FLEXBEAN
Flexibility for Energy Transition PROJECT

D.2.3.3

Upskilling campaign report

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Executive Summary

This report presents the design, implementation, and outcomes of an energy upskilling pilot conducted as part of Work Package 2 of the FlexBeAn project, aiming to enhance household energy literacy and flexibility through a digital intervention. At the heart of the intervention is *One2Day*, a mobile-first application that delivers personalized daily content to encourage sustainable energy behaviors.

Three groups were studied: a *profile group* receiving personalized content based on psychological profiling and energy use characteristics; a *random group* receiving non-tailored content; and a *control group* with no access to the app. Over several weeks, participants were exposed to thematic modules including quizzes, nudges, and informational prompts, with energy literacy and behavioral flexibility assessed at multiple stages.

The findings highlight several key insights:

- App usage significantly improved energy literacy, especially in the early stages of the intervention.
- Personalized content enhanced both literacy and behavioral flexibility more effectively than random or absent interventions, with the *profile group* showing the highest improvement rates.
- Specific behaviors such as voluntary delay of high-energy appliances (e.g., dryers, EV charging) were particularly responsive to targeted content, suggesting that user-driven flexibility actions are most effectively promoted through relevant, trusted messaging.
- Psychological traits (personality, environmental values, tech affinity) alone did not predict improvement but played a role when leveraged through personalization strategies.

The intervention proved effective in promoting learning and change among engaged users, despite decreasing participation over time. The results support the use of adaptive, psychologically informed digital tools to engage citizens in energy transition efforts. Recommendations include further tailoring of content, reinforcement of trust in grid actors, and prioritization of user-initiated flexibility behaviours.

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1. Introduction

1.1. Overall description of the pilot study

As electricity systems evolve towards decentralisation and decarbonisation, there is a growing need to mobilise household flexibility to support grid stability and enable efficient integration of renewable energy sources. However, unlocking this flexibility requires more than technological readiness. It demands behavioural change, informed decision-making, and active engagement from consumers. The FlexBeAn project addresses this challenge by investigating how energy literacy, personalisation, and behavioural incentives can drive household participation in demand-side flexibility.

This report presents the design and implementation of a pilot study aimed at upskilling residential users and enhancing their engagement with flexible energy practices. The study builds upon the development of an experimental mobile application, One2Day, which delivers tailored educational content and behavioural nudges. The content is curated through a recommender algorithm that considers user characteristics such as personality traits, environmental values, equipment ownership, and baseline literacy levels.

The central aim of the project is to determine whether personalised content delivery, supported by psychological profiling and user segmentation, can effectively increase energy literacy and promote behavioural flexibility. To this end, several hypotheses are tested, focusing on the relationship between engagement, literacy, and flexibility, as well as the role of personalisation and non-monetary incentives in shaping user behaviour.

1.2. Experimental groups

Participants were divided into three experimental groups based on their level of exposure to the One2Day mobile application and the type of content received:

Profile group: Participants in this group received content tailored to their individual characteristics, including personality traits (BFI), environmental values (EPVQ), equipment ownership, and baseline energy literacy. The content was selected using a recommender algorithm that matched users to thematic chapters and daily activities based on their profile and energy literacy level.

Random group: This group also used the app but received content selected at random, not tailored to their personal attributes. The random assignment served to isolate the effect of personalisation from general exposure to energy-related content.

No-app group (control): Participants in this group did not use the app and were only exposed to the initial survey. They did not receive any form of intervention, making them a baseline against which to assess changes in energy literacy and flexibility attributable to the app-based approach.

Participants in the app-based groups were recruited through earlier survey campaigns and randomly assigned to their respective groups. The intervention lasted several weeks and was structured in slots, with each slot comprising five days of thematic content, quizzes, behavioural prompts, and optional feedback mechanisms. Throughout the pilot, participants' engagement was monitored through app activity metrics, and energy literacy was assessed at three points: before the intervention (initial), mid-way through the pilot (intermediate), and after its conclusion (final).

1.3. Data collection

The experimental protocol was developed to test a set of hypotheses linking engagement, personalisation, and literacy to household flexibility. Outcomes were measured both through structured questionnaires and in-app behavioural indicators. The design also allowed for comparative analysis across groups and over time, offering a robust framework to assess the effectiveness of different engagement strategies in promoting energy-related behavioural change.

More specifically, the One2Day app was used by participants over a period of 15 weeks (see deliverable 2.3.1. "Toolkit for energy upskilling" for more details on One2Day).

Before logging in for the first time, new users were asked to complete a questionnaire, which was a shortened version of the survey conducted a few months earlier (see deliverables 2.1.1 & 2.1.4. "Household's energy literacy and flexibility survey"). The survey included:

- several socio-demographic questions (age, gender, country of residence, etc.) and other questions on energy appliances and usage;
- the standardised E-PVQ (Environmental Portrait Value Questionnaire) to measure participants' sensitivity to environmental issues;
- the standardised ATI (Affinity for Technology Interaction) questionnaire, to assess the participant's affinity with technology;
- the standardised BFI-10 (Big Five Inventory) questionnaire, to draw up a personality profile of the participant, based on the Big 5 model.
- 14 questions to measure energy literacy.
- 10 questions to assess participants' flexible behaviour.

The survey is presented in Appendix 4. As with the survey conducted a few months earlier, this survey was used to profile each participant and thus propose tailored content in the One2Day app. It should be noted that participants who had already completed the previous survey were not asked to complete this one.

In the 7th week of using the app, the energy literacy questions (presented in random order) were asked again to the participants.

Finally, at the end of the 15th week, the energy literacy questions and the flexibility questions were asked one last time to the participants.

A summary of the research protocol is presented in Figure 1.

Figure 1. Summary of the experimental protocol.

The findings are expected to contribute to the design of user-centric flexibility programmes, providing insights for both utilities and policymakers on how to activate the latent flexibility potential within households.

1.4. Recruitment of participants

The recruitment of participants for the pilot study was carried out in three stages.

The first stage consisted of contacting by email all users who had given their consent during the online survey conducted in 2023.

The second stage focused on recruiting new participants from a database of 250 candidates who often volunteer for studies conducted in Luxembourg.

The third stage consisted of posting a call for participants on social media. LIST, SnT and CREOS joined forces to post various communications on LinkedIn, Instagram and Facebook. In particular, quizzes posted on Instagram and Facebook were designed to capture users' attention (Figure 2. Visual element shared on social media. & Figure 3. Extract from a post shared on LinkedIn.).

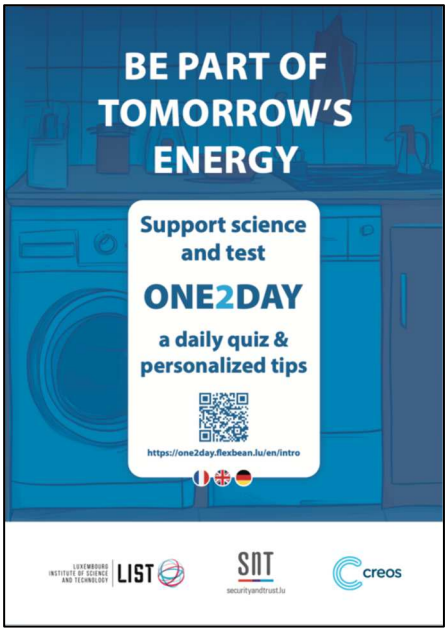


Figure 2. Visual element shared on social media.

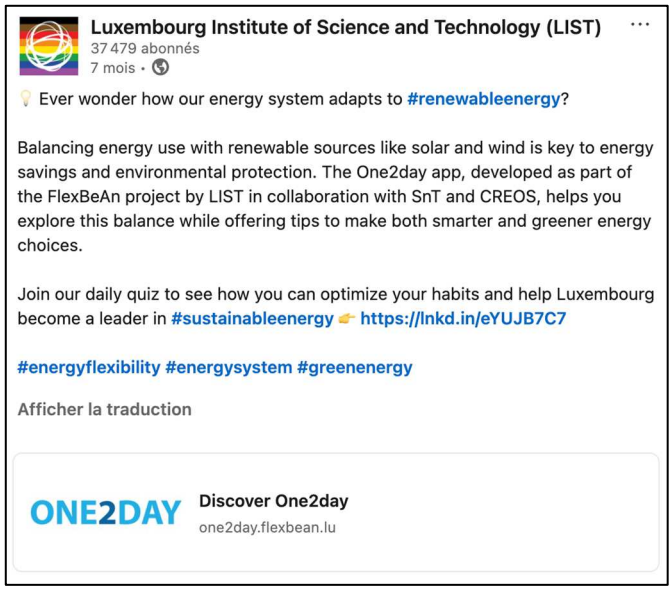


Figure 3. Extract from a post shared on LinkedIn.

A communication plan has been drawn up and is presented in Appendix 1. The results and impact of this communication plan are presented in Appendix 2.

1.5. Sample

Table 1. Detailed sample sizes.) summarises participation in the three energy literacy questionnaires across the three experimental groups at different stages of the pilot. The **profile sample**, consisting of 230 participants (115 from the pilot and 115 from the initial survey), received content tailored to their user profiles. The **random sample**, with 179 participants (64 from the pilot and 115 from the initial survey), received randomly assigned content. The **no-app sample**, composed of 115 participants from the initial survey, served as the control group and did not interact with the application.

While the app-based groups included a larger number of participants overall, a higher proportion of individuals in the no-app group completed the intermediate and final questionnaires. Specifically, 63 and 50 participants from the no-app group completed the intermediate and final EL questionnaires, respectively, compared to 24 and 21 in the profile group and 30 and 26 in the random group. Similarly, 36 participants in the no-app group completed all three questionnaires, compared to 21 and 25 in the profile and random groups, respectively.

Table 1. Detailed sample sizes.

	Initial EL questionnaire	Intermediate EL questionnaire	Final EL questionnaire	Intermediate + Final questionnaire	Initial + Intermediate + Final
Profile sample	115 (from pilot) + 115 (from initial survey)	24	21	21	21
Random sample	64 + 115 (from initial survey)	30	26	25	25
Total (profile + random)	**409**	**54**	**47**	**46**	**46**
No app sample	115 (from initial survey)	63	50	42	36
Total	**524**	**117**	**97**	**88**	**82**

1.6. Descriptive statistics

The **Error! Reference source not found.**) presents the distribution of **Energy Literacy scores** a t three points during the pilot corresponding to the structured questionnaires: **Initial**, **Intermediate**, and **Final**. While the histograms visually suggest a progression in scores over time, the interpretation must be contextualised by the decreasing sample sizes at each stage.

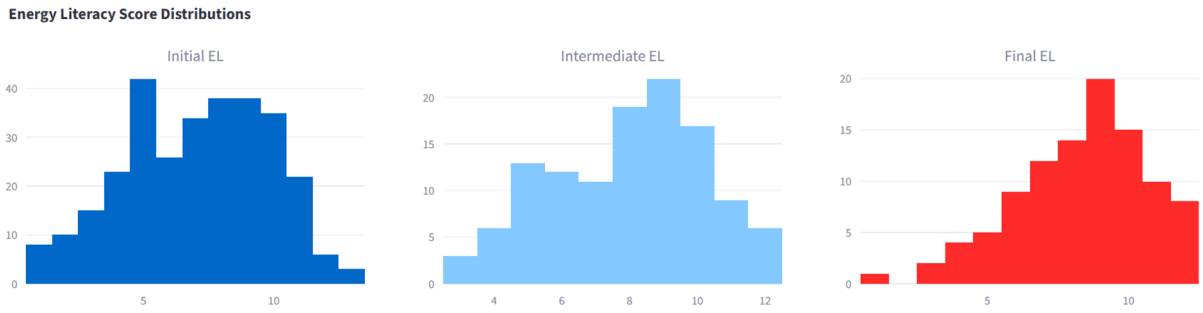


Figure 4. Energy literacy score distributions.

Initial EL (left panel): Based on the largest sample (n = 524), the distribution spans scores from 1 to 13, with a pronounced peak around score 6. The spread is relatively broad and symmetric, indicating a heterogeneous baseline level of energy literacy across participants.

Intermediate EL (centre panel): With a reduced sample size (n = 117), the distribution shifts slightly rightward, with most scores concentrated between 7 and 10. The peak is around score 9, and low scores become less frequent. This change suggests a potential improvement in literacy among those who continued in the study, though the reduced sample may introduce selection effects.

Final EL (right panel): The final measurement, based on 97 participants, shows a more distinct rightward shift. The mode is at score 9, and the proportion of high scores (9–12) increases. Scores below 5 are rare. This pattern indicates continued improvement in literacy among the most engaged participants, though the drop in sample size again limits generalisability.

In summary, the observed increase in energy literacy scores over time is encouraging and suggests a positive effect of the intervention. However, the decline in participation across measurement points implies that the results are increasingly representative of a more engaged subgroup, and this potential bias should be considered in further analysis.

The boxplot in **Error! Reference source not found.**) illustrates the distribution of the change i n energy literacy scores (**difference between initial and final scores**) across three groups: **random**, **profile**, and **no-app**.

Figure 5. Change in energy literacy scores between the initial and final measurements across the three experimental groups.

Group random (left): This group shows a **median increase of about 1.5 points**. The interquartile range (IQR) spans from just above 0 to about 3, indicating that most participants in this group experienced a modest improvement in energy literacy. The lower whisker extends just below 0, and there is one outlier above 6, suggesting a few participants showed stronger gains.

Group profile (centre): Participants receiving personalised content exhibit the highest median gain, around 2 points (gain of 16,6%), and the widest overall distribution. The IQR ranges approximately from 0 to 4.5, while the whiskers span from –4 to nearly 5. This variability reflects a broader range of outcomes, with some participants experiencing notable increases and others showing declines.

Group no-app (right): The control group shows the lowest median improvement, close to 1 point, and the narrowest IQR (from 0 to about 2). The whiskers are symmetrical and extend from –4 to +4, indicating some participants did improve, but the spread is more contained compared to the app-based groups.

The figure suggests that participants who used the app –especially those in the profile-based personalisation group– tended to experience greater improvements in energy literacy over the course of the pilot. However, the greater variability in the profile group also highlights inconsistent responses to the intervention. The no-app control group generally showed smaller and more consistent changes, suggesting that the app may have contributed to learning gains, particularly when content was tailored to user characteristics.

2. Hypotheses

Several research hypotheses have been formulated, some of which are represented in the form of a model (Figure 6. Model of assumptions made for the pilot study analysis.). These hypotheses also form the basis for the rest of this report. We review each of them in the following sections, summarizing the observations and concluding on the hypothesis validity.

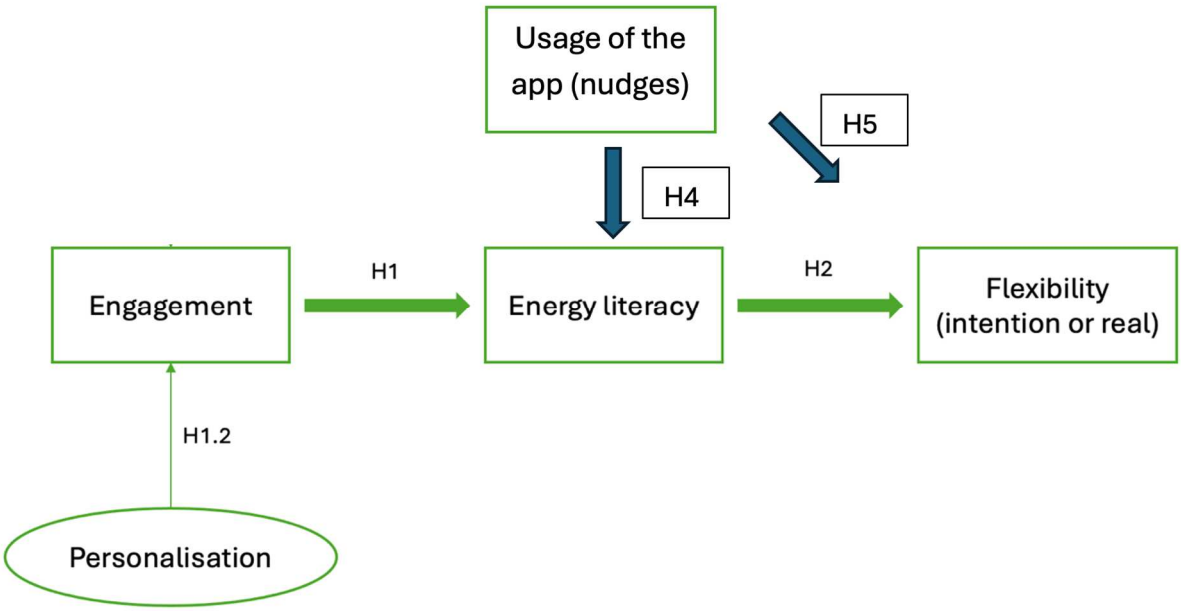


Figure 6. Model of assumptions made for the pilot study analysis.

H 1: Increasing engagement leads to an increase in energy literacy in the pilot participants.

H 2: Using personalisation in the application increases engagement compared to not using it.

H 3: An increase in energy literacy leads to an increase in flexibility.

H 4: Usage of the application increases energy literacy (H4.1 using personalisation in the App increases energy literacy).

H 5: Usage of the application increases flexibility.

H 6: Users like more content selected according to their psychological profile.

3. Hypothesis #1: Increasing engagement leads to an increase in energy literacy in the pilot participants

3.1. Introduction

To assess user engagement in relation to energy literacy (EL), we applied **survival analysis** across three distinct measurement points: initial, intermediate, and final EL scores. Participants were grouped based on their likelihood to remain engaged with the app. We performed **statistical tests** to determine whether EL levels were significantly associated with app engagement at different stages of the intervention. Additionally, **ANOVA** was conducted to compare EL score evolution across experimental groups (profile, random, and no-app).

3.2. Observation

The survival analysis plots show clear differences in engagement trajectories between participants with higher and lower energy literacy scores over time (Figure 7. Statistical tests on engagement level (via survival analysis) among the energy literacy "checkpoints". Users with high probability to stay in the app have a higher score in EL.):

- **Initial EL (initialEL)**: The p-value was 0.0965 (> 0.05), indicating **no statistically significant difference** in engagement at the start of the intervention. All groups had **similar baseline EL**.
- **Intermediate EL (intermediateEL_score)**: The p-value was 0.0000 (< 0.001), suggesting a **highly significant difference** by the midpoint. This implies that **divergence in EL scores** started to appear among participants with different engagement levels.
- **Final EL (finalEL_score)**: Again, a p-value of 0.0000 indicates a **strong significant difference** in EL by the end of the intervention, confirming a **persistent gap** in literacy levels aligned with engagement patterns.

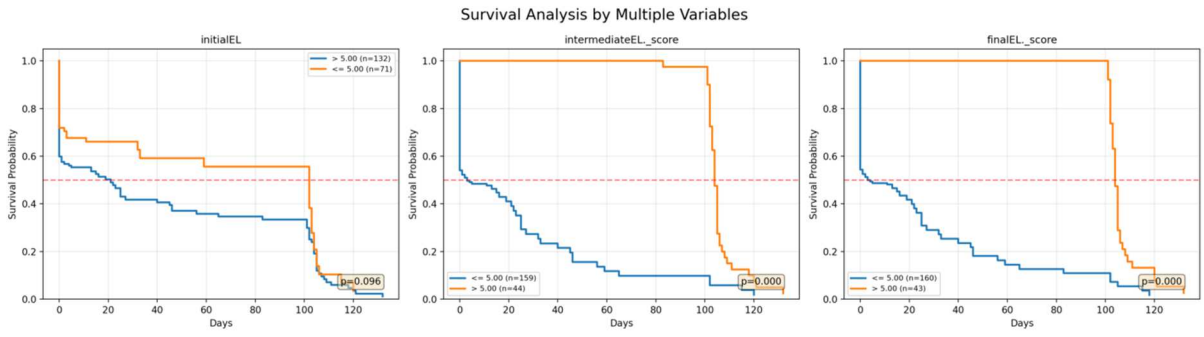


Figure 7. Statistical tests on engagement level (via survival analysis) among the energy literacy "checkpoints". Users with high probability to stay in the app have a higher score in EL.

ANOVA on EL scores across the three groups (profile, random, no-app) showed that **significant differences existed only at the initial stage**. Visual inspection suggests that the **profile group exhibited a more positive progression**, with EL scores increasing over time (Figure 8. Evolution of energy literacy scores according to group (profile, random or no-app).(Table 2. Scores and p-values from ANOVA calculation according to group (profile, random or no-app).).

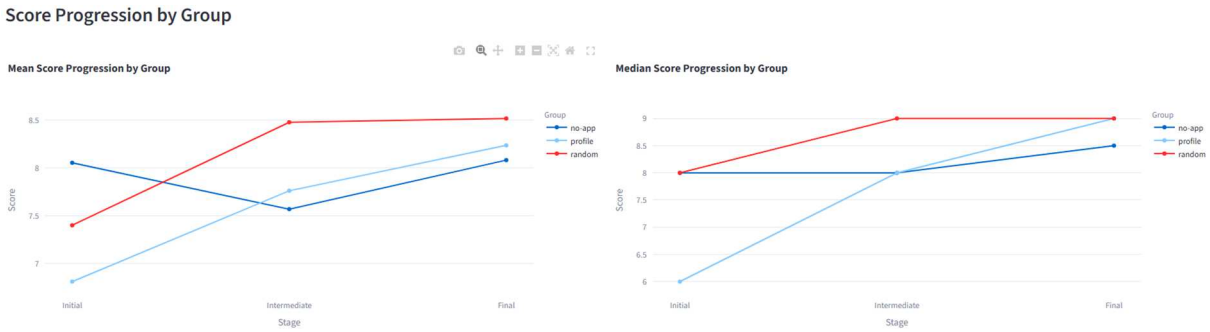


Figure 8. Evolution of energy literacy scores according to group (profile, random or no-app).

Table 2. Scores and p-values from ANOVA calculation according to group (profile, random or no-app).

Variable	F-statistic	p-value	Significant
Initial_EL	9.7118	< .001	Yes
Intermediate_EL	0.9921	0.3739	No
Final_EL	0.34	0.34	No

3.3. Explanation

H1 is validated. The results suggest that while participants started with comparable energy literacy levels, **the intervention had a meaningful impact**–particularly on those who engaged more consistently with the app. The **absence of initial differences** rules out pre-existing literacy gaps as a driver of engagement. Instead, the **rise in EL among more engaged users** implies that **higher literacy may be both a result of and a motivator for sustained engagement**. The profile group's improvement trajectory, combined with the effectiveness of tailored content, highlights the role of **personalized experiences in fostering deeper learning and behavioural change**.

4. Hypothesis #2: Using personalisation in the application increases engagement compared to not using it

4.1. Introduction

To test the effect of personalization on user engagement, we compared two groups within the app: a **"profile" group** that received personalized content and a **"random" group** that did not. Engagement was analysed using **survival analysis**, with time-to-disengagement as the primary outcome variable. This allowed us to assess whether personalization had a measurable impact on user retention throughout the intervention.

4.2. Observation

The survival curve illustrates **similar engagement trends** for both the random and profile groups. No **statistically significant difference** in engagement duration was found between the two groups. This suggests that **personalization did not significantly extend user retention** in the app (Figure 9. Survival Curves by Group (Profile vs. Random).).

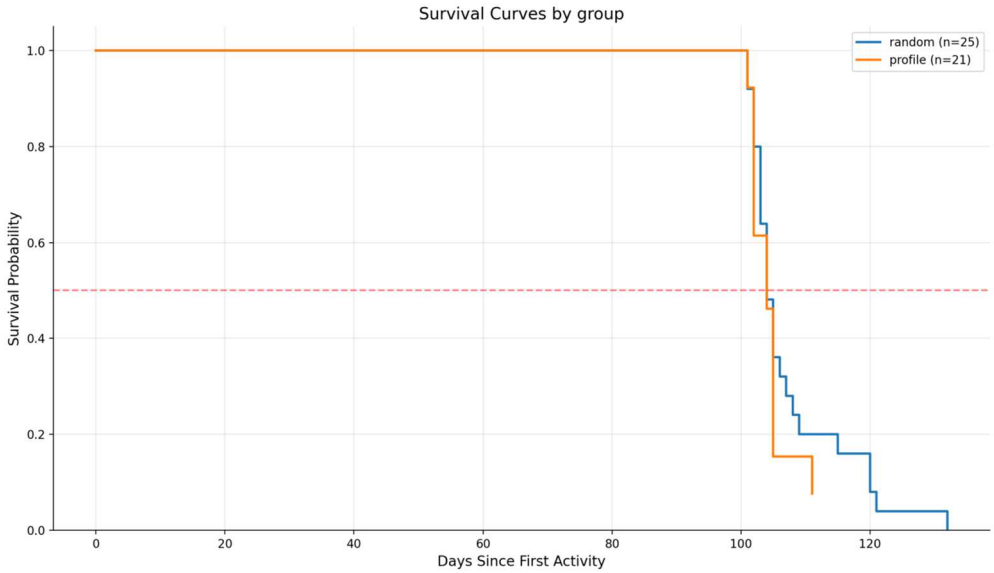


Figure 9. Survival Curves by Group (Profile vs. Random).

However, as referenced in Hypothesis 4 (H4), participants in the **profile group demonstrated significantly higher gains in energy literacy (EL)**. While engagement time did not vary notably, **literacy outcomes did**—highlighting a divergence between behavioural engagement and learning outcomes.

4.3. Explanation

H2 is not validated, but although personalization did not increase the **duration of app use**, it likely enhanced the **quality of engagement**. The similarity in survival curves suggests that

both groups remained active for similar periods, but the **profile group's higher literacy improvements** (as shown in H4) indicate that **personalized content may have made interactions more meaningful and effective**. These findings imply that personalization, even without increasing total time spent, can enhance the **impact of the experience**, especially in terms of cognitive gains like energy literacy.

5. Hypothesis #3: An increase in energy literacy leads to an increase in flexibility

5.1. Introduction

To explore whether user flexibility in energy-related behaviours is associated with changes in energy literacy (EL), participants were grouped based on their **flexibility scores** for two behaviours: **dryer delay** and **heat switch control**. Flexibility was classified as **high** or **low** based on predefined thresholds. We then analysed how these groups differed in their change in EL, measured as the difference between **intermediate and initial EL scores** (`el_diff_final_intermediate`)

5.2. Observation

The first boxplot shows that users with **high flexibility in dryer delay** had **significantly greater improvements** in energy literacy compared to those with low flexibility. This difference is **statistically significant** (Figure 10. Energy Literacy Gains by Flexibility Group with dryer delay.).

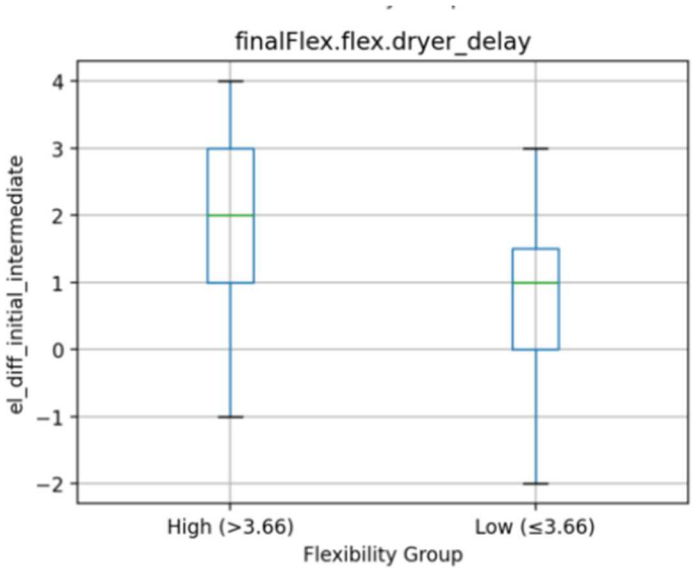


Figure 10. Energy Literacy Gains by Flexibility Group with dryer delay.

In contrast, although the second plot (heat switch by user) shows a **visual trend**–with the high-flexibility group appearing to have slightly higher EL gains–the difference is **not statistically significant** (Figure 11. Energy Literacy Gains by Flexibility Group in heat switch by user.).

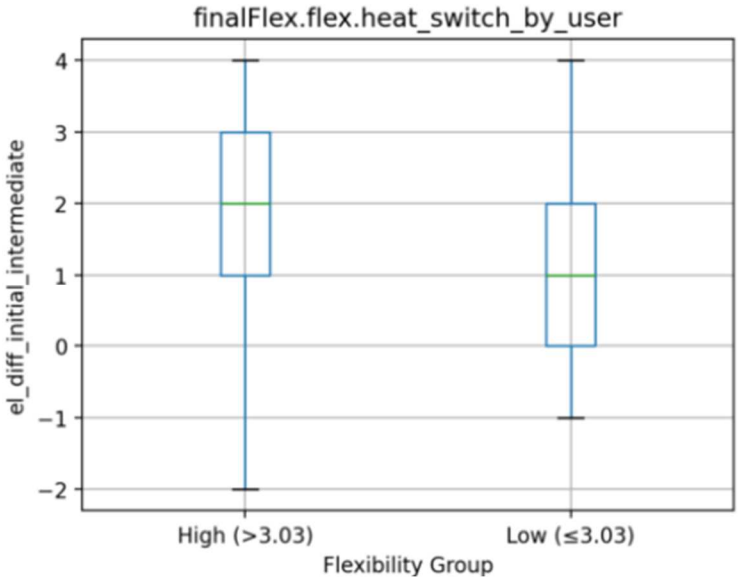


Figure 11. Energy Literacy Gains by Flexibility Group in heat switch by user.

5.3. Explanation

H3 is only partially validated and would require a deeper dedicated study. The findings suggest that **specific types of behavioural flexibility**, such as willingness to delay dryer use, are **more closely associated with energy literacy improvements** during the intervention. This may be because such behaviours directly reflect a user's **active engagement with energy-saving strategies**, reinforcing what they learn in the app.

On the other hand, flexibility in **heat switch control** may be less directly tied to the content of the intervention or less visible to users, leading to weaker associations with literacy gains. This highlights the importance of **targeting and reinforcing specific behavioural cues** that are more likely to enhance both learning and engagement.

6. Hypothesis #4: Usage of the application increases energy literacy (H4.1 using personalisation in the App increases energy literacy)

6.1. Introduction

This study examined the impact of mobile app interventions–personalized (profile-based) and randomly generated–on energy literacy (EL) across the three assessment stages: initial, intermediate, and final. The three groups of participants were compared (no app, random app, and profile app). The objective was to evaluate whether app usage significantly influenced the change in EL scores over time, and to assess the comparative effectiveness of personalized versus random app content. To identify statistically significant differences in EL improvement across groups, pairwise comparisons (Tukey HSD) and overall ANOVA tests were conducted on the score changes between the different time points.

6.2. Observation

Statistical analysis revealed significant improvements in EL scores from the initial to intermediate stage for both app intervention groups compared to the no-app group. Specifically, the no-app vs. profile group comparison yielded a mean difference of 1.423 ($p = 0.0083$), and the no-app vs. random group comparison yielded a mean difference of 1.5689 ($p = 0.0015$), both statistically significant. However, no significant difference was found between the profile and random groups ($p = 0.9595$), indicating similar short-term effectiveness. From initial to final assessment, the profile group maintained a significant improvement over the no-app group (mean difference = 1.4063, $p = 0.0156$), while the random group showed only a marginal effect ($p = 0.055$). Again, no significant difference was found between the profile and random groups at the final stage. The statistical summary confirms these patterns, with significant overall differences observed from initial to intermediate ($p = 0.0004$) and initial to final ($p = 0.008$), but not between intermediate and final stages ($p = 0.5461$) (Figure 12. Differences in energy literacy scores between groups.).

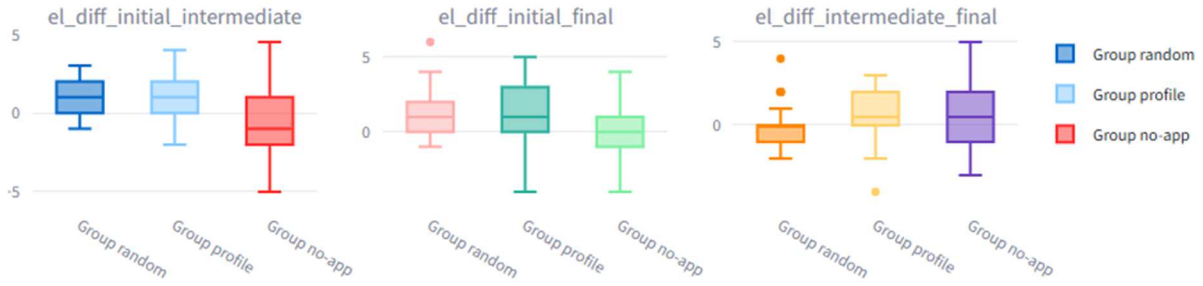


Figure 12. Differences in energy literacy scores between groups.

6.3. Explanation

H4.1 is partially validated. The results suggest that both app interventions effectively enhanced energy literacy in the short term, with the most substantial gains occurring

between the initial and intermediate assessments. The lack of significant improvement from intermediate to final stages implies that most of the learning occurred early in the intervention. While both the personalized and random content apps improved EL compared to no intervention, the profile-based approach showed slightly more sustained effectiveness over time. However, the absence of a statistically significant difference between profile and random groups suggests that the added value of personalization, while promising, may be modest or context-dependent. These findings underscore the potential of mobile interventions to drive short-term educational gains and highlight the need for further research to optimize long-term engagement and impact through personalization.

7. Hypothesis #5: Usage of the application increases flexibility

7.1. Introduction

To investigate whether engagement with the app is associated with increased behavioural flexibility, we analysed user actions categorized under various flexibility domains. Flexibility was binarized (high vs. low) based on the mean value of responses. A survival analysis was conducted to explore whether **higher flexibility scores** correlated with **greater retention** in the app.

As described in the experimental protocol in section 1, we also assessed **flexibility behaviours** across participants at the end of the pilot and used statistical tests to determine whether specific types of flexibility were more likely to differ between groups.

Additionally, we explored the **relationship between targeted content and flexibility outcomes**, linking specific content types to improved behaviours in flexibility categories such as self-consumption, smart grid interaction, and ecofriendly gestures.

7.2. Observation

7.2.1. Flexibility behaviours

We first identified two groups of users based on their flexibility scores, using the overall average obtained for all participants: a first group with users having flexibility scores below the overall average, and a second group with users having flexibility scores above the overall average. The survival analysis then revealed three significant results about flexibility: users who have higher probability to keep using the app see their flexibility increasing, in agreement to delay car (manually), dryer, and washing machine.

Table 3. Statistical Significance of Flexibility Behaviours at End of the Pilot.

	Variable	p-value	Significant
1	finalFlex.flex.car_delay_by_user	0.0107	Yes
4	finalFlex.flex.dryer_delay	0.0114	Yes
8	finalFlex.flex.washingmachine_delay	0.0247	Yes
2	finalFlex.flex.dishwasher_delay	0.2632	No
7	finalFlex.flex.heat_switch_by_user	0.4223	No
6	finalFlex.flex.heat_switch_by_grid_operator	0.4996	No
9	finalFlex.flex.washingmachine_start	0.5388	No
5	finalFlex.flex.dryer_start	0.6477	No
3	finalFlex.flex.dishwasher_start	0.7951	No
0	finalFlex.flex.car_delay_by_operator	0.8492	No

Table 3. Statistical Significance of Flexibility Behaviours at End of the Pilot.) presents the results of statistical tests assessing the significance of different flexibility behaviours measured at the end of the pilot. Each row corresponds to a specific action, with p-values indicating whether differences observed across groups or conditions are statistically significant (threshold: $p < 0.05$). Three behaviours emerged as statistically significant:

- User-initiated delay of EV charging (**`car_delay_by_user`**, $p = 0.0107$)
- Delay of dryer usage (**`dryer_delay`**, $p = 0.0114$)
- Delay of washing machine usage (**`washingmachine_delay`**, $p = 0.0247$)

These results suggest that participants were more likely to engage in **voluntary postponement of appliance use**, particularly for high-energy devices where the timing of operation is more flexible. Such actions may have been facilitated by the awareness and prompts delivered through the app, especially in cases where personalised content or nudges supported user autonomy.

In contrast, no statistically significant effects were observed for other actions, including **start-time shifts**, **heat switching**, or **flexibility actions triggered by the grid operator**. This indicates that **externally managed or automated flexibility** was less frequently adopted or accepted by participants, potentially due to concerns over control or convenience.

Overall, the findings underscore the relevance of designing flexibility programmes that prioritise **user-initiated actions** and clearly communicate the benefits of shifting consumption, particularly for appliances that are already perceived as adaptable within daily routines.

7.2.2. Usage of targeted content vs Energy Literacy

Figure 13. Usage of targeted content vs Energy Literacy.) displays the average improvement in energy literacy scores (from initial to final) for participants based on the **type of content received**. Each bar represents the mean difference in energy literacy (`el_diff_initial_final`), comparing participants who **received** a specific content type (green bars) to those who **did not** (red bars).

The checkmark (✓) indicates content types for which the difference in improvement was **statistically significant**, suggesting that exposure to this content had a meaningful positive impact on participants' energy literacy. Notably, content related to tumble drier and washing machine (**TDandWM**) showed the strongest effects. Smart charging and energy transition also show important differences, but these are not significant and can be interpreted as trends. This highlights the importance of tailoring app content to specific topics that most effectively support users' learning and engagement.

Figure 13. Usage of targeted content vs Energy Literacy.

7.2.3. Targeted content by group

Figure 14. Targeted content by group (personalisation).) illustrates the average energy literacy (EL) improvement, segmented by **content type** and **intervention group** (*profile* vs. *random*). Each content category represents a thematic area addressed in the app (e.g., flexibility, grid actors, heating), and the bars compare the mean improvement in EL scores from initial to final for users in the **profile group** (dark blue) and the **random group** (light blue).

The data reveal that for all content types shown, participants in the **profile-based intervention group** consistently demonstrated **greater gains in energy literacy** than those in the random content group. The largest differences are observed in **flexibility**, **grid actors**, and **power grid** content, suggesting that **personalized delivery of targeted content** enhances the impact of energy education—especially for topics that may require more contextualization or trust-building.

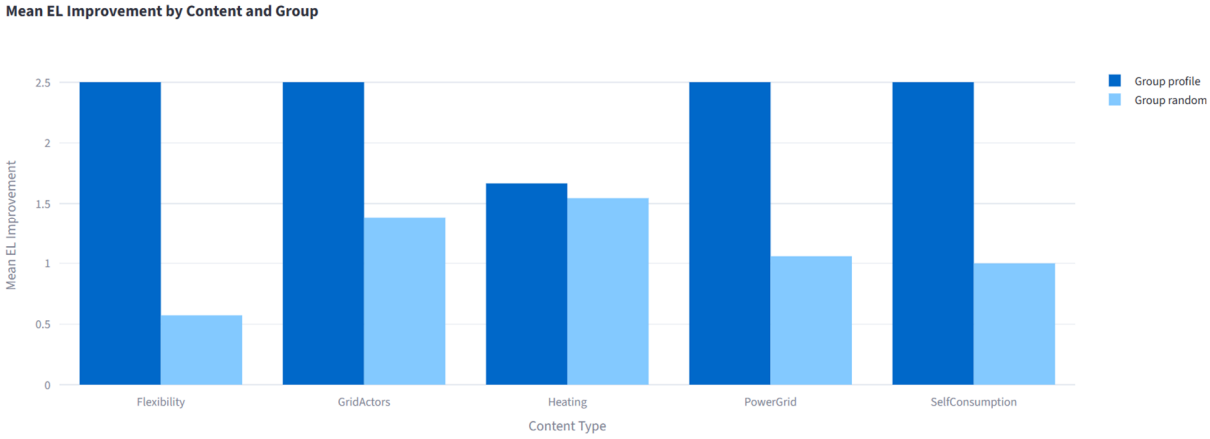


Figure 14. Targeted content by group (personalisation).

7.2.4. Usage of targeted content vs Flexibility

Table 4. Usage of targeted content vs Flexibility.) highlights the content types that were **significantly associated with improved flexibility behaviours** at the end of the intervention.

For each content theme (e.g., eMobility, Grid Actors, Self-Consumption), specific user actions—such as delaying appliance use or shifting start times—were evaluated. A result marked "Yes" indicates that participants who received the corresponding content demonstrated **statistically significant improvements** in the targeted flexibility behaviour ($p < 0.05$).

- Ecofriendly gestures: in the app we suggest the use of the delaying features of appliances, to do it overnight or sunny hours.
- Grid actors: getting to know Creos and other grid actors may increase trust and therefore make people more likely to accept control or shift consumption if suggested.
- Smart grid: also linked to trust, Creos knows more via the smart meters which help monitor, forecast, and manage energy use more efficiently.
- Self-consumption: shifting appliance usage to increase self-consumption can reduce household emissions and energy bills.

Table 4. Usage of targeted content vs Flexibility.

Content	FinalFlex_Variable	Significantly_Better
eMobility	finalFlex.car_delay_by_operator	Yes
eMobility	finalFlex.car_delay_by_user	Yes
GridActors	finalFlex.dishwasher_start	Yes
GridActors	finalFlex.dryer_delay	Yes
SelfConsumption	finalFlex.dryer_delay	Yes
ecofriendlygestures	finalFlex.dryer_delay	Yes
GridActors	finalFlex.dryer_start	Yes
GridActors	finalFlex.washingmachine_delay	Yes
SelfConsumption	finalFlex.washingmachine_delay	Yes
SmartGrid	finalFlex.washingmachine_delay	Yes
ecofriendlygestures	finalFlex.washingmachine_delay	Yes
GridActors	finalFlex.washingmachine_start	Yes

The findings show that:

- **eMobility content** was linked to significant improvements in **EV charging delay** (both user- and operator-initiated).
- **Grid actor content** was associated with greater flexibility in the use of **dishwashers, dryers, and washing machines**—including both delay and start behaviours.
- **Self-consumption** and **ecofriendly gesture content** promoted meaningful increases in **dryer and washing machine delay**, suggesting effectiveness in encouraging sustainable scheduling habits.

- **Smart grid messaging** also supported better flexibility regarding **washing machine delay**, potentially by reinforcing trust in grid-managed recommendations.

These results underscore the importance of **targeted, context-relevant messaging** in supporting behavioural change, particularly when content is aligned with appliances perceived as flexible and energy-intensive.

7.2.5. State transition in Energy Literacy.

Figure 15 displays the distribution of transition patterns (Declined, Improved, Stable) across the three experimental groups: *no-app*, *random*, and *profile*. Each bar represents the number of participants categorized into one of the three transition outcomes. A predominance of stable trajectories is observed across all groups, particularly in the *no-app* condition. The *profile* group shows a relatively balanced distribution between participants who improved and those who remained stable, whereas the *random* group shows very few instances of decline. These patterns suggest that the different experimental conditions may have varying influences on participants' trajectories over time.

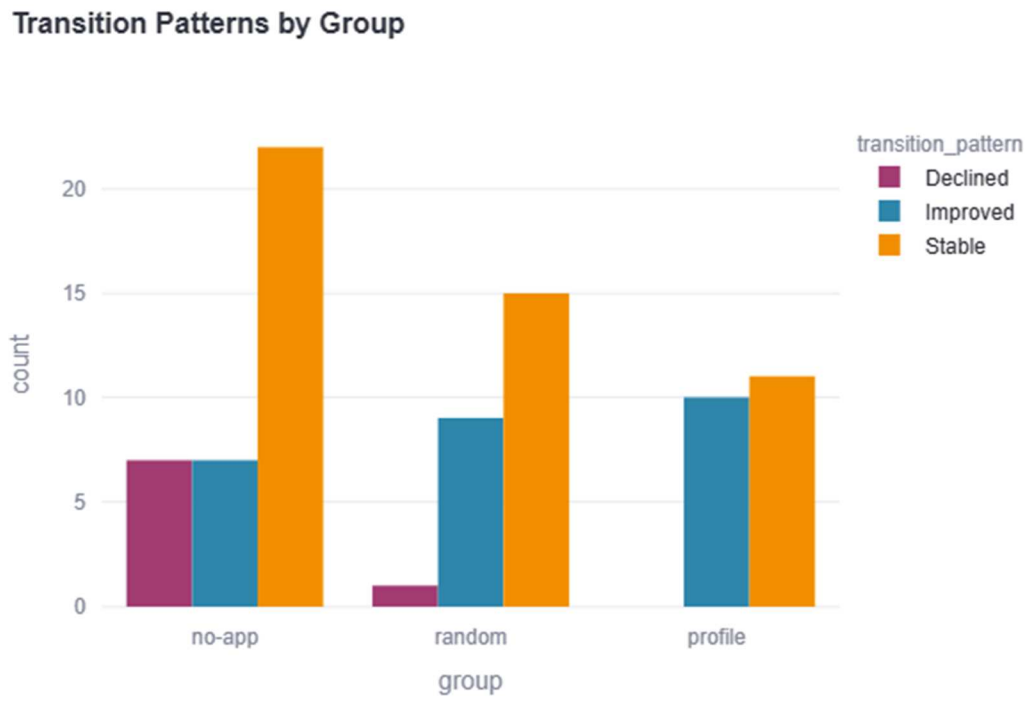


Figure 15. State transition in Energy Literacy.

The Sankey diagram (Figure

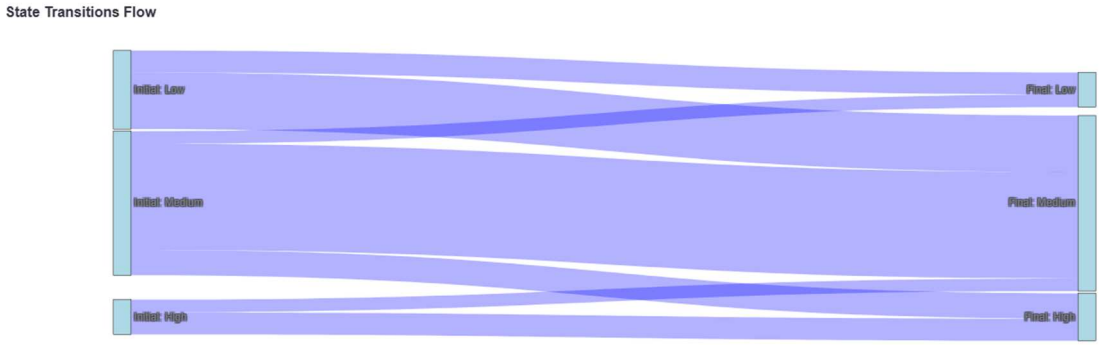


Figure 16) illustrates the flow of participants between initial and final states (Low, Medium, High), offering a dynamic view of how individual trajectories evolved across the study period. This visualization highlights the extent to which each group facilitated upward mobility. Notably, improvement rates varied substantially across groups: the *profile* group exhibited the highest improvement rate (47.62%), followed by the *random* group, while the *no-app* group showed the lowest rate of improvement (19.44%). These findings support the hypothesis that personalized or structured interventions may be more effective in promoting positive change than unstructured or absent interventions.

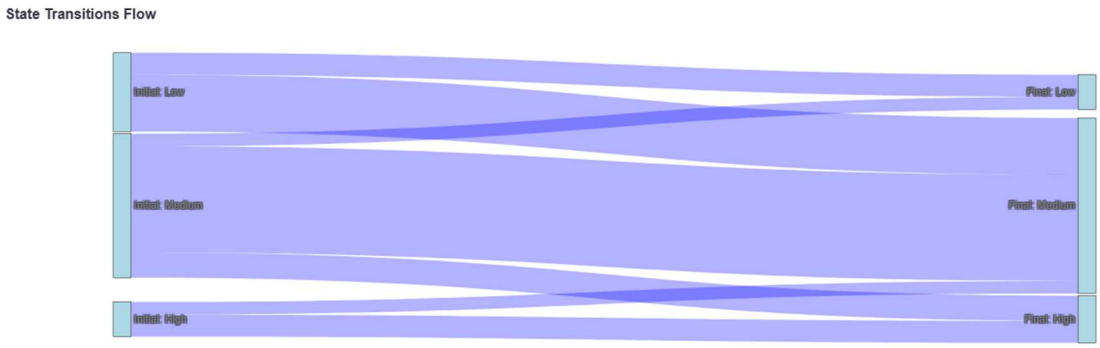


Figure 16. State transitions and improvement rates by group.

7.3. Explanation

H5 is validated, at least on specific cases. The results highlight that **user-initiated flexibility**, particularly for high-energy appliances, is more likely to improve with sustained app engagement. These actions—such as delaying the use of a dryer or EV charging—are easy to implement, carry no loss of comfort, and are **empowered by clear app-based messaging**, especially when personalized or linked to user autonomy.

On the other hand, **automated or grid-initiated behaviours** showed no significant changes. This may reflect a **trust or control gap**: users may be hesitant to adopt flexibility practices that appear imposed or opaque in terms of rationale. Communication that **builds trust in grid**

operators, or explains the personal and environmental benefits of such flexibility (as done in targeted content), could help bridge this gap.

In conclusion, these findings suggest that interventions should prioritize voluntary, user-driven flexibility behaviours while pairing them with context-aware, targeted messages to maximize adoption. Encouraging autonomy and clearly articulating the co-benefits of shifting consumption (e.g., lower emissions, reduced bills, grid resilience) are key for long-term behavioural change.

8. Hypothesis #6: Users like more content selected according to their psychological profile

8.1. Introduction

The psychological profiles of participants are characterised by three aspects:

- their sensitivity to environmental issues, measured using the Environmental Portrait Value Questionnaire (E-PVQ);
- their personality, defined using the 10-item Big Five Inventory (BFI-10) questionnaire;
- their affinity with technology, measured using the Affinity for Technology Interaction (ATI) questionnaire.

The analysis has been focused on the differences that may exist between the different psychological profiles for **groups with different transition patterns in terms of energy literacy**:

1. group whose participants have a stable energy literacy score over time (measured at the start of the pilot phase, after 7 weeks and after 15 weeks at the end of the pilot);
2. group whose score improved
3. group whose score declined.

The objective of this analysis was to determine whether psychological factors play a role in either of these groups.

8.2. Observation

Psychological profiles, in terms of environmental sensitivity (measured by the E-PVQ) (Figure 17), affinity with technology (measured by the ATI) (Figure 18) and personality (measured by the BFI-10) (Figure 19), **do not show significant differences according to progression** (declined/stable/improved): the distribution of scores in each of the observed variables stays similar. Therefore, it is not the psychological profile that plays a role in progress, but rather **the use of the mobile application**.

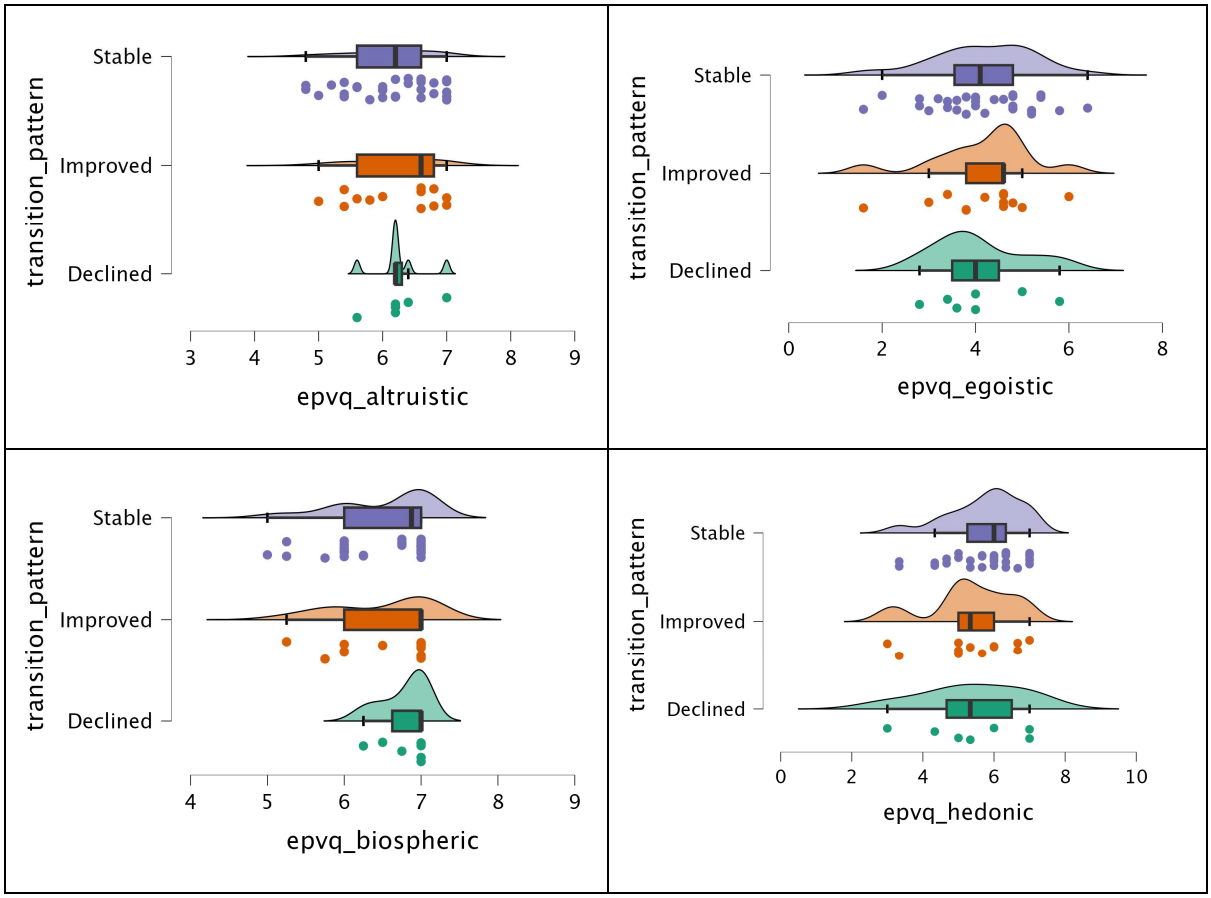


Figure 17. Distribution of scores on the E-PVQ questionnaire according to the type of transition in terms of energy literacy.

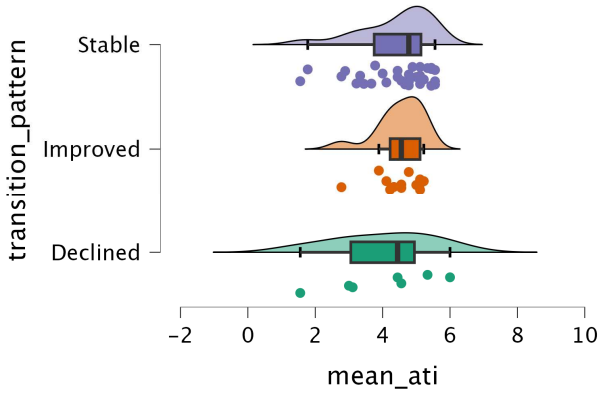


Figure 18. Distribution of scores on the ATI questionnaire according to the type of transition in terms of energy literacy.

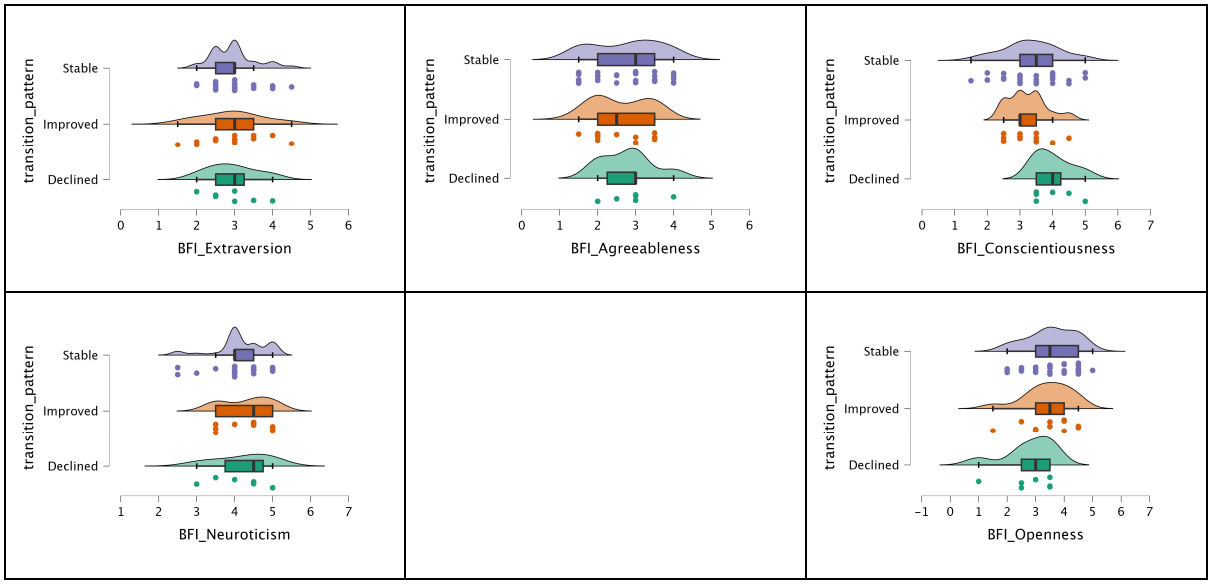


Figure 19. Distribution of scores on the BFI-10 questionnaire according to the type of transition in terms of energy literacy.

8.3. Explanation

The analysis of psychological profiles –based on environmental sensitivity (E-PVQ), personality traits (BFI-10), and affinity with technology (ATI)– revealed no significant differences between participants whose energy literacy scores declined, remained stable, or improved. This suggests that psychological traits alone do not explain the observed progression patterns in energy literacy over the course of the study.

Rather, the differences in participant trajectories appear to be more closely linked to the **type of content exposure**, specifically the use of the mobile application and the nature of content delivery (personalized, random, or absent). These findings provide support for hypothesis H6, which posits that users prefer content tailored to their psychological profile. While the profiles themselves do not predict improvement, **the interaction between the profile and the system delivering the content** –notably in the *profile-based condition*– may have facilitated higher engagement and better outcomes.

In this context, psychological profiles can be understood not as **direct predictors of progress**, but as **moderators** that interact with the intervention format. This is particularly evident in the higher improvement rates observed in the *profile* group (47.62%) compared to the *no-app* group (19.44%). The effectiveness of content aligned with users' values, personality, and technological preferences may thus rely less on the profiles per se and more on **how well these profiles are leveraged** to personalize and deliver relevant content.

9. Conclusion, future work, and practical implications

9.1. Conclusion

The pilot phase of the FlexBeAn project demonstrates that psychologically informed digital interventions can meaningfully enhance both energy literacy and behavioural flexibility among household users. The One2Day mobile application, by delivering daily educational content and behavioural nudges –especially when tailored to user characteristics– proved effective in driving positive change.

Participants who engaged with the app, particularly in the personalized content group, showed greater improvements in energy literacy and voluntary flexibility behaviours (e.g., delaying high-energy appliance use). These findings support the value of personalization not necessarily to extend engagement duration, but to enhance the quality and impact of interactions.

Importantly, the analysis revealed that psychological profiles –while not directly predictive of improvement– acted as useful moderators when used to adapt content. This insight confirms the potential of adaptive systems to better align interventions with users' needs and preferences.

Moreover, the results highlight that adapting content to users' existing energy literacy level, environmental awareness, and preferred communication formats (e.g., informational texts, quizzes, or calls to action) can further increase the effectiveness of such nudging strategies. Personalized multimedia content, tailored to cognitive and motivational traits, proves more impactful in fostering behavioural change.

Despite these promising results, several limitations point toward areas for further research and refinement:

- Sustaining engagement: The progressive drop in participation highlights the need to investigate strategies that maintain user interest and motivation throughout longer interventions.
- Optimizing personalization: Future work should explore how to balance depth of personalisation with content variety to avoid user fatigue or redundancy.
- Expanding behavioural scope: Additional flexibility behaviours –especially those less visible or more automated (e.g., grid-initiated actions)– require further examination, particularly regarding user acceptance and trust.
- Integrating trust-building communication: As trust emerged as a key factor in flexibility uptake, future designs should test content that strengthens understanding and confidence in energy providers and automated systems.
- Scalability and real-world application: Pilot results must now be validated in broader, more diverse user populations to assess generalizability and policy relevance.

- Measuring and segmenting users by their energy literacy level and environmental attitudes should also be prioritized, as it enables content to be tailored more precisely and increases the relevance and impact of energy awareness strategies.

In summary, the pilot offers a solid foundation for advancing user-centric demand-side flexibility strategies. By combining behavioural science, personalization, and mobile technologies, the FlexBeAn project provides a scalable model to empower households in the energy transition.

A well-targeted and psychologically grounded nudging approach –based on accurate user profiling– appears as a promising lever to support both literacy and behavioural flexibility in the context of smart energy systems.

9.2. Practical implications

For Creos, as the national distribution system operator involved in this pilot, the findings carry direct operational and strategic relevance. The study shows that users are more willing to engage in flexibility actions when they are voluntary, clearly communicated, and perceived as beneficial. This highlights the need for flexibility actors (suppliers, aggregators or grid operators), to develop user interfaces, communication strategies, and control mechanisms that are transparent and user-empowering.

The limited adoption of grid-initiated flexibility actions observed in the study signals a trust gap that relevant flexibility actors must actively address. While smart grid technologies and automation offer great promise for load balancing, their effectiveness depends on user acceptance. Flexibility actors should therefore prioritise communication strategies that clearly explain the rationale behind control requests, the safeguards in place, and the benefits for both the flexibility actors and the individual user.

Moreover, the positive results achieved through personalisation offer a strategic opportunity for flexibility actors to collaborate more closely with academic and technological partners to develop next-generation consumer engagement platforms. These could integrate grid data with behavioural segmentation to deliver real-time, tailored messages that align operational needs with user motivation.

Finally, the pilot demonstrates the feasibility of integrating behavioural interventions into the operational practices of a flexibility actor. With the appropriate regulatory support and investment in digital infrastructure, Creos could move from being a passive infrastructure manager to an active orchestrator of demand-side flexibility, enhancing resilience, efficiency, and sustainability across the Luxembourgish energy system.

10. Appendix #1. Statistical Methods

This study utilized several statistical methodologies to analyze data gathered during the pilot phase of the FlexBeAn project, aimed at investigating energy literacy (EL), participant engagement, and energy flexibility. Many methods have been used during the investigation. However, only some of these methods answered to most of our questions.

10.1. ANOVA (Analysis of Variance)

Analysis of Variance (ANOVA) was employed to determine if statistically significant differences existed in energy literacy scores across different experimental groups (profile, random, no-app). The general ANOVA equation is:

$$F = Between-group\ variability\ /\ Within-group\ variability$$
$$= [\Sigma\, n_j\, (\bar{x}_j - \bar{x})^2\ /\ (k - 1)]\ /\ [\Sigma\, \Sigma\, (x_{ij} - \bar{x}_j)^2\ /\ (N - k)]$$

Where:

- $\bar{x}_j$ is the mean of group j
- $\bar{x}$ is the overall mean
- k is the number of groups
- n_j is the number of observations in group j
- N is the total number of observations

10.2. Survival Analysis

Survival analysis techniques were used to examine participant engagement over time, particularly focusing on the probability of sustained app usage. The Kaplan-Meier estimator was applied to model survival functions, which estimate the probability S(t) of continued engagement at time t: $S(t) = \prod (1 - \frac{d_i}{n_i})$, for all $t_i \leq t$

Where: d_i is the number of events (dropouts) at time t_i and n_i is the number of individuals at risk at time t_i

10.3. Markov Chain State Transition

The progression of participants' energy literacy scores was analyzed using state transitions via a Markov chain approach. The Markov transition matrix P provides the probabilities of transitioning from one state to another:

$$P_{ij} = P(X_n + 1 = j\ |X_n = i)$$

Where: P_{ij} represents the probability of transitioning from state i to state j

10.4. Non-parametric Tests

Non-parametric tests, such as the Kruskal-Wallis and Mann-Whitney U tests, were employed to analyze data not conforming to normal distribution assumptions. The Kruskal-Wallis statistic H is calculated as:

$$H = [12\ /\ N(N+1)]\ \Sigma\ (\frac{R_j^2}{n_j}) - 3(N + 1)$$

Where:

- R_j is the sum of ranks in group j
- n_j is the size of group j

10.5. References

Field, A. (2017). Discovering statistics using IBM SPSS statistics. Sage.

Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. Journal of the American Statistical Association, 53(282), 457-481.

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). Cluster analysis. John Wiley & Sons.

These methods collectively provided a robust statistical framework to evaluate the impact of personalized content delivery and app usage on energy literacy and behavioural flexibility.

11. Appendix #2. Communication plan for participant recruitment

COMMUNICATION PLAN: FLEXBEAN PROJECT

BACKGROUND

In the framework of the **FlexBeAn project**, the partners aim to provide a comprehensive view of the behavioral aspects of energy consumers, focusing on their influences, knowledge, and motivation regarding flexibility provision. The **One2Day app**, currently in its beta testing phase, offers consumers tailored quizzes on energy flexibility. While raising awareness about good practices to reduce environmental impacts and save energy, this pilot project collects valuable data on consumer habits and knowledge. This data advances understanding and informs appropriate actions.

CAMPAIGN OBJECTIVE

Raise awareness among consumers and Luxembourg citizens about the importance of energy flexibility for achieving both energy savings and environmental benefits.

KPIS:

- **Awareness:** Evaluate shifts in stakeholder awareness through post-campaign surveys and quiz answers.
- **Reach:** Measure reach via media coverage, the number of external mentions or shares, and the number of quiz participants (excl. identified consumer pool).
- **Engagement:** Track website traffic, social media interactions, and returning users on the One2Day app.

TARGET AUDIENCE

- **Primary:** Luxembourg citizens
- **Secondary:** CREOS consumers
- **Tertiary:** Businesses and organizations involved in energy management and sustainability

KEY MESSAGE

- **Energy Flexibility saves money and resources:** Highlight how adopting flexible energy consumption practices can lead to tangible savings for individuals while reducing strain on energy grids.
- **Empowering individuals to make a difference:** Showcase how personal behavioural changes, guided by the One2Day app, contribute to environmental protection and energy system sustainability.
- **Science-Driven solutions for a greener future:** Underline the importance of the FlexBeAn project in gathering actionable data to drive innovative and effective energy policies.

CAMPAIGN TIMING

Type	Actions	Target audience	Timing
Social media	Instagram & FB stories on fun-related facts and the One2Day platform	Primary/Secondary	02.2025
Social media	LinkedIn sponsored ad on the One2Day app	Primary/Secondary	12.2024
Social media	Video (YT-FB – Insta) on the FlexBeAn project	All	03.2025
Web	LIST.lu news on the global / aggregated results	Primary	TBD

LINKEDIN SPONSORED CONTENT

💡 Ever wonder how our energy system adapts to #renewableenergy?
Balancing energy use with renewable sources like solar and wind is key to energy savings and environmental protection. The One2day platform, developed as part of the FlexBeAn project by LIST in collaboration with @SnT and @CREOS, helps you explore this balance while offering tips to make both smarter and greener energy choices.
Join our daily quiz to see how you can optimize your habits and help Luxembourg become a leader in #sustainableenergy 👉 https://lnkd.in/eYUJB7C7
#energyflexibility #energysystem #greenenergy

INSTAGRAM CONTENT

The partners will be mentioned directly in the stories. Publication is scheduled for the first or second week of February. Confirmation will be sent by e-mail.

Story 1: The Energy Myth Buster 1/2

Text: "True or False: An empty freezer, if opened occasionally, consumes more energy than a full freezer.

Story 2: The Energy Myth Buster 2/2

Text: "💡 True! The less cold is stored in the food, the greater the air exchange when the freezer is opened. Cold air is lost, and warmer air then needs to be cooled down.
CTA: "Try One2Day!"

Story 3: Did you know? 1/2

Text: "Which appliance consumes the most electricity in an average 2-person household?

a. Electric cooker
b. Dishwasher
c. Washing machine

Story 4: Did you know? 2/2

Text: "1. Washing machine – 400kWh/year
2. Electric cooker – 250kWh/year
3. Dishwasher - 210kWh/year

CTA: "Discover tips and tricks—play the quiz!"

Story 5: Global fun fact 1/1

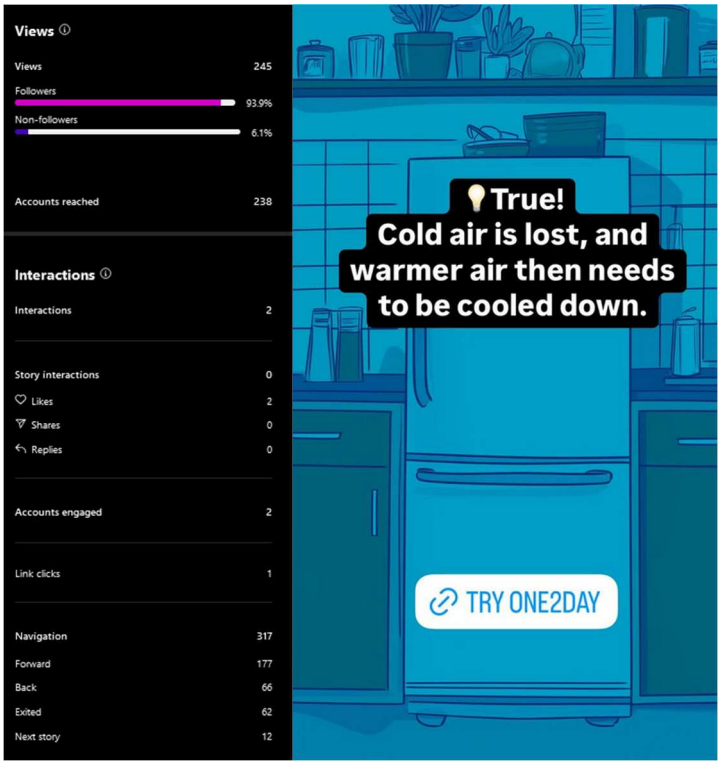
Text: 100 google searches would consumes about as much power as a 60-watt light bulb in 30minutes.

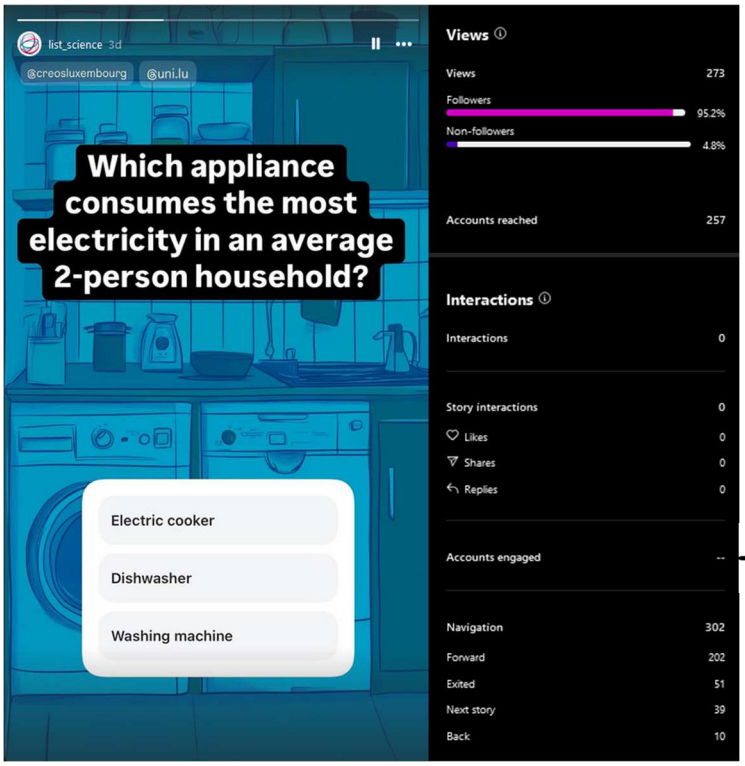
Story 6: Try One2Day 1/1

Short and dynamic explanatory story of the One2Day platform by Guillaume Gronier.
Shooting scheduled early February.

12. Appendix #3. Results and impact of the communication plan

Instagram

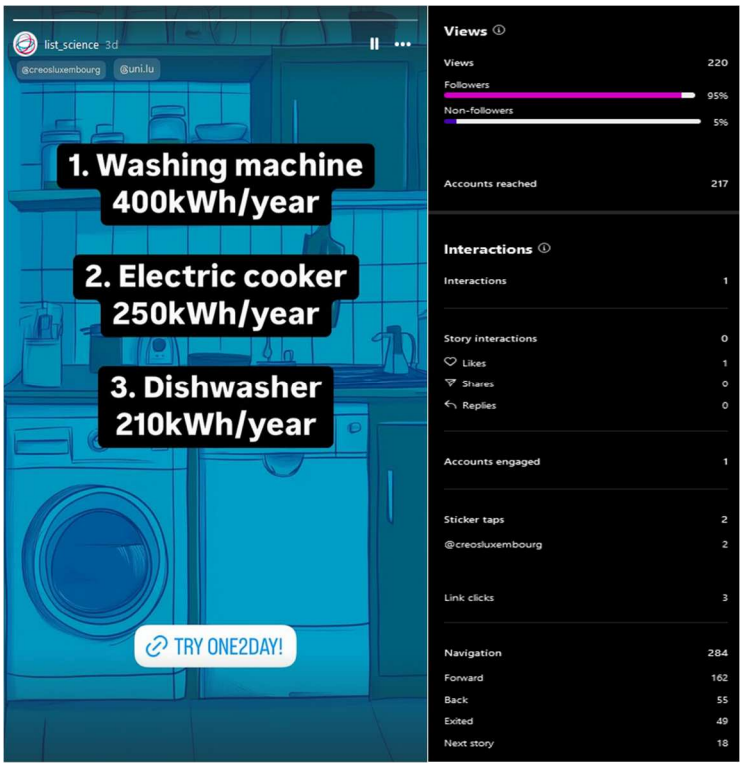


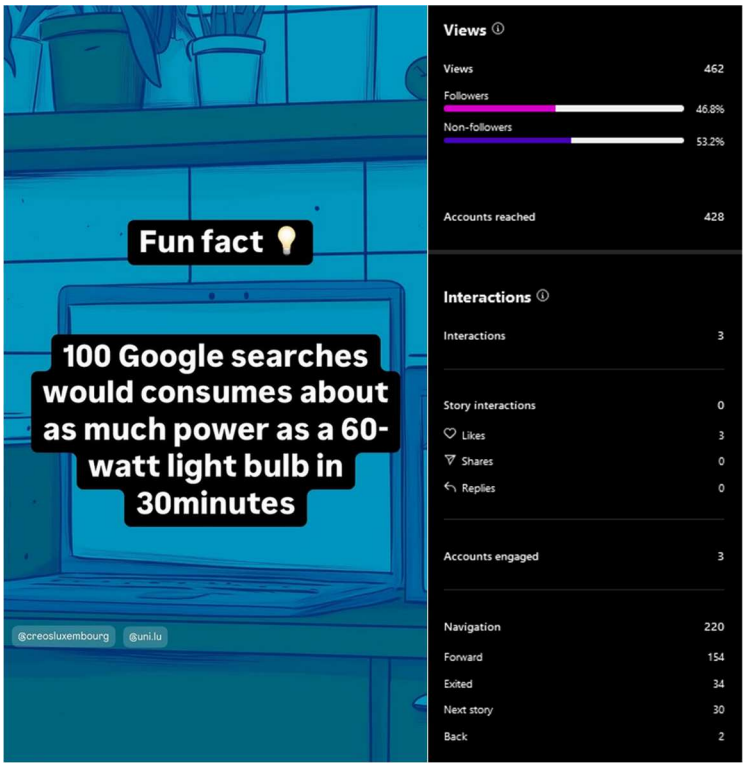


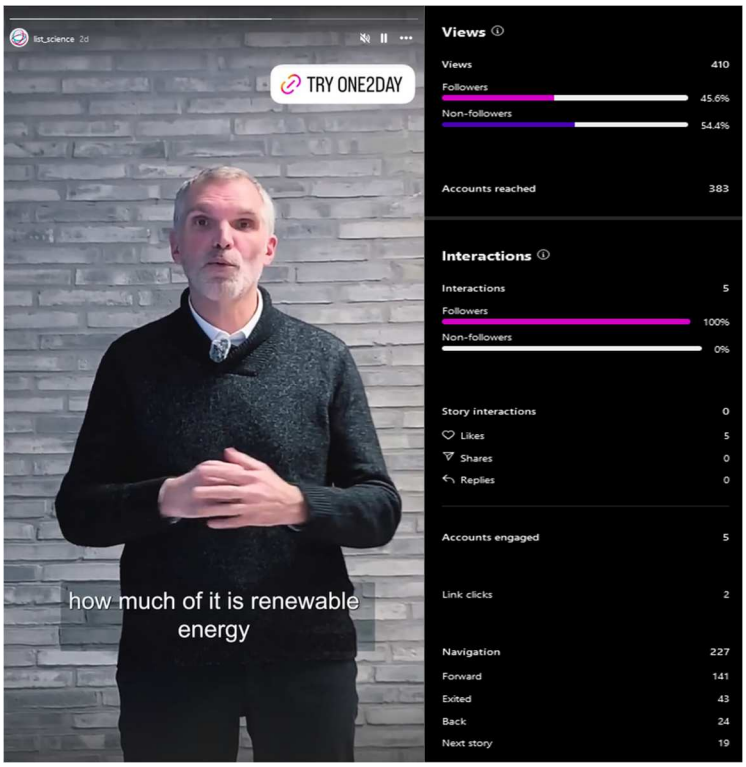
Electric cooker: 28 votes

Dishwasher: 11 votes

Washing machine: 23 votes

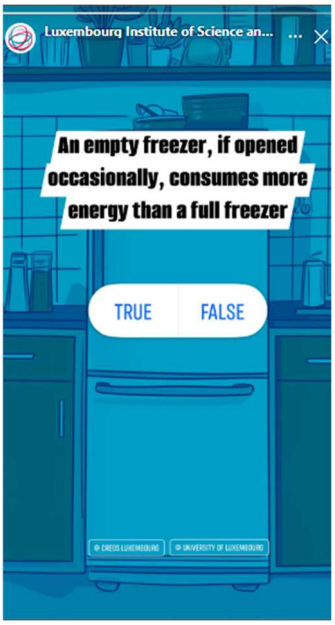




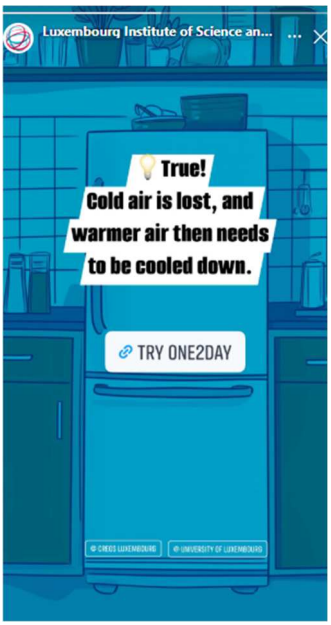


Facebook

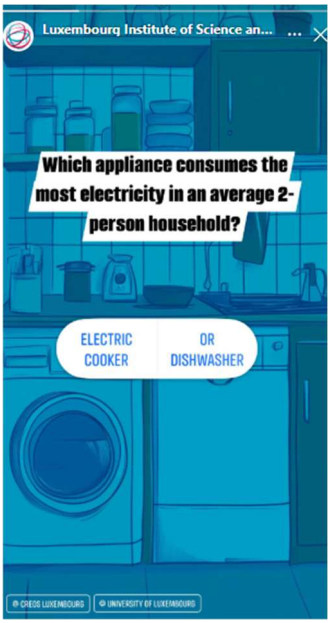
All stories were released on 20 February 2025.



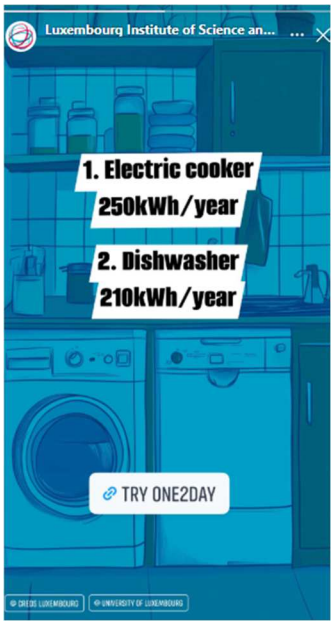
Couverture	56
J'aime	1
Commentaires	0
Partages	0
Impressions	56
Vues	68



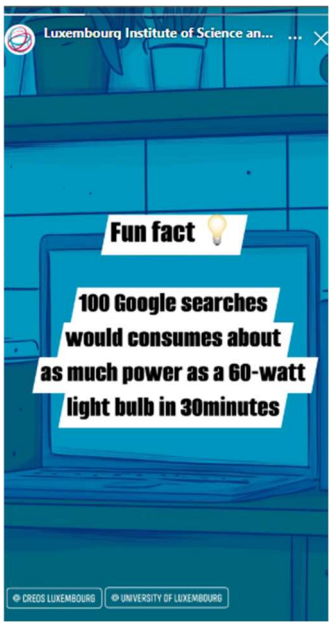
Couverture	39
J'aime	0
Commentaires	0
Partages	0
Impressions	39
Vues	49



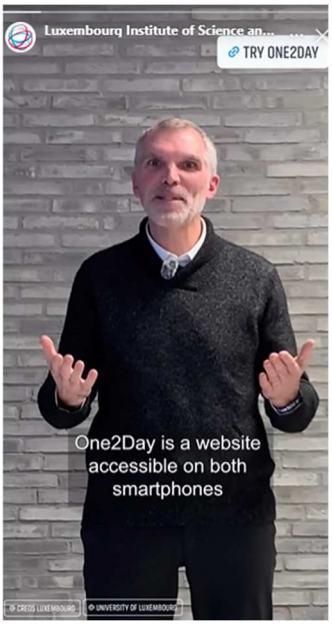
Couverture	29
J'aime	0
Commentaires	0
Partages	0
Impressions	29
Vues	37



Couverture	34
J'aime	0
Commentaires	0
Partages	0
Impressions	34
Vues	42



Couverture	28
J'aime	0
Commentaires	0
Partages	0
Impressions	28
Vues	35



Couverture	27
J'aime	0
Commentaires	0
Partages	0
Impressions	27
Vues	33

Appendix #4. Initial survey

Sociodemographic questions

1. **What is your gender?**
   - Woman
   - Man
   - Non-binary
   - Prefer not to disclose

2. **How old are you (value in years)?**
   - Select a choice

3. **What is your country of residence?**
   [Drop-down menu with Luxembourg in first position, then below, separated by a line, the border countries - Germany, Belgium, France - and Other].

4. **Which highest degree of education do you have?**
   - No school diploma
   - Middle School and Highschool
   - General Educational Diploma (GED) / Vocational training
   - Bachelor's degree
   - Master's degree
   - Doctoral degree

5. **What is your household monthly net income? (yours and other adults incomes combined)**
   - < 1000 €
   - 1000-2999 €
   - 3000-4999 €
   - 5000-6999
   - 7000-8999 €
   - ≥ 9000 €
   - Prefer not to disclose

6. **How many people live in the household?**

   [number]

7. **Do you live in your own house/apartment or rent one?**
   - I am an owner
   - I am a renter

8. **What is your household type?**
   - Apartment
   - Detached house
   - Semi-detached house

- Row house (attached to another house on both sides)
- Other, please specify: *Enter other household type*

9. **Do you have a Smarty+ dongle?**
   - Yes
   - No
   - I don't know what it is
   - I plan to buy one

Energy appliances and usage

1. **Is your household participating in our "Smarty+ campaign"?**
   - Yes, we are registered under the following email address: *Enter your email address*
   - No, we are not participating

2. **Which of the following devices are regularly in use in your household?**
   - Washing machine
   - Tumble dryer
   - Electric water heater
   - Fridge
   - Deep freezer
   - Dish washer

3. **Do you have a heat pump?**
   - Yes
   - No
   - No, but we plan to buy it in the next 3 years

4. **Do you have an electric water boiler?**
   - Yes
   - No
   - No, but we plan to buy it in the next 3 years

5. **Is your household owning or using an electric vehicle?**
   - Yes
   - No
   - No, but we plan to buy it in the next 3 years

6. **Does your household have a photovoltaic (solar panels) installation?**
   - Yes, with a battery storage system
   - Yes, without battery storage system
   - No
   - No, but we plan to buy it in the next 3 years

7. **Overall, do you feel comfortable with technology?**

   Not at all comfortable o o o o o o Absolutely comfortable

Values related to environmental behaviors and beliefs

This section focuses on your values related to environmental behaviors and beliefs.

You will find several brief descriptions of different people. For each person we describe what is very important to him or her. Please read each description carefully and indicate how much this person is like you.

The meaning of the scores is as follows:

- 1 means that the person is totally not like you
- 7 means that the person is totally like you

The higher the score, the more the person is like you.

There are no right or wrong answers. Answer spontaneously.

1. It is important to [him or her] to prevent environmental pollution.
   Not like me at all o o o o o o o Very much like me
2. It is important to [him or her] to protect the environment.
3. It is important to [him or her] to respect nature.
4. It is important to [him or her] to be in unity with nature.

Some questions about your personality

The following statements concern your perception about yourself in a variety of situations. Some personality aspects provide a better understanding of the behaviours related to energy flexibility.

For each statement, please indicate your level of agreement using a scale from 1 "Disagree strongly" to 5 "Agree strongly".

There are no right or wrong answers. Please answer spontaneously.

How well do the following statements describe your personality?

I see myself as someone who...

1. …is reserved
   Strongly disagree o o o o o Strongly agree
2. …is generally trusting
3. …tends to be lazy
4. …is relaxed, handles stress well
5. …has few artistic interests
6. …is outgoing, sociable
7. …tends to find fault with others
8. …does a thorough job
9. …gets nervous easily
10. …has an active imagination

Energy literacy

This part of the survey aims to assess your energy literacy.

Energy Literacy is an understanding of the nature and role of energy in the world and daily lives accompanied by the ability to apply this understanding to answer questions and solve problems.

1. **In general, from a household perspective, which period marks the time where the electricity consumption is the highest? (peak consumption hours)**
   - From 23:00 to 03:00
   - From 14:00 to 17:00
   - From 17:00 to 20:00
   - I don't know
   - I don't understand the question

2. **What is the impact if you largely increase your consumption during peak consumption hours (e.g. by charging your Electric Vehicle)?** *You can select maximum up to 3 choices*
   - There is no impact
   - Increased stress on the electricity grid
   - Provoking the necessity for electricity expansion works in the electricity grid
   - A shorter battery life time as batteries of smartphones, laptops or Electric Vehicles heat up more if charged during peak consumption hours
   - I don't know
   - I don't understand the question

3. **What are the benefits of shifting your consumption from peak hours to a time of day where the consumption is lower?** *You can select maximum of 3 choices*
   - Charging an electric vehicle, smartphone or laptop is faster
   - To have a lower electricity bill due to lower grid expansion costs
   - There is no benefit for the household consumer
   - Generally lower CO2 emissions because fewer gas power plants need to be deployed
   - I don't know
   - I don't understand the question

4. **Assuming there are a lot of Photovoltaic - PV (solar) installations in your neighbourhood. Are there any benefits of shifting your consumption from peak hours to a sunny time of day?**
   - Yes, it is important to consume the electricity when and where it is produced to prevent grid congestions
   - Yes, otherwise the electricity is lost as soon as it enters the grid
   - No, we can easily store all excess energy in summer and use it in winter

- No, the electricity can easily be transported over long distances, so it can be consumed elsewhere
- No, there is not a lot of electricity production during sunny weather
- I don't know
- I don't understand the question

5. **Do you know how to delay the start of your dishwasher?**
   - Yes
   - No
   - It does not have this function
   - I don't have a dishwasher
   - I don't understand the question

6. **Do you know how to delay the start of your Electric Vehicle charging?**
   - Yes
   - No
   - It does not have this function
   - I don't have an Electric Vehicle
   - I don't understand the question

7. **What challenges does the switch to 100% renewable electricity generation entail?** *You can select maximum of 4 choices*
   - Renewable energy generation is highly volatile (changes constantly)
   - Renewable energy generation is decentralized (a lot of small production plants instead of few large ones)
   - Difficult to store renewable energy
   - Difficult to align generation and consumption
   - I don't know
   - I don't understand the question

8. **This is an attention question, please tick "Yes".**
   - Yes
   - No
   - I don't know

9. **On average, when a device works for one hour, rank them from the highest (up) consumption to the lowest (below) consumption**
   - Dishwasher / laundry (4)
   - Tumble dryer (3)
   - 5 light bulbs, each at 10 W (6)
   - Electric Vehicle (1)

- TV and music player (5)
- Heat pump (2)

10. How much electricity does it take to fully charge an electric vehicle?

- 0.3 - 1 kWh
- 1 - 30 kWh
- 30 - 100 kWh
- 100 - 300 kWh
- 300 - 1000 kWh
- I don't know
- I don't understand the question

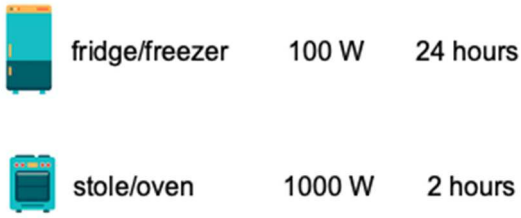
11. Do you know the amount of your monthly electricity bill? NB: Please indicate your best guess without checking your bill!

- No
- Yes, I pay approximatively: *Enter your bill amount €/month*

12. Which heating system would you prefer for your home, considering both have a 15-year lifespan?

- Model A with a retail price of €3750 and a monthly bill of €100
- Model B with a retail price of €5000 and a lower monthly bill of €80
- I have no preference, both models are equally adequate
- I don't know
- I don't understand the question

13. Which of these household appliances uses the most electric energy during one day?



- fridge/freezer
- stove/oven
- I don't know
- I don't understand the question

14. Which of these household appliances generates the highest peak power demand?


fridge/freezer 100 W 24 hours


stole/oven 1000 W 2 hours

- fridge/freezer
- stove/oven
- I don't know
- I don't understand the question

Flexibility questions

Would you delay the use of your washing machine if it was requested by Creos?
Would you allow Creos to control the start time of your washing machine if needed?

Would you delay the use of your dishwasher if it was requested by Creos?
Would you allow Creos to control the start time of your dishwasher if needed?

Would you delay the use of your tumble dryer if it was requested by Creos?
Would you allow Creos to control the start time of your tumble dryer
if needed?

Would you temporarily switch on or off your heating system if it was requested by Creos?
Would you allow Creos to switch on or off your heating system if needed?

Would you delay charging your electric vehicle if this was requested by Creos?
Would you allow Creos to delay the charging of your electric vehicle if needed?

Response scale: 0 = Strongly disagree, 1 = Disagree, 2 = Slightly disagree, 3 = Slightly agree, 4 = Agree, 5 = Strongly agree

