Variables	M	Me	SD	Sk.	Kurt.	Min	Max	W	*p*
EA T1	2.05	2.00	0.58	0.71	1.05	1.00	4.33	0.96	<0.001
EA T4	2.13	2.17	0.63	0.19	−0.41	1.00	3.83	0.98	0.016
EA T5	2.06	2.00	0.61	0.29	−0.56	1.00	3.67	0.97	0.006
EM T1	3.16	3.18	0.71	−0.06	−0.09	1.24	4.88	0.99	0.895
EM T4	3.30	3.41	0.72	−0.21	0.16	1.29	5.00	0.99	0.364
EM T5	3.39	3.41	0.75	−0.12	0.12	1.59	5.00	0.98	0.033

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