How Gain- and Loss-Framed Incentives Affect Water Usage Behavior

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Abstract

This study examined the impact of gain- and loss-framed monetary incentives on a peak shift in water usage behavior. Based on the idea that framing incentives as losses (e.g., "You will lose $13 if you fail to shift your water consumption from peak to off-peak hours") may enhance the perceived value of the monetary component, triggering a greater peak shift compared to gains (e.g., "You will receive $13 if you shift your water consumption from peak to off-peak hours"). This study found that both gain- and loss-framed incentives significantly triggered a peak shift; however, the loss frame proved more effective than the gain frame. Moreover, participants prioritizing multiple environmental values were more likely to adjust their usage. Nonetheless, no interaction was observed between values and framing. These findings shed light on individual environmental values' influence on pro-environmental behavior, offering more profound insights into the cognitive processes that drive these actions.

Keywords: Framing Effects; Time-of-Use Pricing; Water Demand Management; Judgment and Decision-Making

Introduction

When logically equivalent information is presented in gain or loss terms, framing this information can influence decision-making processes. This phenomenon is called the framing effect (Tversky & Kahneman, 1981). The framing effect is generally categorized into three types: (1) risk-choice framing, which involves encouraging individuals to choose a preferred option between two risks; (2) attribute framing, which asks individuals to evaluate the desirability of a particular object or feature; and (3) goal-framing, which concerns whether an individual engages in a specific behavior or not (Levin et al., 1998).

Among these, the goal-framing effect refers to the phenomenon that emphasizes either the benefits of achieving a goal (gain frame) or the drawbacks of failing to achieve the goal (loss frame) and affects individuals' attitudes and behaviors without altering the goal itself (Levin et al., 2002). A well-known example is a Breast Self-Examination (BSE) study by Meyerowitz and Chaiken (1987). Their study demonstrated that emphasizing losses was more effective in promoting the intention to perform BSE than emphasizing gains.

Prospect theory often explains the goal-framing effect (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). This theory posits that logically equivalent information, when framed as losses, is perceived as having greater subjective value than when framed as gains. Furthermore, Meyerowitz and Chaiken (1987) attribute the effectiveness of a loss frame in goal framing to negativity bias, which suggests that loss information tends to attract more attention and exerts a more substantial influence than gain information (Baumeister et al., 2001). Based on these discussions, it can be predicted that loss framing has a more significant impact on attitudes and behaviors than gain framing in the context of goal framing.

Recently, increasing interest has been in applying the goal-framing effect to address environmental challenges. Grazzini et al. (2018) found that when hotel guests were encouraged to recycle, messages framed as losses were more effective in promoting recycling behavior than those framed as gains. Similarly, loss-framed messages have occasionally been more effective in climate change mitigation than gain-framed messages in encouraging low-carbon household behaviors (Li et al., 2023). These findings suggest that framing environmental issues, such as losses, may elicit stronger behavioral motivation.

This study investigated the goal-framing effect in promoting sustainable household water use, focusing on encouraging actions that shift peak water demand to off-peak periods. Reducing the peak water demand can significantly lower the capital and operational costs associated with water infrastructure, including pumps, pipes, and storage facilities (Cole et al., 2012). Moreover, reducing the peak demand can help minimize environmental impacts such as energy consumption. This study explores two types of monetary incentive framing: a gain frame (e.g., "You will receive $13 if you shift your water consumption from peak to off-peak hours") and a loss frame (e.g., "You will lose $13 if you fail to shift your water consumption from peak to off-peak hours"). Specifically, this study hypothesizes that loss framing increases the perceived monetary value of the reward compared to gain framing, thereby leading to more significant reductions in peak water demand.

Furthermore, environmental values are recognized as key determinants of pro-environmental behavior (Tolppanen & Kang, 2021) and influence individual water-use behaviors and responses to interventions. Previous research has identified four key value orientations that predict environmental beliefs and behaviors (Bouman et al., 2018; Steg et al., 2014). These include (1) biospheric values (herein Bio: These emphasize the importance of environment and nature for their intrinsic value, including ecosystems and non-human life. (2) Altruistic values (herein Alt): These prioritize

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the welfare and well-being of others, focusing on equity and social justice. (3) Hedonic values (herein Hed): These focus on pleasure, comfort, and effort reduction, emphasizing the immediate satisfaction of personal desires. (4) Egoistic values (herein Ego): These center on maximizing personal benefits, such as wealth, power, and achievement, with a focus on self-interest and resource acquisition. Variations in emphasis on these values may affect how individuals perceive framed monetary incentives. This study also explored whether these value orientations moderate the effects of loss framing, aiming to experimentally determine which environmental value orientations make individuals more responsive to the influence of framing.

Procedure and Stimuli

Experimental Period and Target Area

This study was conducted in collaboration with the Waterworks Division of Kosai City, Shizuoka Prefecture, Japan, focusing on the Chibata-Iride District, part of the city's water distribution area. The experimental period spanned two weeks, from Friday (September 27, 2024) to Thursday (October 10, 2024). The two weeks before this period (September 13–26) were designated as the pre-intervention phase, during which baseline water usage was measured. In Chibata-Iride District, all 1,890 households were equipped with smart water meters capable of recording hourly water usage. This study used hourly water consumption data (measured in m^3/h).

Time-of-Use Pricing System and Incentive Design

A time-of-use (TOU) pricing system was implemented to mitigate peak water usage (see Figure 1). Under this system, higher rates were applied during peak hours in the morning (06:00–09:59) and evening (17:00–22:59), whereas discounted rates were offered during off-peak periods, including late-night and early morning hours (23:00–05:59) and daytime hours (10:00–16:59). The primary goal of this strategy was to encourage households to shift their water consumption from peak to off-peak hours.

Households that consented to participate in the experiment were randomly assigned to one of the two treatment groups (gain-framed or loss-framed) to ensure that water usage levels during the pre-intervention phase were balanced across the groups to minimize bias. Households that Installed smart meters but chose not to participate in the pricing system experiment were the Control group. Consequently, this study established the following three groups:

1. Control group: Households not participating in the pricing system experiment continued with the standard pricing structure.
2. Gain and Loss groups: Households in this group received additional rewards to achieve their target water usage levels during peak periods.

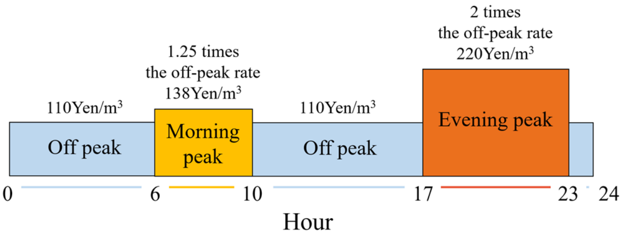

Figure 1. Tariff structure during the intervention period.

Participants

The study recruited approximately 1,500 households registered with the SMS (Short Message Service) system of the Waterworks Division of Kosai City and equipped with smart water meters. Of them, 267 agreed to participate in the study. The participants were randomly assigned to either the Loss group (133 households) or the Gain group (134 households).

After excluding households with prolonged absence during the experimental period, the final sample comprised 114 households in the Loss group and 117 in the Gain group. Additionally, data from 1,224 nonparticipating households (those that expressed no interest in adopting the TOU pricing system) were used as the Control group.

Information Provided to Participants

Participants in the experiment were informed about implementing a TOU pricing system. They were instructed to assume this scenario daily from Friday, September 27, to Thursday, October 10. They were asked to adjust their water usage behavior accordingly during this period. In this system, the total water consumption was set at 100%. The participants' rewards were calculated based on the proportion of water used across four designated periods: Late Night or Early Morning (23:00–05:59), Morning Peak (06:00–09:59), daytime (10:00–16:59), and Evening Peak (17:00–22:59).

The instructions provided to participants were as follows: "In this experiment, you will live your daily life from Friday, September 27, to Thursday, October 10, under the assumption that a TOU pricing system is in place. In Kosai City, approximately 20% of daily water consumption occurs during the morning peak hours (06:00–09:59) and approximately 40% during the evening peak hours (17:00–22:59). Based on this benchmark, the reward was calculated according to the water usage patterns during the experimental period. The reward system reflects the proportion of water consumed during each period.

1. Late Night or Early Morning (23:00–05:59)
2. Morning Peak (06:00–09:59)
3. Daytime (10:00–16:59)
4. Evening Peak (17:00–22:59)"

Reward Structure

All participants who completed the experiment and responded to the survey received a fixed gift card worth 1,000 yen (approximately 6 USD). Additional rewards of up to 2,000 yen (approximately 13 USD) were provided based on the participants' water usage patterns to achieve peak shift behavior. Participants could choose either an Amazon gift card or a QUO card (a prepaid card that could be used at convenience stores and bookstores) for both fixed and additional rewards.

Framing Manipulation

The study divided the participants into the Gain group and the Loss group to evaluate the impact of different goal-setting frameworks on water conservation behavior. The pricing structure was identical in both groups, and participants were charged the same amount for water usage when their consumption volumes were equal.

1. Gain group Instructions:

For the morning peak period (06:00–09:59), the baseline was set at the citywide average of 20%. Participants earned 84 yen for every 1% reduction below the baseline, with a maximum reward of 420 yen (approximately 2.5 USD) for a 5% reduction.

For the evening peak period (17:00–22:59), the baseline was set at a citywide average of 40%. Participants earned 165 yen for every 1% reduction below the baseline, with a maximum reward of 1,650 yen (approximately 10.5 USD) for a 10% reduction.

2. Loss group Instructions:

For the morning peak period (06:00–09:59), the baseline was set at 15%. Participants were penalized 84 yen for every 1% increase above this baseline, up to a maximum penalty of 420 yen (approximately 2.5 USD) for a 5% increase.

For the evening peak period (17:00–22:59), the baseline was set at 30%. Participants were penalized 165 yen for every 1% increase above baseline, with a maximum penalty of 1,650 yen (approximately 10.5 USD) for a 10% increase.

Online Survey

At the end of the experimental period, participants were asked to complete an online survey that included the following items:

Engagement in Peak-Shift Behavior: Participants were asked, “Did you attempt to shift your water usage from peak to off-peak hours during the experiment?” Responses were recorded as binary data, with 0 representing “no shift” and 1 representing “shifted.”

Prioritized Values: Participants were asked, “Why did you decide to consider (or not consider) altering your water usage timing or adopting water conservation practices?” They rated the importance of the following values using a Visual Analog Scale (VAS) ranging from 0 (not important at all) to 100 (extremely important).

1. Bio: Reflects concerns about the environmental impact of water consumption.
2. Alt: Acknowledging the broader social implications of water conservation.
3. Hed: Reflecting on the importance of having the flexibility to use water without restrictions.
4. Ego: Considering the financial burden associated with water bills.

This study used the same items as those employed in previous research to construct the scales (Otaki et al., 2024).

Results

Figure 2 shows the hourly median water usage volumes (m³/h) for the Control, Gain, and Loss groups during the two weeks prior to the intervention. Medians were calculated by summarizing the median usage of each participant at each hour. Error bars represent the interquartile range (IQR), with the lower limit at the 25th percentile and the upper limit at the 75th percentile. Blue, yellow, and red indicate the off-peak, morning, and evening peak hours, respectively. Figure 3 illustrates the differences in water usage volume (m³/h) between the pre-intervention and intervention periods.

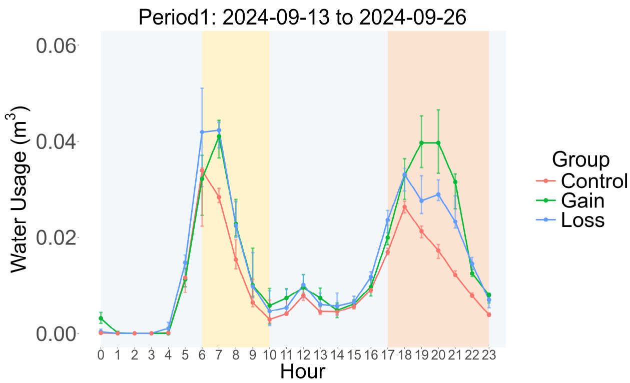

Figure 2. The median water usage during the pre-intervention period.

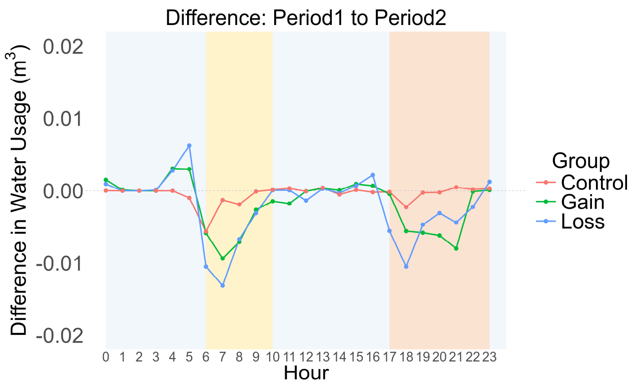

Figure 3. The difference in water usage between the pre-intervention and intervention periods.

Using a Difference-in-Differences (DID) analysis, data from the pre-intervention and intervention periods were examined across the three groups at each hour of the day. As shown in Figure 2, participants in the Gain group tended to exhibit higher baseline usage levels compared to those in the Loss and Control groups during the 19:00–21:00 period. When such baseline differences exist, it becomes difficult to determine whether post-intervention group differences are attributable to the intervention itself or to pre-existing group disparities. To address this issue, we employed a DID approach and calculated each participant’s average water usage during the pre-intervention period. This value, defined as the individual baseline, was included as a covariate in the linear mixed-effects model (GLMM). Table 1 summarizes the hourly regression results, focusing on hours with statistically significant differences. For the Loss group, significant positive intervention effects occurred at hours 3, 4, 5, 10, 15, 16, and 23, whereas significant negative intervention effects appeared at hours 6, 7, 8, 9, 17, 18, 19, 20, 21, and 22. For the Gain group, significant positive intervention effects emerged at hours 4, 5, 10, and 16, while significant negative intervention effects were observed at hours 6, 7, 8, 9, 18, 20, 21, and 22. Across all these results, the intercept was statistically significant ($p < .001$).

Table 1: Results of the DID analysis by the hour, examining how variations between the pre-intervention and intervention periods, including differences among the Gain, Loss, and Control groups, affected water usage. "Gain: Intervention" suggests the interaction between gain and intervention. "Loss: Intervention" indicates the interaction between loss and intervention.

Term	Estimate	*t*	*p*	Hour
Loss: Intervention	0.00	6.69	<.001	3
Loss: Intervention	0.01	11.17	<.001	4
Gain: Intervention	0.01	8.82	<.001	4
Loss: Intervention	0.01	10.01	<.001	5
Gain: Intervention	0.01	5.03	<.001	5
Loss: Intervention	-0.01	-6.03	<.001	6
Gain: Intervention	-0.01	-4.22	<.001	6
Loss: Intervention	-0.01	-8.73	<.001	7
Gain: Intervention	-0.01	-5.22	<.001	7
Loss: Intervention	-0.01	-5.00	<.001	8
Gain: Intervention	-0.01	-5.42	<.001	8
Loss: Intervention	0.00	-3.07	.002	9
Gain: Intervention	0.00	-2.84	.004	9
Loss: Intervention	0.01	4.77	<.001	10
Gain: Intervention	0.00	2.67	.008	10
Loss: Intervention	0.00	2.44	.015	15
Loss: Intervention	0.01	8.41	<.001	16
Gain: Intervention	0.01	8.15	<.001	16
Loss: Intervention	-0.01	-4.11	<.001	17
Loss: Intervention	-0.01	-5.62	<.001	18
Gain: Intervention	-0.01	-3.14	.002	18
Loss: Intervention	-0.01	-3.02	.003	19
Loss: Intervention	-0.01	-2.63	.009	20
Gain: Intervention	-0.01	-2.86	.004	20
Loss: Intervention	-0.01	-3.36	.001	21
Gain: Intervention	0.00	-2.09	.037	21
Loss: Intervention	0.00	-1.98	.048	22
Gain: Intervention	0.00	-2.85	.004	22
Loss: Intervention	0.00	2.35	.019	23

Hourly DID analysis was used to examine the differences between the Gain and Loss groups in the data collected before and during the intervention. The individual baseline was included as a covariate in the GLMM. Interaction effects between intervention periods (pre-intervention vs. during-intervention) and group type (Gain vs. Loss) were observed during 03:00 (Loss: Intervention: Intercept = 0.00, Estimate = 0.00, t = 3.42, p .001), 05:00 (Loss: Intervention: Intercept = -0.01, Estimate = 0.01, t = 3.11, p .002), and 07:00 (Loss: Intervention: Intercept = 0.00, Estimate = -0.01, t = -2.57, p = .010) time slots. "Loss: Intervention" indicates the interaction between loss and intervention. During the intervention, the loss frame resulted in a significant reduction in peak usage and a greater increase in off-peak usage than the gain frame. Across all results, the intercept was statistically significant ($p < .001$).

The web-based survey measured the following four dimensions: Bio, Alt, Hed, and Ego. Using NbClust (Charrad et al., 2014), which applies approximately 30 objective indices to the data to determine the optimal number of clusters, this analysis determined that two clusters were the most appropriate. Consequently, the dataset was divided into two clusters. The mean scores for the four value dimensions in Cluster 1 were: Bio = 32.04, Alt = 39.07, Hed = 48.60, and Ego = 61.60. In Cluster 2, the mean scores were: Bio = 64.39, Alt = 69.82, Hed = 70.79, and Ego = 83.56. Cluster 1 comprised 100 participants, whereas Cluster 2 included 131 participants. Figure 4 presents the average responses regarding shifts in water usage from peak to off-peak hours—that is, the proportion of participants who, according to the questionnaire, reported having attempted to shift their water consumption from peak to off-peak periods (0 = no shift; 1 = shift)—categorized by cluster and by Gain and Loss groups. A two-sample t-test revealed a significant difference in peak-shift behavior between Cluster 1 (M = 0.49) and Cluster 2 (M = 0.71), $t(201.74) = -3.43$, $p < .001$. A logistic regression analysis was conducted separately for each cluster to examine whether participants in the Gain and Loss groups shifted their peak consumption behavior (0 = no shift, 1 = shift), based on their survey responses. The independent variables included group (Gain or Loss) and the four value dimensions, whereas the dependent variable was whether a peak shift occurred. Interaction terms between the groups and clusters were also included in the analysis. The logistic regression analysis results indicated that the intercept was not statistically significant (Estimate = 0.23, SE = 0.28, z = 0.83, p = .406).

The interaction between Loss and Cluster 2 was not statistically significant (Estimate = 1.04, SE = 0.56, z = 1.85, p = .064).

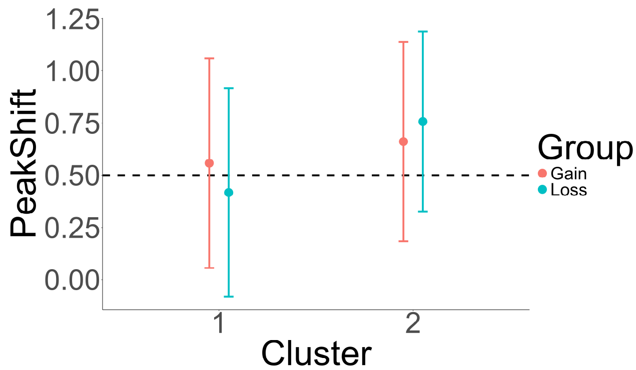

Figure 4. Average responses for shifts in peak consumption behavior by cluster and framing group. The vertical axis shows the proportion of participants who, according to the questionnaire, reported having attempted to shift their water usage from peak to off-peak hours. The dots represent the average, and the error bars indicate the standard deviation.

General Discussions

This study experimented with encouraging peak shifts, which involve shifting water usage from peak hours (06:00–09:59 in the morning and 17:00–22:59) to off-peak hours by manipulating monetary incentives. Specifically, two experimental groups were established: a gain framing group (e.g., “You will receive 2,000 yen [approximately $13] for shifting your usage from peak to off-peak hours”) and a loss framing group (e.g., “You will lose 2,000 yen [approximately $13] if you fail to shift your usage from peak to off-peak hours”). The effects of these groups on the participants’ peak shift behaviors were then compared. The results revealed that both the gain and loss frames significantly encouraged peak-shift behavior compared to the Control group, which comprised households not participating in the pricing scheme. A significant intervention effect promoting peak shifting was observed, particularly during the morning (6:00–9:00) and evening (17:00–22:00) peak hours. The introduction of monetary incentives alone was shown to have a certain level of effectiveness, consistent with prior research (Onuki & Otaki, 2025). Furthermore, the results demonstrated that the loss frame was more effective than the gain frame in encouraging peak-shift behavior. The implications of this result are discussed later in this study. Considering the cost-saving benefits of reducing peak demand, such as savings in capital and operational costs (Cole et al., 2012), these findings suggest that presenting monetary incentives in a loss frame may more effectively promote efficient water infrastructure management.

Previous research has shown that the effects of the TOU pricing system on water usage behavior, which change over a two-week period, tend to persist for several months thereafter (Onuki & Otaki, 2025). Therefore, this study was conducted with a two-week intervention period. However, the current research does not examine the long-term effects of framing differences on water usage behavior. Future studies should consider employing a longer intervention period to more accurately assess the effects of framing.

Environmental Values and Peak-Shift Behavior

While price-based interventions are often considered more cost-effective than non-priced programs for managing demand (Olmstead & Stavins, 2009), the introduction of monetary incentives poses the risk of crowding out intrinsic motivation (Frey & Jegen, 2001; García-Valiñas & Suárez-Fernández, 2022). Interventions that are effective in a non-pricing context have been reported to lose their impact when combined with pricing strategies (Otaki et al., 2024).

In this study, an analysis of participants’ relationships with four environmental values (Bio, Hed, Alt, and Ego) (Bouman et al., 2018; Steg et al., 2014)—revealed that participants who placed high importance on all four values (Cluster 2) were more likely to engage in peak-shift behavior than those who primarily emphasized ego values (Cluster 1). Furthermore, no interaction effects were observed between the cluster type and the gain or loss frame, suggesting that framing effect reversal did not occur regardless of the participants’ value orientations. All participants received the same monetary incentives, yet those in Cluster 2—who placed high importance on intrinsic environmental and altruistic values—were more likely to shift their peak usage. This suggests that intrinsic motivations related to environmental concern and social welfare remained influential alongside the uniform financial reward. This finding contradicts prior research, which posits that monetary value and intrinsic motivation combination leads to a crowding-out effect. In this study, monetary value and intrinsic motivation may have coexisted because only participants willing to join the TOU pricing system were assigned to the group that experienced a change in framing. Future research should examine whether similar tendencies are observed among participants who do not voluntarily opt for changes to the pricing system.

Effects of Framing on Peak-Shift Behavior

Research on environmental issues frequently indicates that loss framing effectively promotes behavioral changes. For example, Grazzini et al. (2018) and Li et al. (2023) demonstrated that loss-framed messages emphasizing the disadvantages of inaction tend to increase behavioral intentions. Our findings similarly showed that loss framing promoted peak-shift behavior more effectively than gain framing. By manipulating the framing of monetary incentives, the observed differences in peak-shift behavior can be interpreted through two complementary psychological mechanisms. First, prospect theory posits that people evaluate outcomes relative to a reference point and experience losses more intensely than equivalent gains—a phenomenon known as loss aversion (Kahneman & Tversky, 1979, 1992). In the value function of prospect theory, the curve is steeper for losses than for gains, meaning the subjective impact of losing money is greater than the pleasure of gaining the same amount. Consequently, when the same monetary incentive is framed as a potential loss ("You will lose $13 if you fail to shift your water consumption from peak to off-peak hours") rather than as a gain ("You will receive $13 if you shift your water consumption from peak to off-peak hours"), participants perceive the loss-framed message as more salient and motivating. Second, negativity bias suggests that negative information attracts more attention and exerts a more substantial influence on cognition and behavior than positive information (Baumeister et al., 2001). Loss-framed messages are therefore more likely to capture and hold participants' attention, reinforcing the motivational pull identified by prospect theory. In our experiment, this heightened sensitivity to losses drove stronger peak-shift behavior under the loss frame than under the logically equivalent gain frame. Thus, by leveraging both the asymmetric value function described in prospect theory and the heightened attentional weight of negative outcomes in negativity bias, loss framing elicited greater engagement with off-peak water usage. Future research should examine whether participants in the Loss group perceived the reward as a loss, and whether those in the Gain group perceived it as a gain. Measuring these perceptions would allow for a more precise investigation of framing effects.

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